University of California
Santa Barbara

Adaptations to Changes in Environmental Conditions and Policies

A dissertation submitted in partial satisfaction
of the requirements for the degree

Doctor of Philosophy
in
Environmental Science and Management

by

Steven James Miller

Committee in charge:

Professor Christopher Costello, Chair
Professor Steven Gaines
Professor Robert Deacon
Professor Olivier Deschênes

June 2015

The Dissertation of Steven James Miller is approved.

Professor Steven Gaines

Professor Robert Deacon

Professor Olivier Deschênes

Professor Christopher Costello, Committee Chair

May 2015

Adaptations to Changes in Environmental Conditions and Policies

Acknowledgements

This dissertation would not have been completed without the valuable input and guidance from many others.

First and foremost, I wish to acknowledge co-authors for two of the chapters contained herein: Bruno Nkuiya (Chapter 1) and Robert Deacon (Chapter 2). I am especially grateful for their contributions and advice.

More broadly, I thank my doctoral committee for their patience and wisdom throughout. I also appreciate all of the suggestions and feedback from members of the Costello and Gaines labs at UCSB, participants in the environmental economics lunch, and seminar and conference participants at a number of universities, research organizations, and conferences.

Finally, I am indebted to those who provided funding and other resources for this work. Funders include UCSB, the Bren School of Environmental Science & Management, Conservation International, and California Sea Grant. California, Oregon, and Washington state fisheries agencies were generous in providing access to data at the heart of Chapter 2 and also provided invaluable feedback on the work itself.

Curriculum Vitæ

Steven James Miller

Education

2015	Ph.D. in Environmental Science & Management (Expected), University of California, Santa Barbara.
2004	B.S. in Computer Science, Stanford University.

Publications

Deacon, R.T. and S.J. Miller (2012). Aligning Incentives for Fisheries Governance: Can Industry Lead the Reform Process? PERC Research Paper No. 13-3.

Caron, B, D. Toole, P. Wicks, and S Miller (2011). DigitalOcean: building a platform for scientific collaboration and social media sharing on the Drupal content management system. Earth Science Informatics (4): 191-196.

Teaching

Master's Level, Bren School of Environmental Science & Management, UCSB

2011-present	Instructor: Excel workshops on environmental modeling, resource management, optimization
2013	Mentoring: PhD advisor for two Master's level group projects
2012	Teaching Assistant: Environmental Modeling (ESM 232)

Undergraduate Level, Stanford University, Stanford, CA

2001, 2004, 2006	Teaching Assistant: Programming Methodology (CS 106A)
2002, 2003	Teaching Assistant: Programming Paradigms (CS 107)

Fellowships, Grants, & Funding

2010-present	Chancellor's fellowship, University of California
2012-2014	California Sea Grant Traineeship
2011-2012	Researcher and Data Coordinator, Conservation International

Professional Experience

2004-2009	Google Inc.: Product Manager on AdSense, mobile search, Google Earth (incl. ocean features)

Abstract

Adaptations to Changes in Environmental Conditions and Policies

by

Steven James Miller

Economic incentives for users of natural resources depend on both environmental conditions and policies in place to govern use of those resources. Similarly, polluting firms are financially impacted by the regulatory context in which they operate and the manner in which natural systems exposed to their pollution are affected. Shifts in environmental conditions or policy thus may alter the economic incentives and behavior of resource users and polluting firms. To the extent that such shifts impose higher costs, economic theory suggests that economic agents will seek ways to mitigate their exposure to such costs, either through preventative behavior or adaptation. As a result, the economic effects of change will depend upon the responses of affected individuals or firms. Here, I examine the effects of three types of change on the behavior of natural resource users and polluting firms. The first chapter employs dynamic game theory to examine the effect of a potential environmental regime shift on coalition formation in a shared fishery, finding that the threat of such shifts can support enhanced cooperation as a means to avoid the shift. The second chapter focuses attention on a policy shift in a multi-species fishery, studying how resource users respond to the introduction of tradable permits for bycatch species. That study uses a combination of theory and panel econometric approaches to identify multi-margin responses to the regulatory change, and in so doing, estimates the marginal costs of conservation for overfished species. In the final chapter, I continue to examine regulatory change, but shift systems to examine how environmental policy may stimulate innovation. In particular, I explore how tradable emissions permits

can create incentives for unregulated firms to innovate, illustrating the consequences of such spillovers for policy analysis using both theory and an empirical application to the European Union Emissions Trading System.

Contents

Chapter 1

Coalition formation in fisheries with potential regime shift

1.1 Introduction

Many natural systems can undergo sudden, dramatic changes in their dynamics in response to a change in environmental conditions or human activity. When such a system provides value through the provision of an ecosystem service such as shoreline protection by mangroves or the harvest of fish, such a change in productivity, known as a regime shift, can have substantial economic consequences. Large swings in the abundance and growth of Pacific sardines led to the cessation of fishing in the early 1950s and a formal moratorium in 1967 (Radovich, 1981). Similar dramatic shifts in productivity have impacted cod fisheries in various parts of the Atlantic Ocean. Importantly, those shifts may have been affected by the level of fishing to which the stocks were subjected. In the Atlantic Cod fishery in the North and Baltic seas, Lindegren et al. (2010) find that areas subject to trawl fishing bans were less likely to experience regime shift than areas subjected to full commercial-scale fishing. The influence of fishing on regime shifts could act directly through reduction in growth rates or indirectly by making a fish population more susceptible to otherwise exogenous environmental drivers of regime shift (Collie et al., 2004).

While a substantial body of research examines the economic consequences of uncertainty in fisheries (e.g. Clark and Kirkwood 1986; Costello and Polasky 2008; Sethi et al. 2005) and a number of ecologists have studied the mechanisms behind regime shifts (e.g. Folke et al. 2004), the economics literature examining how the potential for such regime shifts affects optimal management of a fishery focuses only on harvest decisions.[2] Early work by Reed (1988) highlights two competing effects of such a threat. First, the threat of collapse acts in a similar way to a higher discount rate, since expected future harvest is smaller, suggesting higher optimal harvest rates. However, if the threat of collapse

[2]A related literature examines the effects of regime shift in other contexts, such as forestry, ozone depletion, or greenhouse gas emissions. Examples include Cropper (1976); Nkuiya et al. (2014).

increases as the stock is fished down, there may be a countervailing incentive to reduce exposure to the threat by harvesting less. More recent work by Polasky et al. (2011) and Ren and Polasky (2014) clarifies the role that different assumptions about the consequences of the regime shift have on optimal harvest policies. In an applied setting, Costello et al. (1998) examine the value of information pertaining to a potential shift in a coho salmon fishery caused by El Niño.

All of these studies examine how a single resource user should adjust management choices when faced with the threat of a regime shift. However, there is also some evidence suggesting that such threats may motivate cooperation among multiple resource users in fisheries. The rock lobster fishery in New Zealand offers one compelling example. That fishery has been managed under a property rights scheme since 1990, but despite management efforts, catches showed signs of decline by 2006. In response to declining catches, fishers worked with scientists to evaluate management alternatives and in 2007 each voluntarily surrendered a fraction of his or her individual quota in order to avoid collapse of the stock and a shift to an extremely low productivity regime (Breen et al., 2009). This example suggests that the threat of regime shift may alter not only individual harvest choices, but also the calculus of cooperation.

This paper examines how the threat of a regime shift alters the incentives for cooperation in a shared fishery. In particular, we study how the threat of a regime shift alters both harvest and coalition membership decisions, and ask how those effects vary with (i) whether the threat is exogenous (stock-independent) or endogenous (stock-dependent), and (ii) the type of shift (complete collapse or drop in productivity). We address these questions using a stochastic dynamic game of harvest in which fishers repeatedly choose whether to join a fishing coalition and how much of the resource to extract. This framework builds upon the standard fish wars model (Levhari and Mirman, 1980) used by Kwon (2006) to study coalition formation in a deterministic setting. Our primary contribution is to unite that study of deterministic coalition formation with the sole owner literature on the threat of regime shift. Our work also complements studies by Fesselmeyer and Santugini (2013) and Sakamoto (2014), which examine the impact of regime shifts on harvest in a shared fishery but do not examine how such shifts affect (endogenous) cooperation decisions.

Our analysis suggests that the threat of regime shift alters harvesters' responses as compared to the standard cases where either such a threat is absent or the decision to join a coalition is ignored. We first examine the scenario where the abrupt occurrence of the shift reduces the resource growth rate but does not cause extinction. Analytical results indicate that when the probability of regime shift is exogenous and known, no more than two players cooperate. The threat may induce a stable coalition with two fishers that would not exist in the absence of the threat, but overall an exogenous threat of regime shift supports only small coalitions. In addition, we find conditions under which, prior to the shift, members of a stable coalition reduce their harvest whereas each non-member increases his harvest. When we instead consider the case where the probability of regime shift is endogenous (depends on harvest decisions), we find that larger stable coalitions are sustainable prior to the shift. In particular, we find in this context that the threat may induce full cooperation as an equilibrium outcome. We repeat these analyses for a doomsday scenario in which the shift entails a doomsday event in which the stock collapses. We find that a harvester may undertake cautious behavior in response to the threat when the probability of regime shift is exogenous. In the case where the likelihood of the shift is affected by harvest decisions, we show numerically that the grand coalition can be stable. We of course do not interpret these findings as implying that full cooperation will always arise in fisheries. However, our analysis does suggest the threat of regime shift may play an important role in determining the level of cooperation that occurs in shared resource use.

The remainder of this paper is organized as follows. In section 2 we present our dynamic model, including the system dynamics, player objectives, and game structure. Section 3 presents the equilibrium and its properties for the post-shift era after a drop in productivity. Section 4 does the same for the pre-shift era when the threat of a shift is exogenous, and the fifth section presents numerical results for the pre-shift era with endogenous threat. We then consider the doomsday scenario in which the shift causes a lump-sum bad payoff for all players. The final section concludes.

1.2 Model

1.2.1 Overview

We model the exploitation of a common-pool renewable resource by a fixed and finite number of identical users in a discrete-time, infinite horizon dynamic game. Harvest of the resource provides immediate benefits and also affects the future availability of the resource, thereby affecting future benefits. Each user may make harvest decisions independently or may choose to join a coalition and jointly agree upon harvest choices with other coalition members. Coalition membership is re-evaluated at the start of each period.

Members of the coalition choose harvest so as to maximize their aggregate discounted sum of benefits, while each non-member considers only his or her own benefits. The benefits earned by the coalition are shared equally among members due to the identical nature of players. Individuals join the coalition only if their share of the coalition benefits exceeds the payoff that they could earn by leaving the coalition and harvesting independently.

Our assumption of identical harvesters simplifies much of the analysis that follows, but it requires that we specify how harvesters form expectations about future payoffs. To compute future returns a harvester needs to know whether he will be in the coalition in the future. However, identical harvesters will have the same membership preferences and it remains unclear which harvesters will get to join. To resolve this issue, we adopt the Random Assignment Rule,[3] in which current coalition members and non-members have the same expected future payoff.

The focus of the model is on how the threat of regime shift alters the decision of whether or not to join the coalition and the resulting effects on equilibrium harvest rates. The regime shift works as follows: the system starts in a preferable state with high resource growth and during any period may permanently switch with some probability to a less productive, low growth state. We examine the case where the probability of that shift is exogenously given and the case where the probability depends on the current level of the stock. In the latter case, because the stock is a function of users' harvest decisions, the threat of regime shift is endogenous. More precisely, an increase of total harvest reduces the resource stock, which in turn increases the probability of regime shift.

With this overview of the game in place, we next formalize the model mathematically.

1.2.2 Dynamic game structure

A set of N identical resource users exploit a shared resource in a discrete-time dynamic game. In each period t, the environment is in regime $\theta_t \in \{H, L\}$ (where H denotes "High" and L "Low"), the stock is of size $S_t \in [0, 1]$, and the following sequence of events takes place:

1. In the absence of harvest, the stock grows naturally according to a growth function

[3] See Nkuiya (2012) and Nkuiya et al. (2014) for examples and a survey on this technique. There are, of course, many other ways to resolve coalition membership, but we focus on the Random Assignment Rule for consistency with the literature and tractability.

$g(S_t, \theta_t)$. For comparison with the Fish Wars literature we restrict our attention to Gompertz growth:

$$g(S_t, \theta_t) = S_t^{1-b_{\theta_t}}, \tag{1.1}$$

where b_{θ_t} is a regime-specific growth parameter. We assume $1 > b_H > b_L \geq 0$ so that $g(S_t, H) \geq g(S_t, L)$ $\forall S_t \in [0, 1]$, i.e. the "High" regime is characterized by greater growth.

2. Users form and announce preferences for joining or free-riding on a coalition based on a comparison of the discounted net benefits that accrue to members and free-riders. These preferences determine the stable coalition size n_t such that no member would prefer to leave and no free-rider would prefer to join. A coalition is then formed, with the set of members denoted K_t and $n_t = |K_t|$.

3. The coalition and non-members simultaneously choose and apply harvest. Coalition member i harvests h_{it}, while non-member j harvests h_{jt}. Harvest has two consequences. First, it subtracts from the post-growth stock $g(S_t, \theta_t)$ to produce the next period stock S_{t+1}:

$$S_{t+1} = g(S_t, \theta_t) - \sum_{i \in K_t} h_{it} - \sum_{j \notin K_t} h_{jt} \tag{1.2}$$

Second, harvest provides current benefits $\pi(h_{jt})$ for each non-member and $\sum_{i \in K_t} \pi(h_{it})$ for the coalition. For consistency with the Fish Wars literature, we use $\pi(h) = ln(h)$.

4. The environmental state updates from θ_t to θ_{t+1} according to a Markov process with transition probabilities $P(\theta_{t+1}|\theta_t)$. These transition probabilities $P(\theta_{t+1}|\theta_t)$

are such that the probability of shift from H to L is given by $\rho(S_t)$, and the shift from H to L, if it occurs, is permanent. Formally:

$$P(\theta_{t+1} = L|\theta_t = H) = \rho(S_t), \qquad P(\theta_{t+1} = H|\theta_t = H) = 1 - \rho(S_t), \tag{1.3}$$
$$P(\theta_{t+1} = L|\theta_t = L) = 1, \qquad P(\theta_{t+1} = H|\theta_t = L) = 0.$$

In the case of exogenous threat, $\rho(S_t) = \bar{\rho}$ and does not depend on S_t, while in the case of endogenous threat, $\rho(S_t)$ weakly decreases in S_t.

Steps 2 and 3 constitute a two-stage game that occurs every period: a first-stage membership game and a second-stage harvest game. Because the Random Assignment Rule affects both coalition formation and calculation of the future component of benefits in step 2, we briefly clarify the role of the Random Assignment Rule before turning to a discussion of those two stage games.

1.2.3 Expected payoffs under random assignment

Under the Random Assignment Rule, once a coalition size n_t has been determined by the membership game in period t, since players are identical they are randomly assigned to the coalition until the coalition is of that size. Since this assignment rule implies that all players share the same expected *future* payoff, regardless of their *current* membership status, we should define the expected future payoff. Let $V_i^C(S_t, \theta_t, n_t)$ be the value of being a member of a coalition of size n_t with stock S_t and regime θ_t, and let $V_j^F(S_t, \theta_t, n_t)$ be defined analogously for an individual free-riding on that coalition. Denoting the equilibrium coalition size by $n^*(S_t, \theta_t)$, in period $t-1$ all players face the same expected future payoff in period t:

$$W(S_t,\theta_t) = \frac{n^*(S_t,\theta_t)}{N} V_i^C(S_t,\theta_t,n^*(S_t,\theta_t)) + \frac{N-n^*(S_t,\theta_t)}{N} V_j^F(S_t,\theta_t,n^*(S_t,\theta_t)). \quad (1.4)$$

We next write down the problems faced by harvesters, beginning with the second-stage harvest game and working backwards.

1.2.4 Second-stage harvest game

Assume that in period t the first-stage coalition formation game has taken place. In the second-stage harvest game, the coalition and each non-member take the stock, environmental state, coalition size, and harvest decisions of others as given and choose harvest levels to maximize the discounted sum of current and expected future benefits. Recall that coalition members seek to maximize their joint benefits from harvest, while each free-rider considers only his own benefits. Note that there are no returns to scale for coalition members; the benefits of cooperation stem solely from making joint harvest choices that partially internalize of the externalities of harvest.

Formally, we write the harvest problems facing the coalition and individual free-riders as follows:

$$V^C(S_t,\theta_t,n_t) = \max_{\{h_{it}:i\in K_t\}} \sum_{i\in K_t} ln(h_{it}) + n_t\delta \sum_{\theta_{t+1}} P(\theta_{t+1}|\theta_t) W(S_{t+1},\theta_{t+1}), \quad (1.5)$$

$$V_j^F(S_t,\theta_t,n_t) = \max_{h_{jt}} ln(h_{jt}) + \delta \sum_{\theta_{t+1}} P(\theta_{t+1}|\theta_t) W(S_{t+1},\theta_{t+1}), \quad (1.6)$$

where $0 \leq \delta \leq 1$ is the discount factor.

