Three Essays on Crisis Management under Uncertainty

Drought, Climate Change, and Pandemic

by

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Abstract

This dissertation is a collection of three essays that studies decision-making under uncertainty in a crisis context.

The first essay examines the rational behavior of decision-making authority in providing water to a municipality facing drought. The forward-looking decision-making authority optimally chooses the size and time of building a desalination plant. The essay formulates the question as a dynamic programming problem with uncertainty in rainfall. By solving the problem numerically, the essay studies the behavior of the model through simulation. The correlation patterns produced by the simulations from the model are consistent with the correlation patterns observed in real-world data.

The second essay examines the interactions of three different green innovations to combat climate change. It revisits Jevons' paradox, which states that if demand is sufficiently elastic, an improvement in the fuel efficiency (FE) increases the flow of fuel consumption and, in the modern context of climate change, the flow of carbon emissions. An improvement in fuel efficiency also increases the stock of total carbon emissions. However, with carbon capture and storage (CCS), the effect on the total carbon emissions stock depends on the time pattern of emissions. Strong enough innovation in CCS reverses the paradoxical impact of FE. A similar (but reversed) logic holds for innovation in clean energy (CE) backstops. CE innovations reduce the stock of total carbon emissions. However, the improving CCS technology reduces the benefits of clean energy innovation, and strong enough, CCS reverses their beneficial impact.

The third essay examines the interaction of re-election pressure and asymmetric information in politicians' decision-making. Politicians and voters update their beliefs in a Bayesian way. Politicians have asymmetric information and seek re-election. The closer the election, the more the incumbent politicians refrain from implementing the welfare-maximizing policy and deviate towards their voting base's bias. The theoretical model's implications are tested with a dataset on gubernatorial decisions during the national Covid-19 crisis. A difference-in-difference empirical strategy shows that the governors who had an upcoming election in 2020 were biased towards their base. The Democrat and Republican governors who did not face a forthcoming election behaved statistically similar to each other.

Lay Summary

This thesis aims to provide a framework to improve our understanding of crisis management and decision-making under uncertainty. To achieve this goal, I studied three different crises and relevant decisions around those crises.

The first essay concerns local droughts and the decision of cities to install some water desalination capacity to combat drought. In the second essay, I studied the role of innovation in the fight against the global warming crisis. The last essay concerns the 2020 covid pandemic and the decisions of politicians to close down economic activity.

The contribution was to model different aspects of crisis decision-making and show the implications of uncertainty in different situations. It is possible to use some of the frameworks developed in this paper to study the behavior of decision-makers and measure the quality of their decisions.

Preface

Chapters two and four of this dissertation are my original independent work. Chapter three is joint work with one of my advisers, Professor Ralph A. Winter of the UBC Sauder School of Business. In this chapter, we collaborated on developing the propositions and their proofs. Part of this chapter is published as Siami, Winter (2021) in the journal Economics Letters under the title of "Jevons' paradox revisited: Implications for climate change."

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All the shortcomings in this thesis are mine.

Dedication

I want to dedicate my work to the memory of Herbert A. Simon. the genius who insisted that our rationality is bounded, yet we need to think about this limited rationality in a rational way, even though it may be limited.

Chapter 1

Introduction

This thesis is a collection of three essays that study decision-making under uncertainty in the context of a crisis. The first essay studies the dynamic decisions of municipal authorities to provide desalination plants to combat drought. In this essay, I try to answer this question, "What is the optimal time to build a desalination plant, and what is its optimal capacity when there is uncertainty in rainfall?" and test whether the behavior of municipalities matches the optimal predicted behavior. The second essay studies interactions of different exogenous green innovations and how they affect the long-term cumulative greenhouse gasses in the biosphere and combat climate change. In this essay, my coauthor and I try to answer this question,"In the absence of the first-best policy of emission pricing, how does green innovation affect the total cumulative emission?" and shed light on the optimal second-best policies. The third essay studies the decisions of gubernatorial authorities to limit economic activities to combat the pandemic. In this essay, I address this questions, "How does the ballot box pressure affect the decisions of the politicians to limit economic activity" and find out "how the interaction of uncertainty and ballot box pressure can deviate politicians from implementing the welfare-maximizing policy."

The first essay examines the rational and forward-looking behavior of benevolent decision-making authority. The decision maker solves a dynamic programming problem with uncertainty in rainfall to optimally choose the size and time of building a desalination plant. We can observe correlation patterns between the model parameters and the time and size of building a plant through simulation of multiple scenarios. I test these patterns against the real-world data and show that they are consistent.

The second essay examines the effect of different green innovations and how they interact as a portfolio. Without correct carbon pricing, innovations are the second-best policies to fight the adverse effects of climate change. Economists have been aware of unintended consequences and paradoxical effects of green innovations, at least since Jevons. Jevons paradox states that if demand is sufficiently elastic, an improvement in the fuel efficiency (FE) of internal combustion engines increases fuel consumption flow and, in the modern context of climate change, raises the flow of carbon emissions. This paper revisits Jevons' paradox and show that an improvement in fuel efficiency increases the stock of total carbon emissions. However, if carbon capture and storage (CCS) is operating, the effect on the total carbon emissions stock depends on the time pattern of emissions. With strong enough innovation in CCS, the paradoxical impact of ICE efficiency is reversed. A similar (but reversed) logic holds for innovation in clean energy backstops. Clean energy innovations reduce the stock of total carbon emissions on their own. However, an improving CCS technology reduces the benefits of clean energy innovation, and when strong enough, CCS can reverse their beneficial impact.

The third essay examines the interaction of re-election pressure and asymmetric information in decision-making under uncertainty by politicians. Politicians and voters form their beliefs and update their information in a Bayesian way. Politicians have asymmetric information and seek re-election. This paper shows that given exogenous information structure, election timing interacts with the decision quality of the politicians. The closer the election, the more the incumbent politicians refrain from implementing the welfare-maximizing policy and deviate toward their voting base's bias. Moreover, endogenizing the politicians' information gathering leads to a higher level of information asymmetry between the politicians and voters. The theoretical model's implications are tested with a dataset on gubernatorial decisions during the national Covid-19 crisis. A difference-in-differences empirical strategy shows that the governors who had an upcoming election in 2020 were biased towards their base. The Democrat and Republican governors who did not face a forthcoming election behaved similar to each other statistically.

Economists use uncertainty to describe a situation where an agent, a player, or a decision-maker has imperfect information relevant to their decision-making objective. The source of uncertainty may be natural (as in the realization of next month's rainfall or realization of global warming), or it could be about other agents' beliefs and actions. This thesis studies both of these situations.

Another distinguishing dimension between different uncertainty classes is whether the uncertainty is quantifiable (risk) or non-quantifiable (Knightian). On one end of this spectrum lies the perfectly quantifiable uncertainty, where all possible outcomes and the probability of each realization are perfectly known beforehand (like rolling a dice). On the other end of this spectrum is the idea of a fundamental degree of ignorance, a limit to knowledge, and an essential unpredictability of future events. I used the term Uncertainty in this thesis to refer to a quantifiable degree of imperfect knowledge.

In the first essay, the primary source of uncertainty is the unpredictability of rainfall, and I assume that the decision-maker knows the distribution of rainfall. In the second essay, uncertainty comes from the fact that innovation is not predictable. Although I model innovation with a Poisson process of a known magnitude that reduces the price of an input, the results are more general and do not depend on this quantification for expositional purposes. In the final essay, the source of uncertainty is how events unfold, and people's beliefs evolve about specified actions. The underlying model is a Poisson process of known characteristics, but the results are more general like the second essay.

The results will hold if people's beliefs converge to the truth over time.

In this essay, the crisis is used to describe a situation where the public and decision-makers believe that inaction (or status quo) leads to severe difficulty for the public with a relatively high probability. These challenging situations give unique opportunities to study the public decision-making process. The decision-makers are under pressure to make decisions without having all the necessary information. Since the stakes are perceived to be high, we expect decision-makers to pay much attention to these decisions. Moreover, a crisis occurs in a time of heightened uncertainty, making it much more essential to study crisis management under uncertainty.

In the first essay, a city faces a drought crisis, and the planners have to decide whether or not to build a desalination plant to combat that risk. The second paper concerns the climate change crisis and how innovation affects the long-run climate outcome. The final essay concerns the Covid crisis and the political decisions to contain the virus spread.

All three chapters tackle the same fundamental question of crisis management under uncertainty, though the methodologies vary widely. Although the science of decision-making is at least as old as the ancient Greeks, the application of various mathematical and computational tools to everyday decision-making is relatively young, and the field suffers from a lack of consensus among its practitioners. One group of practitioners, mainly computational economists and rational expectation theorists, emphasize the role of probabilistic rational dynamic models to explain the optimal behavior of decision makers directly. With the recent progress in computation power and the computational tools developed around it, more scientists are attracted to this camp of thinking about decision-making under uncertainty. The first essay of this thesis is primarily in line with the concerns and standards of this field—the first model detailed aspects of the decision-making problem at hand. Then try I solve the model that resembles reality as much as the computational power allows and compare the model's predictions with what is observed in the real world to see if there is a good match between the models and reality.

Another group of practitioners, mainly empirical economists and applied theorists, believe that many real-world limitations play an essential role in decision-making. Therefore, an indirect approach to the problem is necessary. For example, in many cases, even though the first best solution is clear, it is impossible to be implemented due to complex political and psychological biases. The second essay is in line with this style of thinking. In this essay, we assume the first-best policy (carbon pricing) cannot be implemented without analyzing the underlying political reasons. Therefore, instead of studying the dynamics of the interaction between the environment, economy, and decision makers, we focus on one measure of environmental variables (cumulative emissions in the biosphere) and study the effect of one set of economic variables (an innovation portfolio). There is ample scientific evidence that cumulative emissions are a good predictor of the long-term effect of climate change, and in this paper, our focus is on long-term decision-making under uncertainty.

The third group of practitioners, primarily political economists and industrial organization theorists, focuses on the incentives of the decision maker and aims to model a specific behavior of a decision maker, rather than to assume that the decision maker is benevolent or it actually solves the problem we expect a benevolent decision maker to solve. The third essay is in line with this kind of thinking. Politicians, who are supposed to act quickly in an uncertain environment of international crisis (e.g., pandemic), look at their electoral incentives and makes decisions that maximize their chance of re-election, rather than maximizing social welfare.

These three essays tackle the problem of decision-making by finding an optimal solution in a simplified world. For the sake of completeness, I must add that in contrast to these ways of thinking, there is also a fourth group of practitioners, primarily behavioral and experimental economists, who put an emphasis on the limitations of human rationality. They study psychological biases, heuristics, and actual behaviors of decision makers to make a satisfactory decision in a more realistic and complex world. In this thesis, I do not study this important approach to decision-making.

Chapter 2

Markovian rainfall and Desalination Demand

2.1 Introduction

Water shortages have caused significant problems throughout history. At present, many cities struggle with water supply problems, especially in areas where droughts are common. Desalination, the technology that turns saltwater into freshwater, has become an important tool for ensuring adequate water supplies. As of 2019, more than 300 million people relied on desalination for some or all of their daily water needs.

However, desalination plants are costly to build and costly to operate. Therefore, building or expanding desalination capacity is an important and difficult decision for many political jurisdictions, especially because criticism of such decisions is commonplace. Sometimes current desalination capacity is insufficient to meet current municipal needs, and yet sometimes, costly excess capacity is left unused. One source of difficulty in making decisions is the underlying randomness of rainfall patterns. Merely observing ex post insufficient or excess desalination capacity does not necessarily mean that one has made poor decisions. Studying decision-making with rainfall uncertainty is the focus of this paper.

The main research question is whether the observed decisions are consistent with a rational expectation model of rainfall. First, I develop a model for how a rational decision maker provides desalination capacity optimally. Then I ask whether the actual records of desalination capacity construction are consistent with the model.

The decision to build some capacity depends on how this capacity will be used. Therefore, both aspects of building and operating the desalination plant are explicitly present in the dynamic model. The model is a dynamic programming problem with uncertainty in rainfall with numerous state and control variables. I solve the model numerically for given parameter values to obtain the capacity trajectory. Simulating the model for different parameter values and different realizations of the uncertainty provides the comparative dynamics needed to characterize the model numerically.

Then I compare the dynamics obtained from simulation with the dynamics observed in real-world desalination construction decisions. The time-series data consist of all the municipal desalination capacity built worldwide, the historical rainfall, temperature, population, and average GDP for more than 60 years. This comparison implicitly tests whether actual desalination decisions can reasonably match the outcome of a rational decision-making process.

The correlation dynamics produced by the model are consistent with the actual data on construction decisions. For example, one interesting property of the model is that the cities with higher variation in their rainfall patterns would, other things held equal, build more desalination capacity. A similar correlation is present in the data. Desalination works as an insurance instrument against probable unfavorable rainfall outcomes.

This analysis is consistent with the hypothesis that decision makers are, on average, approximating optimal decision rules. However, one advantage of explicit modeling of rational decision-making is that it can be expanded and used as a decision-making tool. The model is flexible enough to incorporate the data on the actual usage of the plant.

Section 2.2 contains a brief review of the related literature; section 2.3 summarizes the data, section 2.4 studies the theoretical model. Section 2.5 tests the theoretical model, and section 2.6 concludes.

2.2 Literature Review

This paper combines two aspects of inventory management and investment under uncertainty in the context of water provision with desalination. These aspects are unified in a single dynamic programming equation that takes short-run and long-run trade-offs into account. Therefore, the current paper is related to a broader literature in inventory management (e.g., Gustafson (1958), Samuelson (1971) , Scheinkman, Schechtman (1983), and Asche et al. (2015)) and investment under uncertainty which was pioneered by Lucas, Prescott (1971), Kydland, Prescott (1977), and Kydland et al. (1982).

The first application of dynamic programming to water management dates back to the works of Burt (1964), who studied the optimal allocation of groundwater. Tsur et al. (1991) improved on Burt's work and showed the value of groundwater as an insurance option (or, as they call it, a buffer) to surface water supplies. Truong (2012) studied the effects of water storage capacity on the agricultural sector.Xie, Zilberman (2018) showed the substitutability and complementarity patterns of water storage capacity and water use efficiency. This paper is the first to apply dynamic programming to water management with the option to build a desalination plant.

The literature on desalination plants has recognized the importance of desalination plants as an insurance strategy to mitigate the risk of drought (e.g., Schoengold, Zilberman (2007), Bensoussan, Farhi (2010), Clarke (2014)). Scholars have also studied factors that affect desalination demand (Ghaffour (2009), Ghaffour et al. (2013) , and Amy et al. (2017) and how to prepare for future capacity building (**?**. But a quantitative analysis of desalination as an insurance policy is missing from the literature.

This paper contributes to this literature by highlighting the role of uncertainties introduced by rainfall patterns and the trade-offs that municipalities face in their optimal choice. Here, I develop a framework for studying the optimal timing of construction and optimal size of desalination plants.

Many economists used dynamic programming problems with continuous decision variables and inequality constraints to model optimal timing problems (e.g.,Deaton (1991)). The standard way to deal with inequality constraints is to discretize the choice space to rule out any violation of the inequality constraint by design. This discretization increases the dimension of the state space, so it suffers from the curse of dimensionality.

Rendahl (2015) proposed the method of time iteration. This is a faster method based on the corresponding problem's Euler equation. This method is faster than traditional value function iteration methods when we need to discretize a continuous state space. In this paper, I implement the time-iteration algorithm to solve the dynamic programming model.

It is necessary to clarify the relationship between this work and relatively well-developed literature on dynamic choice models because this literature empirically studies dynamic decision making under uncertainty. The famous bus engine replacement model by Rust (1987) is suitable for comparing this literature and the current work. Rust estimated a dynamic discrete choice model by solving a fixed-point problem for every iteration of the estimation procedure because, for every iteration, a fixed-point problem has to be solved; his method suffers from the curse of dimensionality (meaning that the state space grows exponentially as the number of state variables increase).

Hotz, Miller (1993), Ai, Chen (2003), and Su, Judd (2012) allow the econometricians to sidestep one aspect of the curse of dimensionality. They directly estimated the value functions and inferred the model's parameters from the estimated value functions without the need to calculate a fixed-point problem on each iteration.

The current work contributes to understanding dynamic models in two ways. First, rather than estimating the parameters (or a family of non-parametric functions) of an underlying dynamic model, in this paper, I test whether or not the dynamics produced by the model match with the real-world data. Second, these models are data intensive. Multiple observations of each decision maker are necessary to estimate the underlying model. With the proposed simulation approach in this paper, there is not need to estimate each agent's behavior explicitly. Instead, I compare the collective patterns produced by the model's simulation and what is observed in the real-world data.

2.3 Data

The information on desalination plants is from the DesalData.com. This database has comprehensive information on all desalination plants built all around the globe. The geolocation of each plant, the building date, and information such as capacity, technology, and construction prices are variables of interest. There were 19,232 plants in the data as of March of 2017. I selected 3,262 plants in municipalities with a population of more than 300,000 in January 2017. This criterion narrows down the focus of this paper to municipal demand for desalination plants.

The data on the cities' population are from the population division of the United Nations. This dataset consists of information on the population of cities with a current population larger than 300,000. The geolocation of these cities is used to match each desalination plant with the corresponding city. A match happens if a desalination plant is within 100km of the city's centroid. If a desalination plant is within the boundaries of two cities, the closest city is chosen.

Table 2.1: Descriptive Statistics

Variable	Min.	Median	Mean	Max.
Capacity	1	1000	14388	880000
Nominal Prices	3.500e+04	1.170e+06	3.164e+07	1.800e+09
Population(/1000)	0.0	668.5	2064.6	35861.0
Average Rainfall	4.39	309.15	620.07	3452.37
Average Temperature	3.118	23.194	21.330	29.168
GDP per Capita	168	16094	20333	88565

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The data on rainfall are from the U.S. Department of Commerce—National Oceanic and Atmospheric Administration website. The data used in this paper are monthly average rainfall from 1900 onward on a 1° by 1° grid. Each city is matched to its closet grid. The monthly rainfall levels are summed up to provide the annual rainfall for each city. Long-term average rainfall (mean rainfall from 1900 to the present), the long-term standard deviation of rainfall, and each year's rainfall average are calculated and used in the analysis.

The data on temperature are from CRUTEM (Berkeley). The resolution of the data is similar to the rainfall data, and all the relevant variables are similarly calculated. The GDP per capita and populations are from World Development Indicators of the World Bank. I calculated the year-to-year GDP per capita from this source.

2.4 Demand

The theoretical framework for modeling desalination is a time-discrete dynamic programming problem. A benevolent central planning authority wants to provide water to a city. The planning authority faces a trade-off between two types of losses, population dissatisfaction, and monetary costs.

If it does not provide enough water, the population gets dissatisfied, and that incurs a loss. However, there are long-term and short-term costs associated with building and running the plant, respectively. In the long-term, the planning authority chooses how much desalination capacity to build. In the short run, it has to decide how much of the installed capacity to use.

There are three main mechanisms that derive the investment behavior and usage rate of the model: the trade-offs between utilizing the plant and not providing enough water, the trade-off between building the plant (and incurring a cost) now and running the risk of not having enough water, and the interaction of these trade-offs.

The first trade-off is easy to understand if we assume the city's optimal water need is constant and it has built all of its required desalination plants or cannot build any. In both situations, the planner acts similar to an agent that wants to smoothen its consumption over time. In the first case, if the planner's constraints bind, they will provide enough water such that the marginal utility of providing water in each period equals the marginal cost of providing desalinated water. In the second case, the planner acts like a consumer who maximizes its consumption utility intertemporally when its income is uncertain.

The second trade-off is easy to understand if we assume that the planner has to either provide a fixed amount of water to the municipality (if it has the water) and zero otherwise. This planner will not build a plant if there is enough water to provide next year no matter what the realization of rainfall is and would always build a plant if it does not have enough water to provide again no matter what the realization of rainfall. The planner is indifferent between building and not building if the expected value of not providing water equals the cost of building the plant. So there is a threshold amount of water in the reservoirs above which the planner would not build and below which would always build.

The interaction effect comes into play while cities have not yet transitioned to their steady-state equilibrium level of desalination capacity. Before transitioning to the equilibrium level of capacity, if the planner not only takes next-period water needs into account but also considers that if in this year they provide more water to the city or desalinate just enough water to meet this year's needs, then they increase the chance of having to build a plant in the following year. Therefore, before reaching the equilibrium levels, the planner desalinates more water and provides less water than if it had an equilibrium capacity level. This effect can only be captured in a dynamic programming framework.

2.4.1 Variables and Dynamics

Three state variables describe the dynamic programming problem:

1. K_t desalination capacity at the beginning of period t;
2. W_t water reserves available at the beginning of period t;
3. R_t rainfall in period t.

All these states are observable at the beginning of the period. After observing these state variables, the planner decides on three variables:

1. w_t^f amount of fresh water to provide;
2. w_t^d amount of desalinated water to provide;
3. x_t amount of capacity to build.

Define $S = (K_t, W_t, R_t)$ as the vector of state variables and $d = (w_t^f, w_t^d, x_t)$ as the vector of decision variables.

The state variables evolve according to three dynamic equations D_t. The evolution of capacity is deterministic; capacity in next period is the capacity from the beginning of this period plus the capacity built in this period. The plants are assumed to have an infinite life-time.

$$K_{t+1} = K_t + x_t \tag{2.1}$$

The evolution of water reserves is deterministic conditional on current period rainfall. Water reserves available during the period t (W_{t+1}) comprise the sum of current rainfall R_t, and water remained from the last period minus the freshwater provided.

$$W_{t+1} = W_t + R_t - w_t^f$$

This equation does not take water evaporation into account; therefore, the amount of reserves might diverge. Taking water evaporation into account, I modify the equation in the following way, where (θ) is the fraction of water that evaporates from the reserves:

$$W_{t+1} = (1 - \theta)W_t + R_t - w_t^f. \tag{2.2}$$

Rainfall follows a Markov distribution. For simplicity, we assume that rainfall can only have two states (h,l) with corresponding rainfall levels R_h, R_l. We denote the probability of remaining in state i by p_i. Finally, the transition matrix is given by:

$$\Theta = \begin{bmatrix} p_h & 1 - p_h \\ 1 - p_l & p_l \end{bmatrix}. \tag{2.3}$$

The first element in the first row of Θ is the probability that the state remains in high rainfall (p_h), and the second element is the probability of moving from high to low rainfall ($1-p_h$). In the second row, the first element is the probability of moving from low to high rainfall ($1-p_l$). The second element is the probability of remaining in the low rainfall state.

The variable R_t is known at time t. Its future value R_{t+1} is a probabilistic function of current value. Variation in rainfall is the only source of exogenous uncertainty in this model.

Equations 2.1, 2.2, and the Markov processes described in 2.3 constitute the dynamic equations. These equations fully describes the transition of the state $S_{t+1} = D_t(S_t, d_t)$.

2.4.2 Loss Function and Constraints

In each period, the planning authority incures a per-period loss of l_t. Its goal is to minimize the stream of discounted (β) expected losses subject to constraints ($G_t \geq 0$) and dynamics ($S_{t+1} = D(S_t, d_t)$).

$$L = \min_{d_0, d_1, \ldots} \sum_{t=0}^{\infty} \beta^t (\mathbb{E}_t[l_t]) \qquad s.t. \quad G_t \geq 0, \quad S_{t+1} = D(S_t, d_t) \tag{2.4}$$

In equation 2.4 $\mathbb{E}_t$ is the expectation conditional on the informations available at time t.

This per-period loss does not directly depend on time. It depends on time only through the state of the system (S_t) and the planner's decision (d_t) at time t. Therefore, it is possible to drop the t subscript on l and write is as a function of S_t, d_t:

$$l_t \equiv l(S_t, d_t). \tag{2.5}$$

The loss in each period consists of three terms.

$$l(S_t, d_t) = \underbrace{(\alpha P - (w_t^f + w_t^d))^2}_{1} + \underbrace{(FI(x_t \geq 0) + \kappa x_t)}_{2} + \underbrace{c w_t^d}_{3} \tag{2.6}$$

1. the loss of the planning authority from water underprovision;

2. the cost of building new desalination capacity;

3. the cost of using current capacity.

The first term in equation 2.6, P, represents population of the city. On average, each city targets α units of water per capita annually. The planner provides $w_t^f + w_t^d$ liters of water to the city dwellers. Any deviation from the target level gives the planner a quadratic loss. This damage is meant to be a convex function of the amount of under-provision. A second-degree polynomial simplifies the computation while preserves the convexity.

The second term in equation 2.6 concerns the cost of building new capacity. It costs κ to build one unit of capacity. The planner decides to build x_t units of capacity. F models the economies of scale, and I is the indicator function. If the planner chooses to build some capacity, they must pay a fixed cost to build the plant.

And finally, in the last term, it costs c to use one unit of an already built capacity. The last term is a linear function of the amount of provided desalinated water, which lies between zero and current desalination capacity.

Note that the loss function defined as a convex utility function incorporates many aspects of our perception when we think of water shortage. If available water is slightly below the abundance level (desired level), then society adopts simple measures to compensate for this: water efficiency and conservation technologies would be adopted (e.g., lower pressure tap and showers, reuse water for specific purposes), certain activities would be limited (no extravagance large fountain in the middle of a park), or water prices may increase. All of these incur some minor costs or cause a minor inconvenience.

At the mid-size level of water shortage, the government may start to import water, ban or severely limit certain water-consuming activities, or even enact some rationing measures. AT higher levels of water shortage, the government may limit the water supply to the bare minimum. Cities may start to leave cities, and people who remain may suffer diseases or even premature death due to water shortage. A convex utility function captures all of these effects in a relatively simple formulation.

The set of constraints ($G_t \geq 0$) limits the choice set of the planner.

1. $x_t \geq 0:$ the planner can only build new capacity and cannot reduce capacity.
2. $K_t \geq w_t^d \geq 0:$ The desalinated water cannot exceed current capacity, and it cannot be negative.
3. $W_t(1-\theta) + R_t \geq w_t^f \geq 0:$ The fresh water cannot exceed the water available, and it cannot be negative.

2.4.3 Bellman Equation and Solution Concept

To solve the stochastic dynamic programming problem, I first rewrite the loss function as a Bellman equation, then simplify it analytically, and finally use known quantitative methods to numerically solve it.

Let's start from the loss minimization problem of equation 2.4. Multiply both sides of 2.4 by a minus sign and define $V^*(S_0) \equiv -L$. This converts the problem to a maximization problem shown in equation 2.7.

$$V^*(S_0) = \max_{d_0,d_1,\ldots} (\sum_{t=0}^{\infty} \beta^t \mathbb{E}_t[-l_t]), \quad s.t. \quad G_t \geq 0, S_{t+1} = D(S_t, d_t) \tag{2.7}$$

$V^*(S)$, which we call ex ante value function (similar to **?**) plays an import role in setting up the Bellman equation. This function tells us intuitively the lifetime value of being in a state S. Bellman's principle of optimality allows us to translate the infinite horizon programming problem to a corresponding functional equation for the ex ante value function of **?**.