Since players are identical, coalition members share payoffs equally, and each coalition member in a coalition of size n_t receives $\frac{1}{n_t}$ of the coalition payoff:

$$V_i^C(S_t, \theta_t, n_t) = \max_{\{h_{it}\}, i \in K_t} \frac{1}{n_t} \sum_{i \in K_t} ln(h_{it}) + \delta \sum_{\theta_{t+1}} P(\theta_{t+1}|\theta_t) W(S_{t+1}, \theta_{t+1}). \tag{1.7}$$

We restrict attention to harvest policies that depend only on the current state of the system (resource stock and current regime), i.e. Markov strategies. Alternatively, one may also consider history-dependent strategies. We adopt Markov strategies as, in addition to yielding time-consistent and tractable solutions, they are sufficient to isolate the role that the threat of regime shift plays in influencing cooperation. As the restriction to Markov strategies and dynamic game structure suggest, the equilibrium concept we will ultimately apply is Markov Perfect Nash Equilibrium.

1.2.5 Membership stage game

In the first-stage membership game, harvesters non-cooperatively decide whether or not to join a coalition based on the potential gains to cooperation. We rely on the stability conditions of d'Aspremont et al. (1983), which state that a coalition of size n_t is stable if it satisfies:

$$V_i^C(S_t, \theta_t, n_t) \geq V_j^F(S_t, \theta_t, n_t - 1), \tag{1.8}$$

$$V_j^F(S_t, \theta_t, n_t) \geq V_i^C(S_t, \theta_t, n_t + 1). \tag{1.9}$$

The internal stability condition (1.8) states that no coalition member can become better off by leaving the coalition. Likewise, the external stability condition (1.9) states that no free-rider would gain from joining the coalition. These two stability conditions can be summarized using the stability function (see, for example, Nkuiya et al. 2014)

$$\phi(S_t, \theta_t, n_t) = V_i^C(S_t, \theta_t, n_t) - V_j^F(S_t, \theta_t, n_t - 1). \tag{1.10}$$

The largest coalition size n_t^* satisfying $\phi(S_t, \theta_t, n_t) \geq 0$ is stable. To see this, note that if n_t^* satisfies $\phi(S_t, \theta_t, n_t) \geq 0$, it is clearly internally stable. Since n_t^* is the largest coalition satisfying $\phi(S_t, \theta_t, n_t) \geq 0$, then we must have that $\phi(S_t, \theta_t, n_t^* + 1) < 0$. By the definition of $\phi(S_t, \theta_t, n_t)$, this in turn implies that $V_j^F(S_t, \theta_t, n_t^*) > V_i^C(S_t, \theta_t, n_t^* + 1)$, and so the coalition of size n_t^* is also externally stable. Therefore, in this paper we define the equilibrium coalition size as the largest coalition size satisfying the internal stability condition (1.8). Finally, note that, in general, n_t^* may be a function of both S_t and θ_t, so we write it more generally as $n^*(S_t, \theta_t)$.

Together, (1.2), (1.3), (1.4), (1.6), (1.7), (1.8), and (1.9) define the dynamic game and its equilibrium. We turn next to finding and analyzing that equilibrium, beginning with decisions after the regime shift has taken place ($\theta_t = L$) and working backwards.

1.3 Post-shift equilibrium

We begin our analysis after a regime shift has taken place, i.e. for times t for which $\theta_t = L$. We do so for three reasons: first, players making decisions prior to the regime shift must anticipate the payoffs they would receive in the future if regime shift does occur. Second, comparing the post-shift outcome with the benchmark of cooperation in the absence of threat allows us to understand the effects of the shift itself. Third, the solution of the post-regime shift case will allow us to completely derive the equilibrium of the game.

We solve the post-shift problem as follows. First, we make a conjecture about the functional form of $W(S_t, L)$. Second, under that conjecture, we solve the harvest problems faced by coalition members and free-riders to derive expressions for both equilibrium harvest policies and the players' payoffs. Third, we use the players' payoffs to evaluate the stability conditions and show that the equilibrium coalition size n_L^* is independent of the stock size S_t. Fourth, we use the definition of $W(S_t, L)$ under the random assignment rule, the second-stage value functions, and the stock-independence of n_L^* to show that $W(S_t, L)$ takes the conjectured form. Finally, we use the solution to derive an expression for n_L^* and use that result to show that the equilibrium coalition size cannot be larger than two after the regime shift has taken place.

1.3.1 Second-stage harvest game

Based on the logarithmic form of the instantaneous benefit function, we conjecture that $W(S_t, L)$ takes the following form

$$W(S_t, L) = A_L ln(S_t) + \gamma_L, \tag{1.11}$$

where A_L and γ_L are constants that depend on model parameters but do not depend on S_t.

Under this conjecture, we may write the second-stage harvest problems faced by the coalition and non-members as follows:

$$V^C(S_t, L, n_t) = \max_{\{h_{it}: i \in K_t\}} \sum_{i \in K_t} ln(h_{it}) + n_t \delta \left[A_L ln(S_{t+1}) + \gamma_L \right], \tag{1.12}$$

$$V_j^F(S_t, L, n_t) = \max_{h_{jt}} ln(h_{jt}) + \delta \left[A_L ln(S_{t+1}) + \gamma_L \right], \tag{1.13}$$

subject to (1.2). First-order conditions for members and free-riders, respectively, give

$$\begin{aligned}\frac{1}{n_t}\frac{1}{h^*_{it}} =& \frac{\delta A_L}{g(S_t, L) - n_t h^*_{it} - (N - n_t)h^*_{jt}},\\ \frac{1}{h^*_{jt}} =& \frac{\delta A_L}{g(S_t, L) - n_t h^*_{it} - (N - n_t)h^*_{jt}}.\end{aligned}$$

Note that $h^*_{jt} = n_t h^*_{it}$, i.e. each non-member harvests as much as the entire coalition. Using this fact we solve for h^*_{it} and h^*_{jt}:

$$h^*_{it} = \frac{1}{n_t}\frac{g(S_t, L)}{\delta A_L + N - n_t + 1}, \tag{1.14}$$

$$h^*_{jt} = \frac{g(S_t, L)}{\delta A_L + N - n_t + 1}. \tag{1.15}$$

We may plug these harvests into (1.12) and (1.13) and substitute for $g(S_t, L)$ using (1.1) to get expressions for $V_i^C(S_t, L, n_t)$ and $V_j^F(S_t, L, n_t)$. Algebra yields

$$\begin{aligned}V_i^C(S_t, L, n_t) =&(1 + \delta A_L)(1 - b_L)ln(S_t) + \delta A_L ln\,(\delta A_L) + \delta\gamma_L \qquad (1.16)\\ &- (1 + \delta A_L)ln(\delta A_L + N - n_t + 1) - ln(n_t)\\ V_j^F(S_t, L, n_t) =&V_i^C(S_t, L, n_t) + ln(n_t). \qquad (1.17)\end{aligned}$$

Since $W(S_t, L)$ is defined in (1.4) as a function of the equilibrium coalition size $n^*(S_t, L)$, in order to verify the conjectured form for $W(S_t, L)$ we must determine the equilibrium coalition size. Thus, we carry through our conjecture to consideration of the first-stage membership game.

1.3.2 First-stage membership game

To determine the outcome of the first-stage membership game, we use the stability concept defined in section 2.5. Substituting (1.16) and (1.17) into (1.10) we get that $\phi(S_t, \theta_t, n_t) \geq 0$ holds only when

$$ln(n_t) \leq (1 + \delta A_L)\, ln \left(1 + \frac{1}{\delta A_L + N - n_t + 1}\right). \tag{1.18}$$

Immediately we see that the largest coalition size satisfying (1.18) is independent of S_t. As a result, from here on we write $n_L^*(S_t, L)$ simply as n_L^*.

Plugging (1.16) and (1.17) into the definition of $W(S_t, L)$ as given in (1.4) and rearranging gives

$$\begin{aligned} W(S_t, L) =& (1 + \delta A_L)(1 - b_L) ln(S_t) \\ &+ \delta A_L ln\left(\delta A_L\right) + \delta\gamma_L - (1 + \delta A_L) ln(\delta A_L + N - n_L^* + 1) - \frac{n_L^*}{N} ln(n_L^*) \end{aligned}$$

This equation is of the form we conjectured for $W(S_t, L)$, and so we have verified the conjecture. Equating coefficients yields

$$A_L = \frac{1 - b_L}{1 - \delta(1 - b_L)} \tag{1.19}$$

$$\gamma_L = \frac{-(1 + \delta A_L) ln(\delta A_L + N - n_L^* + 1) + \delta A_L ln(\delta A_L) - \frac{n_L^*}{N} ln(n_L^*)}{1 - \delta}. \tag{1.20}$$

With the equilibrium defined, we summarize the properties of the coalition size in the following result:

Result 1 *In the post regime shift phase ($\theta_t = L$), the equilibrium coalition size (i) cannot be larger than 2, and (ii) is non-increasing in the post-shift resource productivity b_L.*

Proof: See the appendix. ■

The first part of Result 1 strengthens the result obtained in the deterministic framework by Kwon (2006), where membership decisions are made once and for all at the start of the initial period (an open loop membership game). In this paper, membership decisions are revised at the start of each period. We find that the coalition size stays constant in the post-shift era not by assumption, but as an equilibrium outcome. Still, as in Kwon, the intuition underlying this result is that the gains to free-riding dominate the gains to cooperation for any coalition with more than two members. Free-riding offers harvesters immediate private returns from increased harvest, while the only benefit of cooperation in this model is a larger future stock size, which benefits all players.

The second part of Result 1 allows us to compare the level of cooperation in the post-shift era to that which would arise in the high productivity regime if there were no threat of regime shift. Since the post-shift era itself involves no threat, the solution for the no-threat case can be obtained from that for the post-shift era with b_L replaced by b_H. Part (ii) of Result 1 indicates that, since $b_H > b_L$, the coalition in a zero-threat setting is no larger and possibly smaller than that in the post-shift era.

We next move back to the pre-shift era and examine the consequences of the threat of regime shift on harvest and cooperation decisions. The presence of any such threat will clearly alter harvester incentives, since a player seeking to maximize discounted returns must contend with the possibility that future returns will be reduced through a shift to a lower productivity regime. Importantly, the way in which the threat alters incentives depends upon the type of threat, since an endogenous threat means harvest choices change not only the future resource stock but also the probability of regime shift. As a result, we must analyze the two types of threat separately; we begin with the case of an exogenous threat.

1.4 Pre-regime shift, exogenous threat

Consider the pre-shift era when $\theta_t = H$ and the probability of a shift to the lower productivity regime is exogenous, i.e. $\rho(S_t) = \bar{\rho}$ for all $0 < S_t \leq 1$.

1.4.1 Second-stage harvest game

We use the same methodology as for the post-shift case. First, we conjecture that the first-stage value function is again log-linear in the resource stock. That is:

$$W(S_t, H) = A_H ln(S_t) + \gamma_H, \tag{1.21}$$

where A_H and γ_H are again constants that depend on model parameters but not on S_t. Under this conjecture, the second-stage harvest problems faced by coalition members and free-riders can then be written as

$$\begin{aligned} V^C(S_t, H, n_t) = &\max_{\{h_{it}: i \in K_t\}} \sum_{i \in K_t} ln(h_{it}) \\ &+ n_t \delta \left(\bar{\rho}\left[A_L ln(S_{t+1}) + \gamma_L\right] + (1-\bar{\rho})\left[A_H ln(S_{t+1}) + \gamma_H\right]\right), \quad (1.22) \\ V_j^F(S_t, H, n_t) = &\max_{h_{jt}} ln(h_{jt}) + \delta\left(\bar{\rho}\left[A_L ln(S_{t+1}) + \gamma_L\right] + \delta(1-\bar{\rho})\left[A_H ln(S_{t+1}) + \gamma_H\right]\right). \quad (1.23) \end{aligned}$$

The first-order conditions for the maximization of the right-hand side of (1.22) and (1.23) can be respectively written as

$$\begin{aligned} \frac{1}{h_{it}^*} =& n_t \frac{\delta \bar{A}}{g(S_t, H) - n_t h_{it}^* - (N - n_t) h_{jt}^*}, \\ \frac{1}{h_{jt}^*} =& \frac{\delta \bar{A}}{g(S_t, H) - n_t h_{it}^* - (N - n_t) h_{jt}^*}, \end{aligned}$$

where $\bar{A} = \bar{\rho}A_L + (1-\bar{\rho})A_H$. These conditions state that a member chooses the harvest rate that equates his marginal benefit with all signatories' aggregated expected inter-temporal marginal cost whereas a non-member chooses his harvest such that his marginal benefit and his expected inter-temporal marginal cost are identical.

We combine these first-order conditions with the resource dynamics, giving the following expressions for equilibrium harvest strategies:

$$h^*_{it} = n_t \frac{g(S_t, H)}{\delta\bar{A} + N - n_t + 1}, \tag{1.24}$$
$$h^*_{jt} = \frac{g(S_t, H)}{\delta\bar{A} + N - n_t + 1}. \tag{1.25}$$

Note that these harvest policies imply that, as with the post-shift era, each non-member harvests as much as the entire coalition ($i.e$, $h^*_{jt} = n_t h^*_{it}$).

Plugging these equilibrium policies into the harvest problems and simplifying, we get the following expressions for the second-stage value functions:

$$\begin{aligned} V_i^C(S_t, H, n_t) = &\left(1+\delta\bar{A}\right)(1-b_H)ln\left(S_t\right) \\ &+ \delta(1-\bar{\rho})\left[A_H ln\left(\delta\bar{A}\right) + \gamma_H\right] + \delta\bar{\rho}\left[A_L ln\left(\delta\bar{A}\right) + \gamma_L\right] \\ &- \left(1+\delta\bar{A}\right)ln\left(\delta\bar{A} + N - n_t + 1\right) - ln(n_t), \end{aligned} \tag{1.26}$$
$$V_j^F(S_t, H, n_t) = V_i^C(S_t, H, n_t) + ln(n_t). \tag{1.27}$$

Since the definition of $W(S_t, H)$ as given in (1.4) depends upon these values and the equilibrium coalition size $n^*(S_t, H)$, in order to complete the verification of our conjecture for the form of $W(S_t, H)$, it may be helpful to determine the equilibrium coalition size. To do so, we turn to the first-stage membership game.

1.4.2 First-stage membership game

To determine the outcome of the membership game, we evaluate the stability conditions (1.8) and (1.9). Substituting (1.26) and (1.27) into (1.10), we find that the condition $\phi(S_t, \theta_t, n_t) \geq 0$ holds only when

$$ln(n_t) \leq (1+\delta\bar{A})ln\left(1+\frac{1}{\delta\bar{A}+N-n_t+1}\right). \tag{1.28}$$

Recall that $n^*(S_t, H)$ is the largest coalition size satisfying this condition. As with the post-shift case, the stability condition clearly does not depend on S_t, and so $n_H^* = n^*(S_t, H)$ is independent of the stock size S_t. Hereafter we simply write the equilibrium coalition size as n_H^*.

Using the stock-independence of n_H^*, we may plug the expressions for $V_i^C(S_t, H, n_t)$ and $V_j^F(S_t, H, n_t)$ as given by (1.26) and (1.27) into the definition of $W(S_t, H)$ as given in (1.4) and simplify to give

$$\begin{aligned}
W(S_t, H) = &\left(1+\delta\bar{A}\right)(1-b_H)ln(S_t) \\
&- (1+\delta\bar{A})ln(\delta\bar{A}+N-n_H^*+1) + \delta\left[\bar{A}ln(\delta\bar{A}) + \bar{\rho}\gamma_L + (1-\bar{\rho})\gamma_H\right] \\
&- \frac{n_H^*}{N}ln(n_H^*).
\end{aligned}$$

This equation is of the conjectured form for $W(S_t, H)$, thus completing our verification. Equating the coefficients for both $ln(S_t)$ and the constant term and solving gives expressions for A_H and γ_H:

$$A_H = \frac{1-\delta(1-\bar{\rho})(1-b_L)}{1-\delta(1-\bar{\rho})(1-b_H)}\frac{1-b_H}{1-\delta(1-b_L)}, \tag{1.29}$$

$$\gamma_H = \frac{\delta\bar{A}ln(\delta\bar{A}) + \delta\bar{\rho}\gamma_L - (1+\delta\bar{A})ln(\delta\bar{A}+N-n_H^*+1) - \frac{n_H^*}{N}ln(n_H^*)}{1-\delta(1-\bar{\rho})}. \tag{1.30}$$

With the equilibrium defined, we provide a summary of its properties in the following proposition:

Proposition 1 *Assume the probability of regime shift is exogenous and known. Before a regime shift takes place, coalitions of size greater than 2 are not stable. That is,* $n_H^* \leq 2$.

Proof: See the appendix. ■

In short, the *maximum* stable coalition size across all fisheries is unaffected by exogenous regime shift. While the threat of a shift increases the expected future costs of current harvest (via reduced growth) the benefits of free-riding on the coalition remain strong.

That said, higher future costs of current harvest should intuitively induce more cautious harvesting behavior when fishers equate marginal benefits and marginal costs in their harvesting decisions. Those changed harvesting decisions may have more subtle effects on coalition membership in a particular fishery, even if the maximum coalition size across all fisheries is unaffected. This effect is summarized in the following proposition:

Proposition 2 *Assume that the probability of regime shift is exogenous and known. Before the occurrence of the shift, the equilibrium coalition size is weakly increasing in the probability of regime shift. That is,* $n_H^*(\bar{\rho}_2) \geq n_H^*(\bar{\rho}_1)$ *for* $\bar{\rho}_2 \geq \bar{\rho}_1 \geq 0$.

Proof: See the appendix. ■

Proposition 2 says that as the threat level is increased, the incentive to join the coalition cannot diminish. An important consequence of this result is that it allows us to compare the case where there is zero probability of a regime shift to a case where there is a nonzero probability. In particular, Proposition 2 says that the equilibrium coalition under a nonzero probability of regime shift will always be at least as large as the equilibrium coalition in the absence of such a threat.

While our primary focus is to examine the incentive to join the coalition, we also look at the impact of the threat of regime shift on harvest decisions. We report two main results, concerning changes to individual and total harvest, respectively.

Proposition 3 *Assume that the probability of regime shift is exogenous and the set of parameters satisfies*

$$\bar{\rho} < \bar{\rho}^R \quad \textit{and} \quad (1+\delta\tilde{A}_H)\ln(1+\frac{1}{\delta\tilde{A}_H+N-1}) < \ln(2) \leq (1+\delta\bar{A})\ln(1+\frac{1}{\delta\bar{A}+N-1}), \tag{1.31}$$

where

$$\bar{\rho}^R = \frac{(1-\delta(1-b_L))(1-\delta(1-b_H))}{\delta\left[(b_H-b_L)+(1-b_H)\left(\delta(1-b_L)-\frac{1-\delta(1-b_L)}{1-\delta(1-b_H)}\right)\right]} \quad \textit{and} \quad \tilde{A}_H = \bar{A}_{|\bar{\rho}=0}. \tag{1.32}$$

While the threat of regime shift increases a non-member's harvest rate, it diminishes each member's harvest rate.

Proof: See the appendix. ■

Proposition 3 provides conditions under which individual signatories facing the threat of regime shift reduce their harvest whereas non-members increase their harvest.[4] These results are driven by the effects of the threat on the inter-temporal marginal costs of harvest (marginal benefits are unaffected). As long as condition (1.31) holds, the threat of regime shift increases each coalition member's expected inter-temporal marginal cost, but that same threat causes each non-member's expected inter-temporal marginal cost to decrease. The latter effect occurs because, when condition (1.31) holds, the threat of a shift causes the coalition to grow in size. Members of that larger coalition reduce their harvest, which in turn lowers the marginal cost of harvest for non-members.

[4]Using the set of parameters $N = 4, b_H = 0.1, b_L = 0.01$, and $\delta = 0.89$, we verify numerically that conditions in (1.31) and these results hold for plausible values of $\bar{\rho}$.

While Proposition 3 indicates that the threat of regime shift has heterogeneous effects on harvester behavior, we can still definitively sign the effect of such a threat on total harvest. In particular, despite the fact that non-signatories may increase harvest in response to the threat of regime shift, we find that total harvest declines:

Result 2 *An increase in the exogenous threat of regime shift causes a decrease in total harvest at a given stock level.*

Proof: See the appendix. ■

1.5 Pre-regime shift, endogenous threat

Thus far, we have focused on exogenous threats: those for which harvester behavior does not influence the probability of a shift occurring. That assumption may be appropriate for some types of threats, such as permanent climatic shifts (e.g. driven by warming or acidification) or unforeseen disasters (e.g. oil spills), but is likely inappropriate for harvest-driven threats. For example, the collapse of some fish stocks (e.g. Atlantic cod) is believed to be at least partly due to overfishing.

In order to analyze such cases, we examine the scenario where the probability of regime shift is endogenous (i.e., $\rho(S_t)$ decreases in S_t). The methods used in the post-shift and exogenous threat pre-shift cases are based on proofs by conjecture. The dependency of $\rho(S_t)$ on S_t introduces new terms in the second-stage value functions that depend on S_t in ways that it becomes impossible to conjecture the expected payoff given in (1.4) and thus analytical solutions are not sustainable in this section. As such, we use numerical simulations to illustrate our results.

To solve the pre-regime shift game numerically, we use a version of value function iteration. We approximate the second-stage value functions for both coalition members and free-riders with piecewise linear functions that are anchored at a finite number of discrete stock sizes (see, for example, Judd 1998).[5] Because the first-stage value function W is a weighted combination of those second-stage value functions, our first-stage value function is also a piecewise linear approximation.

We begin with initial guesses for the value of the first-stage value function at the discrete lattice points. We then iteratively update guesses for the second-stage value functions, harvest policies, equilibrium coalition size, and first-stage value function until a convergence criterion is satisfied. The steps are as follows:

1. Initialize guesses for the functions $W(S_t, H), V_i^C(S_t, H, n_t)$, and $V_j^F(S_t, H, n_t)$ to the values they take on in the no-shift case.

2. Given the current guess for $W(S_t, H)$, for each discrete stock size and possible coalition size, compute the equilibrium harvest policies according to (1.6) and (1.7).

3. Using the current guess for $W(S_t, H)$ and the harvest policies computed in step 2, update the guesses for $V_i^C(S_t, H, n_t)$ and $V_j^F(S_t, H, n_t)$ for all possible combinations of discrete stock and coalition sizes using (1.6) and (1.7).

4. Using $V_i^C(S_t, H, n_t)$ and $V_j^F(S_t, H, n_t)$ as computed in step 3, calculate the equilibrium coalition size for each stock size $n^*(S_t, H)$ using stability function (1.10).

5. Given the current guesses for $V_i^C(S_t, H, n_t)$ and $V_j^F(S_t, H, n_t)$ as computed in step 3 and the equilibrium coalition size guesses as computed in step 4, compute an updated guess for $W(S_t, H)$ according to (1.4).

6. Denote the guess for $W(S_t, H)$ as computed in step 4 as $W_{cur}(S_t, H)$, and the previous guess by $W_{prev}(S_t, H)$. If $\max_{S_t} |W_{cur}(S_t, H) - W_{prev}(S_t, H)| \leq 0.01$, accept the

[5] For a large number of grid points, the difference between piecewise linear and other approximation techniques (e.g. splines) should be negligible

current guesses for $W(S_t, H)$, $V_i^C(S_t, H, n_t)$, $V_j^F(S_t, H, n_t)$, $h^*_{it}(S_t, H), h^*_{jt}(S_t, H)$, and $n^*(S_t, H)$ as the solution. Otherwise, return to step 2.

We apply this algorithm using the piecewise probability function

$$\rho(S_t) = \begin{cases} 0.9 & \text{if } S_t < 0.5 \\ 0 & \text{if } S_t >= 0.5. \end{cases} \tag{1.33}$$

With this probability function, the probability is near zero at high levels of S_t and near one for small values of S_t. The probability of a shift changes suddenly at $S_t = 0.5$.

Using this approach, we are able to verify one of the main propositions of this paper:

Proposition 4 *Prior to the shift, if the threat of regime shift from H to L is endogenous, i.e. $\rho(S_t)$ is a non-constant function of S_t, (i) coalitions of size larger than two can be sustained, and (ii) the grand coalition is sustainable as an equilibrium outcome.*

Proof: Since the proposition claims only existence of larger stable coalitions, we may prove the proposition numerically. We use the numerical approach outlined above, discretizing the state space at intervals of 0.01. We set parameters as follows: $\delta = 0.95, b_H = 0.4, b_L = 0.01$. Our simulations suggest that for $N = 8$, the grand coalition (of size 8) is stable for an initial stock size $S_0 = 0.17$. ∎

We next examine the sensitivity of this result with respect to parameters, beginning with the size of the shift $(b_H - b_L)$. We fix b_H at 0.4 and vary b_L from 0.4 to 0, computing the equilibrium outcome for each b_L. The equilibrium level of cooperation varies from full non-cooperation to full cooperation, as indicated in Figure 1.1. In addition, our simulations suggest that the effect of increasing the size of the shift on the equilibrium coalition size is non-monotonic. The equilibrium coalition size first increases with the size of the shift, but as the size of the shift grows increasingly large, the level of cooperation may actually decline.[6]

The non-monotonic relationship between the magnitude of the shift and equilibrium coalition size stems from two opposing forces. First, as the size of the shift increases, so too does the incentive for players to avoid it by keeping the stock at a level where the probability of the shift is low. This incentive tends to favor larger coalitions, since coalition members harvest less and increased membership can thus help avoid the shift. However, as the size of the shift continues to grow, the gains to free-riding also increase. To see why, note that for a large enough shift, coalitions of several sizes all reduce harvest just enough to keep the stock at the critical threshold at which the probability of the shift drops ($S_t = 0.5$). Only the smallest such coalition can be internally stable: a member of a larger coalition can gain by becoming a free-rider and increasing his or her harvest with no future consequences, since the remaining members of the smaller coalition will reduce harvest and leave the same residual stock. The interaction of these two forces gives rise to the non-monotonic relationship in Figure 1.1.

Further intuition can be gained by examining the evolution of the stock and coalition size through time. Figure 1.2 depicts the time paths of both for several starting stock levels. As is evident from the plots, cooperation arises for low initial stock levels, and serves to help bring the stock level above the point at which the probability of regime shift increases. Once the stock has reached those higher levels, the players no longer need cooperate to maintain the stock at high enough levels to avoid increased exposure to the

[6] The non-monotonic response of coalition size to an increase in the size of the shift stands in contrast to results found in the context of pollution control by Nkuiya et al. (2014). In that study, an increase in the size of the shift never results in a smaller coalition. The difference in the results likely stems from the combination of different payoff functions and probability functions. Here, the increase in probability is steeper near $S_t = 0.5$ as compared with the quadratic increase used in Nkuiya et al. (2014). When combined with a sufficiently large shift, the steeper rise in probability used here induces a larger response (reduction in harvest) by the coalition, such that only partial cooperation is needed to avoid the large increase in the probability of a shift.

threat of the shift.

Next, we explore how our results depend upon the number of players. Fixing b_L at 0 and keeping all other parameters the same, we vary N from 3 to 25. Our simulations suggest that the grand coalition or a coalition near the grand coalition size is sustainable even for larger numbers of harvesters. These results clearly show the potential for endogenous regime shift to alter equilibrium level of cooperation.

1.6 Doomsday scenario

Suppose that instead of altering the dynamics of the stock in the way outlined above, the regime shift results in a doomsday scenario (stock collapse) in which all users receive a negative,[7] stock-independent payoff D. We examine the sensitivity of our results with respect to various values of parameter D.

Formally, for this scenario we assume

$$V_i^C(S_t, L, n_t) = V_j^F(S_t, L, n_t) = W(S_t, L) = D. \tag{1.34}$$

We next investigate how a threat of this type of event affects harvests and incentives to join the coalition.

1.6.1 Exogenous threat

By defining $A_L = 0$ and $\gamma_L = D$ for the post-shift era, the analysis above can be adapted to derive the equilibrium outcome when there is an exogenous threat of a doomsday event. The main result from Proposition 1 continues to hold: stable coalitions can have at most two members when the threat of regime shift is exogenous.

[7] Because utility is logarithmic in harvest and harvest is less than one, payoffs even in the absence of a shift are negative, so D must be large and negative to constitute a true doomsday event.

As with the productivity shift case, we again examine how an increase in the probability of the shift affects the incentives to join the coalition.

Proposition 5 *When the exogenous probability of a doomsday event is increased, the equilibrium coalition size cannot increase (i.e., $n_H^{*DD}(\bar{\rho}_1) \geq n_H^{*DD}(\bar{\rho}_2)$ for all $\bar{\rho}_2 > \bar{\rho}_1 \geq 0$).*

Proof: See the appendix. ■

Proposition 5 suggests that results of Proposition 2 obtained under the threat of regime shift do not hold under the threat of a doomsday event. Moreover, a clear implication of the result of Proposition 5 is that incentives to join the coalition cannot be increased by the threat of a doomsday event ($n_H^{*DD}(\bar{\rho}) \leq n^*(0)$). Combining the results of Propositions 2 and 5, we obtain that the stable coalition size under the doomsday event is lower than the stable coalition size under the no-shift setting, which in turn is lower than the stable coalition size under the threat of regime shift.

The intuition for this ordering stems from the consequences of defection under each scenario. A harvester who chooses to free-ride on a coalition of a given size gains in current period returns regardless of the type of threat (or lack thereof) facing the fishery. The key difference between the scenarios is the inter-temporal cost of defection. If no threat is present, the costs of defection are those resulting from increased aggregate harvest and a lower future stock. If there is a threat of regime shift, that lower future stock may result in much higher costs if the shift takes place, thereby increasing the expected cost of defection. In contrast, if the threat concerns a doomsday event, the reduced future stock will have no consequences if the event does occur, thereby reducing the expected cost of defection. As a result, $n_H^{*DD}(\bar{\rho}) \leq n_H^*(0) \leq n_H^*(\bar{\rho})$.

In addition to these findings pertaining to coalition size, we can also state two results about equilibrium harvest.

Proposition 6 *Assume that the probability of the shift is exogenous and the set of parameters satisfies*

$$\bar{\rho} < \bar{\rho}^{DD} \quad \text{and} \quad (1+\delta\bar{A})\ln(1+\frac{1}{\delta\bar{A}+N-1}) < \ln(2) \leq (1+\delta\tilde{A}_H)\ln(1+\frac{1}{\delta\tilde{A}_H+N-1}), \tag{1.35}$$

where

$$\bar{\rho}^{DD} = \left(\frac{1}{\delta(1-b_H)} - 1\right)^2. \tag{1.36}$$

(i) The threat of a doomsday event induces fully noncooperative behavior whereas in the no-shift case, stable coalitions are of size two. (ii) Each non-member harvests less under the threat of a doomsday event than in the no-shift case.

Proof: See the appendix. ■

The driving force behind the results of Proposition 6 is that an exogenous threat of a doomsday event reduces incentives to cooperate. If those incentives are reduced enough (i.e. condition (1.35) is satisfied), the coalition dissolves. As a result, fishers who would have been in the coalition in the absence of the threat increase their harvest, which causes a reduction in harvest by non-members.

These results shed some light on a class of economic papers dealing with the threat of the doomsday event in which the post event value function is either stock independent or normalized to zero. In the pollution control setting, for example, Clarke and Reed (1994), Tsur and Zemel (1998), de Zeeuw and Zemel (2012), and Nkuiya and Costello (2014) all find that it is always optimal to act aggressively under the threat of a doomsday event as long as the threat is exogenous. In a fisheries setting, Polasky et al. (2011) show that a single harvester will never harvest less under the threat of a doomsday event. In all those papers, there is only one player (the optimal control approach). In this paper, however, we allow for partial cooperation in which each harvester can join or leave a coalition as long as it is beneficial to do so. Proposition 6 suggests that this additional flexibility gives rise to behavior not previously identified in the literature: in certain circumstances, an exogenous threat of a doomsday event can cause non-members to reduce their harvest.

We conclude our analysis of a doomsday event with exogenous probability by moving from individual harvest decisions to aggregate harvest levels. We find that the threat of a doomsday event can never reduce total harvest:

Result 3 *When the probability of regime shift is exogenous and the shift has not yet occurred, total harvest in the doomsday scenario is at least as large as harvest in the absence of such a threat.*

Proof: See the appendix. ■

Together, Results 2 and 3 imply an ordering on total harvest between the regime shift, doomsday, and no-shift scenarios when the threat of any type of event is exogenous. In particular, total harvest under an exogenous threat of regime shift is smallest, followed by the no-shift scenario, and finally, total harvest under the threat of a doomsday event is largest. In the context of real-world threats, this suggests that the threat of catastrophic events, such as severe oil spills, may cause decreased cooperation and increased total harvest, while an exogenous threat of regime shift, such as lower productivity due to changing environmental conditions (see, for example, Reid et al. (1998)), may enhance cooperation and reduce total harvest.

1.6.2 Endogenous threat

This section focuses on the scenario where the probability of occurrence of the doomsday event is endogenous. To examine this scenario, we adapt the algorithm presented above to the doomsday case and use the probability function given in (1.33). Using the same set of parameter values as for the regime shift case presented in Section 1.5, we solve for the equilibrium coalition size and harvest decisions.

Our simulations suggest that threat of a doomsday event has effects on cooperation that are qualitatively similar to the threat of regime shift. The stable coalition size at a given stock level varies non-monotonically with the severity of the doomsday event. Further, the stable coalition size depends upon the stock level. These results are captured in Figure 1.3, which depicts the stable coalition size as a function of the size of the doomsday event at two example stock levels. Over the range $-150 < D < -100$, the stable coalition size at $S_0 = 0.33$ first increases, then decreases, while no coalitions form at $S_0 = 0.17$. Finally, the grand coalition is stable for $D = -100$ and $S_0 = 0.40$ (not shown in Figure 1.3). The intuition for these patterns parallels that for the regime shift case: a more negative D increases the cost of the shift for harvesters, just as a smaller b_L does in the regime shift case.[8]

Our finding that coalitions can be larger when the threat of regime shift is endogenous is consistent with patterns observed in some real-world fisheries. As one example, the formation of Regional Fisheries Management Organizations (RFMOs) to cooperatively manage international fisheries has often occurred after stocks have been depleted to low levels and the risk of regime shift or collapse is high. Such delayed formation is often simply attributed to reduction in the benefits of free-riding. Our model provides additional insight on this point, suggesting that one potential reason cooperation may arise at low stock levels is the increased threat of regime shift (recall that when the threat is absent or exogenous, the largest stable coalition contained only two members).

[8]Due to the dependency of coalition size on key parameters b_L and D that are not common between the productivity shift and doomsday scenarios, we avoid comparison between the two endogenous threat scenarios. In the exogenous threat case, we were able to compare outcomes for coalition size only because D did not play a role in determining the equilibrium coalition size in the doomsday scenario.