Bellman's principle of optimality states that the solutions of equation 2.7 is equivalent to the solutions of the functional equation 2.8, if some minimal assumptions are met (theorem 9.4 of **?**). Equation 2.8 is called the Bellman equation

$$V(S_0) = \max_{d_0} \Big(-l(S_0, d_0) + \beta \mathbb{E}(V(S_1)\Big) \quad \text{s.t.} \quad G(S_0, d_0) = 0, S_1 = D(S_0, d_0) \tag{2.8}$$

In our case the decision space is Euclidean ($d \in \mathbb{R}^3$) and $-l \leq 0$. Therefore, the conditions of theorem 9.4 of SL are satisfied. Hence, the solutions of equations 2.8 and 2.7 are equivalent. Intuitively, equation 2.8 tells us that one obtains the ex ante value of being in a state (before realization of uncertainties) by making the optimal decision to balance out the current utility and future expected continuation value.

Abstractly speaking, the Bellman equation maps from functional space (space of bounded functions from $\mathbb{R}^3$ to $\mathbb{R}$) to itself with the sup norm. Equation 2.8 is concisely written as $V = T(V)$, where T is the right-hand side of equation 2.8 for any S_0 including the constraints.

First, I need to show that this equation is a contraction mapping, meaning that the sup norm distance between two output functions of the functional will be smaller than the distance between any two input functions. This means that for any two functions V_1 and

V_2 there exists some $0 \leq k < 1$ such that

$$||T(V_1) - (V_2)||_\infty \leq k||V_1 - V_2||_\infty \tag{2.9}$$

I take advantage of the Blackwell sufficient condition to prove that the current Bellman equation is a contraction mapping. Blackwell Sufficient Condition states that (Theorem 3.3 **?**):

Let $X \subseteq \mathbb{R}^l$ and $B(X)$ be the space of bounded function $f : X \to R$, with a supnorm. T is a contraction mapping with modulus β if:

a. [Monotonicity] If $f, g \in B(X)$ and $\forall x \in X : f(x) \leq g(x)$, Then $\forall x \in X : (Tf)(x) \leq (Tg)(x)$

b. [Discounting] $\exists \beta \in (0, 1)$ such that $\forall f \in B(X), a \geq 0, x \in X : [T(f + a)](x) \leq T(f)(x) + \beta a$

It suffices to show that these monotonicity and discounting hold for the current Bellman equation and that the Bellman equation is bounded on $B(X)$. Let's clarify the correspondence between the variables in Blackwell sufficient condition and our problem:

$$X \subseteq \mathbb{R}^3, \text{is the space of state triplet } S := (K_t, W_t, R_t) \in X$$

$$B(X) : \text{the space of bounded functions on } X \to \mathbb{R}, V(K_t, W_t, R_t) \in B(X)$$

$$T := \max_{D_0}[u(D_0, S_0) + \beta p V(S_1(D_0) + \beta(1 - p)V(S_2(D_0))]$$

Proof.

[Monotonicity] :

$$V_1(S) \leq V_2(S), \quad \forall S \in B(S) \quad (*)$$

$$T(V_1(S_0)) = \max_{D_0}[u(S_0, D_0) + \beta p V_1(S_1(D_0)) + \beta(1-p)V_1(S_2(D_0))]$$

Define

$$\hat{D_0} := \arg\max_{D_0}[u(S_0, D_0) + \beta p V_1(S_1(D_0)) + \beta(1-p)V_1(S_2(D_0))]$$

$$T(V_1(S_0)) = u(S_0, \hat{D_0}) + \beta p V_1(S_1(\hat{D_0})) + \beta(1-p)V_1(S_2(\hat{D_0}))$$

from (*) :

$$T(V_1(S_0)) \leq u(S_0, \hat{D_0}) + \beta p V_2(S_1(\hat{D_0})) + \beta(1-p)V_2(S_2(\hat{D_0}))$$

Then using the definition of max, the RHS of last equation is smaller than the RHS of the following:

$$T(V_1(S_0)) \leq \max_{D_0}[u(S_0, D_0) + \beta p V_2(S_1(D_0)) + \beta(1-p)V_2(S_2(D_0))]$$

Therefeore,

$$T(V_1(S_0) \leq T(V_2(S_0))$$

Monotonicity is satisfied.

[Discounting]

$$T(V+a) = \max_{D_0}[u(D_0, S_0) + \beta p(V(S_1(D_0) + a) + \beta(1-p)(V(S_2(D_0) + a)]$$

$$T(V+a) = \max_{D_0}[u(D_0, S_0) + \beta p(V(S_1(D_0)) + \beta(1-p)(V(S_2(D_0)) + \beta a]$$

$$T(V+a) \leq \max_{D_0}[u(D_0, S_0) + \beta p(V(S_1(D_0)) + \beta(1-p)(V(S_2(D_0))] + \max_{D_0}(\beta a)$$

$$T(V+a) \leq \max_{D_0}[u(D_0, S_0) + \beta p(V(S_1(D_0)) + \beta(1-p)(V(S_2(D_0))] + \beta a$$

Discounting is satisfied.

[bounds]

V is bounded from above by 0 and it is bounded from below by $\dfrac{min(u)}{1-\beta}$ ■

Since it is established that T is a contraction mapping, the Banach fixed point theorem (Theorem 3.2 in **?**) guarantees that T admits a unique fixed point and that value function iteration converges to that fixed point.

The number of states and decisions are large (9 dimensions, 3 state variables, and 3 decision variables of period 0 and 3 state variables of period 1), so the curse of dimensionality makes the problem hard to solve numerically. We take three steps to make the problem manageable.

In the first step, note that the variable w_t^d only appears in the per-period loss function (l) and inequality constraints ($G \geq 0$). It does not appear in the dynamic equation ($S_{t+1} = D_t$). This allows us to take the derivative of equation 2.4 with respect to w^d and obtain the first-order condition.

We start from the Bellman equation 2.8 and use the Dynamic equation to replace $S_1 = D(S_0, d_0)$. We can specify the exact dependence of S_1 on S_0 and d_0 . This gives the equation:

$$V(S_0) = \max_{d_0} \Big(-l(S_0, d_0) + \beta \mathbb{E}(V(K_0 + x_0, (1-\theta)W_0 + R_0 - w_0^f, R_1)) \Big) \quad s.t. \quad G_0 > 0.$$

To get the F.O.C. for w_0^d, we must write down the Lagrangian with the inequality constraints.

$$\mathcal{L} = -l(S_0, d_0) + \beta \mathbb{E}(V(K_0 + x_0, (1-\theta)W_0 + R_0 - w_0^f, R_1)) + \lambda G_0$$

Then the F.O.C. would be given by the derivative of $\mathcal{L}$ with respect to w_0^d.

$$-\frac{\partial l(S_0, d_0)}{\partial w_0^d} + \lambda \frac{\partial G_0}{\partial w_0^d} = 0$$

Where the inequalities do not bind, we get $\lambda = 0$ and the following solution holds:

$$w_0^d = P - w_0^f - \frac{c}{2}.$$

If the inequalities bind, either $w_0^d = 0$ or $w_0^d = K_0$. Therefore, the final solution would be given by equation 2.10. This provides w^d as a function of only one state variable (K_t) and one decision variable (w^f).

$$w_0^d = \max(0, \min(K_t, P - w_0^f - \frac{c}{2})) \tag{2.10}$$

Therefore, by plugging the value of w_t^d (2.10) into the Bellman equation 2.8, we can reduce the dimension of the decision space from 3 to 2 (total dim: $9 \to 8$).

The next step is to get rid of the dynamic equation as a constraint. We can directly plug in the dynamic constraints (equations 2.1 and 2.2) to rewrite the Bellman equation as a function of state variables of this period and state variables of the next period. In this way, we eliminate one constraint and reduce the dimension of the problem from 8 to 6.

Although the problem is simplified significantly, the curse of dimensionality still prevents convergence in a reasonable time. For the contraction mapping to converge in a reasonable amount of time, the quality of the first guess becomes crucial: the better the initial guess, the lower the number of iterations.

To develop a reasonable initial guess, I develop an intuitive heuristic specific to the current problem that significantly helps find the starting point for the optimization. The idea behind this heuristic is intuitive and straightforward. It suggests that instead of having a planner that makes two decisions simultaneously, have two decision makers that take two independent decisions, taking the decision of the other decision maker as given.

This intuition behind this model is similar to the solution concept of a Cournot game. The first player takes the behavior of the second player as given and plays its optimal strategy. The second player does so by taking the behavior of the first player as given. By reiterating this process, the solution converges to the answer.

In the actual problem, the planning authority takes two related decisions. It decides on how much capacity to build in the next period and how much water to keep in the reservoirs.

The heuristic suggests that first, I fix the capacity and allow the first planner to find the optimal amount of water remaining in the reservoirs. This heuristic is a 2-dimensional dynamic programming problem, and it can be solved quickly, using conventional methods. I used time-iteration, which is usually faster than value function iteration in 2-dimensional problems.

After that, I let the second planner choose the optimal capacity to be built while taking the solution of the first planner as given. This problem is also 2-dimensional and easy to solve.

I am then to repeat these two stages by feeding the answer of each of them to the other one. After a few iterations, the result of this procedure serves as a starting point for the value-function iteration procedure. This procedure makes the algorithm converge faster in a reasonable number of steps by providing a suitable initial guess.

Figures 2.1-2.9 depict the behavior of some variables of the model as a function of current capacity and water reserves. These graphs are obtained for some specific parameters of the model, but they capture the important qualitative behavior of the model.

Figure 2.1 shows capacity building as a function of current capacity and water reserves. The population water target (P) in this model is 50, and the minimum rainfall is 40. The maximum amount of desalination must be smaller than 10, and we can see that it is between 8 and 9.

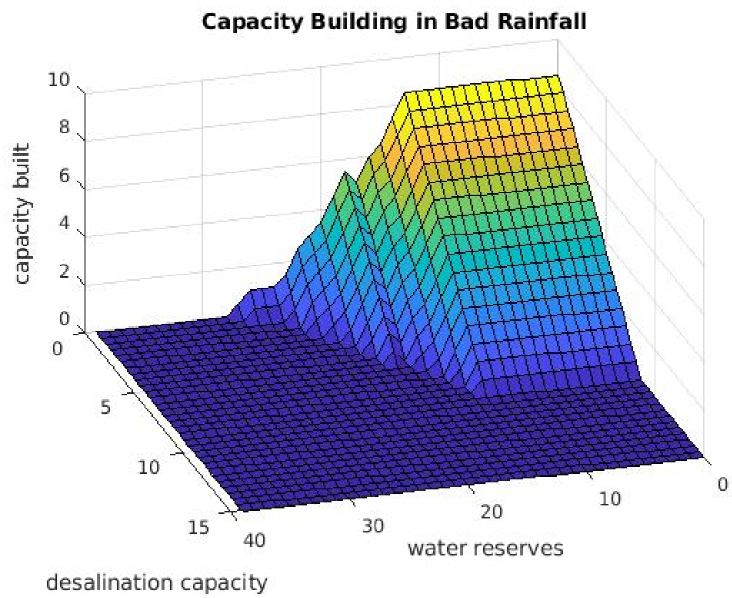


Figure 2.1: **Capacity building as a function of current capacity and water reserves during years with unfavorable rainfall**

Figure 2.2 shows that there would be no capacity building in the good rainfall years. Because in good years the rainfall is 65, which is much larger than the population water target ($P = 50$), it is not efficient to build capacity in good years. But this is not a general result, and for some parameters some capacity would be built even in the good years.

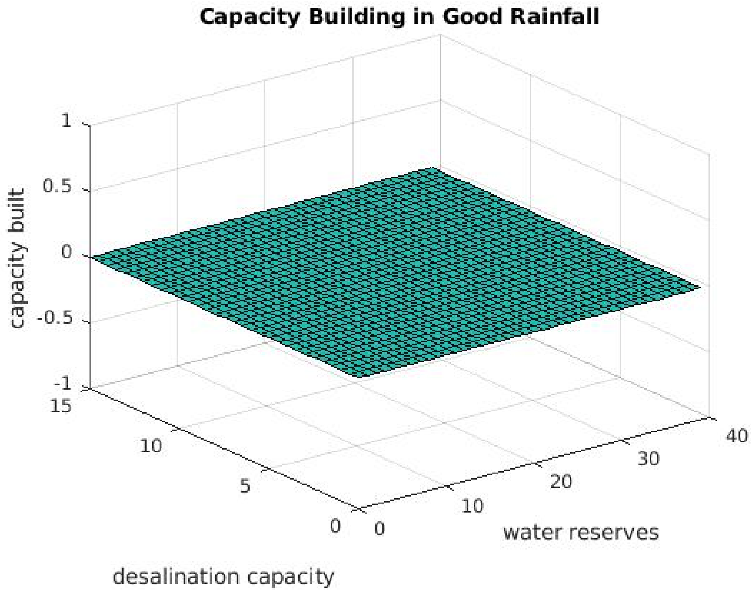


Figure 2.2: **No capacity would be built in years with favorable rainfall**

The first two figures showed capacity building, and the next two figures show the amount of next period water reserves for good and bad rainfall years. Generally, the amount of reserves will be higher in good years.

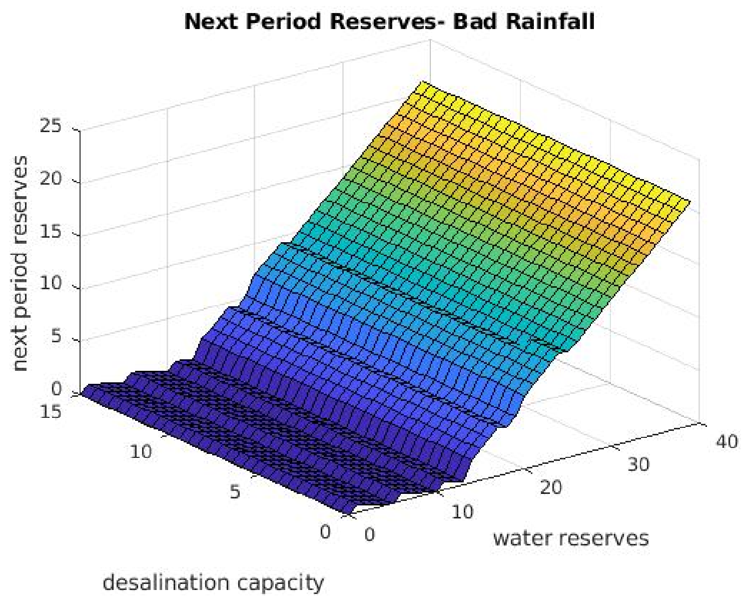


Figure 2.3: **With small fixed costs the reserves are independent from current capacity. The plot is for years with bad rainfall.**

For the parameters of this simulation, the amount of reserves are independent from the current capacity. This is not a general feature of the model. For high enough fixed costs, the reserves will depend on current capacity.

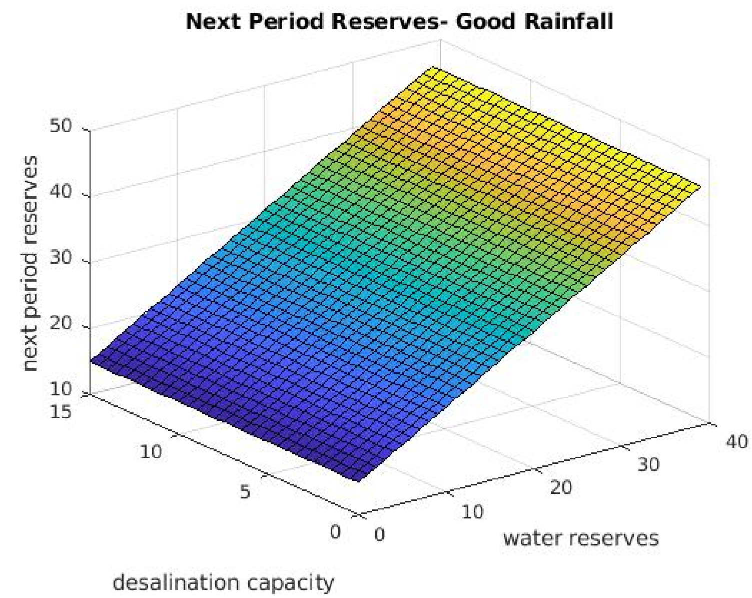


Figure 2.4: **With small fixed costs the reserves are independent from current capacity. The plot is for years with good rainfall.**

The fixed cost (F) and variable costs (κ) of building a plan in last two figures were relatively low. The next few figures show the behavior of the solution under these parameters.

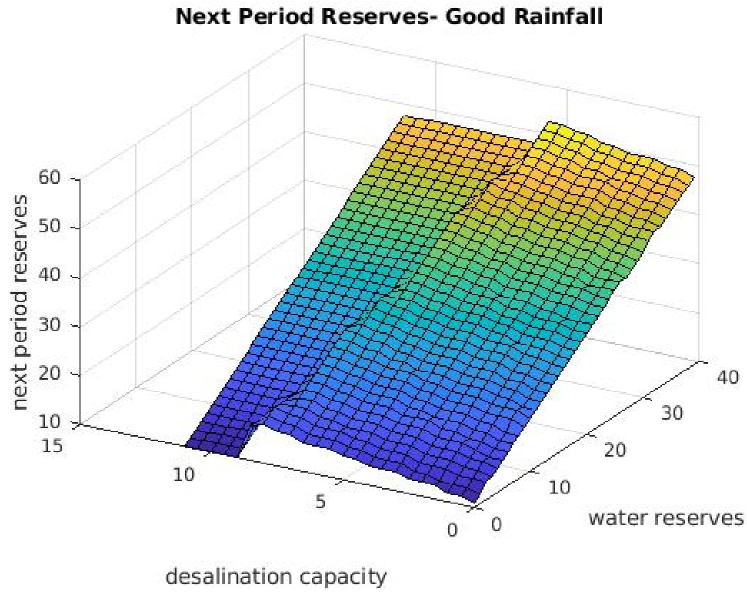


Figure 2.5: **For high enough fixed costs the reserves will depend on current capacity**

Figure 2.5 shows the 3-dimenstional plot of next period reserves for the case with high costs of building a desalination plant for good rainfall draws.

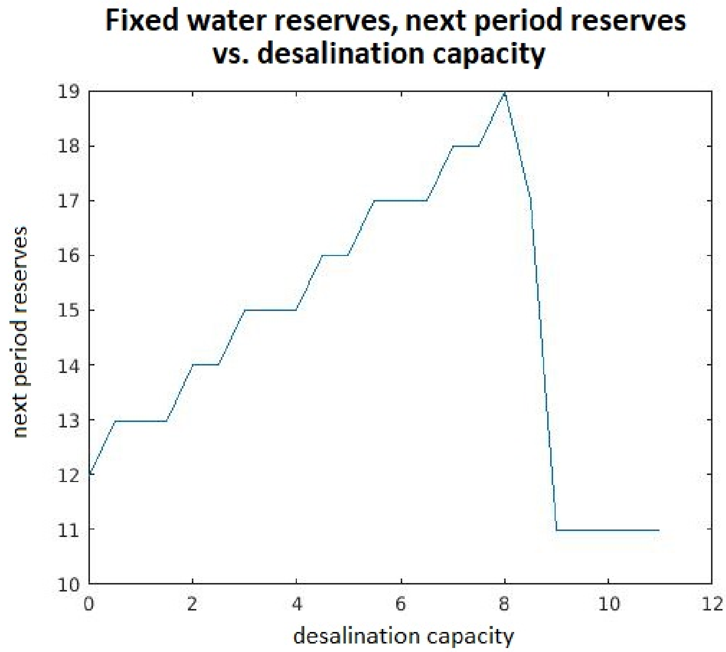


Figure 2.6: **Future water reserves vs. current capacity: for current capacity above 8.5 the decision maker would keep smaller reserves for the next period because there would be enough capacity even in a low rainfall realization.**

Figure 2.6 shows a slice of the 3-dimenstional plot in Figure 2.5. For a fixed level of current water reserves, future water reserves are plotted against current capacity. If the current capacity is high enough (above 8.5), the decision maker would keep smaller reserves for the next period because there would be enough capacity in the next period even in a low rainfall realization.

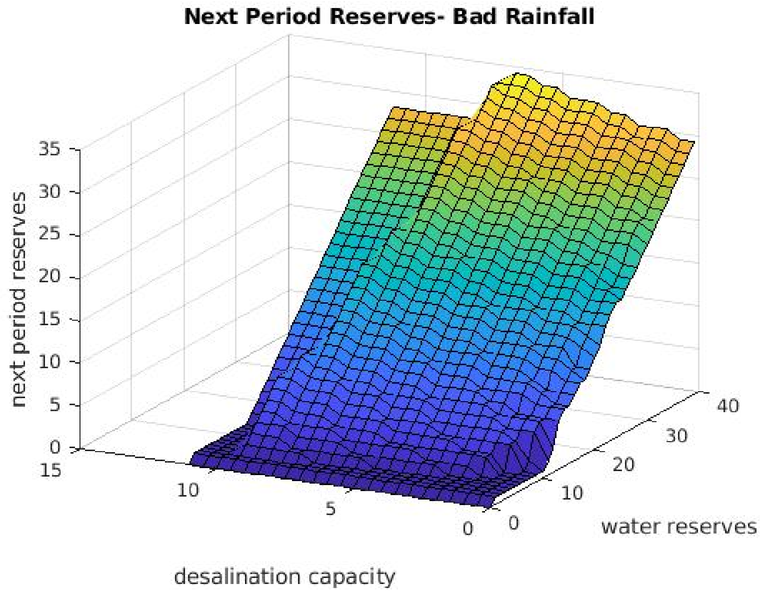


Figure 2.7: **Next period reserves in bad years are qualitatively similar to the ones in good years**

Figure 2.7 shows next period reserves for parameters similar to Figure 2.5 but for a bad rainfall realization. The results are qualitatively similar.

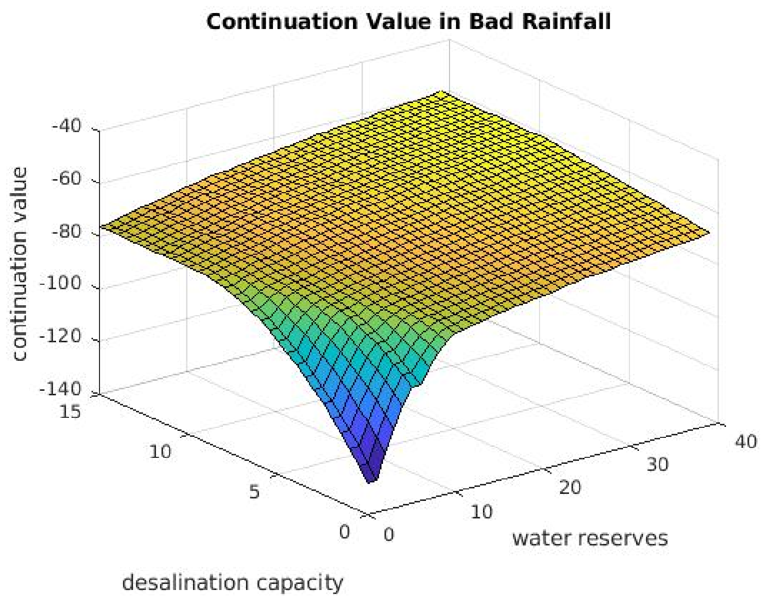


Figure 2.8: **In a year with bad rainfall if water reserves are low, not having enough desalination capacity is very costly**

Figures 2.8 and 2.9 show the continuation value function for both good and bad rainfall draws. The continuation value function is continuous. It is lower when the rainfall is bad becasue the municipality has to use desalination capacity or provide a less than ideal amount of water. For the same reasons, the function is smaller when there is less water reserves or less installed capacity.

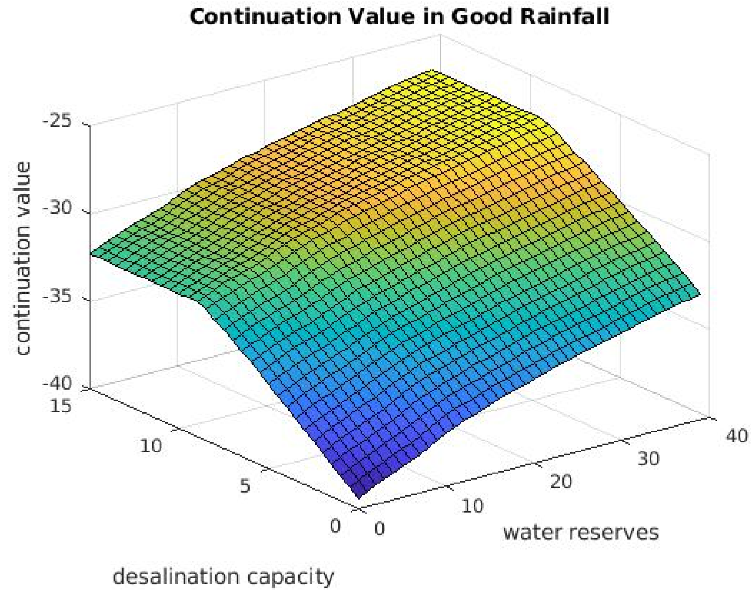


Figure 2.9: **In a year with good rainfall, when water reserves are low, not having enough desalination capacity is not as costly as good rainfall years, but it increases the probability of building a desalination plant soon.**

2.5 Testing the model

A theoretical model is a simplified version of reality. A model captures some essence of reality and neglects the rest. At this stage, I am primarily concerned about the qualitative implications of the model. Many simplifications have been made in the literature. For example, the dynamic programming model has only two possible states, yet I classified any year with below (above) median rainfall as bad (good). In reality, the decision maker might consider more than two states, or the criteria for good vs. bad year might be different.

There are other potential issues. It may be that transition probabilities from one state to another are not always Markovian, or the loss function of a municipality is different from my specifications.

The task is further complicated because, in our dynamic model, many variables are in principle observable to the decision maker, but the econometrician only has noisy proxies of the data. Table 2.2 shows what data the decision maker observes versus what data is available to the econometrician.

If the model is rich enough, and the econometrician simulates the model for many different parameters, it is possible to identify some correlations between the variables of the model's solution. These correlations should qualitatively match the correlations that we observe in the data. Note that the data is a noisy proxy of what the decision maker could observe.

What I do is similar to what empirical researchers do. They explain how a model behaves. Iin many cases, they do so verbally or symbolically. They make a quantitative prediction (e.g., signs of some parameters) in a regression model based on those explanations. Then by running a regression, they test the proposed hypothesis. Instead of verbally explaining the model, I propose and numerically solve a dynamic programming problem for multiple random parameters. Then I simulate numerous draws and develop a prediction for the signs of many observable variables in a separate regression with the real-world data. Then I run the regression with the data and test those hypotheses. Specifically, I solve the dynamic model for fifty different random parameters drawn from jointly normal distributions.

[H]

Table 2.2: Simulation Parameters

Variable	Model	Proxy
P	population	observed
R	volume of water made available by rainfall	average monthly rainfall in mm
θ	annual evaporation rate	average monthly temperature
σ_R	difference in average annual rainfall	sd of annual rainfall
α	water target per population unit	-
c	yearly cost of using capacity	-
κ	marginal cost of building more capacity	partially observed
F	fixed cost of building	partially observed
μ	conversion rate of waterunderprovision	GDP per capita

-

The parameters of the distribution are listed in Table 2.3. Some of these variables in the model have a corresponding variable in the real-world data. The variables in the real-world data are proxies for the variables in the theoretical model.

Table 2.3: Simulation Parameters

Variable	Proxy	Distribution
P	Population	N(50,5)
μ	GDP per Capita	N(1.5,5)
θ	average Temperature	N(0.2,0.02)
R	average Rainfall	N(50,10)
σ_R	sd Rainfall	N(5,3)
α	-	1
γ	-	0.1
f	-	1
F	-	0

-

Each solution of the model for these fifty different parameters represents one city. Each city goes through one hundred years of simulation stream. But this may introduce a spurious correlation because some cities may build desalination capacity early on, not because the parameters dictate that they are more likely to build early but because they randomly got bad initial rainfall draws. If each city gets multiple rainfall realization streams, we can capture a city's average behavior. Therefore, each city is simulated for 200 realizations. Eventually, there would be fifty distinct city types, 200 rainfall realizations streams, and a hundred years of simulation for each city-realization pair. Both the simulated data and the real data are panels, and each observation corresponds to one year for one city.

The simulated data contains information on the simulated endogenous variable (when and what capacity is being built) and respective parameters and timing of rainfall realizations. The goal is to compare the sign of coefficients in a regression with the simulated data and the real-world data. If the model is a good approximation of reality, we expect the regression results for both tables to have similar signs.

The empirical model that I use to compare the simulation data and real-world data is shown in equation 2.11. In the following model, U_i is a city-specific random effect, and ϵ_{it} is the error term distributed with 0 mean.

$$d_{it} = \beta_0 + \beta_1 P_i + \beta_2 R_{it} + \beta_3 \bar{R}_i + \beta_4 \bar{\theta}_i + \beta_5 \mu_i + \beta_6 \sigma_i + U_i + \epsilon_{it} \tag{2.11}$$

The regression Table 2.4 shows the coefficients of a random effect model 2.11 applied to the simulated data.

Table 2.4: Simulated Data, Random Effects

Capacity	Coeff.	std. error	t-Value
(Intercept)	0.47	0.077	6.08 ***
population	0.0121	0.0008	15.2 ***
relativerain	-0.59	0.03	-17.0 ***
ave Rain	-0.0128	0.0004	-31.0 ***
ave Temp	1.07	0.24	4.46 ***
GDP per capita	0.018	0.009	1.96 .
sd Rain	0.01595	0.0017	9.3 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Table 2.5 applies the same empirical model of equation 2.11 to the real data.

Table 2.5: Actual Data, Random Effects

Capacity	Coeff.	std. error	t-Value
(Intercept)	-2.55e+03	2.84e+02	-9.0 ***
Population	1.45e-01	3.8e-02	3.9 ***
relative rain	-5.39e+02	1.47e+02	-3.7 ***
ave Rain	-5.6e-01	1.7e-01	-3.4 ***
ave Temp	9.1e+01	1.5e+01	6.2 ***
GDP per capita	7.60e-02	4.3e-03	17.7 ***
sd Rain	7.00e+03	9.0+02	7.8 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

We should compare the results in Tables (2.4 and 2.5) qualitatively only, meaning that what matters are the sign and significance, but the values do not matter. Comparing the two tables tells us that all the six variables have similar signs and are statistically significant. This match indicates that the proposed dynamic demand model captures essential features of reality, and its predictions agree with real-world data.

One alternative hypothesis would be that factors other than temperature and rainfall affect the timing of the desalination plant. For example, cities could decide how much desalination they need in the long run and randomly build the plant. It is also possible that the institutional hurdles determining the available budget for desalination play a more decisive role in building a plant. This hypothesis means that building patterns would be independent of rainfall. In this hypothesis, there would be no correlation between rainfall patterns and building desalination. Another important feature that does not seem intuitive is that this model and real-world data predict that cities with higher s.d. in rainfall would build more desalination capacity. It could well be that cities rely on desalination for their entire water needs. Still, it seems that desalination acts more as an insurance policy than the primary water provision source.

The reason behind the dramatic increase of desalinatoin capacity in the previous years is a combination of multiple factors. The model predicts that each city has an equilibrium level of desalination based on its geographic characteristics, demographic characteristics, price of desalination construction, and price of desalination operation. The significant factors that affect demand for desalination have been widely studied. Some of the more important ones that explain the major adoption of desalination plants are: an increase in population, an increase in marginal willingness to pay for water in super arid areas (think of population booms in prosperous cities in the middle east and Mediterranean), a sharp drop in desalination construction cost, an improvement in desalination efficiency.

It is theoretically possible for an increase in extreme weather events and a drop in average rainfall levels to cause an increase in the adoption of desalination, but it has not yet been documented to this day. This model can allow for all of the aforementioned changes and give a specific and quantitative prediction on the equilibrium level of desalination capacity for each city in the long run.

I estimated another version of this model regarding the relative value of constructing a plant in good vs. bad times. I moved this estimation, along with some other analyses regarding optimal utilization rate, the possibility of mistakes on rainfall probabilities, and estimating the price elasticity of demand for construction of desalination plants, to Appendix A. These results are not directly contributing to the central intellectual contribution of this paper but are part of my explorations about decision-making regarding desalination plants.

2.6 Conclusion

This paper first investigates the question of optimal timing and optimal size of building desalination plants, given the uncertainties inherent to rainfall patterns using seventy-six-years-long panel data on desalination plant construction worldwide. Secondly, this paper aims to explicitly define the criteria of rationality in a specific problem and test whether decision makers act consistently with these criteria in this limited domain.

This paper adopts a dynamic programming framework to answer the first question. A rational decision maker maximizes the expected utility of building the plant. The decision-making authority considers decisions on both the plant construction and plant use. It finds the optimal time to build a plant and its size. All three aspects of optimal use, optimal timing, and optimal size of the plants are critical issues that experts face in the real world. By calibrating the elements of this model to dimensions of cities in need of building a desalination plant, this model can serve as a tool to provide a baseline for the needs of a city and a tool to measure the quality of decisions made by decision-making authorities.

To compare the behavior of the real-world decision makers with the optimal behavior provided by this model, I compare the correlations predicted by simulations from the model and the correlations observed in the real-world data. All of the compared variables had the correct signs and were significant in the correct directions.

In this paper, the micro-level behavior of the decision maker was observed. Admittedly, this is not the only micro-level rational model to write for decision-making in this context. This paper is evidence that the predictions of a dynamic model are consistent with real-world behavior on average. To develop more robust tests, we should develop further models and gather more data on the usage of desalination plants and local characteristics.

Another limitation of this paper is that I implicitly assumed that the management of desalination plants is relatively similar in different cities. Any difference observe in construction patterns is due to observables or year-city-specific shocks. With more data on desalination plants' annual usage rate, it would interesting to see if there are inherent differences in the management of these plants.

This model can be used to make some some predictions about desalination adoption due to climate change. In this model, the rainfall patterns follow a Markov process in its steady state. If we model climate change as a one time shift in the probabilities of different rainfall patterns, which increases the standard deviation of rainfall and decreases the mean value of rainfall in arid areas, then this model predicts that:

1. Cities in arid areas would build more desalination per capita to compensate for lower rainfall levels

2. Cities would generally build more desalination to use desalination as an insurance policy against extreme events

3. It can explain how does the timing of these transitions work: cities would wait until the available freshwater in the reservoir to fall below a threshold, and then they start building desalination capacity

Another aspect worthy of exploration is relaxing or improving the rationality assumption of decision makers. In this paper I assumed that decision makers believe that their need for water follows a Markov process that is a function of observables and shocks. In principle, the municipalities can overreact or underreact to observables, or they might have superior information on predicting water needs that the econometrician does not observe. It is interesting to know how decision-making authorities come up with decisions consistent with a relatively complex dynamic programming problem.

Chapter 3

Can Innovation Help Us in the Battle against the Climate Change?

3.1 Introduction

Climate scientists, economists, and politicians run out of superlatives while describing the disastrous long-term effects of climate change. They agree on the enormity of climate change's threat. But when it comes to action, the agreement seems to fade away. While climate scientists emphasize the long-term catastrophic effects of climate change, politicians tend to think in the short-term. Economists are somewhere in between, balancing the short- to mid-term costs of mitigating climate change and its mid-to-long- term consequences of action (or lack of it). There is also a sea of disagreement about the best instruments to fight climate change. Some climate scientists, overwhelmed by the sheer magnitude of this disaster, prefer an outright ban of any form of greenhouse gas emission. At the same time, politicians tend to prefer innovation policies to combat climate change. Economists, again, take the middle ground by accepting the merits of both emission restrictions and innovation policy. Their studies show a preference for carbon pricing, either through taxes or cap and trade systems.

Some OECD countries like Canada, Japan, Chile, and some European countries implemented some forms of carbon pricing. But according to the World Bank [1], as of 2021, less than 22 percent of the total carbon emissions would be priced. This does not take into account the fact that the prices in many jurisdictions vary, and they may be far below the marginal damage of carbon.

In the United States, carbon pricing proved to be politically impossible at the federal level, as evident from the latest environmental policy of the Biden administration. In 2022, the Biden administration would increase the budget to fight climate change from $22 billion to more than $36 billion without any indication of a carbon tax. The main bulk of this funding would be spent on research, innovation, and infrastructure.

The emphasis on innovation without a clear taxation policy raises a fundamental question that we plan to address in this chapter: **Is innovation even *helpful* in the battle against climate change?** In some cases, it does, but a closer look at the portfolio of innovations and their interactions raises multiple paradoxes that rule out a simple answer to this question.

In this paper, we set out the economic logic of the impact of innovation on climate change. We primarily focus on the portfolio of the most promising green technological innovations that have been pursued in the past decades: clean energy innovation, innovation in fuel efficiency of internal combustion engines, and innovation in carbon capture and storage. We ask when innovations help the battle against climate change and how these innovations interact with each other.

Our focus is to study the long-term effect of a green innovation portfolio on climate change. While the economic literature neglected these long-term effects and focused on the short-to-medium range, we know from climate studies that long-term (beyond fifty

[1] https://carbonpricingdashboard.worldbank.org/

years) climate outcomes are much more predictable than short-to-medium-range climate outcomes. Many climate studies emphasize the long-term disastrous effects of carbon emission and climate change. These studies show that the long-term climate outcome is independent of the emission patterns. A simple measure of cumulative carbon emissions is a sufficient statistic for long-term climate outcomes. Therefore, we study the effect of the green innovation portfolio on one measure of impact: cumulative carbon emission.

While trying to answer when innovation helps us against climate change, we revisit some of the well-known strong green paradoxes and introduce some new ones. A strong green paradox arises when a policy or innovation intended to improve climate outcomes end up causing greater cumulative environmental damage. In the rest of this introduction, we set out the green paradoxes that we visit in this paper.

The history of strong green paradoxes dates back to the late nineteenth century. Jevons (1865) first observed an improvement in energy efficiency involves the so-called rebound effect: the demand for output will increase as fuel costs fall, and in terms of the overall impact, this increase in demand may increase the overall *flow* of fuel consumption and carbon emissions.

Our first contribution is the introduction of a new paradox: an improvement in fuel efficiency will always increase the total *stock* of fossil fuel extracted. Fossil fuel deposits vary in the cost of extraction. In a simple setting, fossil fuel deposits are extracted in order of extraction cost until they reach a point where the marginal cost of extraction, say c_1, justifies using a clean-energy backstop, which is the alternative to an internal combustion engine. If the fuel efficiency (FE) of internal combustion engines increases, with a drop in the fuel requirement per unit output, fossil fuels will continue to be used until the marginal cost of extraction at a higher level, say c_2, is reached. All fuel with extraction costs in (c_1, c_2) will be extracted under the new technology instead of being left in the ground, thus adding to total carbon emissions. Innovation in fuel efficiency on its own leads to a strong green paradox.

The logic applies not only to internal combustion engines but also to fossil fuel production of energy. With an increase in fossil fuel energy production efficiency (as ith the introduction of combined-cycle natural gas generation in the 1960s), fossil fuel will be used to a greater extent for energy production. The switch to a clean alternative such as solar or wind power would take place at a higher cost of fossil fuel extraction.

Our next contribution involves innovation in carbon capture and storage (CCS). An innovation in CCS (given that it is implemented) always improves long-term climate outcomes. Moreover, this kind of innovation alleviates and may even reverse the paradoxical result of a FE innovation. If energy demand is inelastic enough, a substantial innovation in FE pushes more emissions into the future; these emissions will occur when CCS technology is more advanced so that the emissions *net* of CCS are reduced.

Then we turn our attention to innovation in clean energy (CE). It is well-known in the literature that innovation in clean energy (e.g., wind energy, solar energy) or even the threat of it reduces the expected future rents of fossil fuel owners, hence reducing the current price of fossil fuel. If demand is elastic enough, current emission will increase, meaning that CE innovation causes a weak green paradox: a green-intentioned policy (innovation) leads to greater short-term environmental damage.

We establish that the effect of CE innovation on its own is always positive for the long-term cumulative emissions. CE acts as a backstop (or alternative) to fossil fuel deposits. With cheaper green backstops, the deposits that would otherwise be extracted are left in the ground. Hence, CE innovation will not lead to a strong green paradox on its own.

We show, as our final contribution, that for an elastic demand, the CE innovation is less beneficial if CCS improves over time: the greater the share of emissions that occurs in the near future (when CCS technology is less advanced than in the distant future) the greater the emissions *net* of carbon captured and sequestered. CE innovation accelerates the fossil fuels extraction flow and, therefore, the flow of emissions. For strong enough innovation in CCS, the CE innovation becomes harmful, and the interaction of these two innovations yields a strong green paradox.

The starting point of our analysis is the Hotelling model of an exhaustible fossil fuel resource with variable costs. Throughout the paper, we represent innovations in FE and CE as Poisson processes on a one-time improvement of known magnitude, following established literature. We represent CCS innovation, in contrast, by an exogenous and increasing fraction $a(t)$ of emissions that are captured at zero cost over time. This representation reflects an underlying assumption that the government (regulator), not firms, bears the cost of the CCS. In reality, this cost is mainly the cost of storage and the cost of the network to transport CO2 to storage.

In the appendix B, we extend the model to allow for the endogenous choice of a by the regulatory agency by assuming a CCS technology represented by a cost function $c(a;\theta_t)$, in which θ_t is a technological parameter representing (possibly) improving technology over time. In the extension, the regulator decides how intensively to use existing CCS technology at any time given the cost function and the state of technology in the dimensions of clean energy or fuel efficiency. The use of CCS changes with the discovery of a clean energy substitute or an increase in fuel efficiency. We show that our central results are preserved in this extension.

In the next section, we give a brief survey of the literature. Then we introduce the theoretical setup and discuss our assumptions in section 3. In sections 4 and 5, we study the effects of FE innovation and CE innovation, respectively. In section 6, we conclude by discussing the limitations of our results and the policy implications of our paper.

3.2 Literature Review

Fossil fuel innovation affects both the flow pattern of emissions and the total stock of emissions. The impact on the flow of emissions involves the *rebound* effect studied by Fullerton, Ta (2019), Gillingham et al. (2016) and possibly Jevons' paradox (1865).[2] An increase in the efficiency of car engines, for example, will increase the current flow of demand for gasoline if the elasticity of the demand for car travel is sufficiently high because the cost per mile of travel falls with the innovation; the extra miles driven may offset the lower fuel needed per mile. The rebound effect is well known. But a paradoxical *stock* effect of an innovation in fuel efficiency has, to our knowledge, gone unnoticed.

The paper contributes to the green paradox literature. In his seminal work, (Sinn (2012)) coined the term "the Green Paradox". According to Ploeg van der, Withagen (2012), the green paradox is the idea that well-intended policies to improve the climate outcome lead to outcomes that are below the social optimal and counter-productive. This is because such policies reduce the expected rent collectible by fossil fuel producers, and they choose to produce more fuels and sell them at a lower price. More specifically, this paper contributes to the literature on innovation and green paradox, which focuses on the unintended consequence of innovation policies to improve the climate outcome.

Werf, Maria (2012) review more than 20 papers on the climate change policy and the green paradox. Several papers in the literature have investigated the interaction of innovation and climate change (Hoel (2009), Ploeg van der, Withagen (2012), Winter (2014), Acemoglu et al. (2016)). The models developed in most of these papers contain assumptions that imply that in the long-term the environment will converge to a steady-state independent of any temporary effects of policy.

[2] Jevons' paradox is a rebound effect from an increase in the efficiency of internal combustion engines that is so strong that it more than offsets the direct, negative effect of the increased efficiency on fuel demand.

This independence is explicit in Hoel (2009) and Ploeg van der, Withagen (2012). But Acemoglu et al. (2016) operate at a higher level of abstraction: environmental quality is represented at a state variable S_t, which either reaches 0 ("environmental disaster") during any period of carbon emissions and remains at that level, or converges to complete environmental recovery in the long-term. The assumption of a categorical connection between short run policy and the long-term environment ("disaster" or perfection) rules out consideration of the effects we examine in this paper.

Winter (2014) pairs an economic model of innovation in clean energy with climate dynamics that incorporate feedback effects. Dynamical systems with feedback effects yield tipping-point dynamics, which link short-term to long-term effects of innovation. In this paper we explore a different link between innovation and long-term climate outcome, motivated by the scientific evidence cited above, that cumulative carbon emissions are a good indicator of the long-term climate impact of the emissions. Gans (2012) examines the incentives for innovation in clean technologies induced by policy. Gans considers essentially the same portfolio of technologies as this paper, and establishes a parallel result: only for technologies that directly abate carbon pollution is there an unambiguously positive impact on innovation. In our paper, only for these technologies is exogenous innovation unambiguously beneficial. Gans investigates incentives for innovation. We investigate a more basic issue, the impact of exogenous innovation.

Our paper is related to the literature on second-best climate policies and their interactions.Fischer, Newell (2008), Grimaud, Lafforgue (2008), and Hart (2019) assessed the interaction of carbon tax and clean energy subsidies. They showed that they both have substantial welfare effects in the optimal general equilibrium and quantified different deviations from the first best.

Lafforgue et al. (2008), Hoel, Jensen (2012), and Kalkuhl et al. (2015) examined the optimal pattern of CCS with constant technology when there is clean energy innovation. However, they did not consider improving CCS technology and infrastructure. With an improving CCS, the percentage of emissions captured may increase over time.

Because the theoretical starting point of our paper is the Hotelling model of resource extraction, it is worth discussing the relevant literature on Hotelling model and empirical evidences for it. It has been empirically established that in the short-run, aggregate oil production is inelastic in price (Griffin (1985) ; Dahl et al. (1991); Ramcharran (2002); Güntner (2014).

As Cairns (2014) points out, Hotelling style models will break-down in the short-run because production cannot be re-arranged at will. But aggregate oil production, in the long run, is determined by both how much firms produce from existing wells (intensive margin) and how many new drilling projects do firms initiate (extensive margin). A recent study (Anderson et al. (2018)) shows that an extension of the Hotelling model (that takes drilling into account) explains why the Hotelling model can only hold in the long run. Because our scope of analysis is long-run, the Hotelling model deems appropriate.

3.3 Setup

3.3.1 The Green Innovation Portfolio and Damage Function

We set out three classes of clean-tech innovation, clean energy (CE), fuel efficiency (FE), and carbon capture and storage (CCS). We study both the *ex post* realization and the *ex ante* threat of FE and CE innovations on their own and their interaction with a steady improvement in CCS technology.

Clean energy (**CE**) alternatives consist mainly of solar energy and wind energy. The cost of generating electricity from solar power depends upon geography, but the cost of solar panels per kw generated has dropped by 2 orders of magnitude since the 1970's. Solar power bids for generating electricity have in places reached \$ 50 dollars per megawatt hour, substantially less than the cost of coal,[3] but the cost of storingand transmission of this energy has to this point ruled out significant global market share to date for either solar or wind energy.

Fuel efficiency (**FE**) innovation in the of internal combustion engines in particular and any form of fossil fuel production of energy in general is our second source of innovation. This innovation is illustrated by the increases in average automobile fuel efficiency of about 90 percent since 1975. [4] and in efficiency gains of generating electricity from fossil fuel, such as the development of combined-cycle fossil fuel plants in the 1960's.

We represent innovation in a clean energy alternative more simply by the exogenous discovery of a single new technology. Following much of the economic literature on innovation, we assume a Poisson process for the discovery of the new innovation, with probability of discovery ρdt in any instant dt at any date for which the innovation has not been discovered. We adopt the same process in examining the impact of fuel efficiency innovation. For both clean-energy and fuel-efficiency innovation, we distinguish between the ex post effect of a realized discovery on long-term climate change and the ex ante effect of the threat of innovation, as this threat alters the equilibrium in the existing market for fossil fuel as an exhaustible resource.

Carbon capture and storage (**CCS**), or sequestration consists of capturing the carbon dioxide produced with combustion and moving the gas to a storage facility such as an underground geological site.[5] Innovation in this area is promising but highly uncertain: IPCC(2005) Metz et al. (2005) predicts that the economic potential of CCS will be between

[3] Jeremy Berke (2018)

[4] https://www.epa.gov/fuel-economy-trends/highlights-co2-and-fuel-economy-trends#Highlight2

[5] We set aside innovation (prior to T, the maximum date of significant carbon emissions) direct carbon capture and sequestration from air as well as other green-tech innovation such as large scale batteries.

10% and 55% of the total carbon mitigation effort until year 2100. We represent CCS by an increase over time in the fraction $a(t)$ of emissions captured. CCS is exogenous, costless and implemented by regulation. We represent CCS simply by an increase over time in the fraction $a(t)$ of emissions captured.

We consider the ex post and ex ante impact of innovation of various types on the **cumulative carbon emissions** over a finite period $[0, T]$ over which carbon emissions are positive. (T is the termination date of fossil fuel extraction with no prospect of innovation.) Our focus on total emissions is motivated by scientific evidence that cumulative emissions are a close proxy for the long-term impact of emissions on climate. A recent editorial in *Nature* Allen et al. (2009) discussed evidence supporting the "insight that cumulative CO2 emissions determine the long-term climate outcome, essentially independent of the evolution of CO2 releases over time."[6]

It is helpful to elaborate on the physics of *why* the pattern of emissions of a given amount of cumulative emissions might be irrelevant, or nearly irrelevant, within the range of parameters contained in a realistic climate model. Why might an earlier path of a given amount of carbon emissions, for example, have only a small impact on the state of the environment at T? Such a shift would (1) have a negative (i.e., beneficial) impact on the atmospheric concentration of carbon at T because the emitted carbon would have on average a longer time to settle back to the earth's surface. But this beneficial impact would be offset or mitigated by: (2) a significant portion of carbon emitted remaining in the atmosphere for hundreds or thousands of years; (3) the feedback effects of higher temperature (realized earlier) on the flow of carbon into the atmosphere, even if not to the extent of triggering runaway global warming; (4) the earlier settling of carbon into the

[6] *Nature Geoscience* Vol.2, December 2009. This editorial refers to Meinshausen et al (2009), which reports that for the wide set of emission scenarios modeled, cumulative carbon emissions up to 2050 is a robust indicator of the probability that twenty-first century warming will not exceed 2 degrees C relative to pre-industrial temperatures.

ocean in reducing the capacity of the ocean to absorb additional carbon and heat; and, (5) the carbon and heat settling earlier into the ocean has itself a longer time to damage the ocean through increased acidity, higher temperatures and decreased oxygen. From the *Nature*(2009) editorial cited before, in terms of the net long-term environmental impact, these effects evidently balance out. In seeking to understand the long-term environmental impact of carbon emissions, it is therefore, reasonable to focus as a first approximation on a simple parameter, cumulative emissions.

Government policy to reduce carbon emissions falls into two general classes: carbon pricing (taxes or cap-and-trade) or other means of incentivizing reductions in emissions, and policies to encourage innovation that would reduce carbon emissions. Although carbon pricing is the preferred policy, for political reasons, incentivizing innovation is more widely implemented. With optimal carbon pricing, all policies are beneficial, and there would be no green paradox. But the current levels of carbon prices are well below the optimal carbon price.

Formulating an optimal policy on carbon pricing and stimulating *endogenous* innovation requires an understanding of the impact of *exogenous* innovation. If a technological discovery or the mere possibility of a discovery makes climate change worse, for example, this should be known. Our focus is limited to the consideration of the long-term impact of innovation. While the long-term environmental impact is only one component of the total welfare impact of innovation, it is a critical component and often under-emphasized in economic models. By limiting our focus to long-term impact of exogenous innovation, we can set out a potentially complex economic logic in simple terms.

By long-term damage, we mean any damage that may occur after extracting all fossil fuels. Because many geophysical interactions are very slow, it may take centuries after raised carbon levels that these adverse effects come into effect. This damage includes an increasing extinction probability of various life forms on earth, including humans. If the extinction probability spikes decades after extracting all fossil fuels, then the total damage is a function of cumulative carbon emission after the exhaustion of all fossil fuels. Our analysis explores the possibility of strong green paradoxes in green innovations with damage function dependencies as described.

3.3.2 Vanilla Model

Our starting point is the standard Hotelling model of a competitive market for an exhaustible resource, fossil fuels. The distribution of deposits at various extraction costs is $G(c)$, with density $g(c)$ and support $[\underline{c}, \overline{c}]$. We assume a stationary demand for an output such as miles driven, $Q(P)$, which can be produced by either an internal combustion engine or a clean energy backstop such as electric cars. The backstop supply of output costs y_0 dollars per unit. The ICE requires inputs of cost z other than fuel. The fuel requirement is λ_0 per unit output.

The markets for both machines and fuel are competitive, with prices over time given by $P(t)$ and $p(t)$. We adopt a regularity condition on output demand, $Q(P)$, that the elasticity of demand be non-decreasing in price. The variables $q(t)$ and $x(t)$ represent both the flow and cumulative fuel extracted and (by choice of units and in the absence of sequestration) the flow and cumulative amounts of carbon emissions. Finally, there is a constant interest rate, r.

The equilibrium of this well-known model is studied in the literature(Heal (1976), Stiglitz (1976)). The resource is extracted in order of lowest extraction-cost deposits until a date T at which production of energy switches entirely to the backstop. The dynamics of $p(t), q(t), c(t)$, and $x(t)$ (price and quantity of fuel, cost of extraction, and cumulative emissions) are determined by the following conditions:

$$q(t) = \lambda_0 Q(z + \lambda_0 p(t)). \tag{3.1}$$

The date of extraction of a deposit of cost c, $\tilde{t}(c)$, maximizes the present value of rents for the owner of the deposit:

$$\tilde{t} = argmax_t [p(t) - c] e^{-rt}. \tag{3.2}$$

The function $c(t)$ is the inverse of $\tilde{t}(c)$.