1.7 Summary and Conclusion

This paper has examined harvesters' responses to the threat of an abrupt shift in the biological growth for a renewable resource. In contrast to the existing literature, we focus on the implications of such a threat for both cooperation and harvest in a partial coalition framework. We have studied four different types of threat and compared them to the baseline scenario where the shift is absent. In the case where the probability of regime shift is exogenous, we have found that the threat of regime shift tends to slightly increase incentives to join the coalition, while the threat of a doomsday event has the opposite effect. In addition, stable coalitions are of size equal to or less than two under both the exogenous threat and no-threat cases. However, when the probability of regime shift depends on harvest decisions, larger coalitions may be stable, and in some cases full cooperation is an equilibrium outcome. Further, we find that the size of the stable coalition is non-monotonically related to the size of the shift. The equilibrium coalition size first increases as the shift becomes more severe, but above a threshold, the potential gains from cooperation are reduced, resulting in smaller coalitions.

These impacts of the threat of regime shift on coalition size give rise to novel harvest responses. Prior analyses of regime shift have focused on behavior of sole owners, fully cooperative harvesters, or a set of fully non-cooperative harvesters. In such cases, all players respond to a threat identically (trivially so in the case of sole ownership). This paper has focused on the scenario where each harvester may join a coalition as long as it is beneficial do so. In so doing, we have identified conditions under which some resource users increase harvest while others reduce harvest in response to the threat. In particular, we find that an exogenous threat of regime shift may cause non-members to increase harvest while members reduce harvest. These heterogeneous responses are driven by the effect of regime shift on coalition size. The threat of regime shift provides a direct incentive for all players to reduce harvest, but if the coalition grows in size, the resulting reduction in harvest by members also provides a counteracting incentive for non-members to increase harvest. We identify conditions in which that indirect effect is larger than the direct effect.

In light of increasing concerns about regime shift due to climatic shifts, oil spills, nutrification, and overfishing, the results developed here may help inform expectations about cooperation and harvest in shared fisheries facing such threats. The basic setup presented here invites a number of extensions that may enhance the model's applicability. In some cases the size of the shift or the relationship between actions and the probability of the shift may not be fully known. In such a case harvest incentives and the gains from cooperation might be altered, and thus the equilibrium coalition size is likely to change. In addition, while we focus on homogenous harvesters so as to isolate the impacts of regime shift on cooperation, heterogeneity may play an important role in determining coalition membership. Resource users could have differing payoffs from harvest. Alternatively, the type of fundamental change to system dynamics considered here might have heterogeneous effects on harvesters. How exactly these features would affect the results is an avenue for further research.

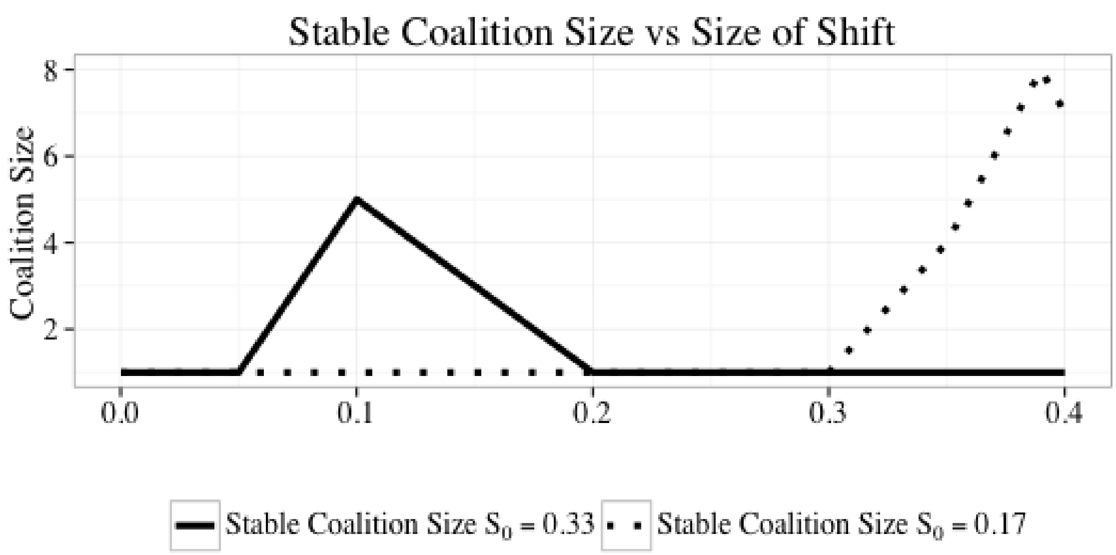

Figure 1.1: Maximum stable coalition size at $S_0 = 0.33$ and $S_0 = 0.17$ under endogenous probability of regime shift as a function of the size of the shift $(b_H - b_L)$.

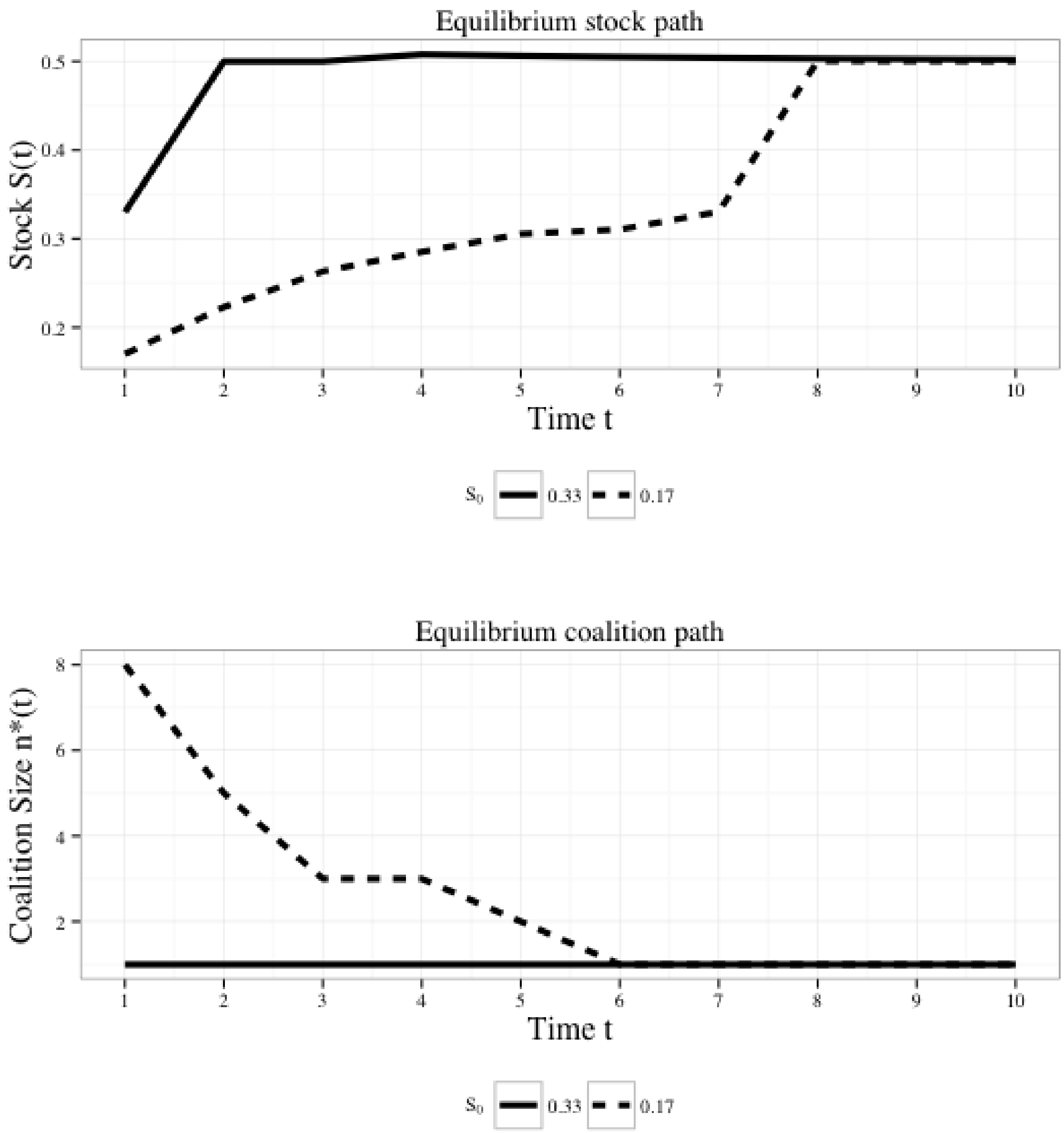

Figure 1.2: Top panel: Equilibrium path of stock as a function of time for starting stock levels $S_0 = 0.33$ and $S_0 = 0.17$. Bottom panel: Equilibrium path of coalition size as a function of time for starting stock levels $S_0 = 0.33$ and $S_0 = 0.17$.

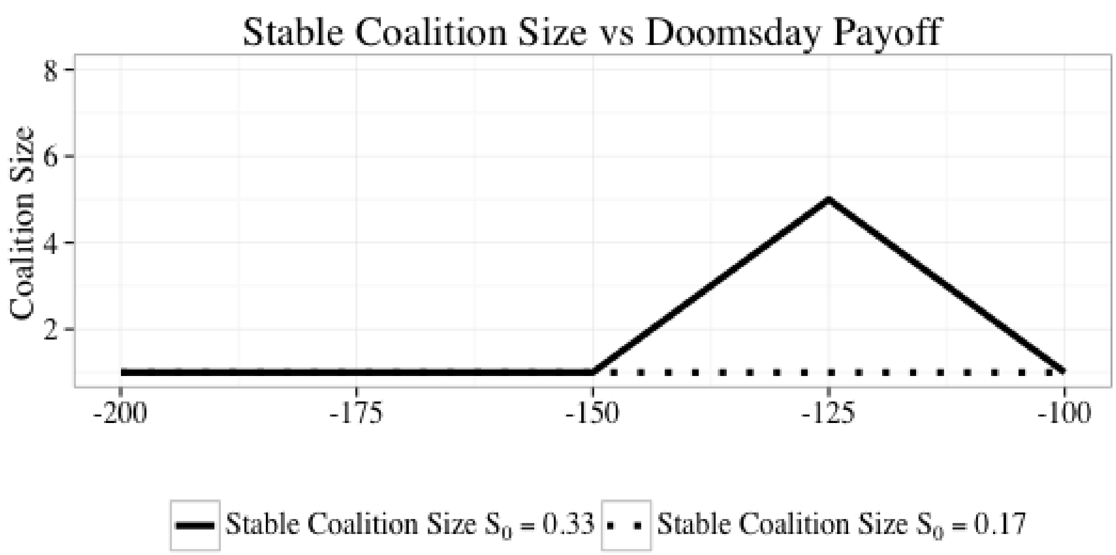

Figure 1.3: Maximum stable coalition size at $S = 0.33$ and $S = 0.17$ under endogenous probability of a doomsday event as a function of the doomsday payoff. (D).

Chapter 2

Protecting Marine Ecosystems: Prescriptive Regulation versus Market Incentives

2.1 Introduction

The absence of an exclusive property right to any asset prevents the execution of contracts and transactions that could in principle lead to efficient use. This lack of exclusion, or open access, is a key feature of many marine fish stocks. It results partly from physical features of the resource that make monitoring and enforcement difficult, such as the fact that fish stocks are hidden beneath the sea and their sometimes mobile nature. Exclusion can also fail because legal institutions do not recognize a right of exclusive access by any particular party (Cheung, 1970, pp. 50, 67). Absent property rights to the resource, contracting and market exchange will not occur and the necessary conditions for efficient resource use will not in general be satisfied. The result can be a degradation of potentially valuable resources, an unfortunate outcome that has been documented for commercially important fish species around the world (Worm et al., 2009).

This point is now widely understood, and this understanding has led to management policies based on creating partial property rights to the flow a resource can provide. In fisheries, the cap and trade system known as the individual transferable quota (ITQ) has emerged as a leading example of this approach. With ITQ management, a biologically determined limit on total harvest is divided into discrete units that are then allocated to individual fishers as rights to catch specific quantities of fish. The creation of these property rights has enabled contracting, transactions, and the emergence of formal markets for access rights to fish stocks (Newell et al., 2005), or more precisely, to the flows from them. This has led to demonstrated efficiency gains (Newell et al., 2005; Grafton et al., 2000; Arnason, 2012). Stocks managed in this way also tend to be in better shape biologically than stocks managed differently (Costello et al., 2008).

Early ITQ programs were located predominantly in New Zealand, Iceland, and Australia, while more recent programs are spread across the globe. In 2010 the U.S. National Oceanic and Atmospheric Administration (NOAA) began actively promoting 'catch share' management for the nation's fisheries (NOAA 2010); catch share refers to a category of policies based on creating property rights that includes ITQs. In the U.S. state-level management reforms are moving in the same direction. The U.S. trend toward ITQ management can be explained by its efficiency advantages. Creating harvest rights to 'target' stocks, the commercially valuable fish that harvesters intend to catch, provides individual incentives that promote efficient fishing practices and rational organization of fishing fleets. Pre-existing management was largely prescriptive and rule based, providing neither incentives nor latitude for finding least cost outcomes. While success in managing target stocks is an important achievement, a separate problem remains. Commercial fishing often results in the unintended catch of over-fished species, causing collateral damage to marine ecosystems. Controlling this phenomenon, termed 'bycatch', is increasingly important in management decisions and is the dominant concern in many fisheries. Regulators typically have tried to fix this problem with the same rule-based, prescriptive strategies traditionally applied to target stocks, such as spatial and temporal closures and restrictions on fishing gear. This regulatory approach provides only limited incentives for individual fishers to find least cost ways to limit bycatch.

In theory, the problem of managing bycatch can also be addressed by creating property rights (Boyce, 1996). However, this approach is seldom taken in practice and evidence comparing this property rights-based approach to more common rule-based strategies is scarce. , Our central contribution is to help fill this gap. We exploit a recent policy shift in the US West Coast groundfish fishery to provide evidence on how fishing practices changed, and how bycatch outcomes were affected, when a rule-based strategy was replaced by a property rights regime. Most of the catch in this fishery is harvested by non-selective trawl gear. Trawling involves towing a bag-shaped net through the water, which catches most fish in its path; in the fishery examined, over 40 different species are commonly landed by such gear. Bycatch of rockfish and other species groups by trawl gear has been a problem in this fishery for over a decade. Incidental harvests impose the greatest ecological harm when the bycatch stocks are long-lived, slow growing, have low fecundity, and have been reduced to precariously low levels. We use the term 'weak' stock to describe such populations. Prior to 2011, federal regulators sought to protect weak stocks with several prescriptive policies. First, extensive areas were entirely closed to trawl fishing. The boundaries of these closures changed from year to year, differed for different types of trawl nets, and the prescriptions often shifted during a season to keep projected catch aligned with targets as new information arrived. Second, catch limits and gear restrictions were imposed on commercially valuable species in order to avoid weak stock species found in the same habitats. Third, upper limits were placed on weak stock harvests for the entire fishery, and the entire fishery (including all target stocks) could be closed if the cap for a single weak stock species was violated or projected to be so. Because these caps were fishery-wide, individual fishers had no strong incentive to minimize bycatch. Prior to 2011 the management of target stocks was also rule-based. Regulators fixed the number of commercial fishing permits and each permit holder faced upper limits on catches of each target species for specific periods during the year.

In 2011 this fishery transitioned to a rights-based management scheme known as Individual Fishing Quotas (IFQs). The main difference between IFQs and ITQs is that transferability of the former is somewhat restricted. Nevertheless, IFQs are individual rights to harvest specific quantities, and each permit holder was allocated a portfolio of such rights for both target and weak stock species. Creating IFQs for non-target weak stocks is unusual. Each fisher is required to hold sufficient rights to cover any weak stock catches made and rights are deducted from the fisher's account as catches occur. These rights are limited in supply and hence valuable. Consequently, each fisher faces an individual penalty for weak stock catches, which creates an incentive to discard them. Recognizing this, regulators require mandatory on-board monitoring, count all discards against quota allocations, and impose severe penalties for violations. Shortly after the IFQs were created, transactions in quota for weak stock and target species emerged and a market began to function.

Harvesters must surrender a valuable unit of quota, or incur the cost of acquiring a unit of quota from someone else, for each unit of weak stock catch landed. Harvesters therefore have a profit motive to find minimum cost strategies for avoiding bycatch. Two obvious strategies are available: avoid fishing in areas where weak stock catches are common (Toft et al., 2011), and switch to more selective gear, such as from trawl nets to traps and hook and line assemblies that can target species more precisely. More subtle adjustments are also possible, however, such as altering the deployment of trawl gear in order to either gain more precise information on the location of weak stock concentrations or to exploit the differential migration patterns of weak stock species (Grafton et al., 2005). Further, fishers can organize themselves into groups to take collective actions to avoid bycatch (Holland, 2010). Our empirical analysis demonstrates that the industry took each of these steps after weak stock IFQs were introduced and that weak stock catches declined dramatically. Some commercial fishers shifted from trawling to the use of highly selective fixed gear, while those who kept trawling made both spatial and nuanced behavioral adjustments. The end result was a suite of adaptations on several margins, an outcome that would be difficult to achieve with prescriptive regulation, but that occurred naturally when property rights for bycatch were created.

The primary evidence we present is from individual logbook entries for every trawl tow on the U.S. West Coast during the period 2005-2012. Our most detailed analysis concerns spatial avoidance, i.e., shifts in fishing effort across spatial areas or 'patches' to avoid concentrations of weak stock species. We demonstrate that substantial spatial avoidance did in fact take place and use the cost of these spatial shifts to shed light on the shadow price, or implicit penalty, that fishers assigned to weak stock catches.