From the first-order conditions for the maximization problem (3.2) we get the following differential equation:

$$\frac{\dot{p}(t)}{p(t) - c(t)} = r. \tag{3.3}$$

with a terminal condition given by:

$$p(T) = c(T) = (y_0 - z)/\lambda_0 \tag{3.4}$$

Here, T is the date of the switch to the backstop. At T, the costs of the two technologies are equal: $z + \lambda_0 c(T) = y_0$.

The variable $x(t)$ is the cumulative extraction of fossil fuel (first carbon reservoir). Without sequestration (CCS), this variable also represents the cumulative addition of carbon to the atmosphere(second carbon reservoir). The total extraction of fossil fuel is given by:

$$x(T) = G((y_0 - z)/\lambda_0). \tag{3.5}$$

CCS is represented by the fraction of emission that is captured from emission $a(t)$.

With CCS, the dynamics of carbon in two reservoirs changes: $q(t)$ still measures the rate of carbon removed from the earth, but now the rate of carbon added to the atmosphere is now $[1 - a(t)]q(t)$.[7]

Each technology is represented by one parameter in our model. The parameter y represents the per-unit cost of CE technology. Lower levels of y_0 means cheaper (superior) technology. The FE technology is represented by λ_0. A smaller λ means more efficient (superior) technology. And finally, a represents CCS technology. Larger a means more (superior) sequestration technology.

3.4 Clean Energy Innovation

Initially, the per-unit cost of CE backstop is y_0. But there is the possibility of a single innovation at any time that would lower the costs to $y_1 < y_0$. The probability of discovery of the new CE technology follows a Poisson process: if at date t the new backstop has not been discovered, then with probability ρdt the new technology will be discovered in the interval $[t, t + dt]$ for dt vanishingly small.

3.4.1 Unexpected CE innovation on its own is a boon

In asking about the impact of innovation on climate change, we distinguish between the *ex post* effect of realized innovation, and the *ex ante* effect that of the threat of innovation. To isolate the ex post effect, suppose that innovation has zero (or vanishingly small) probability but is possible, and consider the impact of a *realized* discovery of the new technology.

Before discovery, the equilibrium follows the same path as if innovation were impossible.

[7] A third reservoir, the cumulative carbon stored, is potentially important in reality since the underground space required to store CO2 is several times the space taken up by the fossil fuel prior to extraction and combustion. Storage space may be limited. We set aside this complication in our simple model, however, assuming that the cost of CCS does not include the shadow price of a limited amount of storage space.

After a discovery, the equilibrium is described by the set of equations above, with y_0 replaced by y_1. The time of switch to backstop is given by $\tilde{t}((y_1 - z)/\lambda_0)$. If discovery occurs at a date at or beyond $\tilde{t}((y_1 - z)/\lambda_0)$, then fossil fuel extraction stops immediately and production switches to the new backstop technology.

The following proposition is immediate.

Proposition 1 *The ex post effect of the discovery of a new clean-energy technology at a date $t \in [0, \tilde{t}((y_1 - z)/\lambda_0)]$ is a reduction in cumulative emissions, E, by the following amount:*

$$\int_{(y_1-z)/\lambda_0}^{(y_0-z)/\lambda_0} g(c)dc = G(\frac{y_0 - z}{\lambda_0}) - G(\frac{y_1 - z}{\lambda_0}).$$

The effect of a discovery at date $t \in [\tilde{t}(b_1), T]$ is a reduction in cumulative emissions by:

$$G(\tilde{t}((y_0 - z)/\lambda_0)) - G(c(t)).$$

An unexpected CE innovation always reduces the long-term cumulative carbon and it is beneficial for the climate in the long-term.

3.4.2 CE-CCS interaction: The devil is in the details

To study the interaction of CE and CCS, first we need to define innovation in CCS technology. Innovation in CCS is taken to be a monotonic increase over time in $a(t)$, starting at $a(0) = 0$. "Stronger" innovation in CCS is the partial order given by: $a_1(t)$ is stronger than $a_2(t)$ if $a_1'(t) > a_2'(t)$ for all t. (A statement S is true with "sufficiently strong" innovation in CCS means that there exists a pattern of innovation $a^*(t)$ such that for all $a(t)$ stronger than $a^*(t)$ the statement S is true.)

CCS does not affect the patterns of extraction, but it reduces the amount of carbon emitted to the atmosphere. Therefore, CCS innovation is beneficial on it its own. With no innovation in clean energy, the impact on total *net* emissions of an innovation in CCS from $a_1(t)$ to $a_2(t)$, given the equilibrium flow of fossil fuel $q(t)$ is $\int_0^T [a_2(t) - a_1(t)]q(t)dt$.

This generalizes easily to the case of clean-energy innovation at any date:

Proposition 2 *Given the discovery of clean energy technology at any date t, or no innovation in clean energy, an increase in CCS efficiency lowers cumulative carbon emissions.*

To apply the clean-energy model in the presence of CCS innovation in the next section, we need to characterize the impact of innovation not just on cumulative extraction but also on the entire path of extraction. To this end, let $\mathbf{p}(s) \equiv p(x^{-1}(s))$ be the equilibrium price path as a function of the amount s extracted to date in the basic model; with innovation introduced, $\mathbf{p}_0(s)$ represents the price path when the backstop technology fixed at y_0 and $\mathbf{p}_1(s;\tau)$ is the price path for $t > \tau$ when the new technology is discovered at date τ. For $t > \tau$, the current extraction cost is $c_1(t;\tau)$, the inverse of this function (in t) is $\widetilde{t}_1(c;\tau)$ and total extraction to date is $x_1(t;\tau)$.

Innovation accelerates extraction:

Lemma 1 *With discovery of the new backstop $y_1$at date τ, we have: $\mathbf{p}_1(s;\tau) < \mathbf{p}_0(s)$, for all $s > x_0(\tau)$; for all $t > \tau$, $x_1(t;\tau) > x_0(t)$; and for all $c > c(\tau)$, $\widetilde{t}_1(c;\tau) < \tilde{t}_0(c)$.*

Proof: in the Appendix.

The *interaction* of CCS innovation and clean-energy innovation is central. The acceleration of emissions that results from clean energy innovation brings the emissions from the fossil fuel available at each extraction cost c forward in time to a date when CCS is less developed.

Proposition 3 *In the presence of CCS innovation $a(t)$, the impact of clean energy discovery at a date $\tau \in [0, \tilde{t}_0((y_0 - z)/\lambda_0)]$ is a change in cumulative emissions given by*

$$\int_{c(\tau)}^{(y_1-z)/\lambda_0} [a(\widetilde{t}_0(c) - a(\widetilde{t}_1(c;\tau)]dG(c) - \int_{(y_1-z)/\lambda_1}^{(y_0-z)/\lambda_0} [1 - a(\widetilde{t}_0(c))]dG(c) \tag{3.6}$$

For sufficiently strong innovation in CCS, the first term on the right-hand side of (3.6) dominates, so that total cumulative emissions increase with the clean energy discovery.

Proof. In (3.6), the first term represents the increase in emissions net of CCS of those units of carbon that are emitted with or without the discovery of the new clean-energy alternative. This term is positive (by Lemma 1) because all deposits of extraction cost between $(y_1 - z)/\lambda_1$ and $(y_0 - z)/\lambda_0$ are extracted more quickly and therefore, subject to the lower value of $a(t)$. The second term represents the emissions released under the original clean energy technology but not under the new technology.

Choosing $a^*(t)$ greater than $1 - \varepsilon$ over, for arbitrarily small ε, makes the second term arbitrarily small for all innovation patterns stronger than $a^*(t)$. Thus, for sufficiently strong innovation in CCS, the discovery of clean energy leaves the environment worse off in the long-term. ■

3.4.3 CE innovation threat and a green paradox

We have, to this point, examined the impact of a *realized* discovery on the long-term climate outcome. To isolate the *ex ante* effect of a threat on innovation, we compare two paths for fossil fuel prices: the price path that the fossil fuel market would follow if innovation is impossible, and the price path that the market follows if innovation is possible (with probability ρdt in a small interval dt) but never realized. This comparison captures the impact of the *threat* of innovation on prices and consequently on the extraction path and cumulative extraction.

We start with the model of clean-energy innovation. The examination of the ex ante impact of clean energy innovation requires ex ante price paths for both the innovation-is-impossible case and the innovation-is -possible case. The former price path is given by (3.3). The innovation-is-possible price path we derive from a recursive model with state variables (x, δ), where x is the cumulative extraction to date and δ takes on the value 0 if the new technology has not been discovered to date and the value 1 if it has. We again let $p_0(t)$ denote the price path prior to innovation and $p_1(t;\tau)$ denote the price at date t following discovery of the technology at date $\tau \leq t$. Thus, $p_1(t;t)$ is the equilibrium price in the market established immediately upon discovery at date t. The differential equation for the ex ante price path is determined by the condition that the owner of a deposit of extraction cost c be indifferent, as dt approaches 0, between extracting at date $\tilde{t}(c)$ and extracting at date $\tilde{t}(c) + dt$. This condition is:

$$p_0(t) - c(t) = lim_{dt \to 0} e^{-rdt}[(1 - \rho dt)p_0(t + dt) + \rho dt \cdot p_1(t;t) - c(t)]. \tag{3.7}$$

Taking this limit yields the following lemma, proved in the Appendix B:

Lemma 2 *With clean-energy innovation under the parameter ρ, the price path prior to discovery satisfies:*

$$\dot{p}_0(t) = r\{[p_0(t) - c(t)] + \rho[p_0(t) - p_1(t,t)]\}. \tag{3.8}$$

We denote the variables before and after discovery with the subscripts 0 and 1. The endogenous variables without subscripts refer to the innovation-is-impossible case. Equation (3.8) differs from the price innovation-impossible path, (3.3), only in the inclusion of the last term on the right-hand side. This term reflects the additional opportunity cost for which the holder of reserves of cost $c(t)$ must be compensated to be indifferent between holding the reserves for an additional instant and selling them at t: the threat of a capital loss with a price drop to $p_1(1,1)$.

Proposition 7 below characterizes the impact of the threat of unrealized innovation on the price path: the price starts lower as a result of the threat and moves more steeply, under (3.8) than under (3.3). This means that the date at which reserves of cost c are extracted, $\widetilde{t}(c)$, is reduced by the threat of innovation, for all c up to the terminal cost, b. The earlier date means that for each c, emissions at c are subject to CCS at any earlier date. If there is innovation in CCS, then this earlier date leads to greater *net* emissions. The proposition is proved in the appendix.

Proposition 4 *(a) In the absence of CCS innovation, the ex ante impact of clean-energy innovation on cumulative emissions is zero.*
(b) With CCS innovation , $\dot{a}(t) > 0$, *the ex ante impact of clean energy innovation is to increase emissions by:*

$$\int_0^{(y_0-z)/\lambda_0} [a(\tilde{t}(c)) - a(\widetilde{t_0}(c))g(c)dc > 0$$

The threat of innovation does not affect the *gross* cumulative carbon emissions (i.e., emissions prior to the application of CCS) but increases net emissions because each unit of fossil fuel is subject to the less well-developed CCS technology at an earlier date.

3.5 Fuel Efficiency Innovation

In this section, we turn off innovation in CE technology and fix the backstop cost at y. Our focus in this section is the effect of innovation in FE technology. First, we study the effect of a realized but unexpected innovation in FE. Then we study the interaction with CCS in two scenarios: first, an inelastic demand. This example helps solidify the intuition. And later, we allow for a general demand function, which brings the Jevons paradox into play. Finally, we study the effect of the threat of innovation in FE.

3.5.1 Paradoxical effect of an unexpected FE innovation

Similar to CE innovation, we consider a single innovation in fossil fuel efficiency that would lower the fuel requirements per unit of machine output from λ_0 to λ_1. Only the date of discovery is uncertain, and this date follows a Poisson process with ρdt being the probability of an exogenous innovation in a small interval dt if the innovation has not yet been discovered.[8] In the absence of CCS innovation, the cumulative amount of carbon emission after innovation is given by changing λ_0 to λ_1 in equation 3.5.

$$x(T) = G((y - z)/\lambda_1)$$

The following proposition summarizes the FE innovation paradox.

Proposition 5 *Suppose that with an initial technology described by fuel requirements per unit of λ_0, the terminal date for fossil fuel extraction in this model is T. An innovation in $[0, T]$ that reduces the fuel requirements to $\lambda_1 < \lambda_0$ raises the cumulative fuel extraction and carbon emissions by:*

$$G((y - z)/\lambda_1) - G((y - z)/\lambda_o).$$

Fuel of extraction cost in the interval $[(y - z)/\lambda_0, (y - z)/\lambda_1$ becomes economic only

[8] We assume that innovation requires that the market for fossil fuels has a positive quantity; that is, we ignore the possibility that new innovation occurs after the fossil fuels market is closed that would render fossil fuels once again economic.

with the discovery of the new fossil fuel technology. The new technology allows each unit of fuel to produce more machine output, offsetting the higher cost. The proposition is easily generalized to the case where the backstop technology is improving over time(i.e. where y is a decreasing function of t). [9]

3.5.2 CCS innovation saves the day: Inelastic demand

The impact of fuel efficiency innovation if CCS innovation is in place depends on the elasticity of demand for machine output. We start with the assumption that this demand is perfectly inelastic, at a fixed quantity h. In interacting fuel efficiency innovation and CCS, we have in mind ICE's in industrial production as well as electricity production, rather than transportation.

With the original technology, the date of extraction of a fuel reserve of cost c is given by $\widetilde{t}_0(c) = G(c)/\lambda_0 h$ for values of c up to the maximum cost of reserves extracted, $(y-z)/\lambda_0$, because fossil fuel is extracted at the rate $\lambda_0 h$. With discovery of a new fuel-efficiency technology at date τ, the rate of emissions drops to $\lambda_1 h$. That is, the emissions rate is identical up to the reserves of cost $c_0(\tau)$, but then decreases to $\lambda_1 h$ up to the (higher) terminal cost $(y-z)/\lambda_1$. Thus for $c > c_0(\tau)$,

$$\widetilde{t}_1(c;\tau) = \frac{G(c_0(\tau))}{\lambda_0 h} + \frac{G(c) - G(c_0(\tau))}{\lambda_1 h} > \frac{G(c)}{\lambda_0 h} = \widetilde{t}_0(c). \tag{3.9}$$

Given CCS innovation, $a'(t) > 0$. Hence, from (3.9), $a(\widetilde{t}_1(c;\tau) > a(\widetilde{t}_0(c))$.

Proposition 6 *With the discovery of a new fossil fuel technology at date* $\tau \in [0, (y-z)/\lambda]$,

[9] And we conjecture that endogenizing innovation in the clean backstop magnifies the detrimental effect of an increase in fuel efficiency. Successful innovation in clean energy would be rewarded with delayed presence in the market if the innovator were competing against a higher FE. This would decrease the incentives to innovation and the reduced innovation would in turn allow the fossil fuel power generation to survive until the fossil fuel extraction cost reached a higher level.

given CCS innovation, cumulative emissions fall by

$$\int_{c_0(\tau)}^{(y-z)/\lambda_0} \left[a(\widetilde{t}_1(c;\tau)) - a(\widetilde{t}_0(c))\right] dG(c) - \int_{(y-z)/\lambda_0}^{(y-z)/\lambda_1} \left[1 - a(\widetilde{t}_1(c;\tau))\right] dG(c) \tag{3.10}$$

For sufficiently strong innovation in CCS, the first term dominates, and the discovery decreases cumulative emissions.

There is no change in emissions up to the discovery date τ(i.e., no change in emissions from reserves of cost $c \in [\underline{c}, c(\tau)]$). Beyond this cost interval, the first term of (3.10) represents the reduction in cumulative emissions net of CCS from those deposits that are used under either technology. This is positive because the lower rate of emissions following fuel-efficiency innovation means that $\widetilde{t}_1(c;\tau) > \widetilde{t}(c)$ in this interval. The emission of carbon from the deposits of cost c, which had resulted in net emissions of $1 - a(\widetilde{t}_0(c))$ prior to the discovery of the new fossil fuel technology, result in smaller net emissions of $1 - a(\widetilde{t}_1(c;\tau))$ after the discovery. The second term of (3.10) represents the emissions from deposits that are rendered economic only by the more efficient new fuel technology. For sufficiently strong CCS innovation, this second term is smaller than the first term, proving the proposition.

3.5.3 CCS-FE interaction: General demand

We have to this point discussed two paradoxes. FE innovation on its own can damage the environment in the long-term. CE innovation with sufficiently strong CSS innovation has the same effect. If demand is sufficiently elastic, then in extending the model of FE innovation the logic brings into play a third paradox, *Jevons paradox*. The increase in fuel efficiency reduces the cost and thus the competitive price for machine output. If the demand is elastic, this price reduction raises the quantity demanded of machine output, offsets the lower rate of fuel required per mile, and increases the demand for fuel.[10]

Jevons' paradox, or the rebound effect, like our fuel-efficiency paradox, is about the impact of a decrease in the fuel requirements of internal combustion engines and electric generation from fossil fuels. Jevons' paradox describes the possible short run effect. It does not enter the economic logic of long-term impact when CCS innovation is zero, because it is irrelevant for long-term gross output. But whether Jevons' paradox holds matters when we have CCS innovation in the portfolio because this affects the time path of emissions.

In our model the derived demand for fuel is given by $q(p;\lambda) = \lambda Q(z + \lambda p)$, where Q is the demand for machine output. Jevons' paradox, $dq/d\lambda < 0$, holds if the elasticity of Q exceeds $1/\lambda$. It is easily verified that $\partial^2 q/\partial\lambda\partial p < 0$, so that if Jevons paradox holds at a particular value of p, then it holds at all higher p. Because in equilibrium p is increasing over time, Jevons paradox holds for *all* time if it holds for $p(0)$ and holds at *no* time if it does not hold at $p(T)$. Proposition 5 follows directly.

Proposition 7 *Suppose that the elasticity of demand of $Q(P)$ is increasing in price. Then a sufficient condition for fuel efficiency innovation to increase cumulative emissions with (or without) CCS innovation is that the elasticity of demand for machine output exceed $1/\lambda$ at the price $P = z + \lambda p(0)$. A sufficient condition for fuel efficiency innovation to decrease cumulative emissions with sufficiently strong CCS innovation is that the elasticity of demand for machine output be less than $1/\lambda$ at the price $P = z + \lambda p(T)$.*

3.5.4 Last piece of the puzzle: the threat of FE innovation

In the fuel efficiency model, existing technology in the production of machine output uses λ_0 units of fossil fuel per unit output and requires z dollars per unit output in additional input expenditures. A backstop technology is available at cost per unit y. Innovation

[10] Jevons (1965) argued that the increased efficiency of internal combustion engines might actually increase the demand for fuel. The (misplaced) concern at the time was that reserves of coal would run out.

occurs with probability ρdt in any instant dt and consists of discovery of a new technology $\lambda_1 < \lambda_0$.

The ex ante impact of fuel efficiency innovation refers to the impact on cumulative carbon emissions of the threat, ρ, of innovation - when the innovation is never actually realized. The ex ante impact operates through the impact of ρ on the price. In the clean-energy innovation model, we compare the ex ante price path with the innovation-is-impossible price path. If the ex ante price path is lower, then the fixed amount of cumulative emissions, $G((y-x)/\lambda)$, is released at an earlier time with predictable consequences if we have CCS innovation in the existing portfolio of innovation.

The dynamics of the endogenous variables (using the same notation as in the ex ante clean-energy model) $p_0(t), q_0(t), c_0(t), x_0(t); p_1(t;\tau), q_1(t;\tau), c(t;\tau)$ are governed by the following conditions.

Using a logic parallel to the ex ante case for clean energy, one can show that the ex ante price path follows equation (3.8). The terminal condition is $p_0(T) = c(T) = (y-x)/\lambda$. (That is, if the new technology is not discovered, fossil fuel extraction continues until the alternative technology is equally costly.) The cumulative gross emissions, $G((y-x)/\lambda$, are unaffected by the threat of innovation. The ex ante price given the state x is less than the innovation-impossible price path if and only if the price falls with discovery(i.e., if $p_1(t;t) < p_0(t)$, equivalently, if $\mathbf{p}_1(c;\tau) < \mathbf{p}_0(c)$).

Unlike the case in the clean-energy innovation model, this latter inequality holds, if at all, only in early years. There are two forces at work. First, the new technology reduces future consumption conditional upon innovation, assuming demand elasticity below the critical point for Jevons' paradox to kick in. This increases the length of time that the fuel will last, reducing its scarcity value. To take an extreme example, suppose that the current cost of extraction is zero, but fossil fuel will run out (or become prohibitively expensive to extract) in one year. Then the current price in the market for fossil fuels is bounded below by $[(y-z)/\lambda_0]/(1+r)$ because holders of reserves have the option to wait one year to sell at $(y-z)/\lambda_0$. This fossil fuel price may be very high, if y is high. But suppose that the innovation is so miraculous that if it occurs it reduces the requirements of fossil fuel per mile from λ_0 to $\lambda_1 = 0.001 \cdot \lambda_0$ with the effect that fossil fuel will be available at zero extraction cost for about 1,000 years. The price of fossil fuel will fall to about zero. The *threat* of the capital loss from innovation therefore, reduces the fossil fuel price in this example, accelerating extraction and emissions. In the presence of CCS innovation, this brings emissions forward to a time of low CCS effectiveness. Net emissions rise.

The second force underlying the ex ante impact of fuel efficiency innovation works in the opposite direction. Consider an innovation at the exact date, T, of at which the market would switch to the alternative technology downstream. ($T = G^{-1}((y-z)/\lambda_0)$ The Hotelling rent, $p(t) - c(t)$, jumps from zero to a positive value. (The price after innovation follows an innovation-impossible path, and Hotelling rent is always positive before the end date.) From continuity of the price paths, there is an interval $[t, T]$ over which the impact of an innovation on price is always positive.[11] The ex ante impact of innovation over this interval is therefore, to raise price, due to the promise of the capital gain. This lowers the output for sufficiently elastic demand, deferring emissions to the future. With CCS innovation in place, net cumulative emissions are reduced. In short, the threat of fuel efficiency innovation always helps net emissions late in the game.

The following proposition formalizes this discussion:

Proposition 8

(a) In the absence of CCS innovation, the ex ante impact of fuel-efficiency innovation on cumulative emissions is zero.

[11] This interval may include $t = 0$.

(b) With CCS innovation but perfectly inelastic demand for machine output, the ex ante impact is again zero.
(c) With CCS innovation and $d'(p) < 0$, the ex ante impact of fuel efficiency innovation, beyond some $\hat{t} < T$, is to reduce cumulative net emissions.

The proof is in the appendix B.

3.6 Conclusion

To formulate optimal climate change policy, we must first understand the impact of exogenous innovation. We show in this paper that the impact of the main types of innovation depends on the portfolio of existing innovation. In two cases, clean-tech innovation can have a perverse long-term impact both in terms of realized innovation and, under further conditions, the ex ante threat of innovation.

The models in the paper relied on two technical assumptions (Hotelling Model for price path of fossil fuels and innovation modeled as an unexpected one-time reduction of some input), both of which can be relaxed in an extension of this work. The first assumption is strong in that it requires the price of fossil fuels to increase with the annual interest rate. Our results will still hold if fuel producers collect rent on top of the extraction cost and that rent decreases if renewable prices drop.

The second assumption (of a one-time Poisson process) can be relaxed to allow for multiple Poisson processes. We showed that both an unexpected innovation and anticipation of innovation lead to qualitatively similar results. If the results hold for one Poisson process, it will hold for multiple Poisson processes as well. Therefore, if one can model gradual innovation as the sum of multiple incoming Poisson processes (with different probabilities for the size of each), our results would still hold.

We emphasize that our results about perverse impacts of innovation do not make this an "anti-innovation" paper. The paradoxical results all pertain to a world with no carbon taxes. With optimal Pigouvian carbon taxes, all emission externalities would be internalized and innovation, by expanding the social planner's choice set, could only increase welfare. The main policy implication of this paper is to underscore the importance of carbon pricing. Without carbon taxes, one cannot even be sure that innovation has positive value.

Policy discussions have not appreciated the limitations of innovation as a sole instrument for tackling climate change. One example is the *Green New Deal,* a pair of resolutions submitted to US Congress in 2019, sponsored by Rep. Alexandria Ocasio-Cortez (D-NY) and Sen. Ed Markey (D-MA). These resolutions discuss proposed goals of reducing greenhouse gas emissions, among other objectives. The goal of reducing emissions is laudatory, but the Green New Deal resolutions contain no mention of carbon taxes whatsoever. Instead, the proposed methods for achieving the goals include "making public investments in the research and development of new clean and renewable energy technologies and industries". [12] Our message is that carbon pricing is essential even to ensure that the research and development of clean energy technologies has a positive value, let alone be the central tool for reducing greenhouse gas emissions.

The results of our analysis are one piece of a large issue, the optimal policy towards climate change. This policy would consider not only the long-term impact of innovation but also the full welfare, taking into account short- and medium-term effects. A fuller analysis would also consider the sensitivity of innovation size and likelihood to government subsidies of innovation. In our model, the potential perverse impact of clean-energy innovation of innovation (when the rate of improvement in CCS is substantial) would disappear if the

[12] p.12 of the House resolution

innovation were sufficiently large. A large innovation in clean energy would eliminate all emissions immediately. This suggests a non-concavity in optimal innovation policy. Small subsidies to innovation may have a negative value in the absence of carbon pricing, whereas the marginal value of innovation subsidies may be invariably positive at a sufficiently high subsidy level. The policy implication of this non-concavity; in an optimal world, innovation subsidies cannot be half-hearted.

Chapter 4

Asymmetric Information, Reelection Pressure and Political Decision Making under Uncertainty

4.1 Introduction

A foundational principle of a well-functioning democratic government is that elected leaders have strong incentives to act in the public or voters' interest. We expect a politician who acts against this interest to lose electoral support and be replaced in a future election.

However, some considerations may undercut this principle. One possibility is that voters may be less informed about major issues than are elected officials. A politician seeking re-election may prefer to implement policies consistent with the beliefs of poorly informed voters rather than enact better (welfare-superior) but less popular policies.

In a nutshell, the public relies on the politician to acquire relevant information and make informed decisions. The politician is better informed, but the relatively ill-informed electorate chooses the politician's re-election fate. The information asymmetry creates tension between decisions in the voters' interest and what merely looks good to the voters.

This tension manifests itself in the decisions that the politician makes and the politician's information-gathering efforts.

This paper studies different aspects of this tension, theoretically and empirically. I examine the interaction of the next election's proximity with politicians' distortion towards policies that appear to be in the public's interest - but are not. We expect the asymmetry of information between politicians and the public to diminish over time. Therefore, the politicians who have an imminent upcoming election will be more likely to act toward the ill-informed voters' beliefs. On the contrary, the politicians facing distant elections can act based on voters' interests (and ignore voters' misguided beliefs), knowing that they will update their belief until the election. I also examine how a lack of incentive for the politician to act in the public's interest leads to the politician's sub-optimal information acquisition.

In the paper's theory section, an incumbent politician has to decide on independent issues in an uncertain environment (e.g., response to a crisis). Each particular issue consists of two opposing extremes (i.e., act strongly vs. ignore the crisis). The politicians can choose anywhere between the two extremes.

The politicians' objective is to get re-elected (or their party to stay in power). They act to maximize their re-election probability at the election date in expectation. The voters are not active players. They judge politicians' actions based on the information available to them. The incumbent politicians' chance of re-election declines if their decision deviates from the public's belief about the optimal action. The decline is proportional to the size of the deviation and the quality of public information.

The politician receives an unbiased signal of the best policy before making their decision. Before making any decision, the public receives a noisier version of the same signal. The politician forms an expectation of the public's belief on the election day and takes action. The public receives many more independent signals until the election day and keeps updating its belief. The public can have a diffuse or non-diffuse prior, and their signals may be more or less informative than the politician's signal.

I consider two possibilities for the public's belief and solve the model for those cases: unified and polarized. A unified public means that voters agree about the probabilities of the optimal action, whereas a polarized public means that voters sort themselves into two opposing groups. The group members agree within itself but disagree between the two groups.

In either case, with an innocuous assumption about information asymmetry, I show that the politician deviates from implementing the best action conditional on their information set. Moreover, the closer the election, the more the politician deviates from implementing the welfare optimizing policy, holding everything else constant. The required assumption is that the politician has superior information at the time of decision-making about the best action compared to the public. Some (but not all) of this superior information fades away over time as the public receives more informative signals.

A polarized public implies that any politician must consider two opposing beliefs and its effect on their popularity when making a decision. Polarized elections are decided by voter turnout, and turnouts are proportional to candidates' popularity. Following this logic, I assume that the politicians care about their popularity among their supporters, hoping to excite them to turn out, more than their popularity among their opposition. This assumption allows me to pin down that the direction of the politicians' deviation from the optimal decision. Their bias is towards their voting base.

As the last theoretical contribution, I endogenize the quality of the politician's signal. Exogenous signal quality is unrealistic because the politician can exert time and resources to obtain a higher quality signal. We should investigate if endogenizing the signal quality affects the result. I show that previous results still hold. Moreover, I show that the signal's quality is directly proportional to voters' signal quality and is inversely proportional to the election timing. A politician with a later election spends more resources to acquire a higher quality signal.

In the empirical section of the paper, I use a difference-in-differences strategy to test the following prediction: two politicians who are identical except for their next election's timing behave differently during the crisis. In early 2020, the United States was hit by the Covid-19 pandemic. In this setting, US governors are responsible for deciding on multiple policies to limit business activities and protect citizens' health in their state. About half of these governors were Republican, and the other half were Democrats. One-fifth of these governors have an upcoming election in 2020.

The voting base of Democrats assess the threat of the disease higher than the Republicans and required a more robust response from the government. The voting base of Republicans, however, emphasizes the individual liberties of citizens and oppose decisive government intervention. The situation is highly uncertain since the threat of the disease's infectivity and lethality is unknown, and there are doubts about the effectiveness of different policies.

Eventually, the data shows that the Democrat governors who have an upcoming election in 2020 are the most likely to close economic activity. The Democrats and Republicans who do not have an upcoming election behaved statistically similar to each other. Finally, the Republicans who have an upcoming election in 2020 are the least likely to close any economic activity.

The empirical data are consistent with the hypothesis that the governors with an upcoming election are biased towards their voters. In contrast, the ones without an upcoming election implement their best expectation. It is worth noting that this empirical strategy does not require knowing what the optimal (i.e., correct and informed) action is. It only relies on the observed decisions made by politicians.

In the next section, I review the relevant literature. In section 3, I proceed to explain the model and derive the theoretical results. In section 4, I explain the data, set up the model's empirical implications, and present the results. And I conclude in section 5.

4.2 Literature Review

Retrospective voting is the idea that voters hold the politicians (or parties) accountable for their actions during their tenure. Key (1966) formalizes this idea in his seminal work, the Responsible Electorate. Retrospective voting readily invites the idea of the principal-agent problem faced by the public. Barro (1973) and Ferejohn (1986) model the moral hazard problem in the accountability of the politician to allocate economic resources efficiently. Reed (1994) addresses the adverse selection problem by introducing heterogeneous politicians.

Nordhaus (1975) introduces the idea of political business cycles. If the electorate votes retrospectively, the incumbent chooses the economic policy that maximizes its probability of re-election, which is different from the optimal policy. The incumbent increases its re-election chance by "manipulating" the economy and increasing welfare in the election year (Nordhaus (1975), Suzuki (1992)). The incumbent may also "surf" the economy (i.e., to call elections more (Palmer, Whitten (2000), Roper, Andrews (2003)) or less Smith (2003) opportunistically in favorable economic times). Kayser (2005) studies the case where the incumbent both surfs and manipulates the economy for re-election.

In recent years, researchers started to focus more on studying retrospective voting on issues other than national macroeconomic policies (e.g. school performance Berry, Howell (2007), handling disasters Healy, Malhotra (2010), and relative unemployment in a city Hopkins, Pettingill (2018)). This literature concludes that if a policy influences a tangible outcome and is within the politician's sphere of control, then the incumbent's poor decisions harm their chances in the next election. Moreover, these papers suggest that the incumbent's punishment is mediated by media attention level on an issue.

A laboratory experiment by Woon (2012) confirms these conclusions. Woon asserts that "retrospective voting is a simple heuristic that voters use to cope with a cognitively difficult inference and decision problem and, in addition, suggest that voters have a preference for accountability."

Healy, Malhotra (2013), raise a few open research questions. I partially address two of them in this paper. They uncovered that no one has studied the effect of retrospective voting on policy outcomes. They also state that no one studied the interaction of polarization and political sorting with retrospective voting.

This brings us to the literature on political polarization, specifically the effects of polarization on political decision-making. The consensus among political scientists is that the American political elites have become more polarized over the past few decades Fiorina, Abrams (2008). Most of the literature show polarization by focusing on congress roll calls and deviation from the party ranks McCarty et al. (2006). In addition to that, a historical analysis of politicians' speech by Gentzkow et al. (2019) shows polarization has significantly increased among the political elite since the 1990s.

But there is an ongoing debate on the degree to which the American public is polarized. Some academics Abramowitz, Saunders (2008) assert that polarization has grown among the American public, and people hold more extreme and opposing beliefs. Others point out Fiorina et al. (2008) that only party sorting has increased among the public, and even though opinions are not more polarized, voter-party identification is much stronger.

Political parties play a significant role in this polarization by increasing control over their members and setting a polarized agenda Canen et al. (2020). Whether the public has become more polarized (holds more extreme views) or it becomes more sorted (more people self identify with political parties and its politics), it caused "the nation as a whole to hold more aligned political identities, which has strengthened partisan identity" Mason (2015).

Grumbach (2018) analyzes sixteen issues of gubernatorial policies across US states to study the interaction of decision making and polarization. He shows that party control predicts socioeconomic decisions in polarized topics like health care but not in nonpolarized areas like criminal justice. Moreover, the policy disparity between parties on polarized issues has increased from 1970 up to 2014.

Gentzkow, Shapiro (2010) show that the media find it economically optimal to deviate from reporting an unbiased version of the news. They found evidence that profit-maximizing American newspapers respond to their readership biases by introducing a slant towards their base. In a similar vein, I show here that incumbent politicians find it optimal to introduce a slant towards their base in implementing policies.

In this paper, I make use of the findings of the literature on public learning and opinion formation. Acemoglu et al. (2006) show that it is theoretically possible for the public to be Baysian and holds polarizing opinions . Others showed that pre-existing polarized opinions might lead to a different assessment of similar information (Gerber, Green (1999), Dixit, Weibull (2007)).

This paper can be classified as part of the emerging literature on responses to Covid-19. I contribute to this literature by studying how the governor's party and the election timing affect the governments' decision for implementing social distancing policies. Chernozhukov et al. (2021) study the effect of government policies in the contagion of Covid 19. In a recent study, Allcott et al. (2020) show that Democrats and Republicans perceive Covid-19 differently. Democrats see Covid 19 as more dangerous and expect more stringent behavior from the government. In the absence of the aforementioned political considerations, Alvarez et al. (2021) theoretically study the optimal policies to respond to Covid-19 . To my best knowledge, this is the first paper that discusses the political challenges in finding and implementing the optimal policy.

4.3 Theoretical Model

This section formalizes a game between politicians and voters. Incumbent politicians (and political parties) make decisions during their tenure. The politician wants to win re-election, whereas the voters want the politician to make the welfare-maximizing decision. We need to formally distinguish among welfare maximizing, the politicians' information about it, and what voters believe. These three do not always fully agree. There is an information asymmetry between politicians and voters.

This information asymmetry interacts with election timing through an information channel. Voters learn new information after the politician makes a decision. The politicians form expectations about what voters will learn until the election and bases the decision on that expectation. If the election is in the distant future and enough information becomes available to the voters at the election day, the politicians tend to act based on their superior information. Nevertheless, if the election is in the near future and politicians do not expect the voters to update their information, they tend to act more similarly to the voters' priors.

The model allows for a polarized electorate, and it also paves the way for endogenizing the information gathering efforts of the politician. The model yields a clear difference in differences style prediction that can be tested with real-world data on politicians' decisions.

4.3.1 Setup

To formally model the interaction between the politician and voters, assume that nature sets the welfare-maximizing action and sends a signal to the politician and the public. The politician may be a Democrat or Republican. The public may be unified and receive a signal or be polarized, and each group receives a signal separately.

Every player updates their belief according to their signal. The politician takes action. Then the public receives new signals. Finally, an election takes place. For some politicians, this election is early, and for the others, it is later.

For every politician, the model has the following timing:

- Nature sets the welfare-maximizing action for an issue.
- Nature sends a signal to the politician, and the politician updates their belief with a diffuse prior belief.
- Nature sends a noisier version of the same signal to the public, and the public updates its belief with its prior belief.
- The politician chooses their action.
- The public receives N independent signals from nature and updates their beliefs until the election day.
- Election takes place (it may be early or late).

The real line represents the issue. A point represents the politician's decision on the real line $s \in \mathbb{R}$. I assume that there exists a unique decision point on the issue line that maximizes social welfare. Still, neither the politician nor the public knows the optimal decision point with certainty. They both have a belief about the optimal decision.

A belief is a normal distribution $\sim \mathcal{N}(s_x, \sigma_x)$ over the issue. This belief represents the true probability that a belief holder assigns every decision to be the welfare-maximizing decision. The higher the standard deviation (σ_x), the lower the certainty of the belief holder.

Take the welfare-maximizing action to be s_o. The politician has a diffuse prior. They then receive a signal s_g about the optimal action. The signal is an unbiased random variable with known uncertainty σ_g. Therefore, the signal has the distribution $\mathcal{N}(s_o, \sigma_g)$. The realization of this signal is s_g. Following the Bayes rule, their belief on the best policy after receiving the signal will be $\mathcal{N}(s_g, \sigma_g)$.

Similarly, the public receives a signal $s_g + \epsilon_g$. ϵ_g is a mean-zero normally distributed random variable. The public combines the signal using its initial prior and form its belief. Therefore, the posterior belief will be normally distributed as $\mathcal{N}(s_p, \sigma_p)$. It is possible to write s_p and σ_p as a function of the prior and the signal, which will be done later. Nevertheless, this suffices for the moment.

We can think of the public's belief as the wide-held opinion of the voters. Ideology, past shared experience, and the media slant all influence public opinion. Therefore, it consists of prior information, potential bias, and a noisier version of the politician's signal. The politician knows about this belief; hence, it has no extra information for a politician's inference of s_o. They can safely ignore this belief for inferring s_o.

After the politician and the public both receive the signal, the politician chooses their action. However, the public's belief is dynamic. For simplicity, assume that the public receives exactly N signals from nature up to the election day. Each signal is consistent and distributed as $\mathcal{N}(s_o, \sigma_y)$. Label every realization of these signals as $\hat{s}_p^i$. Therefore, the public opinion on the election day would be normal with the following distribution:

$$s_p(T) \sim \mathcal{N}\left(\frac{s_p\sigma_y^2 + \sum_{i=1}^{N} \hat{s}_p^i \sigma_p^2}{\sigma_y^2 + N\sigma_p^2}, \frac{\sigma_p^2\sigma_y^2}{\sigma_y^2 + N\sigma_p^2}\right) \tag{4.1}$$

The public wants the politician to implement the welfare-maximizing policy, but it does not know about the information set available to the politician. The politician may be incompetent and have high uncertainty. They may have some ulterior motives and not implement the best policy, or they get unlucky, and the signal's realization is far off. Irrespective of the reason, the politician will lose popularity if they deviate from the mean of public belief.

4.3.2 Solution for a unified public

The politician wants to maximize their re-election probability. In Appendix C, I show how to derive a loss-function approach for such a politician. With a unified public, the following loss-function (re-election probability) captures the politician's objective:

$$P = P_0 - \Big(\frac{s^* - s_p(T)}{\sigma_p(T)}\Big)^2. \tag{4.2}$$

The politician does not have to act (s^*) based on what they believe to be the best policy (s_g). As new information emerges, the public's belief about the optimality of politician's action changes. The politician wants to maximize their expected re-election probability. This probability is negatively proportional to the squared difference of what they did and what the public holds to be true on average at the election day (T). The coefficient of proportionality is the inverse of the public's certainty about the best action.

If issues are independent of each other, they enter the probability function in a separable additive way. As a result, the politician can make decisions on each issue separately.

Therefore, as long as each issue is independent of all others, the model can be generalized to multiple issues.

The politician acts to maximize their expected re-election probability conditional on the information set they have at the decision-making time:

$$s^* = \underset{s}{\text{argmax}} P_0 - \mathbb{E}[(\frac{s - s_p(T)}{\sigma_p(T)})^2 | \mathcal{I}]. \tag{4.3}$$

Proposition 9 *With a unified public, the politician's optimal action is a linear combination of the politician's belief and public's belief.*

$$s^* = \frac{1}{\sigma_y^2 + N\sigma_p^2}(s_p\sigma_y^2 + Ns_g\sigma_p^2). \tag{4.4}$$

Proof. From equation 4.1, the politician knows the voters' uncertainty on the election day:

$$\sigma_p(T) = \frac{\sigma_p^2\sigma_y^2}{\sigma_y^2 + N\sigma_p^2}.$$

Therefore, the following first-order condition is obtained:

$$s^* = \mathbb{E}[s_p(T)|\mathcal{I}]. \tag{4.5}$$

Using the linearity of the expectation operator and equation 4.1 we get:

$$s^* = \frac{s_p\sigma_y^2 + \sum_{i=1}^N \mathbb{E}[\hat{s}_p^i|\mathcal{I}]\sigma_p^2}{\sigma_y^2 + N\sigma_p^2}. \tag{4.6}$$

The politician's expectation of the optimal action given their information ($\mathbb{E}[\hat{s}_p^i|\mathcal{I}]$) is s_g, hence equation 4.4 holds. ■

The welfare-maximizing action from the societal perspective, conditional on the information available at the decision-making time, is s_g. This information is available to the politician, yet proposition 9 tells us that they refrain from implementing the optimal action. The amount of deviation decreases with voters' informedness. This channel is the "action channel" of political inefficiency.

Corollary 1 *The politician's deviation from the welfare-maximizing action reduces with voters information.*

$$\frac{\partial(|s^* - s_g|)}{\partial \sigma_y^2} > 0, \frac{\partial(|s^* - s_g|)}{\partial N} < 0. \tag{4.7}$$

Proof. The deviation from the welfare-maximizing action is given by:

$$|s^* - s_g| = \frac{\sigma_y^2}{\sigma_y^2 + N\sigma_p^2}|s_p - s_g|. \tag{4.8}$$

Higher N means the voters receive more signal and lower σ_y means that the voters receive better quality signals. Both increase voters' information.

$$\frac{\partial(|s^* - s_g|)}{\partial \sigma_y^2} = \frac{N\sigma_p^2}{(\sigma_y^2 + N\sigma_p^2)^2}|s_p - s_g| > 0.$$

and

$$\frac{\partial(|s^* - s_g|)}{\partial N} = \frac{-\sigma_p^2}{(\sigma_y^2 + N\sigma_p^2)^2}|s_p - s_g| < 0.$$

■

Note that if the public will be adequately informed by the election day, meaning that either $\sigma_y \to 0$ or $N \to \infty$, the politician will act based on their best knowledge.

4.3.3 Solution when the voters are sorted

If there is more than one group in public, a single number cannot summarize the public belief, and the politician pays attention to multiple opposing opinions. The case where voters sort themselves into two groups is most relevant in a polarized society. In the American society, Democrats hold more left-leaning ideologies and pay attention to similar media. It is similarly true for the Republicans and those right-leaning ideologies.

The loss function introduced in equation 4.2 should be modified to incorporate both opposing views. The problem is set for an incumbent Democrat, but the logic is similar if the incumbent is Republican. If the incumbent's base judges the politician's action poorly, they might get demoralized, refrain from voting, or even switch to the opposition. Yet if the opposition's base judges the politician's action poorly, they might get mobilized and turn out more than usual for the opposition. Hence, each action affects the two groups separately to make different decisions. (For more discussion, see Appendix C) The following expression gives the incumbent Democrat's re-election probability:

$$P = P_0 - \alpha\Big(\frac{s^* - s_d(T)}{\sigma_d(T)}\Big)^2 - \Big(\frac{s^* - s_r(T)}{\sigma_r(T)}\Big)^2. \tag{4.9}$$

The subscript r denotes Republican, and d denotes Democrat. The parameter α denotes the relative strength of the politician's decision effect on different voting groups' turnout. With costly voting and a large enough ideological distance between two parties, the elections are decided by turnouts and less so by voters, switching parties. In such an environment, it is plausible that a Democrat cares more about exciting their base, rather than influencing Republican voters' opinion. Therefore, for a Democrat politician $\alpha > 1$.

The politician chooses the action that maximizes the expected weighted re-election probability among both groups conditional on their information set:

$$s^* = \underset{x}{\operatorname{argmax}} \Big\{P_0 - \mathbb{E}[\alpha(\frac{s^* - s_d(T)}{\sigma_d(T)})^2 - (\frac{s^* - s_r(T)}{\sigma_r(T)})^2|\mathcal{I}]\Big\}. \tag{4.10}$$

Proposition 10 *With a polarized public, the politician's optimal action is a linear combi-*

nation of the politician's belief and both groups' beliefs.

$$s^* = \frac{1}{\sigma_d^2 + \alpha\sigma_r^2}(\frac{\alpha\sigma_r^2}{\sigma_y^2 + N\sigma_d^2}(s_d\sigma_y^2 + Ns_g\sigma_d^2) + \frac{\sigma_d^2}{\sigma_y^2 + N\sigma_r^2}(s_r\sigma_y^2 + Ns_g\sigma_r^2)) \tag{4.11}$$

Proof. Because the politician knows $\sigma_D(T)$ and $\sigma_R(T)$ at the time of decision-making, we can bring those out of expectations. The first-order condition for this maximization problem is the following:

$$s^* = \frac{1}{\sigma_d^2 + \alpha\sigma_r^2}(\alpha\sigma_r^2\mathbb{E}[s_d(T)|\mathcal{I}] + \sigma_d^2\mathbb{E}[s_r(T)|\mathcal{I}])$$

Using the equation 4.1 for both Democrats and Republicans and linearity of the expectation operator we get:

$$s^* = \frac{1}{\sigma_d^2 + \alpha\sigma_r^2}(\alpha\sigma_r^2\frac{s_d\sigma_y^2 + N\sigma_d^2\mathbb{E}[\hat{s}_d^i|\mathcal{I}]}{\sigma_y^2 + N\sigma_d^2} + \sigma_d^2\frac{s_r\sigma_y^2 + N\sigma_r^2\mathbb{E}[\hat{s}_r^i|\mathcal{I}]}{\sigma_y^2 + N\sigma_r^2})$$

The fact that $\mathbb{E}[\hat{s}_d^i(t_e)|\mathcal{I}] = \mathbb{E}[\hat{s}_r^i(t_e)|\mathcal{I}] = s_g$ gives equation 4.11. ■

From equation 4.11, we can derive the comparative statics for how partisanship interacts with election timing. Equation 4.11 gives the incumbent Democrat's action (s_d^*). We can obtain a similar expression for an incumbent Republican (s_r^*) by symmetry ($d \to r, r \to d$). Then, by calculating $s_d^* - s_r^*$ we can compare the level of partisanship for earlier vs. later election timing (small vs. larger N).

From this point onward, I set $\sigma_d = \sigma_r \coloneqq \sigma_p$, mainly because there is no evidence that Democrats and Republicans' uncertainty levels are different, and this assumption marginally simplifies the results. Moreover, by abstracting away from the effects caused by the voting groups' uncertainty levels, we can focus on the effects caused by their belief's difference, which is empirically documented.

The next corollary that readily follows from proposition 10 is the foundation for the main empirical tests. This corollary gives a testable difference-in-differences prediction for the behavior of politicians. Specifically, the equation $\frac{\partial |s_d^* - s_r^*|}{\partial N} < 0$ predicts that the difference between Democrats and Republicans who face an imminent election is larger than the similar difference if the election is in the distant future.

Corollary 2 *The difference in politicians' actions is proportional to the difference in their bases' opinion.*

$$s_d^* - s_r^* = \frac{\alpha - 1}{(1+\alpha)(1+\sigma_p^2 \frac{N}{\sigma_y^2})}(s_d - s_r) \tag{4.12}$$

The difference size shrinks with better-informed voters.

$$\frac{\partial |s_d^* - s_r^*|}{\partial N} < 0, \frac{\partial |s_d^* - s_r^*|}{\partial \sigma_y^2} > 0 \tag{4.13}$$

Proof. Replace both σ_d and σ_r with σ_p in equation 4.11 to get s_d^* for the Democrat incumbent:

$$s_d^* = \frac{1}{\sigma_p^2 + \alpha\sigma_p^2}(\frac{\alpha\sigma_p^2}{\sigma_y^2 + N\sigma_p^2}(s_d\sigma_y^2 + Ns_g\sigma_p^2) + \frac{\sigma_p^2}{\sigma_y^2 + N\sigma_p^2}(s_r\sigma_y^2 + Ns_g\sigma_p^2)).$$

This yields:

$$s_d^* = \frac{\sigma_y^2(\alpha s_d + s_r) + N\sigma_p^2 s_g(1+\alpha)}{(1+\alpha)(\sigma_y^2 + N\sigma_p^2)}.$$

Using the symmetry $d \to r, r \to d$, we can similarly obtain for the Republican incumbent:

$$s_r^* = \frac{\sigma_y^2(\alpha s_r + s_d) + N\sigma_p^2 s_g(1+\alpha)}{(1+\alpha)(\sigma_y^2 + N\sigma_p^2)}.$$

Subtracting s_r^* from s_d^* gives:

$$s_d^* - s_r^* = \frac{\alpha - 1}{(1+\alpha)(1+\sigma_p^2\frac{N}{\sigma_y^2})}(s_d - s_r).$$

By taking the derivative of $|s_d^* - s_r^*|$ with respect to N:

$$\frac{\partial|s_d^* - s_r^*|}{\partial N} = -\frac{\sigma_p^2}{\sigma_y^2}\frac{\alpha - 1}{(1+\alpha)(1+\sigma_p^2\frac{N}{\sigma_y^2})^2}|s_d - s_r| < 0.$$

, and σ_y^2:

$$\frac{\partial|s_d^* - s_r^*|}{\partial \sigma_y^2} = \frac{\sigma_p^2 N}{\sigma_y^4}\frac{\alpha - 1}{(1+\alpha)(1+\sigma_p^2\frac{N}{\sigma_y^2})^2}|s_d - s_r| > 0.$$

■

Informative signals reduce polarization. The more efficient the voters become in getting informed, the less polarized the politicians would act. We expected this result because voters' initial bias is the source of polarization, and with better information, this initial bias fades away.

It is evident from equation 4.13 that as elections are getting closer, the politicians start to act more partisan. So in the cross-section, we expect politicians who have an upcoming election act more partisan than politicians who would not face an upcoming election.

In addition to the comparative statics, it is insightful to examine expression 4.11 for politician's action s^* in the limiting cases. The next corollary concerns two limiting cases that the new incoming signals are highly informative (large N and small σ_y) and not informative at all ($N = 0$ and large σ_y). Define the variable $I_y \equiv \frac{\sigma_y^2}{N}$, as the measure of new signals' informativeness.

Corollary 3 *If signals are highly informative, $I_y \to 0$, both Democrat and Republican incumbents act based on their best information s_g.*

$$\lim_{I_y \to 0} s_d^* = \lim_{I_y \to 0} s_r^* = s_g \tag{4.14}$$

If signals are not informative, $I_y \to \infty$, both Democrat and Republican incumbents ignore their information (s_g) and act closer to their base's beliefs, respectively.

$$\lim_{I_y \to \infty} s_d^* = \frac{1}{1+\alpha}(s_r + \alpha s_d) \tag{4.15}$$

$$\lim_{I_y \to \infty} s_r^* = \frac{1}{1+\alpha}(s_d + \alpha s_r) \tag{4.16}$$

Proof. The result follows from taking the limit of equation 4.11 for Democrats and the corresponding equation for Republicans. ■

Highly informative signals fully break inefficiencies. Both politicians implement their expectation of the optimal policy, and they behave similarly. However, when the new signals are not informative, politicians ignore facts and implement a policy biased towards their base.

Polarization stems from two different sources, both of which are necessary for a disparity in politicians' behaviors. The first one is a divergence in initial opinions (bias) of different groups $s_d \neq s_r$. However, as it is evident is equation 4.12, it is not enough that these two social groups have different opinions for politicians to act differently. It is also necessary that the relative influence that the politician's actions have over their political base to be larger than their influence on the opposition $\alpha > 1$.

4.3.4 Endogenizing the politician's information gathering

The politician's action in both unified and polarized cases crucially depends on the ratio of the public's uncertainty (σ_p) and the signal's quality (σ_y). In the previous sections, I have assumed that nature gives this information structure. This assumption is not realistic because, in many situations, a substantial amount of public learning depends on the politician's information gatherings.