Under rule-based management, regulators created 'marine protected areas' (MPAs), zones where fishing was prohibited or fishing methods were severely restricted, in order to protect marine environments. These pre-IFQ spatial closures remained in place under IFQ management, but the behavior of harvesters toward them changed in interesting ways. Prior to IFQs, fishers would be compliant if they fished along the borders of MPAs, a practice that can be attractive because some target stocks tend to be abundant near these no-fishing zones. The introduction of IFQs for weak stocks changed this calculus, since weak stocks are also abundant near MPAs. We find evidence that fishers voluntarily moved effort away from MPA boundaries creating what we term 'fuzzy MPAs', regions of partial closure around the regulatory no-fishing zones.

We also document behavioral shifts in trawl fishing methods. When weak stock IFQs were introduced, trawl fishers shifted toward fishing at night, a time when some weak stock species migrate up from the sea floor and thus become less vulnerable to trawl gear, while key target stocks remain near the bottom. Trawlers also shifted toward making shorter tows following IFQ introduction. This practice yields higher frequency information on weak stock catches and enables one to change locations when a weak stock concentration is encountered. We also document a shift away from trawling and toward the use of highly selective fixed gear following IFQ adoption. Finally, we provide summary information on the collective bycatch avoidance actions of groups of fishers who organized following the implementation of bycatch IFQs.

The remainder of this paper is organized as follows. The next section provides background for the fishery examined. It includes an extensive description of the management regime in place prior to 2011 and the IFQ system adopted subsequently, and a discussion of the timing of the shift. This information provides essential context for our empirical hypotheses on changes in the fishery following the management change. Section 3 presents the model that underlies our empirical approach. Section 4 explains the data used in estimation, Section 5 presents empirical results on spatial avoidance and Section 6 presents evidence of adjustment on other margins. The paper concludes in Section 7 with a discussion of implications and suggestions for further work.

2.2 The Fishery

Groundfish off the west coast of California, Oregon, and Washington are targeted by commercial vessels primarily employing trawl gear and to a lesser extent by fishers using baited hook and line assemblies and pots and traps, collectively known as 'fixed' (non-towed) gear. 'Groundfish' is a catch-all term for the variety of species living on or near the sea floor, including flatfish such as Dover sole, roundfish such as sablefish, rockfish such as yellow tail and other species such as sharks and skates. Over 40 individual species and species groups are harvested, but most fishing effort is directed toward a small subset of commercially valuable 'target species': whiting (also known as hake), Dover and petrale sole, thornyheads, arrowtooth flounder, and sablefish (also known as black cod). These target species are generally fast growing and their populations can withstand substantial fishing pressure. Several species of rockfish and other 'weak stocks' caught incidentally along with the targets are not as robust.

While commercial exploitation of this fishery pre-dates World War II, effort by U.S. fleets did not become intense until the 1970s. At that time the U.S. implemented a number of federal subsidies, loan guarantees, and special tax provisions intended to increase domestic fishing effort. These measures were partly in response to heavy exploitation by foreign vessels. Following passage of the Magnuson-Stevens Act in 1976 and establishment of 200-mile exclusive economic zones (EEZs) a few years later, U.S. vessels began to supplant their foreign counterparts. The U.S. Pacific whiting catch increased from a few million pounds in 1980 to 200 million pounds by the early 1990s; domestic West Coast catches of groundfish roughly doubled between the mid-1970s and early 1980s.

Groundfish landings peaked in 1981 and 1982, prompting adoption in 1982 of a federal Fishery Management Plan (FMP) intended to control harvesting and a set of regulations that remained in place (with revisions) until 2011. Despite FMP provisions, groundfish stocks entered a period of decline that continued for two decades. In the 1980s the regulatory body in charge, the Pacific Fishery Management Council (PFMC), adopted several effort controls intended to stop or reverse the decline. These included 'trip limits' (explained below), shortened fishing seasons, bycatch limits and gear restrictions. In 1994 the PFMC limited entry by new permit holders for most of the fishery. Despite these protections, the downward trend in stocks, catches, and fishing incomes continued. In 2000, the federal government declared the fishery an economic disaster. In 2003 federal managers, seeking to reduce capacity, instituted a policy of buying back active fishing permits.

Concurrent with declines in target species catches and profits, bycatch emerged as another central management concern. Specific populations were identified as over-fished species (OFS) and new restrictions were adopted to rebuild them. (OFS is the legal term for specific weak stocks that received regulatory protection.) Policies adopted in 1996 required PFMC to identify 'essential fish habitat' (EFH), areas holding OFS concentrations, and to restrict fishing times and gear used in these zones. In 2002-03 an extensive system of rockfish conservation areas (RCAs) was created along the Washington, Oregon and California coasts. RCAs containing high densities of overfished species are off limits to trawl gear. Figure 1 provides a map illustrating these spatial restrictions for a section of the California and Oregon coast.

The regulatory system that emerged was complex, multi-faceted and adaptive. The trip limits imposed on vessels are illustrative. They generally constrained catches by a single vessel during a given block of time and varied by location (for different latitude bands), by species (for over 20 target and weak stock species or species groups), by type of trawl gear used, and by month of year. Trip limits have been adopted in several U.S. fisheries as a way to mitigate the 'race to fish' that occurs in fisheries managed by simply closing a fishery once a fishery-wide target catch is met.

While arguably an improvement on season closures, trip limits clearly constrain effort decisions by vessel owners in complex ways. Trip limits for some species capped a vessel's catch on a 'per trip' basis. For example, as of 2008 large and small footrope trawlers could harvest no more than 20,000 pounds of whiting per trip before the primary whiting season opened, and 10,000 pounds per trip at other times. For most species, trip limits constrained a vessel's cumulative catch over a 1 or 2-month period. For example, the 2008 regulations for sablefish allowed limited entry vessels using 'large or small footrope trawl gear' to harvest up to 14,000 pounds per 2-month period during the months of January-April and November-December, and 19,000 pounds per 2-month period during the months of May-October. The multi-species nature of the fishery and imperfect selectivity of trawl gear added complexity. For example, large and small footrope trawl vessels faced specific 2-month limits on each of several major species they targeted (Dover sole, thornyheads, arrowtooth flounder and various flatfish) as well as prohibitions or tight limits on catching various rockfish. However, vessels using 'selective flatfish trawl gear', which is somewhat different, were subject to different limits. Fishers using non-trawl equipment, e.g., hook and line gear or traps, faced an entirely different suite of restrictions. Because a single tow of a trawl net can scoop up numerous species, this policy encouraged both biological and economic waste. If a vessel hit a trip limit for one species, subsequent catches of this species during the time window in question might be discarded at sea; discarded fish seldom survive. Further, if the binding trip limit pertained to an abundant species, fishers may have found it more profitable to cease fishing for the rest of the regulatory period rather than discard a large portion of their catch.

Other measures for managing weak stock species were equally complex. The rockfish conservation areas, which were mentioned earlier and which remain in effect under IFQ management, are illustrative. RCAs are defined by latitude bands and lines approximating depth contours. The specific depth range closed to fishing varies during the year, with boundaries typically fixed for 2-month periods (January-February, March-April, and so on). Generally, areas between 100-150 fathoms are closed. However, in some areas and seasons the shallower boundary extends to the shore and the deeper boundary extends out to 250 fathoms. Some closures are complete, while others are off-limits only for specific trawl gear. For example, in 2002 the areas shoreward of RCAs were closed to trawlers using large footrope gear, which can fish on rockier bottoms and is therefore likely to inflict more damage, but open to lighter trawl gear. In 2005 those restrictions were tightened such that only fishers using selective flatfish gear can fish shoreward of RCAs north of 40°10’ (approximately 200 miles north of San Francisco). Further closures arrived in June 2006, when several Essential Fish Habitat (EFH) areas up and down the coast were closed to fishers employing certain types of gear, with many closures affecting the use of trawl nets.

Spatial and quantity restrictions were regularly updated in an attempt to keep catches of individual species below regulatory caps. For instance, in 2006 the RCA boundaries and several trip limits were adjusted mid-year due to early indications that the catch of darkblotched rockfish would exceed limits. In extreme cases, the result was early closure of large portions of the fishery. In September 2002 the entire groundfish trawl fishery (for all species) was closed north of 40°10’ for the remainder of the year; in July of the same year fishing south of that boundary was restricted to a small number of target species. These emergency closures were enacted to protect weak stocks of darkblotched and bocaccio rockfish, respectively.

Using prescriptive input controls to simultaneously satisfy catch limits for several species, all of which are harvested with imperfectly selective gear, proved to be an unattainable goal. Target stock landings and weak stock populations failed to rebound. In 2011 the fishery transitioned to a multi-species IFQ scheme that included quota for weak stock species. This timing is easy to understand in light of events in the fishery and the direction of U.S. fishery management policy. As noted earlier, the fishery was declared an 'economic disaster' in 2000. OFS stocks were increasingly problematic in the years following and the entire fishery was shut down prematurely in 2002 due to excessive OFS catches. The reauthorized Magnuson-Stevens Act, adopted by the U.S. Congress in 2007, stressed the use of IFQs and other 'limited access privilege' policies for managing U.S. fisheries. In 2010, the NMFS adopted an official position promoting the use of catch shares (individual quantitative catch rights) for managing the nation's fisheries. Adding support, the number of U.S. fisheries using IFQs increased steadily after 1998 and evidence of gains in efficiency accumulated steadily.

Under IFQ management each permit holder in the West Coast groundfish fishery was allocated a share of the annual total allowable catch (TAC) for each target and weak stock species, based on the permit's history of catches. Each year these quota shares are converted to quantitative annual catch limits, termed quota pounds, by multiplying a vessel owner's quota share for a particular species by the fishery-wide TAC for the corresponding stock. The result is that each permit holder owns a portfolio of quantitative catch rights for various species. A vessel's catches are then monitored and quantities caught are deducted from the vessel's account. If an account is in deficit for any species, the owner must acquire additional quota pounds by leasing them from another vessel, or else borrow against next year's allocation and cease fishing for the remainder of the current season. Both options impose a potentially substantial cost on the vessel owner.

Within a few months of IFQ implementation, an online auction site emerged to facilitate quota pound transactions. This enabled fishers to augment quota holdings when they faced a shortfall in much the same way they would replenish depleted inventories of fuel and ice. The flexibility of marketable, quantitative catch rights allowed one harvester who faced a shortfall of quota for species A but not for species B, to find a trading partner who is in the opposite situation. The possibility of such trades is particularly advantageous for a multi-species, imperfectly selective fishery.

Catch limits for overfished species traditionally were set at low levels in order to rebuild stocks, and they remain low under IFQ management. Historically, trawlers often discarded OFS catches at sea and the incentive to do so was heightened under the new IFQ system. Recognizing this, the IFQ policy instituted a mandatory on-board observer program with 100% coverage for trawl vessels. The low TACs and discard prohibitions for bycatch species resulted in high quota prices and correspondingly strong incentives to avoid OFS catches.

A few items of summary information indicate that the shift to IFQs significantly changed the way the industry treated bycatch. First, average quota prices, shown in Table 2.1, reflect the importance of overfished stocks in both management decisions and fishery profits. Quota prices for sablefish, a highly desired target species, average about $1 per pound, while quota for high volume target species such as Dover sole are near zero. All 7 over-fished stocks commanded significant quota prices, with yelloweye rockfish topping the list at over $30 per pound in 2011. Second, high OFS prices resulted from small quota allocations. The yelloweye rockfish case is an extreme example: the average annual allocation for an individual trawl vessel was 16 pounds, the median allocation was 7 pounds and one-sixth of the fleet had a zero allocation. OFS trawl landings, which had averaged an estimated 825,000 lbs. per year during 2005-2010, fell to an average of 356,400 lbs. in 2011-2012 under IFQ management (Table 2.2). This reduction in

OFS trawl landings and the clear reduction in trawl effort following IFQ implementation are partly due to shifts away from trawl fishing and toward more selective fixed gear. However, the composition of the trawl landings also changed following IFQs; the ratio of OFS landings to total landings dropped by over one-third.

Our main focus in the remainder of the paper is to investigate a possible link between these two summary observations, the significant OFS quota prices and significant OFS catch reductions that followed the introduction of IFQs. Specifically, we seek to answer a straightforward question: In what ways did fishers respond to the introduction of significant, individual penalties for OFS catches? We begin by examining spatial avoidance, an obvious margin of adjustment, and develop a model that leads to an explicit empirical specification. This model also allows for adjustments in fishing methods, which we examine somewhat informally in a subsequent section. An Appendix provides details.

2.3 Modeling Spatial Adaptations to IFQS

A tow of a trawl net generally catches a different mix of species in different locations because fish stocks are not uniformly distributed. The profit from a tow will therefore vary from location to location depending on the densities of stocks present, as well as economic variables such as prices and costs, and on the management regime. The pre-IFQ regime constrained harvesters' actions in various ways, but created little individual accountability for OFS catches; hence, it provided no incentive to avoid locations with high OFS densities. IFQ management changed the profit calculus both by requiring fishers to surrender a unit of valuable quota for each unit of catch and by relaxing several pre-existing constraints. Accordingly, it introduced incentives to adjust fishing locations.

We model spatial choices by a 'representative fisher' who maximizes expected profit. Profit differentials across locations are subject to arbitrage. If the expected profit at one location is abnormally high, more effort will be applied, removing biomass and lowering stock abundance and reducing profit per unit effort. This process equilibrates the distribution of effort. We invoke the equilibrium condition that a unit of effort allocated at any location generates the same expected profit and use this condition to get an empirical specification for the spatial distribution of fishing effort. Profit at each location also depends on the prices of catch and on cost terms such as distance from port, fuel price and wage rates. Profit also depends on the fishing methods used and on regulatory constraints.

Fishers deploy effort at discrete fishing locations called 'patches'. A fisher who deploys a unit of effort in period t at patch j earns revenue by selling catches ht at prices pt, and incurs the variable costs VC_{jt}. The fishery is multi-species and gear is not perfectly selective, which implies that h_t and p_t are S dimensional vectors where S is the number of target species harvested. Further, catch is unknown when the fishing location is chosen, so h_t is a vector of random variables. If an IFQ program is in place, the fisher also faces a vector of per-pound quota prices c_t. With these definitions the expected profit from a unit of effort on patch j in period t is

$$E\left[\pi_{jt}\right] = \left(p_t - c_t\right) E\left[h_{jt}\right] - VC_{jt} \tag{2.1}$$

We assume fishers know relevant prices and cost terms and choose locations to maximize expected profit Catches of different species are linked to their stock densities and to fishing effort according to a simplified Schaefer model of harvesting. This model suits our purpose because it captures the decline in profit per unit effort on a given patch as effort is increased. It also gives an exact mathematical representation of equilibrium effort in each patch as a function of prices, costs, initial stock densities, and the regulatory regime, which is useful for estimation. The Schaefer model specifies that a unit of effort will catch a fixed fraction of each stock that is vulnerable to trawl gear in the location where fishing takes place. For tractability we assume a single catchability coefficient, q, applies to all species.

Our empirical specification for the spatial effort distribution follows from the arbitrage argument—that profit differentials across patches are eliminated in equilibrium. Let the S dimensional vector X^0_{jt} indicate the biological stocks in patch j at the beginning of period t. Fishers can select among a finite set of mutually exclusive actions, or fishing methods, that affect the fractions of these stocks that are vulnerable to trawl gear. The set of possible choices is denoted $A = a_1, a_2, ..., a_K$ and each element of A could represent a combination of the choice of depth, speed, duration, or time of day of a trawl tow. When action k is taken at location j, the fractions of stocks that are vulnerable to trawl gear are given by the S dimensional vector $f(a_{kj})$.

If no effort has been applied, the vector of trawl-vulnerable stocks on patch j in period t using fishing method k is $f(a_{kjt}) \circ X^0_{jt}$, where the operator '$\circ$' indicates element-wise multiplication. Let q be the Schaefer catchability coefficient, i.e., the mortality rate inflicted by a marginal unit of effort. If T_{jt} units of effort have been deployed in patch j in period t, the Schaefer technology implies that the trawl vulnerable stock remaining is

$$f(a_{kj}) \circ X_{jt}(T_{jt}) = f(a_{kjt}) \circ X^0_{jt} e^{-qT_{jt}} \tag{2.2}$$

where $X_{jt}(T_{jt})$ is the biological stock remaining after T_{jt} units of fishing effort. Applying dT units of additional effort will generate catches

$$h(T_{jt}, dT) = qf(a_{kjt}) \circ X_{jt}(T_{jt}). \tag{2.3}$$

Substituting (2.2) into (2.3), and the result into (2.1), the expected profit from a marginal unit (dT) of effort applied in patch j at time t, when T_{jt} units have already been applied, is

$$E\left[\pi_{jkt}\right] = (p_t - c_t) \cdot E\left[qf(a_{kjt}) \circ X^0_{jt}\right] e^{-qT_{jt}} - VC_{jkt}. \tag{2.4}$$

The representative fisher applying a marginal unit of effort on patch j in period t is assumed to use the fishing method that maximizes expected profit, denoted a^*_{jt}, so the vector of expectations on the right hand side of (2.4) is $E\left[qf(a^*_{jt}) \circ X^0_{jt}\right]$. The model implies that a^*_j depends on the arguments of (2.4): prices, quota costs if IFQs are in effect, expected initial biological stocks, costs and aggregate effort applied on the patch. When examining the spatial distribution of effort we do not try to identify the separable effect of fishing method, but seek only to estimate the reduced form effect of price, cost, and stock abundance. The vector of expectations $E\left[qf(a^*_{jt}) \circ X^0_{jt}\right]$ is expected catch per unit effort when no effort has been applied. In what follows we represent this vector with a proxy, $E\left[CPUE^0_{jt'}\right]$, the vector of observed catch per unit effort in patch j in a prior period, t', of the same management regime. We require the proxy to be from a period of the same management regime because the fishers are likely to expect that past catch experience will be a poor predictor of current fishing success if the regime has changed in the meantime. We assume that the most important determinant of effort that we cannot observe, i.e., information available to the fisher but not to us, is expected catch per unit effort in a given patch. Consequently, we append a multiplicative error term, $e^{\epsilon_{jt}}$, to $E\left[CPUE^0_{jt'}\right]$, where ϵ_{jt} is normally distributed.

If fishers are free to apply effort on any patch, the expected profit from applying an additional unit of effort, dT, should in equilibrium be equal across all patches that receive positive fishing effort. Denoting this equilibrium expected profit by $\bar{\pi}_t$, the right-hand side of (2.4) should equal $\bar{\pi}_t$ in equilibrium. Imposing this condition and keeping in mind the error term just introduced, equation (2.4) can be solved for T_{jt}, equilibrium fishing effort on patch j in period t:

$$T_{jt} = \frac{1}{q} ln \left(\frac{(p_t - c_t) \cdot E\left[CPUE^0_{jt}\right]}{VC_{jt} + \bar{\pi}_t} \right) + \frac{1}{q}\epsilon_{jt}. \quad (2.5)$$

The intuition for this empirical specification is straightforward: effort in patch j and period t depends positively on fish prices, negatively on quota prices if IFQs are present, positively on the start of season expected catch per unit effort for various species (proxied by a vector of prior year catches per unit effort), negatively on cost per unit effort, and negatively on the equilibrium profit from deploying effort on other patches. T_{jt} is necessarily left censored at zero in the data and the additive error term is assumed to be normally distributed. This implies that the likelihood for each observation takes a form similar to that for a Tobit. Details are provided in the Appendix.

The basic empirical approach is to estimate a variant of equation (2.5) via quasi maximum likelihood. We observe effort T_{jt} and ex-vessel prices p_t and compute variable costs VC_{jt} using information on input costs. We assume that equilibrium marginal profits are driven to zero in our initial specification, but later allow for positive profits levels that can vary by fishing port. The main objects of estimation are imputed quota prices, c_t, which are estimated from observed fishing behavior when IFQs are in place. Prior to IFQs, these terms are restricted to take zero values. We must also account other fishery regulations. The RCA and EFH trawl closures constrained fishing location choices, but they were in place and essentially constant both before and after IFQ adoption. Their effects will therefore be captured by expected catch per unit effort in various patches, which is proxied by past catch experience. Trip limits presumably affected spatial choices in the pre-IFQ regime (and were designed to shift effort further offshore), but were dropped for most species when IFQs were introduced. Trip limits must therefore be incorporated explicitly in estimation in order isolate the effect of IFQs. For modeling purposes, any catch in excess of a vessel's trip limit can be regarded as commanding a zero price. To incorporate the trip limit effect in estimation we construct a patch-level proxy for the probability that a trip limit will bind for at least one species on a given fishing trip and then multiply expected catch per unit effort in (2.5) by this proxy.

2.4 Data

Empirical analysis is based on data for effort and catch at individual fishing locations, as well as prices for inputs and outputs. The core dataset consists of trawl logbook entries from 2005-2012, supplied by fishers to state agencies and compiled by the Pacific Fisheries Information Network (PacFIN). Logbook entries report detailed information about individual trawl net tows. Each entry provides geographic information (port of departure, latitude and longitude of both the set and the retrieval of the net), temporal data (date and time of departure from and return to port, date and time of set and retrieval of the net), gear characteristics (vessel length, net type), and catch composition (captain's estimates of weight, and landed weight, by species). The time period was chosen to provide maximal coverage of the post-IFQ period, as well as a large number of pre-IFQ data points for a period in which broad-scale spatial management, particularly closures and gear restrictions, was relatively stable. Our analysis of spatial avoidance is necessarily limited to trawl vessels because fishers employing other gear types are not required to provide logbooks to management agencies.

The raw logbook entries were scrutinized for anomalies and missing data. Tows missing any location information (location of set or retrieval, or depth), temporal information (date or time a net was set or retrieved), or weight information (landed pounds) were dropped. Also removed were tows reported to have taken place on land (according to a mask created from the NOAA Medium Resolution Shoreline), tows that started and ended at the same location, and records reporting a tow speed above 7 knots, since realistic tow speeds are roughly 3 knots. The sample was restricted to tows using one of the main forms of bottom trawl gear, excluding midwater trawls and Scottish seine hauls. The excluded gear types comprised 9% of the records available and have a different catch profile than the majority of the trawl fleet. Tows deemed to be participating in the California halibut or sea cucumber fisheries were also dropped since both fisheries have very different characteristics than the main groundfish trawl fishery. Finally, attention was restricted to tows between Point Conception, California and Cape Alava, Washington, an area extending roughly from Santa Barbara, California to a latitude just south of the US-Canada border. Farther north the RCAs have effectively closed the fishery; farther south the bulk of fishing activity focuses on California halibut and sea cucumber. Table 2 shows summary statistics for the logbook data used in estimation.

Converting logbook entries to observations requires defining patches and time periods and assigning logbook and other data to these units. Patches are based on a 0.2 degree rectangular grid, which results in cells 10 miles wide (east-west) by 15 miles high (north-south). Each cell is then subdivided into areas shallower than and deeper than 115 fathoms (if relevant) to account for different fishing opportunities shoreward and seaward of the RCAs. As a result, our full patch specification is a triple (latitude, longitude, shoreward area). Any patches that had no tows during the sample period are dropped. Temporally, each year is subdivided into two-month seasons corresponding to regulatory periods: January-February, March-April, May-June, July-August, September-October, and November-December.

Harvesters' expectations of catch per unit effort on different patches are central to the analysis of spatial avoidance. These expectations are proxied by observed or predicted catch per unit effort, by species, for all tows on a given patch in the same two-month period in the prior two years. As explained earlier, this approach is only appropriate if management is constant across the current and lagged periods. If management changed in that window, fishers will likely anticipate any changes to their own fishing methods that might alter expected catch per unit effort, and our proxy for expected CPUE should adjust accordingly. The adjustment used in estimation is outlined in the Appendix. For all CPUE calculations, a unit of fishing effort is defined to be a tow-hour. Alternative effort measures, such as number of tows or tow distance, are either less precise or less useful.

Economic data were taken from several sources. Annual ex-vessel prices for landed fish, by species and port, are available from PacFIN. Expected revenue per unit effort for a patch and period was computed by multiplying current year prices (which are assumed known when the fishing location is chosen) by expected catch per unit effort based on prior year harvests. Fuel prices are from periodic surveys of West Coast ports. Labor cost is measured by annual observations on county-level wages for the Natural Resources and Mining sector, as reported by the Quarterly Census of Employment & Wages (US Bureau of Labor Statistics). Quota lease prices were obtained from Jefferson State Trading Company, an online auction service for trading quota pounds in the fishery. While our empirical strategy estimates implicit quota prices, the prices listed on this auction site are useful for making comparisons.

Cost per unit effort was computed from data on fuel prices and wage rates, distance from port to the fishing area, and information from a 2008 cost survey for this fishery (National Oceanic and Atmospheric Administration, 2012). The cost survey gives information on crew size (labor per vessel), fuel consumption rates, and cost items such as ice, maintenance, and repairs that vary with the amount of effort. With this information it is possible to compute the labor and fuel costs for a specific trip. Other variable cost items were assumed to bear the same proportionate relationship to labor and fuel expenses as in the 2008 survey. Because the unit of observation is fishing effort at an individual cell at a point in time, a single cost per unit effort must be assigned to each cell for each period. This required designating a single distance from port for each patch; this was deemed to be the distance to the nearest port with at least 100 tows. Dividing the resulting cost per trip by the average number of tow-hours per trip for all trips to that cell yielded our measure of cost per tow-hour.

2.5 Results on Fishing Locations

The evidence indicates that harvesters altered fishing locations in ways that reduced OFS catches following the shift to IFQs. A clear pattern in these changes is the emergence of 'fuzzy MPAs'.

2.5.1 Evidence on Spatial Shifts

Estimates of the spatial adjustment model, represented by eq. (2.5), are presented in Table 3. The parameters estimated are the implicit quota prices, c_t (our main focus), the parameter q, and a parameter for the trip limit proxy. We also report average quota lease prices from the Jefferson State Trading Co. These data are not used in estimation because they are taken from an incomplete, possibly non-random set of transactions, but they are useful for making comparisons to estimates. We also report ex-vessel prices for target species and OFS species for the purpose of discussing results. Interpreting the regression coefficients, c_t, as implicit quota prices follows from the logic of the estimating equation: a large estimated quota price for species s indicates that, holding constant total revenue, variable cost, and quota costs for other species, fishers avoided patches with dense concentrations of species s under IFQ management. Such avoidance is sensible only if IFQ quota for species s has a high price.

In this light, the general pattern of estimated quota prices in Table 3 agrees with intuition. First, among target stocks, the most valuable species tend to have the highest estimated quota prices. The three target stocks with ex vessel prices over $1/lb., Petrale sole, Sablefish north and Sablefish south, also have the highest estimated quota prices and most of these estimates are significant. Several of the next most valuable target species (ex-vessel prices between $.50 and $1.00/lb.), such as chilipepper rockfish, lingcod, and yellowtail rockfish, also have large and significant quota price estimates. Second, among OFS stocks, all estimated quota prices are positive and some are significant. The highest are for bocaccio and yelloweye rockfish, two species that have been the focus of attention in OFS management.

Patterns of spatial avoidance under IFQs can be gleaned by comparing estimated quota prices to ex-vessel prices. If the estimated quota price for a species exceeds its ex-vessel price, then fishers systematically moved away from patches where this species is abundant under IFQs management. This is true for all OFS species except Widow, which was nearly rebuilt by the time IFQs were put into place, making it a less constraining species. In three cases, bocaccio, canary rockfish and yelloweye rockfish, the difference between estimated quota price and ex-vessel price is large, indicating strong spatial avoidance.

There may also be evidence of OFS avoidance in some of the target stock coefficients. The estimated quota price for chilipepper rockfish is far above the average quota lease price (IFQ price) from the auction market, suggesting that the model may under-estimate avoidance of this species. This gap, and similar gaps for other target species, may indicate that fishers base expectations of OFS abundance on factors other than catch per unit effort in a prior period. Certain target species are known to co-occur with OFS species and fishers may use this knowledge when attempting to avoid OFS catches. Chilipepper rockfish, a prominent target, is an apt example: areas abundant in chilipepper also tend to have high concentrations of widow and canary rockfish, both OFS species. Petrale sole, another prominent target, may be another example. The estimated petrale quota price is much higher than the quota price observed on the auction market, which may be a consequence of the fact that several OFS, particularly bocaccio, tend to occur in areas with higher petrale concentrations.

2.5.2 Evidence on Fuzzy MPAs

We hypothesized that the shift to IFQs caused a decline in effort near the RCA and EFH protected areas, effectively expanding the areas of strict regulatory closure with regions of voluntary, partial closure. The regulatory trawl closures were placed in areas where OFS concentrations are high, and it is likely that OFS concentrations are also high just outside these areas. Pre-IFQ regulations did not restrict fishing near RCA and EFH zones, however; if anything, fishing along borders of these zones was attractive because the target stocks inside were unfished. Fishers could therefore be compliant by fishing along closed area boundaries, even though this presumably enhanced the risks of OFS catches. When IFQs were placed on OFS catches, these incentives were reversed. Fishers arguably had reason to avoid OFS concentrations near closed areas, even though fishing in these areas is perfectly legal.

To examine this hypothesis, the estimated model was used to predict the change in effort on each patch following IFQ implementation that can be attributed to bycatch avoidance. The bycatch avoidance effect is isolated by computing predicted effort on each patch with the estimated quota prices, then predicting again with quota prices for OFS species set to zero. The difference between these predictions is the change in effort that our model attributes to bycatch avoidance. For patches with predicted effort reductions, the predicted reduction was plotted against the distance to the nearest protected area's centroid. The resulting plot is shown in Figure 2 and the pattern is evident; the greatest effort reductions occurred near the borders of MPAs. Adopting IFQs for overfished species expanded the existing MPA network, but the protection added to the new areas was partial and the degree diminished with distance. In other words, IFQs for overfished species created 'fuzzy marine protected areas'.

2.6 Results on Other Adaptations

Following the shift to IFQs, harvesters altered trawl fishing methods in ways that reduced the vulnerability of OFS populations. Fishers also shifted away from trawling and toward more selective gear and pursued collective actions that had the effect of reducing OFS catches. This section presents detailed evidence on these adaptations.

2.6.1 Adaptations in Trawl Methods

Trawl fishers can affect the mix of species caught on a given patch by changing fishing methods in ways that alter the vulnerability of biological populations to trawl nets. The shift to IFQ management changed the payoff to a given mix of species, implying that it changed the payoff from applying different fishing methods on a given patch. The same logic implies that the choice of method depends on the densities of biological stocks, on prices and on costs. We examine the effect of IFQs on fishing methods by specifying reduced form models that capture this reasoning. Two changes in trawl fishing methods are examined, the time of day when fishing takes place and the duration of individual tows of trawl nets.

Time of day is potentially relevant because the physical, biological, and ecological dynamics of the ocean present harvesters with fishing opportunities that change through time. While both target and OFS stocks live near the ocean bottom, widow rockfish and other OFS species migrate off the sea floor at night, while target stocks such as Dover sole and other flatfish do not (Hannah et al 2005; Holland and Jannot 2013). Nighttime fishing for flatfish targets may therefore be an effective strategy for avoiding OFS catches. A simple test on the pre- and post-IFQ distribution of trawl fishing starting times indicates that there was a shift in the time of day when sets occurred following IFQ implementation. Figure 3 plots the temporal distribution of set times for the two periods. Visually, the proportion of trawl sets made between the hours of 7:00 pm and 4:00 am increased after IFQ implementation. A two-sample Kuiper test of differences in the empirical distributions of fishing effort within the 24-hour daily cycle before and after the switch to IFQs to indicates that the difference is significant (Kuiper V: 0.024, p= 1.93E-6).

To investigate whether this shift can be attributed to bycatch avoidance we model the fraction of tows in patch j and period t that occur at night as follows

$$\%Night_{jt} = \alpha_j + \beta_{IFQ} IFQ_t + \sum_s \beta_s \Delta CPUE_{jst} + \sum_s \beta_{s*IFQ} \Delta CPUE_{jst} IFQ_t + \epsilon_{jt} \tag{2.6}$$

The specification allows for patch fixed effects and a patch-invariant effect for IFQs. It allows the decision to fish at night in patch j to be influenced by the difference in catch per unit effort ($\Delta CPUE$) between day and night in patch j. The variable $\Delta CPUE$ is coded so that a positive value indicates lower abundance at night. The interaction between $\Delta CPUE$ and the IFQ dummy captures the effect of interest. A positive coefficient for species s would indicate that IFQs encouraged nighttime fishing on patches where species s is less abundant at night than during the day. Because the response variable is bounded above and below, a two-sided Tobit estimation strategy was used.

The model was estimated for trawl tows that targeted Dover sole and Petrale sole, the two most important flatfish species in the fishery. Neither of these species migrates up from the seafloor at night, while some other target species do. Results are presented in Table 4, with standard errors clustered by patch. The positive and significant coefficient estimate for the interaction between IFQs and yelloweye rockfish is consistent with the use of night fishing as a bycatch reduction strategy.

Next, we examine whether the duration of trawl tows changed when IFQs were implemented. While a trawl net is being towed, the composition of species collected is unknown. When bycatch IFQs were introduced, information on the composition of catch became more valuable because a single unfortunate tow could exhaust a vessel's annual quota allocation for some OFS species. Making shorter tows provides higher frequency information on species abundances in the area fished, and better enables a fisher to move away from OFS concentrations. Shorter tows could also be part of an active strategy of learning about the locations of stock concentrations, and hence the areas to frequent or avoid in future fishing trips. Figure 4 plots the distribution of tow durations for trawls shoreward of the RCAs where OFS species are most common. The mean duration of tows clearly decreased following IFQ adoption. Two-sample Kolmogorov-Smirnov and Mann-Whitney tests reject the null hypothesis of identical distributions against the one-sided alternative of shorter tows under IFQs (Kolmogorov-Smirnov D+: 0.235, p-value<2.2E-16; Mann-Whitney W=7.4E7, p-value<2.2E-16).