The public's information has no predictive value conditional on the politician's information, and it consists of the politician's signal plus noise. We can interpret the noise as a measure of the politician's transparency and the public's political awareness. The prior belief of the public is normally distributed with a standard deviation of σ_0, and the noise's standard deviation is σ_n then:

$$\sigma_p = \frac{(\sigma_g^2 + \sigma_n^2)^{0.5}\sigma_0}{(\sigma_g^2 + \sigma_n^2)^{0.5} + \sigma_0}. \tag{4.17}$$

The politician chooses the quality of their signal (σ_g). They can increase their effort to get a better signal(lower σ_g) of the optimal action. The cost of getting better information is proportional to the inverse of the signal's variance: $\dfrac{\theta}{\sigma_g^2}$

Because the intuition does not change with heterogeneous voters, I set the case up with a unified public for the sake of expositional simplicity. As in equation 4.2, the politician cares about their popularity in public:

$$P = P_0 - \Big(\frac{s^* - s_p(T)}{\sigma_p(T)}\Big)^2.$$

The timing of events is similar to before, except for the first step. After nature chooses the optimal action, the politician decides on the quality of the signal. They face a tradeoff between being more informed and paying an extra cost of information. Their utility is given by:

$$U = P - \frac{\theta}{\sigma_g^2}. \tag{4.18}$$

The politician does not know what their realization or the public's realizations would be. However, she knows the public's ability to accurately determine the optimal decision by the election day (σ_y, σ_p). Therefore, they maximize their (unconditional) expected utility.

$$\sigma_g^* = \underset{\sigma_g}{\text{argmax}} \mathbb{E}[P_0 - \Big(\frac{s^* - s_p(T)}{\sigma_p(T)}\Big)^2 - \frac{\theta}{\sigma_g^2}] \tag{4.19}$$

The politician optimizes the equation with backward induction. First, they solve how they would act given a signal quality (as in proposition 1) and then chooses the optimal signal quality that maximizes their utility.

Proposition 11 *The signal quality must satisfy the following first-order condition:*

$$\frac{2\theta}{\sigma_g^3} = \frac{\partial}{\partial \sigma_g}\left(\frac{N\sigma_p^2(\sigma_y^2 + N\sigma_g^2)}{\sigma_y^2(\sigma_y^2 + N\sigma_p^2)}\right). \tag{4.20}$$

Proof. Use equations 4.1 and 4.4 to replace the values of $s^*, s_p(T), \sigma_p(T)$, and write down the first-order condition of equation 4.20:

$$\frac{2\theta}{\sigma_g^3} = \frac{\partial}{\partial \sigma_g}\left(\frac{\sigma_y^2 + N\sigma_p^2}{\sigma_y^2\sigma_p^2}\mathbb{E}\Big[\Big(\frac{s_p\sigma_y^2 + Ns_g\sigma_p^2}{\sigma_y^2 + N\sigma_p^2} - \frac{s_p\sigma_y^2 + \sum_{i=1}^N \hat{s}_p^i\sigma_p^2}{\sigma_y^2 + N\sigma_p^2}\Big)^2\Big]\right),$$

which will be further simplified to:

$$\frac{2\theta}{\sigma_g^3} = \frac{\partial}{\partial \sigma_g}\left(\frac{\sigma_p^4}{\sigma_y^2\sigma_p^2(\sigma_y^2 + N\sigma_p^2)}\mathbb{E}\Big[\Big(Ns_g - \sum_{i=1}^N \hat{s}_p^i\Big)^2\Big]\right).$$

After adding Ns_0 and subtracting it from the term inside the expectation, and noting that s_g and $\hat{s}_p^i$ are independent random variables with mean s_0, we get:

$$\frac{2\theta}{\sigma_g^3} = \frac{\partial}{\partial \sigma_g}\left(\frac{\sigma_p^2}{\sigma_y^2(\sigma_y^2 + N\sigma_p^2)}\left[\mathbb{E}[N^2(s_g - s_0)^2] + \mathbb{E}[\big(\sum_{i=1}^{N}(\hat{s}_p^i - s_0)\big)^2]\right]\right),$$

which yields the result. ■

By plugging the definition of σ_p (equation 4.17) into equation 4.20, we can numerically solve for the optimal quality of the signal. However, it is possible to study two limiting behaviors relevant to the intuition analytically. One is when the public's initial signal is very noisy, so the politician's signal quality does not affect the public. The other is when the public has a diffuse prior and maximally learns from the politician's signal.

In the next corollary, we consider the case that the public receives a very noisy signal ($\sigma_n \to \infty$). Label this signal quality as $\hat{\sigma}_g$. Recall that we have shown new signals' informativeness with $I_y \equiv \dfrac{\sigma_y^2}{N}$

Corollary 4 *If the public receives a very noisy signal ($\sigma_n \to \infty$), the optimal signal quality increases with voters' signal informative quality.*

$$\hat{\sigma}_g^2 := \lim_{\sigma_N \to \infty} \sigma_g^* = \sqrt{I_y \theta\big(1 + \frac{\sigma_y^2}{N\sigma_0^2}\big)} \tag{4.21}$$

Proof. First, calculate the limit for σ_o from equation 4.17:

$$\lim_{\sigma_N \to \infty} \sigma_p = \sigma_0$$

Then use the first-order condition in proposition 3 and replace σ_p with σ_0 to get:

$$\frac{2\theta}{\sigma_g^3} = \frac{N\sigma_0^2}{\sigma_y^2(\sigma_y^2 + N\sigma_0^2)}\frac{\partial}{\partial \sigma_g}(\sigma_y^2 + N\sigma_g^2) = \frac{2N^2\sigma_0^2\sigma_g}{\sigma_y^2(\sigma_y^2 + N\sigma_0^2)}.$$

By moving the terms around, we get:

$$\hat{\sigma_g}^4 = \frac{\theta\sigma_y^2(\sigma_y^2 + N\sigma_0^2)}{N^2\sigma_0^2}.$$

The square root of it gives equation 4.21. ■

Since the initial signal that the public receives is not informative, the public's belief's uncertainty on the election day is proportional to the information quality (I_y) and their initial uncertainty. Since this initial information is a form of bias, the more assured of their initial biased opinion, the less the politician can dissuade them, and their information will not be useful. Smaller σ_0 decreases politician's incentive to obtain higher quality information.

Next, consider the case that the public has a diffuse prior ($\sigma_0 \to \infty$). Label this signal quality as $\tilde{\sigma}_g$.

Corollary 5 *If the public has a diffuse prior ($\sigma_0 \to \infty$), the optimal signal quality increases with voters' signal informative quality.*

$$\tilde{\sigma}_g^2 = \lim_{\sigma_0 \to \infty} \sigma_g^* = \sqrt{I_y\theta}\frac{1}{\sqrt{1 - \dfrac{N\sigma_n^2\sigma_y^2}{(\sigma_y^2 + N\tilde{\sigma}_p^2)^2}}} \tag{4.22}$$

Proof. The proof is similar to the proof of corollary 3.1. ■

In the first scenario, the noise shields the politician's information from the voters; therefore, they can use all of that information to their benefit. In the second scenario, some of the information would leak to voters, and they would use that to judge the politician. Controlling for the signal quality, the politician seeks a lower quality signal if the voters can learn from the politician's information.

The next proposition concerns the general relationship between voters' signal's informative quality and the politician's signal quality.

Proposition 12 *The optimal signal quality increases with voters' signal's informative quality.*

$$\frac{\partial \sigma_g^*}{\partial \sigma_y} > 0, \frac{\partial \sigma_g^*}{\partial N} < 0 \tag{4.23}$$

Moreover, if voters are uninformed ($I_y \to \infty$), the politician obtains no signal.

$$\lim_{I_y \to \infty} \sigma_g^* = \infty \tag{4.24}$$

Proof. For the first part of the proposition, I use the envelope theorem on equation 4.19 and use the results from equation 4.20 to write the following equation for the derivative with respect to σ_y:

$$\frac{\partial \sigma_g^*}{\partial \sigma_y} = -\frac{\partial}{\partial \sigma_y}\left(\frac{N\sigma_p^2(\sigma_y^2 + N\sigma_g^2)}{\sigma_y^2(\sigma_y^2 + N\sigma_p^2)}\right)$$

Taking the partial derivative gives:

$$\frac{\partial \sigma_g^*}{\partial \sigma_y} = -N\sigma_p^2 \frac{2\sigma_y(\sigma_y^4 + N\sigma_y^2\sigma_p^2) - (\sigma_y^2 + N\sigma_g^2)(4\sigma_y^3 + 2N\sigma_y\sigma_p^2)}{(\sigma_y^4 + N\sigma_y^2\sigma_p^2)^2},$$

which gives:

$$\frac{\partial \sigma_g^*}{\partial \sigma_y} = N\sigma_p^2 \frac{2\sigma_y^5 + (N\sigma_g^2)(4\sigma_y^3 + 2N\sigma_y\sigma_p^2)}{(\sigma_y^4 + N\sigma_y^2\sigma_p^2)^2} > 0,$$

and similarly for the derivative with respect to N:

$$\frac{\partial \sigma_g^*}{\partial N} = -\frac{\partial}{\partial N}\left(\frac{N\sigma_p^2(\sigma_y^2 + N\sigma_g^2)}{\sigma_y^2(\sigma_y^2 + N\sigma_p^2)}\right) < 0.$$

For the second part of the proposition, assume the contrary and call the finite value of the limit S:

$$\lim_{I_y \to \infty} \sigma_g^* = S.$$

Then take the limit of the first-order condition given by proposition 3 (equation 4.20):

$$\lim_{I_y\to\infty} \frac{2\theta}{\sigma_g^3} = \lim_{I_y\to\infty} \frac{\partial}{\partial \sigma_g}\left(\frac{N\sigma_p^2(\sigma_y^2 + N\sigma_g^2)}{\sigma_y^2(\sigma_y^2 + N\sigma_p^2)}\right).$$

We can change the order of derivative and limit, and use the fact that the limit of σ_p and σ_g are finite to get:

$$\lim_{I_y\to\infty} \frac{2\theta}{\sigma_g^3} = \frac{\partial}{\partial \sigma_g} \lim_{I_y\to\infty}\left(\frac{N\sigma_p^2}{\sigma_y^2}\right) = \lim_{I_y\to\infty}\left(\frac{\sigma_p^2}{I_y}\right).$$

The left-hand side is finite by assumption, but the right-hand side grows unboundedly. ■

In the first two propositions, we explored the "action channel" of political inefficiency. The politician has the relevant information, yet she refrained from implementing the efficient option. Nevertheless, proposition 4 tells us that if voters cannot collect information by election time, the politician will not have any incentives to obtain any information. Proposition 4 is the "information channel" that prevents the political system from implementing an efficient solution.

4.4 Empirics

The empirical section is an indirect test of the theory developed in the previous section. Specifically, I test the implication of proposition 2, corollary 2.1, which states that the difference between Democrats and Republicans shrinks the further their election since the politicians expect the voters to be more informed regarding later elections than earlier ones. The context of this section is gubernatorial decisions regarding the economy shutdown during the Covid-19 crisis.

4.4.1 Empirical Setup

Alternative models that explain the difference between Democrat and Republican politicians' actions implicitly or explicitly assume preference for actions based on the politicians' types. The politician either acts in their own best judgment and preference or their voting base's best interest and preference. In either case, this should not have any interaction with the election timing. On the contrary, this paper, based on information asymmetry, predicts that the incumbent's bias will be intensified when the election is closer or the signals are noisier.

The optimal action is not directly observable. Hence, it is not possible to directly measure politicians' bias from optimal behavior. If we suppose Democrats and Republicans have different optimal actions, it seems impossible to distinguish whether this action is in line with the corresponding optimal action, or it is a biased behavior to get re-elected. A general disparity of behaviors is consistent with rational decision makers with heterogeneous preferences and strategic bias towards the base.

The Covid-19 crisis allowed us to test the idea that elections interact with political decision making. In 2020, the Covid-19 virus hit all US states. The governments at the state level were partially responsible for responding to the crisis. They enacted policies to protect civilians' life. This paper focuses on a subset of these policies that entailed a trade-off between economic objectives and health objectives.

The subset consists of governors' policies on whether to close specific businesses or not. Some governors closed all but essential businesses early on, while others allowed all businesses to remain open. These decisions embody a clear trade-off between potential health risk and imminent economic costs. Early closure of businesses guarantees that the spread of the virus slows down, but it initially hurts the local economy. The optimal decision on business closure depends on both the perceived severity and infectivity of the virus and the magnitude of economic costs.

The literature shows that in response to Covid-19, Democrats and Republicans' voting base had different opinions about how severe the condition is and what the proper response of the government should be. Democrats believed the virus to be more dangerous compared to what Republicans believed. Democrats also expected the government to react quickly and more intensely. They required the government to limit a broader range of economic activity to prevent the spread of the virus early on. On the other hand, Republicans downplayed the government's role and put more emphasis on individual freedom and economic costs of such policies.

Out of fifty US states, about half of the governors were Republicans (26), and the other half were Democrats. Eleven of these governors had an upcoming election in 2020. This variation allows us to test whether the next election's timing impacted governors' decisions.

Regardless of the election timing, we expect that both parties' governors acted more in line with their bases and differently from each other. We expect a Democrat to limit economic activity more. Taking election timing into account, the model predicts that a Republican governor with an upcoming election will be further away from other Democrats on the issue line than a Republican without an upcoming election. The model predicts that a Republican with an upcoming election is the least likely to close any business. In contrast, a Democrat with an upcoming election is most likely to close all businesses.

I test the implications of the theoretical model by estimating the following difference in differences linear probability regression model:

$$y_i = \beta_0 + \beta_1 I_R + \beta_2 I_{>2020} + \beta_3 I_R \times I_{>2020} + \beta_4 S_i + \epsilon_i. \tag{4.25}$$

The dependent variable represents decisions made by governors. If a governor closes a specific business, then the corresponding y equals one; else, it is zero. The first independent variable (I_R) is an indicator function that equals one if the governor is a Republican and zero otherwise. The second independent variable ($I_{>2020}$) is an indicator function for facing an election later than 2020 (distant elections). If a politician had an upcoming election in 2020, this variable is zero. The third independent variable is the interaction of being a Republican and facing an election later than 2020. And finally, S_i is a variable that linearly controls the severity of the disease in the state during the decision-making period.

The difference between Democrats and Republicans who face an election in 2020 is given by:

$$\mathbb{E}[y_i|D, 2020] - \mathbb{E}[y_i|R, 2020] = \beta_0 - (\beta_0 + \beta_1) = -\beta_1, \tag{4.26}$$

and the difference between Democrats and Republicans who face an election later than 2020 is given by:

$$\mathbb{E}[y_i|D, > 2020] - \mathbb{E}[y_i|R, > 2020] = \beta_0 + \beta_2 - (\beta_0 + \beta_1 + \beta_2 + \beta_3) = -\beta_1 - \beta_3. \tag{4.27}$$

Using equation 4.26 and 4.27 we can calculate the difference of these two differences:

$$(\mathbb{E}[y_i|D, 2020] - \mathbb{E}[y_i|R, 2020]) - (\mathbb{E}[y_i|D, > 2020] - \mathbb{E}[y_i|R, > 2020]) = \beta_3. \tag{4.28}$$

The central coefficient of interest is β_3, which captures the change in the difference between Republicans and Democrats as the next election's time increases. The theory predicts this coefficient to be positive. A competing theory that only relies on preferences predicts $\beta_1 + \beta_3$ to be positive and β_3 to be zero.

4.4.2 Data

The dependent variable consists of decisions of governors to close down economic activity in the middle of the first phase of the pandemic. Each governor had to make different decisions as to whether to close down an economic activity or not. There are two independent variables that are relevant to the main result: Whether a governor's term is finishing in 2020 and whether the governor is a Democrat. There is also a series of control variables that capture the level of virus severity in each state. The control variables used were the cumulative number of deaths and the cumulative number of positive cases per capita in each state.

The data regarding the governors' political parties and their next election are scrapped from Wikipedia. Republicans govern twenty-six and Democrats govern twenty-four states. Eleven of these states have an election forthcoming in 2020, and thirty-nine do not have an election in the coming year.

Table 4.1: Party Affiliation and Election

Party	Election 2020	Election Later	Start < 2016	Total
Repulican	7	19	7	26
Democrat	4	20	7	24

The summary statistic for governors

The data regarding the Covid-19 policies were collected by Raifman et al. (2020). This dataset contains multiple variables on when each state put some policies into place and removed them later. Specifically, it contains data related to economics vs. health trade-off. The decisions are on whether the restaurants, the theaters, the gyms, and non-essential businesses are closed on a particular day.

Table 4.2: Closing Days—Summary Statistics

Variable	count	min	0.25 %	0.5%	0.75%	max
Closed Theatres	50	76	78	82	85	never
Closed Dine-in Restaurants	50	75	77	78	80	never
Closed Gyms	50	76	78	81	85	never
Closed Non-essential Businesses	50	79	84	87	92	never

The summary statistic closing day, starting from the beginning of 2020

Table 4.2 summarizes the distribution of closing decisions for the relevant variables. Similarly, Table 4.3 summarizes the distribution of re-opening decisions for those variables. From these two variables, it is possible to reconstruct whether a particular business within a state was closed on any given day.

Table 4.3: Re-opening Days—Summary Statistics

Variable	count	min	0.25 %	0.5%	0.75%	max
Opened Theatres	50	118	143	163	237	(not opened)
Opened Dine-in Restaurants	50	115	128	139	153	(not opened)
Opened Gyms	50	115	136	153	171	(not opened)
Opened Non-essential Businesses	50	111	122	129	138	(not opened)

The summary statistic for the day of openning, starting from the beginning of 2020

All of the decisions are included as separate decisions. For each day in the data, the dimension of y (200) would be the number of governors (50) times the number of decisions (4).

4.4.3 Empirical Results

The first column of Table 4.4 shows the result of the regression equation 4.25 for the main specification. Columns 2 and 3 shows the regression with probit and logit specifications. In all of these specifications, the interaction coefficient is statistically significant. The ballot box's pressure makes politicians 30.5 percent more likely to act partisan and please their base without acting in their interest.

Table 4.4: Main Specifications

	Close down an activity:		
	(Linear)	(Probit)	(Logit)
Const	1.003***	7.267***	17.766***
	(0.002)	(0.758)	(1.451)
Rep	-0.249**	-5.277***	-14.242***
	(0.126)	(0.422)	(0.927)
" > 2020"	-0.071**	-4.731***	-13.275***
	(0.034)	(0.292)	(0.773)
Rep×" > 2020"	0.305**	6.115***	16.040***
	(0.131)	(0.623)	(1.437)
Severity	0.016*	5.174*	9.426*
	(0.009)	(2.697)	(5.105)
Observations	192	192	192
R^2	0.103	0.2443	0.2383
Adjusted R^2	0.084		
Residual Std. Error	0.241(df = 187)	1.000(df = 187)	1.000(df = 187)
F Statistic	2.344* (df = 4.0; 187.0)	(df = 4; 187.0)	(df = 4; 187.0)
Note:			*p<0.1; **p<0.05; ***p<0.01

Most of this effect comes from Democrats, and Republicans' different behavior who have an election in 2020 ($-\beta_1 > 0$). The behavior difference of politicians from different parties who did not have an election in 2020 is not statistically significant at the 95 percent level. Moreover, the sign of this difference is in the opposite direction of the base's opinion ($-\beta_1 - \beta_3 = -0.0558 < 0$). Republicans who did not face an election in 2020 were more likely to limit economic activity and act not in line with their base's belief. Table 4.5 summarizes these results.

Table 4.5: Summary

	Close down an activity:		
	(Linear)	(Probit)	(Logit)
Difference election later ($-\beta_1 - \beta_3$)	-0.0558*	-0.8384**	1.798**
	(0.0363)	(0.465)	(1.091)
Difference election 2020 ($-\beta_1$)	0.2489**	-5.277***	-14.24***
	(0.1263)	(0.422)	(0.927)
Difference in differences (β_3)	0.305**	6.115***	16.04***
	(0.131)	(0.623)	(1.437)
Marginal effect	0.305**	0.390*	0.416***
	(0.131)	(0.250)	(0.170)

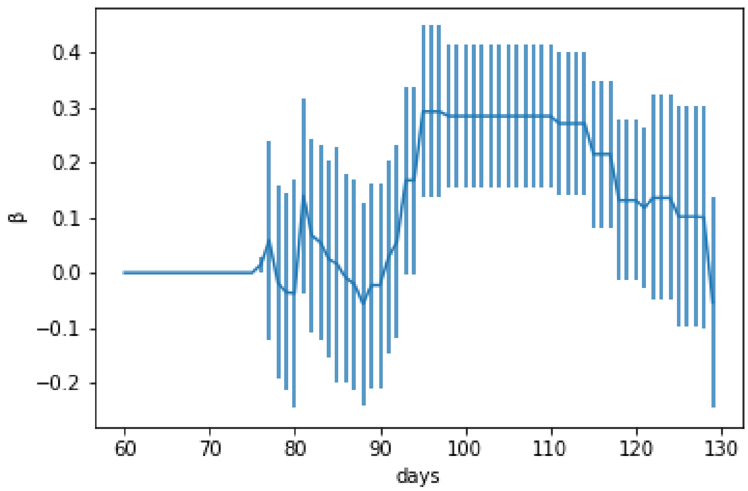
Partisanship increases for decisions made cloeser to elections

To compare the results between linear and non-linear (Probit, Logit) model we need to look at the marginal effect which is given by equation 4.28. These results are statistically and economically significant. The logit model is statistically significant at 0.01 level, while the linear is at 0.05 level, and the probit model is at 0.10 level. Logit seems to be a better fit for the data, but in all specifications, the results are statistically different from zero.

These models predict that election pressure significantly increases the difference between Republicans and Democrats. Democrats and Republicans, under re-election pressure, act between %30 to %40 more polarized than their counterparts who are not under reelection pressure.

The decisions of each governor are correlated. It is necessary to make sure the correlation between different governors decisions does not artificially inflate the significance of the results. I have done so by clustering the standard errors around each state. The reported error bars in Table 4.4 are robust to clustering around states.

Figure 4.1: Daily β_3



Democrats and Republicans with an election in 2020 behave differently as soon as 10 days after implementing the first policy

In the main specification, the decision y is whether a business is closed as of April the 20th. On this day, states have implemented the first phase of limitations, and no state has re-opened any business yet. Figure 4.1 shows the evolution of this interaction term from the time that first business is closed on mid-March until the time that states re-opened the businesses by early May.

A non-linear control for severity led to excluding from the regression the two outlier states of South Dakota and Wyoming, which had the smallest number of deaths per capita in this early period. Both results are robust to dropping/non-dropping multiple states per capita. Table 4.6 summarizes the regression results controlling for the different exclusion of states with low severity. Only the linear probability model is reported; nevertheless, in other specifications (probit and logit), the results' statistical significance does not change.

Table 4.6: Robustness to Outliers

	Close down an activity:		
	(No exclusion)	(Drop 3 states)	(Drop 7 states)
Const	1.004***	1.003***	1.003***
	(0.003)	(0.002)	(0.002)
Rep	-0.249**	-0.249**	-0.299*
	(0.126)	(0.126)	(0.168)
" > 2020"	-0.072**	-0.071**	-0.060*
	(0.034)	(0.034)	(0.034)
Rep ×" > 2020"	0.242*	0.305**	0.344**
	(0.141)	(0.131)	(0.172)
Severity	0.019*	0.016*	0.014
	(0.011)	(0.009)	(0.009)
Observations	200	188	172
R^2	0.060	0.101	0.132
Adjusted R^2	0.041	0.082	0.111
Residual Std. Error (df)	0.281(195)	0.244(183)	0.231(167)
F Statistic (df=4)	2.634**	2.340*	1.830
Note:			*p<0.1; **p<0.05; ***p<0.01

The measure of severity was the number of deaths per capita from the beginning of the epidemic until April 20th. In Table 4.7, the number of infected per capita is used as a measure of severity. Another specification includes a quadratic control of severity.

Table 4.7: Robustness to Measures of Severity

	Close down an activity:	
	(Cases as Severity Measure)	(Quadratic Mesaure)
Const	1.007***	1.029***
	(0.004)	(0.016)
Rep	-0.249**	-0.245*
	(0.126)	(0.126)
> 2020	-0.078**	-0.088**
	(0.036)	(0.039)
Rep$\times > 2020$	0.308**	0.315**
	(0.131)	(0.132)
Severity	0.022*	0.133**
	(0.012)	(0.064)
Severity^2		-0.019**
		(0.009)
Observations	192	192
R^2	0.106	0.114
Adjusted R^2	0.086	0.090
Residual Std. Error	0.241(df = 187)	0.240(df = 186)
F Statistic	2.374* (df = 4.0; 187.0)	1.948* (df = 5.0; 186.0)
Note:		*p<0.1; **p<0.05; ***p<0.01

The results of Table 4.5 is robust to all of these specifications. As is shown in Tables 4.6 and 4.7, the results are robust to including all states, different functional forms (polynomial) for severity, and different measures of severity.

4.5 Conclusion

This paper shows how higher election pressure can lead politicians to act more partisan. The theory suggests that voters' different priors and politicians expecting them not to learn the full truth until the next upcoming election is a potential cause of partisanship. With a longer election horizon, parties act more similarly and, based on the theory, more optimal.

The theory sheds light on why more polarized democracies might be poorly equipped with instruments to respond effectively to a crisis. I discuss how the politician's decision to acquire information interacts with the social signals' informativeness and election dates. When the election is close, the politician spends fewer resources on information acquisition. On top of that, the closer the election, the less they weigh their decision towards that information set, controlling for their information quality.

In a more general setting, the interaction between a politician and the voting base is similar to a principal-agent "P-A" problem. The principals (here, voters) choose an agent to make decisions in an uncertain environment for their benefit. Information asymmetry poses a challenge for the principal to monitor the agent's behavior efficiently and for the agent to signal the quality of their decisions.

Similar to conventional P-A problems, the politician is better informed. They make many decisions over their tenure, and voters later evaluate their performance on election day. The information asymmetry causes an opinion divide between the politician and the voters at the time of decision making, as does the fact that these opinions evolve until the election day as more information immerges.

In this paper, voters are Bayesian learners, and they perfectly update their beliefs given a new signal. This assumption does not hold in reality (people are far from perfect Bayesian updaters). But the results from this model can be extended as long as some learning happens and the voters' beliefs get closer to the truth about the welfare-maximizing policy.

A further avenue for research is to design mechanisms to increase politicians' incentives to acquire high-quality information and stick to the best expectation. I did not explicitly formulate the individual rationality and incentive compatibility of the politician, but a full analysis must consider it.

This paper provides evidence that the pressure of an upcoming oversight induces the decision maker to deviate from implementing the optimal policy towards the principal's bias. Although the example is tailored for a political representative, it can be generalized to other managerial settings. For example, a manager who faces an uncertain decision before a significant event (e.g., merger, critical board meeting) deviates from implementing the optimal action. Can we find similar evidence to show that the manager is more likely to deviate towards the principal's bias if they expect it to affect their evaluation?

If this effect can be found in other settings, we should examine other possible mechanisms that would create similar empirical results. In this paper, I have explained the rational behavior of an agent who forms an expectation of voters' information set at the election date. The mechanism at play may be much more complicated than what was discussed. More research is needed to pin down how this shift occurs. Is it a deliberate calculation of the agent to implement a policy that maximizes their popularity, or is it coming from a psychological bias?

Maybe the psychological pressure of an upcoming election makes it easier for the politician to think of what voters want, which shifts the politicians towards their base's favorite policies. Finding out the mechanism behind this bias is an avenue for further research in managerial decision making under uncertainty.

Chapter 5

Conclusion

This thesis consists of three chapters that study crisis management under uncertainty from the lens of exactly solving simplified models. Each chapter focuses on one aspect of simplification and studies a real-world problem.