To test whether this shift reflected OFS avoidance, we estimate a reduced form model of tow duration. Tow duration on a patch is hypothesized to depend on the variance in total OFS catch per unit effort, and the strength of the dependence is allowed be different in pre- versus post-IFQ periods. If shortening tows is a strategy for gaining information on weak stock concentrations, tows in all periods should be shorter on patches where OFS concentrations are more uncertain and this effect should be stronger under IFQs because of the heightened individual avoidance incentive. The specification also allows for individual fisher fixed effects to account for differences in vessel attributes or the habits of individual fishers; patch and time period fixed effects; depth and depth squared to account for the time required for nets to reach the seafloor; the number of tows the individual has made in the same patch in the same season in the same or prior year, to proxy individual knowledge; and an interaction between the latter term and an IFQ dummy. The model estimated is

$$\begin{aligned} Towduration_{ijt} =& \gamma_i + \alpha_j + \phi_t + \beta_D D_{ijt} + \beta_{D^2} D^2_{ijt} + \beta_{Exp} N_{ijt} + \beta_{ExpIFQ} N_{ijt} IFQ_t \\ & + \beta_{OFS} Var^{OFS}_{ijt} + \beta_{OFSIFQ} Var^{OFS}_{ijt} IFQ_t + \epsilon_{ijt}. \end{aligned} \tag{2.7}$$

The coefficients of primary interest are β_{OFS} and β_{OFSIFQ}. The former term indicates whether or not tow durations were shorter in areas of OFS uncertainty prior to bycatch IFQs and the latter coefficient shows what happened when IFQs for OFS were implemented.

The estimates are shown in Table 5. The key result supports the hypothesis of IFQ-induced avoidance behavior: tow durations were reduced in areas of high OFS uncertainty after IFQs were implemented and the effect is weakly significant. This pattern was not evident prior to IFQs. Other variables in the model have anticipated effects. Increased depth increases tow duration at a decreasing rate; fishers with extensive experience on a given patch tend to extend tow duration under IFQs.

Following IFQ implementation, the OFS portion of trawl catches declined substantially, lending support to the claim that changes in fishing methods were motivated by OFS avoidance. The discarding problem makes a thorough analysis of catch composition infeasible, but simple comparisons can be made using data from the NOAA observer program, a source that includes estimates of discards for a sample of trawl trips. Table 6 reports trawl catches of OFS and non-OFS species in pre- and post-IFQ periods. The ratio of OFS species in the total trawl catch fell by almost three-fourths in the first year of IFQ management; trawl catches of two critical OFS species, cowcod and yelloweye rockfish, essentially vanished.

2.6.2 Changes in Fishing Gear

It is well known that 'fixed (non-towed) gear' such as baited hook and line assemblies and baited fish traps and pots can select target stocks and avoid bycatch more precisely than trawl nets. We hypothesize that introducing quota for OFS catches tilted the profit calculus toward fixed gear fishing and away from trawling, and specify a reduced form model to examine this hypothesis. Fixed gear fishers are not required to keep log books, so empirical analysis must be based on catch statistics rather than effort. The empirical specification must account for two other possibly confounding factors, a regulatory shift that allowed for more fish to be landed using fixed gear and a price spike in certain target species that are best caught with fixed gear.

The outcome variable examined is the fraction of the target catch that is landed by trawl vessels versus fixed gear, by region and by month for the period 2007-2012. If IFQs drove gear switching in order to avoid OFS catches, then switching should be most prominent in months and regions where OFS catch is prominent. This effect is captured by including the fraction of OFS catch in total catch for trawl fishing interacted with an IFQ dummy. A negative coefficient on the interaction term would be consistent with gear switching to avoid OFS catches following IFQ adoption. The specification also includes time fixed effects, which should capture target species price effects; region dummies; and an IFQ dummy interacted with region dummies, to represent the post-IFQ relaxation of constraints on switching gear. The specification is

$$Trawlshare_{jt} = \alpha_j + \alpha_j^{IFQ} IFQ_t + \phi_t + \beta_{OFS} Frac_{jt}^{OFS} + \beta_{OFSIFQ} Frac_{jt}^{OFS} IFQ_t + \epsilon_{jt} \tag{2.8}$$

The coefficient of interest is β_{OFSIFQ}. Because the range of the dependent variable is bounded above and below, a two-sided Tobit estimation procedure is used.

Results are reported in Table 7. The interaction effect is negative and highly significant, indicating that fishers shifted from away trawl nets toward fixed gear partly to avoid bycatch.

2.6.3 Contracting and Collective Actions

IFQ management of bycatch created property rights to catches of OFS species and required fishers to hold rights sufficient to cover OFS catches. This gave rise to individual risks that had not existed previously, but also enabled contractual approaches for managing these risks.

Even with careful fishing, trawling is imperfectly selective. The risk of making an accidental haul of OFS species created a latent demand among fishers for insurance contracts that would spread this risk. During the first year of IFQ operation at least three groups of West Coast groundfish fishers responded to this by forming 'risk pools', contractual arrangements that are essentially mutual insurance organizations. Each risk pool holds the OFS quota of the members who join. The individual OFS quota contributions serve as an insurance premium, and in return the pool insures pool members against accidental hauls of OFS species. To be covered by the pool, an individual must fish according to clean fishing protocols that the pool develops. One prominent pool with members based in Fort Bragg and Morro Bay, California develops a 'fishing plan' each year that delineates areas of high, medium and low risk for OFS catches. The members then agree to acceptable fishing practices for each risk category and these practices must be followed in order to be covered by the pool. The 2012 fishing plan for this pool covered 15 million acres of fishing grounds. It delineated zones of differential risk of OFS catches, specified fishing practices based on scientific information, members' experience and fishing history, and allowed for in-season updates as new information is acquired.

Creating property rights also enabled a contractual solution to an oft-stated concern with IFQs, that fishing activity may exit from traditional fishing communities. Adopting IFQs often results in consolidation of effort due to over-capitalization under previous management. It also gives incentives for more profitable fishing practices to replace less profitable practices, which may cause vessels to move to different ports. Both changes are sources of concern for small coastal communities that identify with commercial fishing and rely on fishing activity as an attraction for tourists. One such community, Morro Bay, California, pursued a contractual solution to this potential problem. The City of Morro Bay, in collaboration with The Nature Conservancy and a local fishermen's organization, formed a new entity, the Morro Bay Community Quota Fund (the Fund). The purpose of the Fund is to acquire and own quota for target and OFS stocks, and then lease this quota to commercial fishers with lease restrictions on fishing activity that address the concerns just described. The Fund's bylaws require that leases be structured to enhance fishing activities in the local community and to achieve various environmental goals.

2.7 Discussion and Conclusions

Adaptations to bycatch IFQs in the West Coast groundfish fishery indicate that creating property rights to the flow from a resource can achieve important ecosystem protection goals effectively. Viewing conservation targets as constraints on joint production functions, satisfying such constraints at least cost is a highly complex, information-demanding management problem. Its solution may involve a mix of spatial avoidance, subtle changes in harvesting methods and switches to different technologies. In the pre-IFQ regime, managers sought to satisfy conservation constraints by imposing trip limits, gear restrictions, and spatial closures. The commercial fishers bound by these constraints clearly needed to comply in order to continue fishing, but their actions were not motivated by the goal of reducing OFS catches at minimum cost. Switching to IFQ management provided this incentive and led to behavioral changes in where, when, and how fishers fished, actions that were overlooked by the pre-IFQ management strategy. Evidently, even detailed regulations in an extensively studied, comparatively information-rich fishery can miss important margins of adjustment. If these margins had been recognized by regulators, achieving them by command and control would have encountered severe monitoring and enforcement problems and, no doubt, political opposition from fishers. Imposing IFQs on OFS catches provided incentives for harvesters to make these adaptations voluntarily because they enhanced profits in the new regime, making it unnecessary to force them upon an unwilling fishing industry.

The nuanced behavioral responses to IFQs in the West Coast groundfish fishery may have important implications for other fisheries. The behavioral adjustments that followed the creation of property rights for bycatch species in the fishery studied here were both nuanced and highly effective, suggesting that the persistent bycatch problem in fisheries still managed under command and control regulation may be largely a matter of incentives rather than a purely technological phenomenon. While trawling is typically considered to be a non-selective method of fishing, fishers are clearly able to make some adjustments to their mix of catch to better match their portfolio of quota holdings. That fishers can make such adjustments in a fishery with so many species (and associated prices) suggests that market approaches to bycatch management may work well in other fisheries.

Evidence that fishers took diverse actions to avoid catches of overfished species does not, of course, imply that IFQs can solve all marine conservation problems. Spatially prescriptive policies, possibly layered onto bycatch IFQs, may remain appropriate if there are reasons beyond limiting bycatch to reduce fishing in specific areas. Such reasons may include protection of spawning grounds that export larvae to surrounding areas or preservation of sensitive seafloor structures. Pairing market-based approaches with spatial policies may well improve on the outcome that either approach alone could realize. Alternatively, making the property rights themselves spatially explicit could, at least in principle, provide sufficient incentives to achieve a particular spatial pattern of fishing at least cost.

Finally, because some fisher responses are likely to be driven by the risk of bycatch rather than expected costs of bycatch, further research into the influence of bycatch risk on fisher behavior is warranted. The introduction of IFQs not only changed the risk to which fishers were exposed, but also created a basis for contracts to manage risk. The formation of risk pools and their development of protocols for fishing practices that minimize bycatch suggest that these changes in risk are likely to be an important determinant of behavior. Direct study of individual responses to risk may shed light on the gains to cooperation and the determinants of risk pool membership. Further, because risk pools can reduce their overall exposure by sharing information, participating fishers may be able to more efficiently utilize their target stock quotas. These and other potential effects of bycatch risk on fisher behavior merit closer study.

Table 2.1: Mean Quota Lease Prices.

Species	Mean Lease Price ($/lb)	
Target (non-OFS) stocks	2011	2012
Dover sole	0.02	N/A
Petrale sole	0.40	0.46
Sablefish - North	1.19	1.15
Sablefish – South	0.80	1.01
Shortspine thornyheads – North	0.05	0.04
Overfished stocks		
Bocaccio rockfish	0.33	0.27
Canary rockfish	1.60	2.07
Cowcod	0.54	1.44
Darkblotched rockfish	0.33	0.39
Pacific Ocean perch	0.26	0.29
Widow rockfish	0.27	0.60
Yelloweye rockfish	33.54	19.29

Table 2.2: Logbook Summary Statistics. Excludes records not used in estimation. OFS catch reported from observer data to address discarding. Number of observations reported are the number of patch x 2 month block observations with valid catch expectations; no observations exist for 2005-2006 since those years are used for computing expectations starting in 2007. Tow duration reported for tows for which the depth is less than 115 fathoms.

Year	# obs	Unique Vessels	Trips	Tows	Total Landings (lb)	OFS Catch (lb)	Avg Tow Length (hr)	%Night Tows for Flatfish
2005	-	114	1,889	12,489	33,430,245	511,251	2.58	34.7
2006	-	112	1,876	13,275	34,287,686	663,591	2.66	34.2
2007	1,393	119	2,048	13,715	42,130,877	910,508	2.70	37.3
2008	1,399	116	2,143	15,137	50,629,774	786,388	2.47	41.4
2009	1,390	114	2,460	17,272	54,364,747	1,076,957	2.47	41.1
2010	1,439	103	1,838	13,147	46,408,945	1,012,141	2.40	40.9
2011	1,435	71	1,059	8,639	36,491,772	349,080	2.10	43.0
2012	1,317	65	991	8,331	36,268,704	363,564	2.27	41.7
SUM	8,373	-	14,418	102,005	334,012,750	5,673,479	-	-

Table 2.3: Quasi-Maximum Likelihood Estimates for Equation (2.5). Lease prices (2011-2012 average) and ex-vessel prices are provided for reference only and are not estimated.

		Est.	SE	Est.	SE	IFQ Auction price	Ex-vessel price
Quota prices: target species	Arrowtooth flounder	0.09	(0.02)***	0.11	(0.01)***	-	0.10
	Chilipepper rockfish	0.62	(0.00)***	0.62	(0.00)***	0.04	0.64
	Dover sole	-0.07	(0.04).	0.11	(0.03)***	0.02	0.41
	English sole	-0.03	(0.16)	0.26	(0.10)*	-	0.32
	Lingcod	0.73	(0.02)***	0.75	(0.04)***	0.05	0.74
	Longspine thornyhead	0.23	(0.07)**	0.29	(0.04)***	0.04	0.42
	Minor slope rockfish	0.61	(0.12)***	0.56	(0.12)***	-	-
	Other flatfish	0.18	(0.06)**	0.26	(0.03)***	-	-
	Pacific cod	0.34	(0.14)*	0.54	(0.09)***	0.03	0.53
	Petrale sole	1.24	(0.03)***	1.29	(0.02)***	0.41	1.40
	Sablefish (North)	1.63	(0.06)***	1.66	(0.00)***	1.17	2.52
	Sablefish (South)	2.67	(0.18)***	1.60	(0.50)**	0.84	2.52
	Splitnose rockfish	0.73	(0.01)***	0.74	(0.01)***	-	0.34
	Shortspine thornyhead	0.08	(0.21)	0.39	(0.12)**	0.05	0.65
	Starry flounder	0.32	(0.08)***	0.47	(0.02)***	-	0.59
	Yellowtail rockfish	0.47	(0.04)***	0.50	(0.09)***	0.01	0.51
Quota prices: by-catch species	Bocaccio rockfish	1.70	(0.36)***	1.59	(0.37)***	0.32	0.62
	Canary rockfish	0.73	(2.01)	1.51	(0.98)	1.91	0.54
	Darkblotched rockfish	0.68	(0.11)***	0.91	(0.10)***	0.35	0.47
	Pacific Ocean perch	0.82	(0.02)***	0.69	(0.01)***	0.29	0.49
	Widow rockfish	0.44	(0.03)***	0.43	(0.01)***	0.40	0.46
	Yelloweye rockfish	18.68	(190.99)	42.85	(26.08)	21.83	0.31
Other model param.	1/q	59.76	(3.44)***	47.26	(1.33)***		
	α	0.14	(0.01)***	0.05	(0.01)***		
	σ_ϵ	1.14	(0.04)***	1.32	(0.09)***		
	Port Fixed Effects	No		Yes			
	# observations	8,373		8,373			

Significance codes: *** 0.001, ** 0.01, * 0.05, . 0.1

Table 2.4: Two-sided Tobit estimates predicting the fraction of tows in a patch and 2 month block that begin at night (6pm-6am). Patch fixed effects omitted for brevity. Standard errors clustered by patch.

	Estimate	Std. Error
(Intercept)	4.84E-01	(1.60E-01)**
IFQ	-1.53E-02	(2.26E-02)
ΔCPUE(Dover Sole)	-3.58E-05	(3.71E-05)
ΔCPUE(Dover Sole)*IFQ	1.13E-04	(9.04E-05)
ΔCPUE(Petrale Sole)	-5.18E-05	(7.07E-05)
ΔCPUE(Petrale Sole)*IFQ	-3.96E-04	(2.25E-04).
ΔCPUE(Arrowtooth Fl.)	1.13E-04	(8.32E-05)
ΔCPUE(Arrowtooth Fl.)*IFQ	9.47E-05	(1.34E-04)
ΔCPUE(English Sole)	-4.14E-05	(2.40E-04)
ΔCPUE(English Sole)*IFQ	2.15E-03	(1.05E-03)*
ΔCPUE(Bocaccio)	2.47E-02	(1.51E-02)
ΔCPUE(Bocaccio)*IFQ	2.99E-03	(5.25E-03)
ΔCPUE(Canary R.)	-7.18E-03	(7.85E-03)
ΔCPUE(Canary R.)*IFQ	-7.34E-03	(1.27E-02)
ΔCPUE(Darkblotched R.)	-3.67E-04	(6.01E-04)
ΔCPUE(Darkblotched R.)*IFQ	1.01E-03	(9.75E-04)
ΔCPUE(Pac. Ocn. Perch)	4.00E-04	(6.11E-04)
ΔCPUE(Pac. Ocn. Perch)*IFQ	-1.91E-03	(1.86E-03)
ΔCPUE(Widow R.)	-5.51E-03	(6.17E-03)
ΔCPUE(Widow R.)*IFQ	5.60E-03	(7.28E-03)
ΔCPUE(Yelloweye R.)	-1.47E-01	(1.25E-01)
ΔCPUE(Yelloweye R.)*IFQ	2.71E+00	(1.36E+00)*

Significance codes: *** 0.001, ** 0.01, * 0.05, . 0.1

Table 2.5: Estimates of model of tow duration. Patch, fisher, and period effects omitted for brevity. Standard errors clustered by patch.

	Estimate	Std. Error
Depth	2.39E-02	(6.22E-03)***
DepthSq	-2.06E-04	(5.20E-05)***
Var(OFSCatch)	-3.76E-07	(3.01E-07)
Var(OFSCatch):IFQ	-1.48E-06	(4.08E-07)***
# PriorTows	-1.68E-03	(6.76E-04)*
# PriorTows:IFQ	6.41E-03	(1.66E-03)***

Significance codes: *** 0.001, ** 0.01, * 0.05, . 0.1

Table 2.6: Trawl selectivity before and after IFQs: Estimated catch of over-fished species relative to landings of other species. Values reported are annual averages over the relevant period: 2005-2010 for Pre-IFQ, and 2011-2012 for IFQ. Total OFS catch figures exclude widow rockfish and petrale sole because their OFS status changed during the period shown. Pre-IFQ OFS trawl statistics for 2005-2010 are estimates from observer data summarized in Bellman et al. (2008). Non-OFS trawl statistics are landings data from the PacFIN database at: `http://pacfin.psmfc.org/`.