Chapter two studies a municipal decision-making authority to provide a public good (water security) to its citizens. In this chapter, I abstract away from complexities arising from political economies of providing a public good and focus on the trade-off that a benevolent decision maker faces. The decision maker uses all of the information available to them. They solve a dynamic problem that balances the risk of not having enough water and the cost of building and operating an expensive water provision facility. The model first explains what a benevolent decision maker would do and then tests the correlation patterns produced by the real-world data against the expected correlation produced by the benevolent planner.

In chapter three, the decision-making's scope is global (climate change), and the decision maker aims to understand the implications of innovation policies for long-term cumulative atmospheric CO2. In this chapter, we abstract away from the optimal dynamic policy. We assume that the decision maker cannot implement the first-best policy (carbon pricing) due to political reasons. Then we ask a theoretical question about whether the effect of an exogenous innovation in clean energy or fuel efficiency is always beneficial for long-term cumulative CO2. We introduce new occurrences of the strong green paradox in fuel efficiency innovation and the interaction of innovation in carbon capture and storage and clean energy innovation.

Chapter four concerns decision-making at the gubernatorial level to combat the Covid-19 pandemic. In contrast to the first two chapters, the decision maker is not benevolent and maximizes their own (party) utility. The decision-making authority faces a trade-off between the policy that they find beneficial for society and the policy that merely looks good to the public. There is inherent uncertainty in the unfolding of future events and the information that the public learns in the future. I develop a theoretical model and predict the behavior of a utility-maximizing politician and test the results against the observed behavior of US governors during the Covid crisis. I show that their behavior is consistent with the predicted behavior in that the politician who faces an imminent election cares more and acts more similarly to what their base deems appropriate.

Decision-making researchers have a plethora of tools at their disposal to examine how authorities manage crises in uncertain situations. But we are yet to find a framework that unites different aspects of decision-making. There are numerous questions regarding the scope of the problem, decision makers' incentives and goals, limitations they face, and even the analytical framework to study decision-making under uncertainty. With the advent of novel computation techniques (e.g., reinforcement learning) and their wide adoption in multiple governing bodies, we will need more convergence in decision-making science.

We may need to re-evaluate what we call a "rational" decision. A decision made by a municipal authority under great public pressure might seem irrational in comparison to the decision suggested by cold calculations of a well-tuned dynamic programming algorithm. Ignoring first-best policies and implementing second bests should be declared irrational when all models suggest otherwise. And having a governor getting swayed by self-interest and making decisions that merely look good must be declared against public interest and irrational if an independent decision-making body can suggest better policies.

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Appendix A

This appendix consists of three sections inspired by the model developed in the second chapter. First, I present the pattern of usage and define the concept of optimal utilization rate. Second, I discuss how does a mistake in the wrong estimation of rainfall probabilities affects decision-making. Finally, I estimate the relative value of being in a good year using a simpler version of the dynamic model.

A.1 Optimal Utilization Rate

The dynamic model is solved numerically, and we are interested in further studying the model and understanding some implications of it. I achieve this by fixing most parameters of the model and change only one or two parameters and simulate the behavior of such city.

The first thing that I look into is how the capacity of a typical city evolves and how this capacity is used. For a city that faces no economy of scale ($F = 0$), the accumulated capacity looks similar to Figure A.1. Initially the city gets a few good draws and there is no need to build any capacity. Then after some bad draws, the city starts to build a desalination plants, and finally some more bad draws and city builds the optimal level of desalination that they maintain forever.

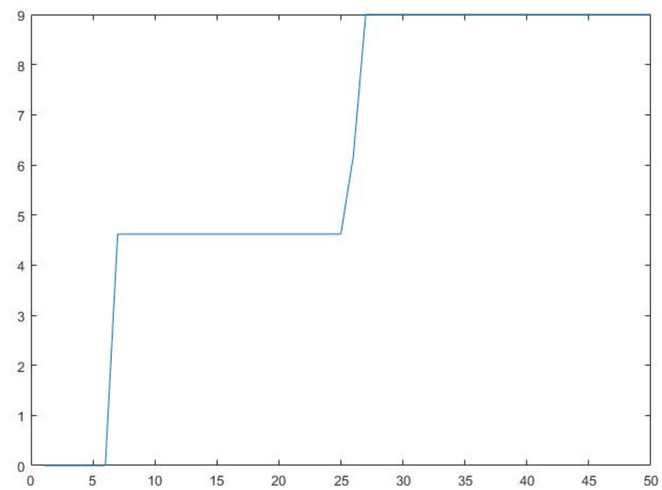

Figure A.1: **Realized capacity over time**

Conditional on building some capacity the city uses some of the capacity in some years and lets it remain idle in others. The blue line in Figure A.2 shows the relative amount of used capacity for each year. For this specific city, the city wont use the capacity in good years (because it gets more waters than it needs) but as you can see in average (the yellow line) only 22 percent of the capacity is used. This usage is spread out over time. Variance of usage is correlated with variance of rainfall.

This pattern of sporadic use of desalination capacity is typical behaviour of desalination usage in many cities. Any city that builds desalination for combating bad draws of rainfall and not for base water needs should see a behavior of this sort. If rainfall patterns accross different cities are not heavily correlated, rainfall patterns of this sort suggests a need for mobile desalination plants. Imagine a large desalination plant installed on a vessel that can move around the world and provides water on demand. This vessel would have a much higher utilization rate and further studies into this area might prove this to be cost effective.

The realization of built capacity in Figure A.1 depends on the specific random rainfall realization. In order to average across these rainfall realizations I simulated different rainfall patterns for each city 1000 times for 300 years. Then each point is the average built capacity for each year. In Figure A.3 each line represents the average capacity built for each city.

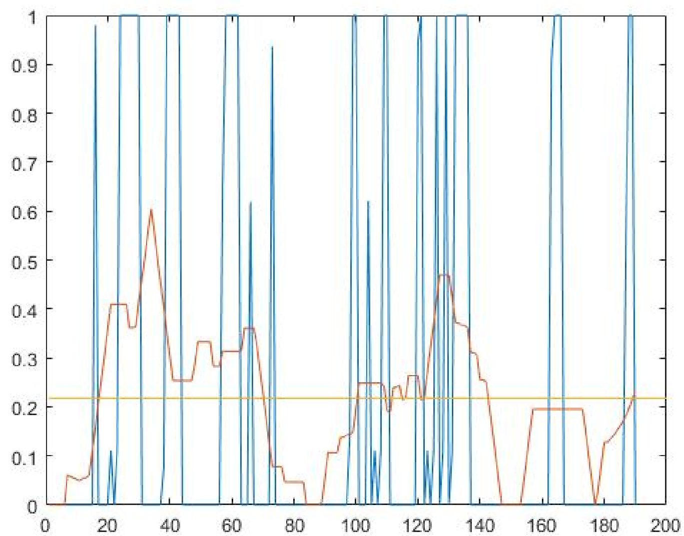

Figure A.2: **Usage over time**

Each line in this figure represents different cities that are faced with changing rainfall variations between good and bad years ($\delta = r_2 - r_1$). After twenty-five turns (years) in simulation most cities converge to the optimal desalination capacity. As expected an increase in rainfall variation leads to an increase in the optimal capacity level.

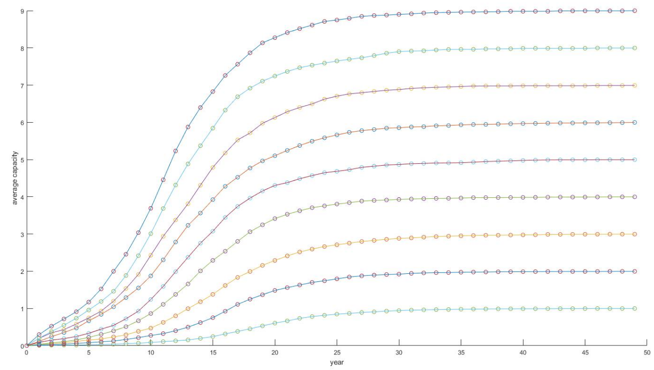

Figure A.3: **Average capacity over time**

A.2 Mistakes in Probability Estimation

Municipalities have to decide on their model of weather dynamics. In the basic setting, the municipality needs to have an estimation of two probabilities (p_{11}, p_{22}). If there is no predictive power in the data, the planner should set $p_{11} = p_{22} = 0.5$. But the data shows different levels of predictivity for different cities $(p_{11} \neq 0.5, p_{22} \neq 0.5)$. The question we will ask in this section is how a mistake in estimating these probabilities would affect the outcome of this model.

The estimation mistake can go both ways. The "availability heuristic" is a psychological bias. It means that there is a "tendency to overestimate the likelihood of events with greater *availability* in memory, which can be influenced by how recent the memories are or how unusual or emotionally charged they may be." This bias may lead to an overestimation of the probability of remaining in bad draws. Another psychological bias is Gambler's fallacy. It means a "tendency to think that future probabilities are altered by past events when in reality they are unchanged." This bias may lead to an underestimation of the probability of remaining in bad draws.

Suppose a city's population in aggregate shows tendencies toward any of these biases. In that case, a decision maker's choice might be affected because the decision maker cares both about the outcome of the decision and the public's judgment.

As in a previous section, I simulated 1,000 cities for 300 years for each remaining probability $p_{11} = p_{22}$. Figure A.4 shows the average capacity built over time. The final capacities of cities are almost equal, but the rate at which they are built is different. Figure A.5 shows the average utilization rate as a function of the probability of remaining in a (good or bad) state. As probabilities of remaining in a state increase, more capacity is used on average.

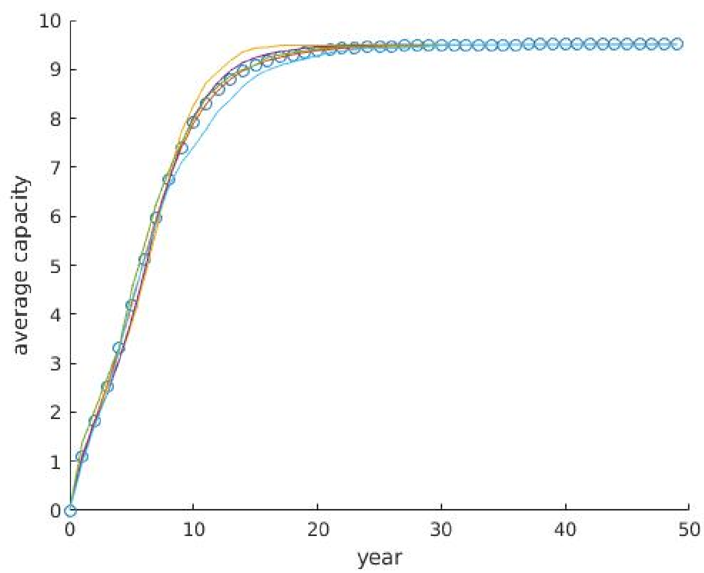

Figure A.4: **Average capacity over time for different probabilities** $p_{11} = p_{22}$

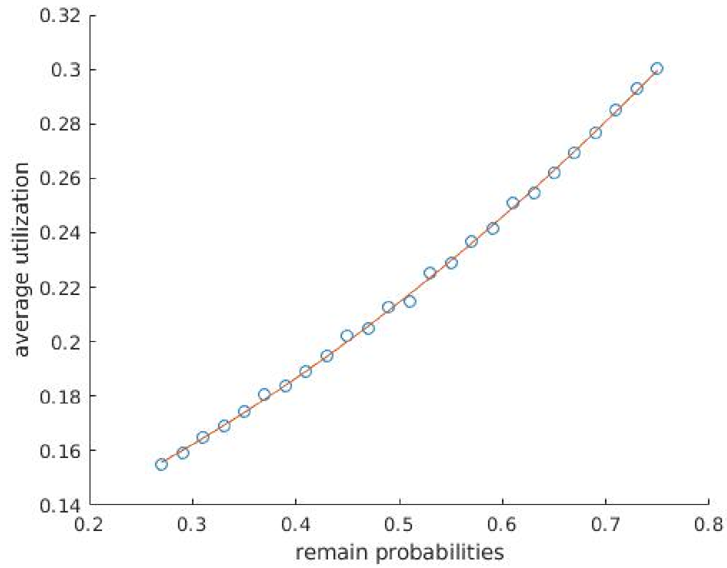

Figure A.5: **Average utilization rate vs. probability of remaining in a state** $p_{11} = p_{22}$

Last plots were about how the optimal behaviour changes with probabilities if there is no mistake in the estimation of probabilities. Now I simulate the same 1000 cities for 300 years and look at how much the utility changes if a city makes its decisions based on a mistaken model rainfall probabilities.

The y-axix of Figure A.6 is the weighted sum (β) of the mean (over different cities) of capacities built with the mistaken beliefs minus the mean of capacities built with the correct belief.

$$y = \sum_{t=0}^{300} \beta^t \frac{1}{1000} \sum_{i=1}^{1000} (\hat{d}_i^t - d_{i,p}^t)$$

If $y > 0$, the optimal thing to do is to build the capacities earlier, and $y < 0$ means the opposite. We can see that for making a small mistake the effect is negligible, but for larger mistakes, underestimation leads to building later and overestimation leads to building earlier.

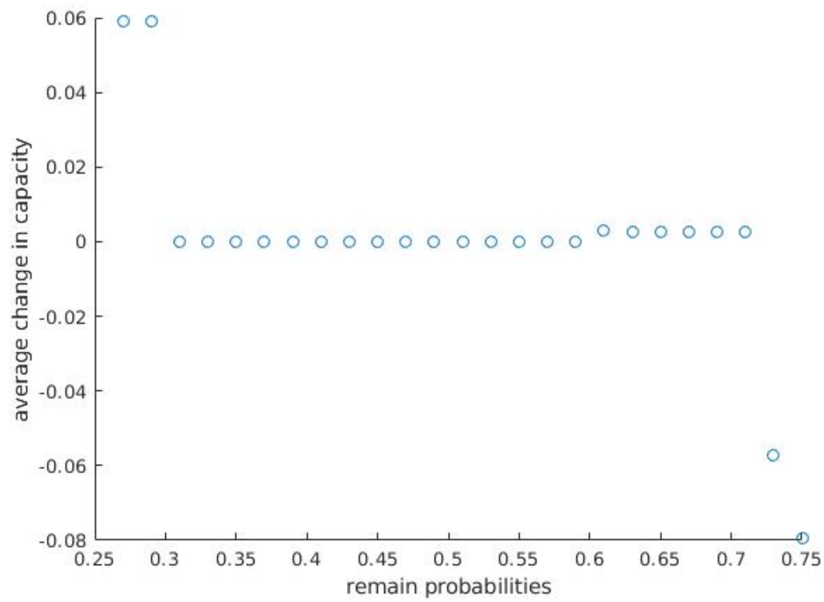

Figure A.6: **Effect of mistakes on capacity, actual transition probability is** $p_{11} = p_{22} = 0.55$

The y-axix of Figure A.7 is the weighted sum (β) of the mean (over different cities) of utilities with the mistaken beliefs minus the mean of utilies with the correct belief.

$$y = \sum_{t=0}^{300} \beta^t \frac{1}{1000} \sum_{i=1}^{1000} (\hat{U_i^t} - U_{i,p}^t)$$

The y-axis shows the utility lost due to mismanagement. For the worst mistake (believing probability is 0.75 when it is really 0.55) the effect is still very small (0.008) where lifetime utility is around -45. This shows that for the current variables, the mistake in estimating the correct form of the weather dynamics is negligible.

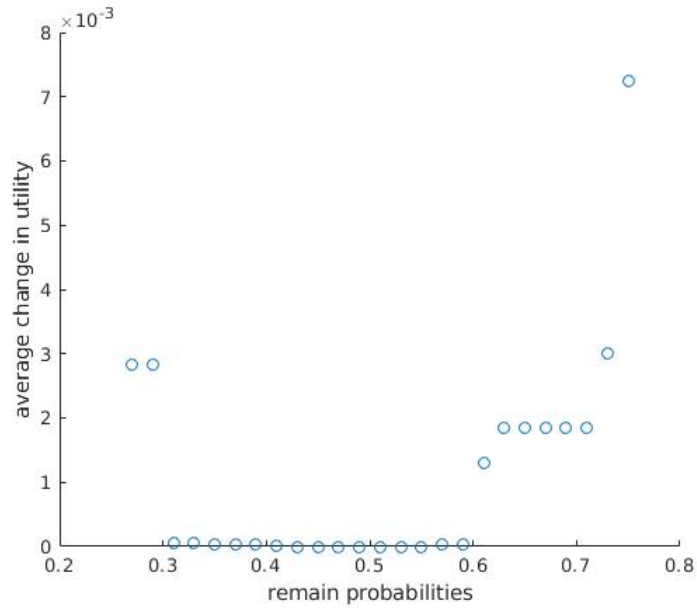

Figure A.7: **Effect of mistakes on utility, actual transition probability is** $p_{11} = p_{22} = 0.55$

A.3 Estimation

It is not possible to fully estimate all the parameters of the dynamic demand model but I can make some progresses by making some simplifying assumptions. It is helpful to estimate the long-term price elasticity of demand for desalination capacity and a structural model that specifies the relative value of plants in years with favorable and unfavourable rainfall draws.

Estimation of the price elasticity requires some supply shifters that do not affect demand separately, and I will discuss them in the next section. With the current data, one can estimate the long-term price elasticity with some simplifying assumptions.

I would continue to estimate a simple structural model which abstracts away from questions about plant size and quantifies the value of building a plant in years with a bad draw of rainfall relative to the similar value in a year with good draw.

A.3.1 Supply

I choose a model-free approach to understand supply. Table A.1 shows what variables affect the volume unit price of constructing a desalination plant using a linear regression model with fixed effects on each subregion and a dummy for technology type. The coefficient for East Asia/ Pacific is set to zero, so all the subregion fixed effects are measured with respect to that.

The coefficient of year variable captures the annual decreasing of prices. This is partially caused by process innovation and learning by doing that consistently reduces the cost of construction of desalination plants. The coefficient on time variable (year) captures this effect. Each year the price of building a new plant drops on average by about 4.0 percent.

The technology fixed effect captures the other aspect of innovation. Major desalination plants are designed based on one of three technologies: multi-effect distillation (MED), multi-stage flash MSF, and reverse osmosis (RO). In Table A.1 the coefficient of MED is set to zero, and other technologies are measured with respect to this technology. RO (the most recent technology) is a revolutionary technology and brought down prices by 61 percent in comparison with with MED or MSF.

The negative coefficient on log(Capacity) captures economies of scale. Building a plant twice the size of a normal plant would reduce the price by 3.6 percent.

Table A.1: Variables Affecting Price

log(Price per Volume)	Coeff.	std. error	t-Value
(Intercept)	8.49	0.13	63.0 ***
Eastern Europe / Central Asia	-0.54	0.28	-1.912 .
Latin America / Caribbean	-0.22	0.15	-1.46
Middle East / North Africa	-0.624	0.064	-9.7 ***
North America	-0.929	0.071	-13.0 ***
Southern Asia	-0.44	0.15	-2.91 **
Sub-Saharan Africa	-0.26	0.23	-1.17
Western Europe	-0.517	0.079	-6.60 ***
MSF (Multi-stage Flash)	0.15	0.11	1.39
RO (Reverse Osmosis)	-0.611	0.089	-6.9 ***
log(Capacity)	-0.0365	0.0096	-3.8 ***
year	-0.0396	0.0020	-20.4 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

In further sections, I treat innovation as an exogenous supply shifter. Two cities with similar observables (population, city size, and climate) but facing different supply due to availability of more modern (hence cheaper) technology would identify the elasticity of demand. Similarly two cities with the same observables except population are helpful in identification, because one city is able to build a larger plant and face a smaller price per capita.

The results in Table A.1 guide us in finding supply shifter and from there instrumental variables that help identify the demand elasticity.

A.3.2 Estimation of demand elasticity

The demand model should be convincing that in the long-term cities move to the equlibrium capacity that is determined by supply and demand fundamentals. A city is in equilibrium if it has passed bad rainfall years and has built its equilibrium capacity.

Demand fundamentals include some observables like GDP, population, and climate patterns (e.g., standard deviation of rainfall) and some unobservables like the cost of water underprovision, average water usage, and local geographic characteristics. Supply fundamentals include the cost of technology and local economic characteristics (e.g., wages, land value, local infrastructure, and environmental characteristics).

To estimate the long-term elasticty of demand, I make the following simplifying assumptions:

1. The desalination capacity is in equilibrium over a five-year period.
2. The log of equilibrium demand capacity is a linear function of log of prices.
3. Conditional on GDP per capita, population of cities, and local climate patterns, cities are similar up to a random constant term and random shocks.
4. Average annual prices of desalination construction that city “i” faces are independent of city “j”’s demand for desalination.

From these four assumptions, I can proceed to the following specification:

$$C_{it} = A_{it} p_{it}^{\beta} R_{it}^{\alpha_1} G_{it}^{\alpha_2} P_{it}^{\alpha_3} T_{it}^{\alpha_4}. \tag{A.1}$$

where $A_{it} = U_i e^{\epsilon_{it}}$ and U_i is coming from a random distribution and ϵ_{it} is the error term.

In equation A.1, C represtents cumulative capacity available for each city, p the predicted price that a city face in building new capacity, R rainfall, G the GDP, P population of the city, T temperature. All the explanatory variables are averaged over five-year periods.

For each city-year observation, the value of p is predicted using a model with year and country fixed effects. p is the price that cities face if they choose to build a desalination plant (though in many years they have not).

Two major worries are that the city specific term A might be correlated with prices and the elasticity β is not measured correctly. To address this issue, I take advantage of an instrument for price based on assumption 4.

Because the average annual price of desalination in cities other than "i" is excluded from demand of city "i", the average price of desalination in cities other than "i" in year "t" p_{-it} can be used as an IV for p_{it}

-

Table A.2: Demand Elasticity

log(Price per Volume)	Coeff.	std. error	t-Value
(Intercept)	-304	30	-7.86 ***
log(price.per.cap)	-0.74	0.12	-6.00 ***
log(rainfall)	0.054	0.099	0.54
log(GDPperCap)	0.728	0.074	9.77 ***
log(temp + 273)	54	6.7	8.08 ***
log(city.pop)	0.376	0.09	4.2 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A.2 summarizes the result of regression A.1. The price elasticy of demand is

-0.74. As you may have noticed, after controlling for temperature, rainfall is no longer significant. This shows that temperature is sufficient statistics for long-term climate patterns, and five years is a suitable time scale for the cities to reach equilibrium.

Table A.3: Demand Elasticity—IV

(Intercept)	-284	39	-7.2 ***
log(price.per.cap)	-0.96	0.13	-7.2 ***
log(rainfall)	0.072	0.099	0.72
log(GDPperCap)	0.635	0.078	8.2 ***
log(temp + 273)	51.0	6.8	7.5 ***
log(city.pop)	0.300	0.090	3.2 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A.3 replicates table A.2 with price of desalination in other countries as an instrument. The results are qualitatively similar, and price elasticity in this case is closer to -1.

A.3.3 Estimation of utility function

In the last section we studied demand from a long-term aspect, and it became clear that the fluctuations in rainfall does not affect demand after controlling for average temperature over a five-year period.

This is in stark contrast to the effect of rainfall in the short run. Both the prediction of the theoretical dynamic programming model and the results of regression in Table 2.5 suggest that rainfall affect the timing of building the plants.

Further evidence supports that lower rainfall in short-term is correlated to an increased desalination demand. Assuming that city characteristics does not change much from this year to the next, we can take advantage of fixed effect models and show that how a relatively bad draw of rainfall is correlated with the city's higher demand for desalination.

Table A.4: Fixed Effects—Capacity Built Is the D.V.

Capacity	Coeff.	std. error	t-Value
lag(relativerain, -1)	-110	142	-0.77
lag(relativerain, 0)	582	142	-4.1 ***
lag(relativerain, 1)	-347	143	-2.4 *
lag(relativerain, 2)	-296	143	-2.1 *
lag(relativerain, 3)	-48	143	-0.33

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The dependent variable in Table A.4 is Capacity. The independent variables, relative rain (rainfall in a given year divided by mean of the city rainfall) and its lead and lags, are defined by dividing corresponding year's rainfall by average rainfalls. The correlation is very strong for current rainfall and significant for the last two previous rainfall. But it soon starts to fade away for years further in time and the year after the plant is awarded. This evidence supports the causal story that a bad draw of rainfall trigerrs building the plant. Municipalities choose to build a desalination plant when the supply of water is stressed.

Figure A.8 shows the same effect in a plot from a new perspective. The y-axis represents the mean of relative rainfall for all cities in year t (x-axix) after a plant is built.

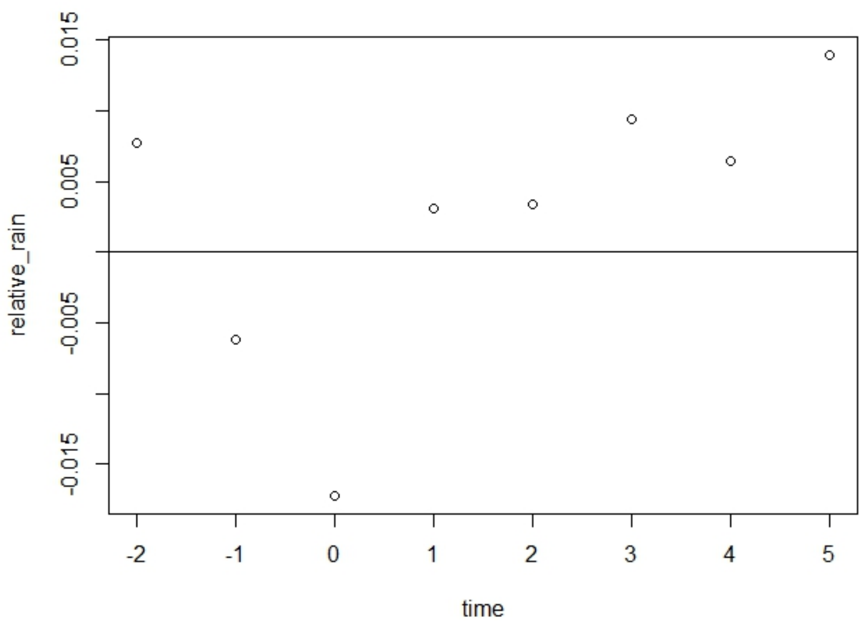

Figure A.8: **relative rainfall around the date of construction**

This evidence motivates me to estimate the relative value of a desalination plant. In this section I eventually estimate the value of building a plant in favorable condition compared to an unfavorable one.

I estimate a simplified version of the dynamic model. The water levels in each city can be in two states. In good g state, the water reserve is high enough to provide water. In bad b state, the rainfall is not enough to provide the required water.

The city can always choose to build a desalination plant, but it takes time for it to be built. Therefore, cities face a tradeoff between building now and paying the costs or postponing the construction and risking incurring the cost of not having enough water.

Eventually, I want to estimate $(u_1(\rho) - u_0(\rho))$, the utility difference of building and not building as a function of relative rainfall ($\rho = \dfrac{R}{\bar{R}}$), and P_{gg}, P_{bb}, the probabilities of remaining in good or bad states. This allows me to quantify the effect of short term rainfall fluctuations on demand.

The estimation framework is a discrete choice model. The planner can choose whether to build a plant. There is only one state variable. An unobserved variable that captures if the city is in water shortage. This unobserved state variable in principle depends on many characteristic which includes: current desalination capacity, temperature, other infrastructes and population. The unobserved variable represents all of these charecteristics in a concise manner.

With probability that is to be estimated any given city is in state g or similarly in state b. With probabilities P_{gg}, P_{bb} any given city will remain in its current state correspondingly and with probabilities $1 - P_{gg}, 1 - P_{bb}$ the city will move to the other state.

The static value of not building a plant is normalized to 0. The static value of building a plant for city i at time t is given by:

$$u_{it} = -\alpha\rho_{it} + \nu_{it} + \epsilon_{it}.$$

$\alpha\rho_{it}$ represents the utility of relatively more rainfall for city i. ν_{it} represents the hidden Markov state. ϵ_{it} is the idiosyncratic preference shock. I assume that the shock is distibuted i.i.d. type-1 extreme value.

Following Bajari et. al. **?** I use four sets of moment conditions, and in total I get 30 moment equalities. Two sets of moments are related to conditional correlation of choices over time.

In city i, at time t, the city chooses j. $j \in 0, 1$ is the decision of whether to build a desalination plant or not.

The first set of moment conditions is related to conditional correlation of choices one period apart:

$$M_1^{jh} = E[Z_t(d_{ij,t+1}d_{ij,t} - \sum_{k,p=1}^{K} \Pi_{kp}\sigma_{ij}^k(t+1)\sigma_{ih}^p(t))], \tag{A.2}$$

where Z_t is an instrumental variable, Π_{kp} represent the stationary distribution of $Pr(\nu_{it} = z_k, \nu_{it} = z_p)$, $d_{ij,t}$ is a dummy that is 1 if city i made decision j at time t. And σ_{ij}^k is the unobserved choice probability of city i choosing decision j in state k.

Similarly, the second set of moment conditions is related to conditional correlation of choices two periods apart:

$$M_2^{jh} = E[Z_t(d_{ij,t+2}d_{ij,t} - \sum_{k,p,r=1}^{K} \Pi_{kr}\Pi_{rp}\sigma_{ij}^k(t+1)\sigma_{ih}^p(t))]. \tag{A.3}$$

The two remaining sets of the moment conditions are related to the Bellman equation. The first one is the Bellman equation for not building choice:

$$M_3 = E[Z_t(V_t) + \beta \sum_{k,p=1}^{K} \Pi_{k,p} log(\sigma_{i0}^k(t+1)) - \beta V_{t+1}], \tag{A.4}$$

where V_t is the conditional value function and β is the discount factor. Similarly, the second one is the Bellman equation for building a plant:

$$M_4 = E[Z_t(V_t) + \beta \sum_{k,p=1}^{K} \Pi_{k,p} log(\sigma_{i0}^k) - \beta V_{t+1} - \alpha\rho_{it} + \sum_{k,p=1}^{K} \Pi_{kp} log(\frac{\sigma_{ij}^k(t)}{\sigma_{i0}^k(t)})]. \tag{A.5}$$

These moment equalities and a set of moment inequalities which states that all probabilities have to be between zero and one identifies the model.

Table A.5: Results

Parameter	Value
P_{bb}	0.43
P_{gg}	0.97
α	0.86

Table A.5 shows the results of the estimation procedure. Three estimated parameters summarizes the data with respect to the effect of rainfall on the utility of building a desalination plants.

Each city which is in good state remains in a good state with high probability (0.97). So, there is a small chance that this city goes to a bad state. Then almost 57 percent of cities move out of a bad state because they either build a plant or the whether condition changes. Then the remaining 43 percent remains in a bad state.

The parameter of interest α is positive. This shows that building a desalination plant is more valuable to cities in when they get relatively low level of rainfall compared to when they rainfall levels are high.

Appendix B

In the first section of this appendix, we offer proofs of lemmas and propositions that we removed from the body of chapter three for ease of exposition. Moreover, in that chapter, we treated the CSS innovation as exogenous. The second section of this appendix provides an extension of the model that endogenizes CCS innovation and proves that the results hold under endogenous CCS innovation.

B.1 Proofs

Lemma 1. With discovery of the new backstop y_1 at date τ, we have: $\mathbf{p}_1(s;\tau) < \mathbf{p}_0(s)$, for all $s > x_0(\tau)$; for all $t > \tau$, $x_1(t;\tau) > x_0(t)$; and for all $c > c(\tau)$, $\widetilde{t}_1(c;\tau) < \tilde{t}_0(c)$.

Proof. At any extraction amount s, equation (3.3) implies that $\frac{ds}{dt} \cdot \frac{dP}{ds} = r[\mathbf{p}(s) - \mathbf{c}(s)]$. From $\frac{ds}{dt} = \dot{x}(t) = q(p(t))$, this yields:

$$\frac{dP}{ds} = r[\mathbf{p}(s) - \mathbf{c}(s)]/q(\mathbf{p}(s) \tag{B.1}$$

where $\mathbf{c}(s)$ is the marginal extraction cost at s, i.e. $\mathbf{c}(\cdot) \equiv G^{-1}(\cdot)$.This is a differential equation describing the evolution of p in s. Note that at s^*given by $\mathbf{c}(s^*) = b_1, p_1(s^*;\tau) = b_1 < p_0(s^*)$, since $p_0(s^*)$ covers not only the extraction cost but also the (positive) Hotelling rent at any s satisfying $c(s) < b_0$. Thus at s^*,the price path is lower after innovation. Suppose that for some $\hat{s}$, the paths cross:

$$p_1(\hat{s};\tau) = p_0(\hat{s})$$

Then because both price paths extending from $\hat{s}$ satisfy (B.1), the price paths must coincide. But this contradicts $p_1(s^*;\tau) < p(s^*)$. Therefore, $p_1(s;\tau) < p_0(s)$ for all s. It follows that $\dot{s}$, given by $q(p)$ is greater at any s post innovation. Therefore, the pre-innovation path and the innovation paths in t start with the same value $x(\tau)$, but at any higher value of s, $\dot{x}$is greater post-innovation. It follows that $x_1(t;\tau) > x_0(t)$. ■

Lemma 2: With clean-energy innovation under the parameter ρ, the price path prior to discovery satisfies

$$\dot{p}_0(t) = r\{[p_0(t) - c(t)] + \rho[p_0(t) - p_1(t,t)]\}.$$

Proof. We aim to show that equation 3.7 in the text

$$p_0(t) - c(t) = lim_{dt\to 0} e^{-rdt}[(1-\rho dt)p_0(t+dt) + \rho dt \cdot p_1(t;t) - c(t)] \qquad (3.7)$$

yields the differential equation

$$\dot{p}_0(t) = r\{[p_0(t) - c(t)] + \rho[p_0(t) - p_1(t,t)]\} \qquad (3.8)$$

We expand the limiting expression on the RHS of (3.7) via Taylor series expansion. Let $o(dt)$ denote all terms involving dt of order higher than 1. Equation (3.7) becomes:

$$p_0(t) - c(t) = \lim_{dt\to 0}[1 - rdt + o(dt)] \cdot \{(1-\rho dt)\left[\dot{p}_0(t) + \dot{p}_0(t)dt + o(dt)\right] + \rho p_1(t;t)dt - c(t)\}$$

$$= \lim_{dt \to 0} (1 - rdt - \rho dt) p_0(t)(1 + \frac{\dot{p_0}(t)}{p_0(t)} dt) + \rho p_1(t;t)dt - (1 - rdt)c(t) + o(dt)$$

$$= \lim_{dt \to 0} [p_0(t) - c(t)] + p_0(t)[\frac{\dot{p_0}(t)}{p_0(t)} dt - rdt - \rho dt] + \rho p_1(t;t)dt + rc(t)dt + o(dt),$$

from which we get

$$0 = \lim_{dt \to 0} p_0(t)[\frac{\dot{p_0}(t)}{p_0(t)} dt - rdt - \rho dt] + \rho p_1(t;t)dt + rc(t)dt + o(dt).$$

Dividing both sides by the non-zero term dt yields:

$$0 = \lim_{dt \to 0} p_0(t)[\frac{\dot{p_0}(t)}{p_0(t)} - r - \rho] + \rho p_1(t;t) + rc(t) + \frac{o(dt)}{dt}.$$

The last term disappears in the limit. We can re-arrange the equation to get

$$\dot{p_0}(t) = (r + \rho)(p_0(t)) - \rho p_1(t;t) - rc(t),$$

which is equivalent to equation 3.8.

■

Proposition 4: (a) In the absence of CCS innovation, the ex ante impact of clean-energy innovation on cumulative emissions is zero.
(b) With CCS innovation , $\dot{a}(t) > 0$, the ex ante impact of clean energy innovation is to increase emissions by:

$$\int_0^{(y_0 - z)/\lambda_0} [a(\tilde{t}(c)) - a(\widetilde{t_0}(c)]g(c)dc > 0.$$

Proof. To prove (a), define $b \equiv (y_0 - z)/\lambda_0$ note that the both the innovation-possible price path and the innovation-impossible price path terminate at $p = b$, with cumulative extraction (and emissions) given by $G(b)$. If $a(t)$ is constant at a, the net emissions under either price path are $aG(b)$. The cumulative emissions are therefore, unaffected by the (unrealized) threat of innovation.

To prove (b), note that it is easily demonstrated first that $p_1(t,t) < p_0(t)$, i.e. the current price falls upon discovery of the clean energy technology at lower cost. For any price and cumulative emissions paths, $p(t)$ and $x(t)$, define $P(x) = p(x^{-1}(x))$. Let$P_0(x)$ and $P(x)$ describe the prices under the innovation-possible and innovation-impossible models as functions of cumulative extraction to date. We first show that $P_0(x) < P(x)$ for all x less than the final value, $x = G(b)$.

Note that $P_0(x) = P(x) = b$ at $x = G(b)$. At this end-point, we have:

$$\frac{\partial P}{\partial x} = \frac{dp/dt}{dx/dt} = \frac{\dot{p}}{q(p)}.$$

Similarly,

$$\frac{\partial P_0}{dx} = \frac{\dot{p}_0}{q(p_0)}.$$

The denominators of the right-hand sides of these equations are the same because at the end-point, $p = p_0 = b$.

And $\dot{p} < \dot{p}_0$ from comparing equations 3.3 and 3.8. Therefore, $\partial P/\partial x < \partial P_0/\partial x$ at the end point, $p = b$. Therefore, within a neighborhood of the endpoint, $x = G(b)$, we have $P_0(x) < P(x)$ Suppose that at some values $x < G(b)$, $P_0(x) \geq P(x)$. Let $\hat{x}$ be the largest such value. It follows the differentiability of the price functions that $P_0(\hat{x}) = P(\hat{x})$ and that evaluated at $\hat{x}$, $\partial P/\partial x \geq \partial P_0/\partial x$. (The two price functions either cross or are tangent at $\hat{x}$.)

But at $\hat{x}$, the two functions have the values of p. $\partial P/\partial x = \dot{p}/q(p)$ (following our earlier derivation) and similarly $\partial P_0/\partial x = \dot{p_0}/q(p_0)$. Comparing equations 3.3 and 3.8 again, we have $\partial P/\partial x < \partial P_0/\partial x$ at $\hat{x}$, which is a contradiction. Hence, $P_0(x) < P(x)$ for $x < G(b)$.

From the assumption of downward-sloping demand, $P_0(x) < P(x)$ implies that $Q_0(x) > Q(x)$, where these are the flows of demands. For each of these functions, $Q(x) = dx/dt$ evaluated at the inverse of $x(t)$. Thus we have two variables, $x_0(t)$ and $x(t)$, for which $x_0(0) = x(0) = 0$ and $\dot{x} < \dot{x}_0$, evaluated not at the same time, but at the same stock y. That is, $\forall y, \dot{x}(x_{imp}^{-1}(y)) < \dot{x}_0(x_o^{-1}(y))$. This implies that x grows more slowly than x_0 and therefore,that $\forall t > 0, x(t) < x_0(t)$. Because $c(t) = G^{-1}(x(t))$, this in turn means that $c(t) < c_0(t)$ and that $\tilde{t}(c) < \tilde{t}_0(c)$.

Part (b) of the proposition then follows. ■

B.2 Extending the CCS Technology

B.2.1 Framework

To this point, we have represented CCS as a function $a(t)$ representing the fraction of carbon emissions that is captured with the technology existing at time t. This allows a simple framework to outline the impact of exogenous innovation, but is based on a narrow assumption on technology (an assumption of zero marginal cost of CCS up to $a(t)$ at each t. The question arises as to whether our results obtain with a more general CCS technology in which the extent of CCS at any time is variable and chosen endogenously by the planner.[13]

We address this question for the analysis of the ex post impact of innovation, for both clean energy and fuel-efficiency innovation. We represent the cost of CCS of a fraction a of emissions q as a function $q \cdot c(a;\theta)$, where θ is the current state of technology. We assume

[13]We will continue to assume that the costs of CCS (mainly the costs of storage and the transportation network) are borne by the government, not by suppliers. The dynamic regulatory game in which CCS standards are set by the regulator but costs borned privately is important but beyond the scope of this paper.

that $c_a > 0$,$c_{aa} > 0, c_\theta < 0$ and $c_{\theta a} < 0$. Thus c is increasing and convex in a and better technology reduces the marginal cost of a. The state of technology at date t is θ_t, and by innovation or improvement over time in CCS technology we mean that θ_t is increasing over time.

Because emissions are a pure externality, the equilibrium extraction rate and emissions, $q(t)$ is uninfluenced by changes in a. The regulator therefore, takes the path $q(t)$ as exogenous in deciding on the path $a(t)$. The regulator's objective in setting $a(t)$ at any time is to minimize costs, comprised of the cost of CCS and the long-run cost of emissions. We let T be a date beyond which all emissions have terminated under any scenarios involving innovation at any date and let the welfare cost (damages) of adding to cumulative emissions (i.e. the stock of emissions at date T), as of date t, be $e^{-r(T-t)}D(E)$. As of date 0, given the exogenous gross emissions path $q(t)$, the regulator's objective function is

$$min_{a(t)}\, e^{-rT} D\left(\int_0^T [1-a(t)]q(t)dt\right) + \int_0^T e^{-rt} q(t) c\left(a(t);\theta_t\right) dt \tag{B.2}$$

and the regulator's objective function at subsequent dates is the obvious extension. Letting E be the cumulative net emissions, $\int_0^T [1-a(t)]q(t)dt$, the first-order condition for the point-wise choice of $a(t)$ yields

$$c'(a(t)) = e^{-r(T-t)} D'(E) \tag{B.3}$$

The left-hand side of (B.3) represents the marginal cost of reducing emissions by one unit;[14] the right-hand side represents the marginal benefit as of date t of reducing emissions by one unit.

[14]Since emissions are $[1-a(t)]q(t)$, the cost of reducing emissions by $q(t)$ units is $c'(a(t))q(t)$;the marginal cost of reducing emissions by only 1 unit are a fraction $1/q(t)$ of this, which equals $c'(a(t))$.

B.2.2 Clean-energy innovation

For the clean-energy innovation model of the previous section, let $q_0(t)$ represent the ex ante path of emissions, i.e. the path followed when innovation is impossible and let $q_1(t;\tau)$ represent the path when innovation occurs at date τ. These paths are exogenous in the regulator's problem (B.2). We let $a_0(t)$ be the solution to the problem given $q_0(t)$. Because innovation occurs with probability zero in the ex post model, in solving for $a_0(t)$ the regulator need not contemplate the possibility of innovation. Once innovation occurs at date τ, we now let the regulator's CCS strategy respond to innovation: the solution to (B.2) given $q_1(t;\tau)$ is denoted by $a_1(t;\tau)$.

Suppose that the improvement in technology θ_t were so strong, with the consequence of a rapidly increasing $a_0(t)$ that

$$\int_0^T a_0(t)[q_1(t;\tau) - q_0(t)]dt > 0$$

That is, *if* the regulator did not respond to innovation by readjusting the optimal CCS strategy, then innovation would have the paradoxical effect of increasing total emissions. This is essentially the case analyzed in section 2.3, with $a(t) = a_0(t)$ being taken as given rather than responsive to innovation. The question for us now is whether endogenizing the regulator's optimal response to innovation will negate our prediction of a paradoxical increase in total emissions if CCS technology is improving sufficiently rapidly. The following proposition shows that the optimal adaptation of CCS by the regulator mitigates, but does not eliminate, a paradoxical increase in emissions with innovation.

Let the cumulative net emissions under the no-innovation path be $E_0 = \int_0^T a_0(t)q_0(t)dt$ and under the innovation-at-τ path be $E_1 = \int_0^T a_1(t;\tau)q_1(t;\tau)dt$. (Both definitions are conditioned on CCS strategy being optimal, i.e. solving (B.2) with the corresponding

$q(t)$.) Now let $\hat{E}_1$ be the cumulative net emissions under the path $q_1(t, \tau)$ and the (sub-optimal) non-innovative CCS, $a_0(t)$; $\hat{E}_1$ is what the cumulative net emissions would be if the regulator did not adjust CCS at all in response to the change in net emissions with innovation. Given $q_1(t;\tau)$ and $q_0(t)$, *suppose that* $E_0 < \hat{E}_1$. *That is, suppose that emissions would increase with innovation at* τ *if the CCS were taken as fixed at* $a_0(t)$. *Then* $E_0 < E_1 < \hat{E}_1$. The proposition states that any (paradoxical) increase in emissions with clean-energy innovation at τ, is preserved when the optimal CCS strategy is endogenous. The regulator mitigates but does not eliminate the increase in emissions. The proof of the proposition is simple, and sketched here. If $a_0(t)$ were unchanged with innovation, with the result that total net emissions equaled$\hat{E}_1$, then the marginal cost of decreasing emissions (the left-hand side of (B.3) would remain unchanged. But because $D(\cdot)$ is convex, the increase in emissions from E_0 to $\hat{E}_1$ would increase the marginal benefit of decreasing emissions. The first-order condition (B.3) would be violated. Because of the convexity of $c(\cdot)$ and $D(\cdot)$, i.e. the second-order conditions for (B.2), an increase in $a(t)$ is optimal. This implies $E_1 < \hat{E}_1$, the second inequality in the proposition. Next, suppose *arguendo* that $E_1 \leq E_0$. This would require an increase in $a(t)$, with innovation, for at least some t $\geq \tau$. But this increase would raise the marginal cost of reducing emissions, the left hand side of (B.3) by the convexity of $c(\cdot)$. But since $E_1 \leq E_0$ by hypothesis, the marginal benefit (the right hand side of (B.3)) would not have risen with innovation. Again the first-order condition (B.3) would be violated. An increase in emissions would be optimal. This proves $E_0 < E_1$. In short, the optimal response to any innovation that increased emissions would be to increase CCS but not to the degree that the increase in emissions were eliminated. For an innovation in clean energy to yield an increase in total net emissions under optimal regulatory choice of CCS, it is sufficient that the innovation yield an increase in emissions with CCS policy remaining at $a_0(t)$. This corollary means that our basic model, in which $a(t)$ is exogenous, captures the conditions under which innovation may will increase emissions, providing the exogenous $a(t)$ is interpreted as the CCS that would be optimal in the absence of innovation.

B.2.3 Fuel-efficiency innovation

The identical analysis analysis and proposition to the case of optimal regulatory choice of CCS in response to a discovery of new fuel-efficiency technology. Let the definitions of $q_1(t;\tau)$, $E_1$and $\hat{E}_1$ now correspond to the event of a fossil-fuel efficiency innovation at τ. Given $q_1(t;\tau)$ and $q_0(t)$, *suppose that $E_0 < \hat{E}_1$. That is, suppose that emissions would increase with innovation at τ if the CCS were taken as fixed at $a_0(t)$. Then $E_0 < E_1 < \hat{E}_1$.*

Appendix C

In the fourth chapter, the politician decided based on minimizing a loss function. This appendix explores the microfoundations of this loss function. It shows that the loss function is equivalent to an enhanced version of the well-known spatial voting model.

C.1 On the Microfoundations of the Loss Fucntion

Since the Hotelling-Downs model of spatial voting was developed, researchers have proposed numerous variants of the model to explain voters' behavior. The main theoretical result from this literature is that when two politicians compete, their platforms on relevant issues are attracted to the median voter. Short-term frictions, uncertainty about the median voter's belief, and primary elections prevent the politicians from becoming identical; nevertheless, political parties should become more similar over time and have to fight over winning the median voter.

However, in the real world, over the last four decades, not only have the parties failed to converge, but also literature showed an increased polarization among the political parties. Moreover, many pundits believe that elections are decided by which party can excite its base more strongly, rather than by convincing the median voter to switch to its side. Finally, the spatial voting models do not have any prediction about turn-outs.

The facts mentioned above makes it is necessary to enhance the contemporary spatial voting models to explain voters' behavior. The politician uses this enhanced model to predict voters' behavior. Exploiting the new model, I show that the politician's optimal behavior (to the first non-zero approximation) is given by a simple form, which was introduced in equations 4.2 and 4.9.

As in the discrete choice literature, voter's i utility for the incumbent I is given by u_I^i, and similarly for the opposition O, the preference is u_E^i. The voter faces a cost c^i. This cost is comprised of the actual cost and opportunity cost of going to the polling booth and casting a vote and all other emotional and intellectual costs of voting. The voter casts his vote for the incumbent (opposition) if $u_I^i - u_O^i > c^i$, ($u_O^i - u_I^i > c^i$), and abstains from voting otherwise.

There are two eqaully large types of voters (D or R). All utility and cost terms can be written as an average plus a mean zero normal shock. For a Democrat voter, we can write:

$$\begin{aligned} u_I^i &= \bar{u}_{ID} + \epsilon_I^i \\ u_O^i &= \bar{u}_{OD} + \epsilon_O^i \\ c^i &= \bar{c} + \epsilon_c^i \end{aligned} \tag{C.1}$$

And similarly for a Republican voter, we have:

$$\begin{aligned} u_I^i &= \bar{u}_{IR} + \epsilon_I^i \\ u_O^i &= \bar{u}_{OR} + \epsilon_O^i \\ c^i &= \bar{c} + \epsilon_c^i \end{aligned} \tag{C.2}$$

The incumbent's vote share is given by the following equation:

$$\begin{aligned} Pr(\bar{u}_{ID} - \bar{u}_{OD} - \bar{c} > \epsilon_O^i + \epsilon_C^i - \epsilon_I^i) + Pr(\bar{u}_{IR} - \bar{u}_{OR} - \bar{c} > \epsilon_O^i + \epsilon_C^i - \epsilon_I^i) = \\ 2 - \Phi(\frac{\bar{u}_{ID} - \bar{u}_{OD} - \bar{c}}{\sigma_\epsilon}) - \Phi(\frac{\bar{u}_{IR} - \bar{u}_{OR} - \bar{c}}{\sigma_\epsilon}) \end{aligned} \tag{C.3}$$

where Φ is the cumulative distribution function of the normal distribution, and σ_ϵ is the standard deviation of $\epsilon^i_O + \epsilon^i_C - \epsilon^i_I$.

The incumbent wins the election if their vote share is higher than their opponents'. Therefore, the incumbent wishes to maximize the difference between their shares and their opponents'. their actions can only affect $\bar{u}_{ID}$ and $\bar{u}_{IR}$

$$\begin{aligned} \max\Big[\Phi(\frac{\bar{u}_{OD} - \bar{u}_{ID} - \bar{c}}{\sigma_\epsilon}) + \Phi(\frac{\bar{u}_{OR} - \bar{u}_{IR} - \bar{c}}{\sigma_\epsilon}) - \\ \Phi(\frac{\bar{u}_{ID} - \bar{u}_{OD} - \bar{c}}{\sigma_\epsilon}) - \Phi(\frac{\bar{u}_{IR} - \bar{u}_{OR} - \bar{c}}{\sigma_\epsilon})\Big] \end{aligned} \tag{C.4}$$

This brings us to the following first-order condition:

$$\begin{aligned} -\bar{u}'_{IL}(\phi(\frac{\bar{u}_{OD} - \bar{u}_{ID} - \bar{c}}{\sigma_\epsilon}) + \phi(\frac{\bar{u}_{ID} - \bar{u}_{OD} - \bar{c}}{\sigma_\epsilon})) \\ -\bar{u}'_{IR}(\phi(\frac{\bar{u}_{OR} - \bar{u}_{IR} - \bar{c}}{\sigma_\epsilon}) + \phi(\frac{\bar{u}_{IR} - \bar{u}_{OR} - \bar{c}}{\sigma_\epsilon})) = 0 \end{aligned} \tag{C.5}$$

Equation C.5 has an straightforward interpretation. Every decision that the incumbent makes has four effects. It causes some of their base to switch between voting for the incumbent to 1. the opposition or 2. abstention or it causes some of their opposition base to switch between voting for the opposition to 3. their or 4. abstention.

To obtain the loss function in the theoretical section of the article, I have to specify what $\bar{u}_{IL}$ and $\bar{u}_{IC}$ are.

$$\begin{aligned} \bar{u}_{ID} = \bar{u}^0_{ID} - \theta_{ID}\big(\frac{s - s_D(T)}{\sigma_D(T)}\big)^2 \\ \bar{u}_{IR} = \bar{u}^0_{IR} - \theta_{IR}\big(\frac{s - s_R(T)}{\sigma_R(T)}\big)^2 \end{aligned} \tag{C.6}$$

In equation C.6, θ_{ID} is the attention that average Democrats pay to the incumbent's decisions and θ_{IR} is the attention of average Republicans to the incumbent's decision. From equations C.5,and C.6, the value α in 4.9 is reconstructed:

$$\alpha = \frac{\theta_{ID}}{\theta_{IR}} \frac{\phi(\frac{\bar{u}_{OD} - \bar{u}_{ID} - \bar{c}}{\sigma_\epsilon}) + \phi(\frac{\bar{u}_{ID} - \bar{u}_{OD} - \bar{c}}{\sigma_\epsilon})}{\phi(\frac{\bar{u}_{OR} - \bar{u}_{IR} - \bar{c}}{\sigma_\epsilon}) + \phi(\frac{\bar{u}_{IR} - \bar{u}_{OR} - \bar{c}}{\sigma_\epsilon})} \tag{C.7}$$

If the preferences are symmetric ($\bar{u}_{ID} = \bar{u}_{OR}, \bar{u}_{IR} = \bar{u}_{OD}$), then alpha is simplified to:

$$\alpha = \frac{\theta_{ID}}{\theta_{IR}} \tag{C.8}$$

Therefore, $\alpha > 1$ if the incumbent's decision affects the Democrat base's utility more than it affects the Republican's base utility, which is a reasonable assumption for a Democrat incumbent.