Total trawl catch (metric tons)	IFQ	Pre-IFQ
Bocaccio	7.08	15.93
Canary Rockfish	3.86	15.85
Cowcod (South of 40°10’ N. lat.)	0.06	1.12
Darkblotched Rockfish	85.15	217.10
Pacific Ocean Perch	41.24	109.97
Yelloweye Rockfish	0.04	0.35
TOTAL OFS catch	137.23	360.32
TOTAL Non-OFS groundfish landings	13,383	20,055
OFS/Non-OFS catch (%)	1.025	1.797

Table 2.7: Estimation results for model of trawl share of catch by month and region. Period and region effects omitted for brevity.

	Estimate	Std. Error
IFQ	0.073	(0.112)
Fraction OFS	2.670	(1.399).
Region*IFQ		
Pt. Conception.*IFQ	0.163	(0.057)**
Eureka*IFQ	0.137	(0.015)***
Monterey*IFQ	-0.020	(0.016)
Vancouver*IFQ	0.092	(0.007)***
Frac(OFS) * IFQ	-6.260	(1.528)***

Significance codes: *** 0.001, ** 0.01, * 0.05, . 0.1

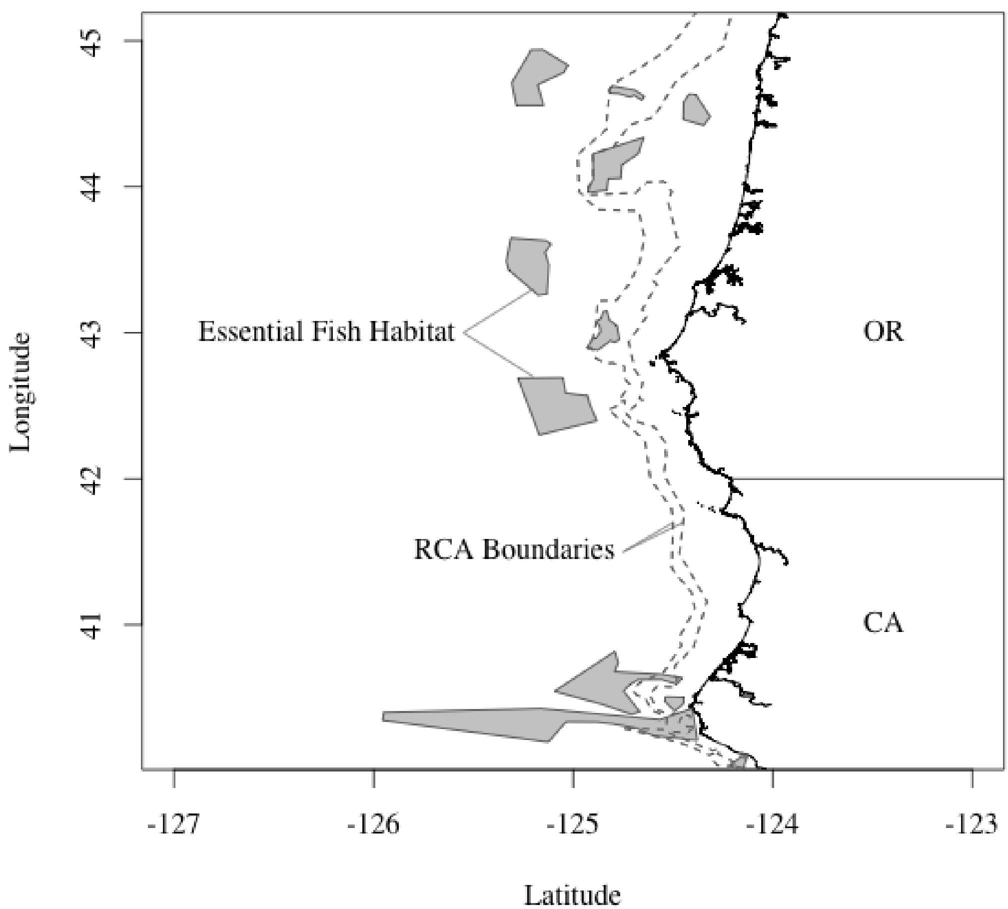

Figure 2.1: Spatial closures near the California-Oregon border. Solid gray areas represent EFH closures. Dashed lines indicate representative RCA boundaries approximating 75 and 200 fathoms. Seaward RCA boundaries represent the maximal extent of the RCAs during the year, and innermost boundaries represent the minimal closures.

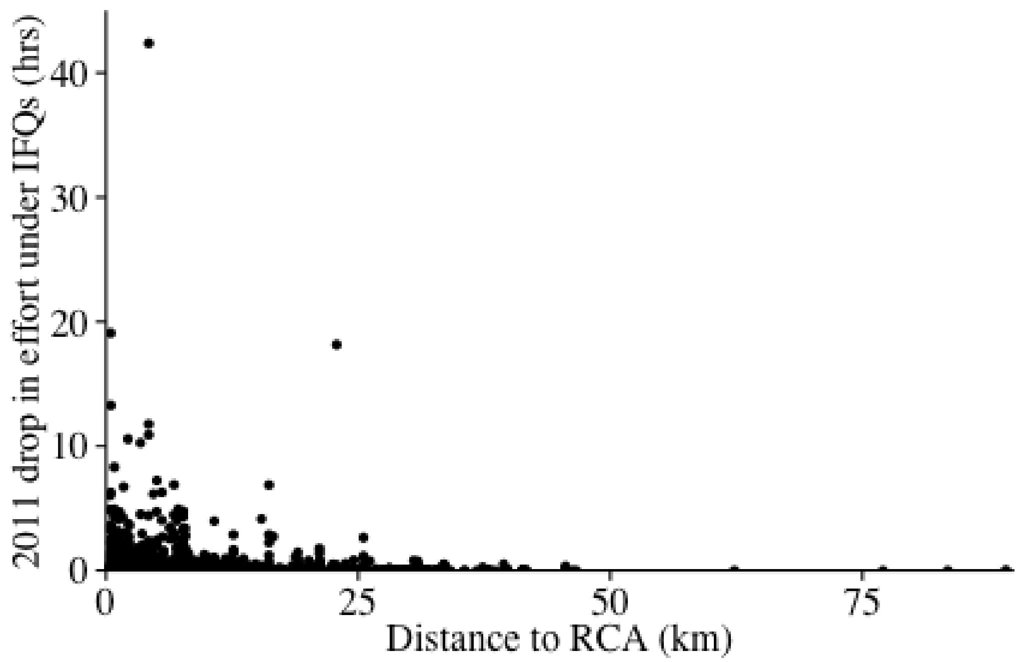

Figure 2.2: Reduction in predicted effort (2010-2011) attributed to OFS avoidance as a function of distance from RCAs. Points represent patch x 2-month period observational units. Areas with higher reductions in predicted effort are generally closer to the RCA boundaries.

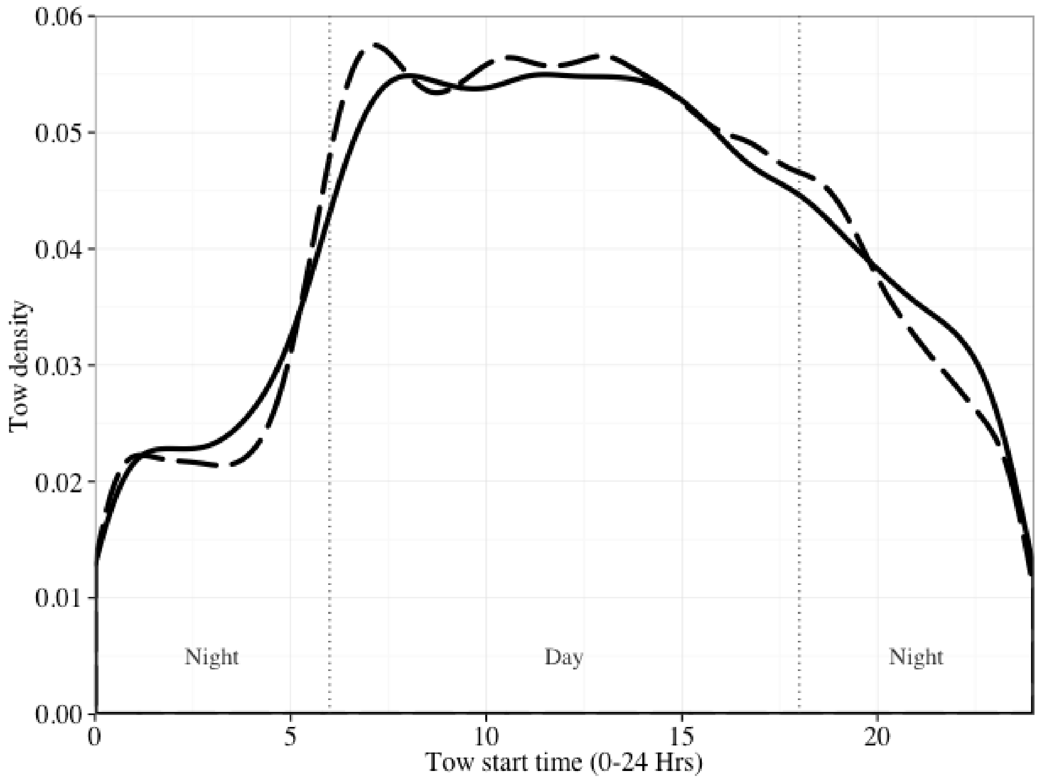

Figure 2.3: Empirical distribution of intra-day timing of fishing effort (net set time) before (dashed) and after (solid) the change to IFQs. Vertical dotted lines indicate 6am and 6pm, the distinctions used for day and night in the reduced form estimation of the effect of bycatch IFQs on night fishing.

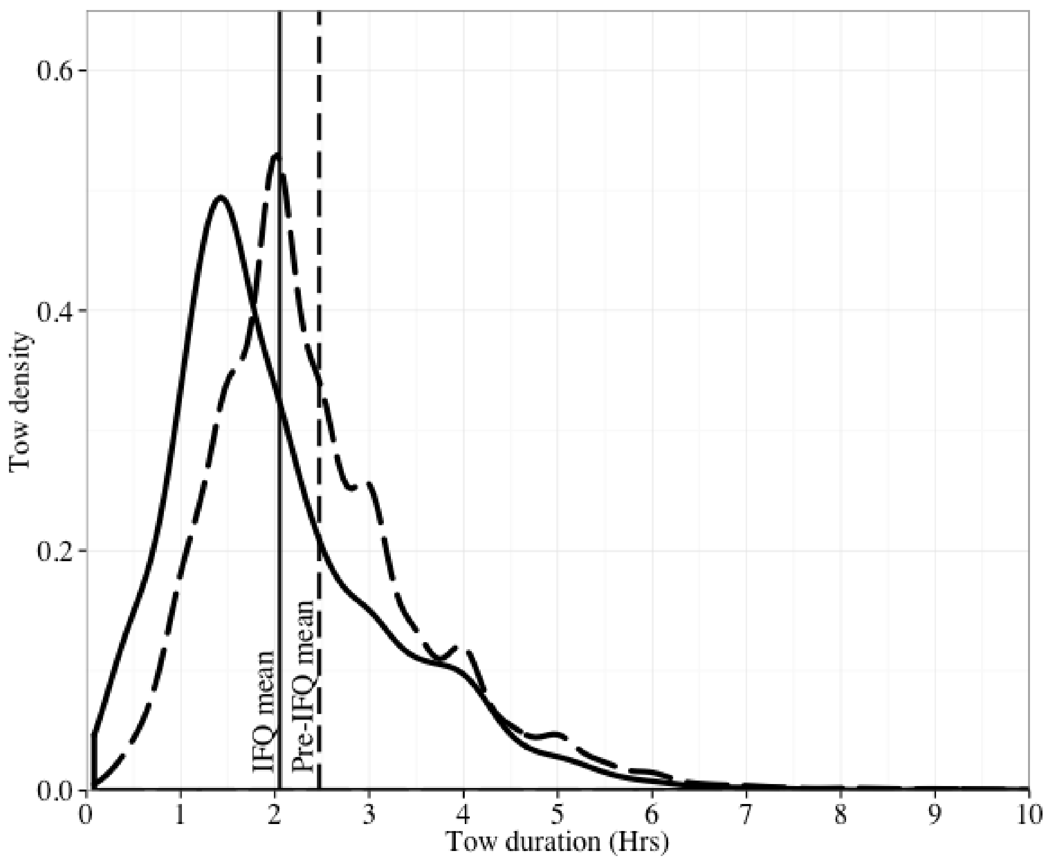

Figure 2.4: Distribution of tow duration before IFQs (dashed) and during IFQs (solid) among tows with average depth < 115 fathoms. Vertical lines indicate mean tow duration for the relevant period.

Chapter 3

Indirectly Induced Innovation: Consequences for Environmental Policy Analysis

3.1 Introduction

Many discussions of climate policy emphasize the prospects for technological change to keep mitigation and adaptation costs at manageable levels. This has led to increased focus on the ability of different climate policies to spur innovation in reducing production and increasing capture of greenhouse gases (Milliman and Prince, 1989; Fischer et al., 2003; Requate and Unold, 2003; Fischer and Newell, 2008). The rationale for this emphasis is straightforward: since environmental policy often increases the costs of polluting, firms will seek ways to avoid those costs, including development of new technologies that reduce pollution. The idea that changes in relative prices should influence innovation traces back to Hicks (1932), with Acemoglu (2002) formalizing that intuition and generalizing to include the importance of relative factor abundance as well. The application of those ideas to environmental policy intensified with a set of provocative claims by Porter and van der Linde (1995). Those authors posited not only that environmental regulation would induce innovation, but also that innovation could lead to enhanced competitiveness for firms (or countries) subject to environmental regulation.

Empirical studies seeking to test these claims by quantifying the innovation induced by environmental policy have thus far produced mixed results. Early studies found suggestive evidence for a link between policy stringency and innovation (Lanjouw and Mody, 1996), but a follow-up study provided no evidence that link was causal (Jaffe and Palmer, 1997). Subsequent work again reversed the conclusions, finding that policy stringency may increase pollution-relevant innovation but has a negligible effect on overall patent rates (Brunnermeier and Cohen, 2003). More recent studies have echoed the importance of outcome variable choice: Johnstone et al. (2010) find that renewable energy policies have heterogeneous effects on innovation across different types of renewable technologies (e.g. wind vs solar).

Most recently, the scale and scope of the European Union's Emissions Trading Scheme (EU ETS) has generated great interest in whether the policy is aiding in the transition to a lower-carbon economy. Analyses thus far have suggested that, while regulated firms have increased their low-carbon patenting activities substantially, the program accounts for only a small fraction of the increase in low-carbon patenting in the EU (Calel and Dechezleprêtre, 2014). Other factors, such as fuel costs and country-specific renewable energy policies, may be driving the bulk of low-carbon patenting (Hoffmann, 2007). The EU ETS may be influencing other types of innovation, such as (disembodied) process innovation like fuel switching (Delarue et al., 2008), but the current best estimates of the effect of the EU ETS on product innovation indicate only a small effect.

In this paper, I revisit the question of how much innovation is induced by environmental regulation, with a focus on the extent to which regulation might also induce innovation by unregulated firms. While some attention has been paid to this issue, the focus of prior work has been on upstream spillovers: does regulation induce innovation by unregulated suppliers of technology to regulated firms (Fischer et al., 2003; Calel and Dechezleprêtre, 2014)? For example, a technology supplier might develop a new scrubber for a regulated polluter. In contrast, the focus here is on downstream spillovers: does regulation induce unregulated firms to develop new technologies that help reduce the use of regulated firm output? Such downstream spillovers may entail fundamentally different technologies than their upstream counterparts.

There are several potential reasons that downstream firms might innovate in response to regulation. I focus on two channels for such indirect effects: knowledge spillovers that augment the knowledge stock available to all firms, and pass-through of regulatory costs into the price of outputs used by unregulated firms as inputs (e.g. electricity).[1,2] Both

[1]In the treatment effects literature, such indirect effects are often referred to as interference (Cox, 1958).

[2]I return to other potential spillover channels in the discussion.

knowledge stocks and energy prices have been shown to impact patenting output of firms (e.g. Popp (2002)), so any impact of a policy on those intermediate quantities should ultimately affect innovation. The aforementioned induced innovation studies offer evidence that regulation can spur innovation by regulated firms, thereby augmenting the knowledge stock available to unregulated firms. A separate line of evidence suggests that regulated firms indeed pass through the costs of EU ETS emissions permits into both wholesale electricity prices (e.g. Sijm et al. (2006, 2008); Fabra and Reguant (2013)) and retail electricity pries (Sijm et al., 2008; Convery et al., 2008). While the empirical component of this paper is focused on that policy setting, cost pass-through has also been raised as an issue in the context of a number of other environmental policies, including but not limited to NO_x reductions in the United States (Burtraw et al., 2001), standards for management of livestock waste (Vukina, 2003), and air pollution regulation under the Clean Air Act (Gianessi et al., 1979). Similarly, fully regulated utilities may have a cost-pass through allowance for new investments needed to comply with stricter environmental regulation, such as water quality standards (Cowan, 1993). Taken together, these strands of the literature suggest that many environmental regulations are likely to induce innovation by downstream unregulated firms, but that topic has not yet been directly addressed.

If such a response occurs, then estimators that attempt to identify the *direct* effect of regulation on innovation by regulated firms are missing part of the *total* effects of the policy. That potential bias affects the most commonly used treatment effect estimators (e.g. difference-in-difference, matching, and propensity score approaches), all of which identify only the differential effects of policy on innovation by regulated firms. Such spillovers have consequences for identification and bias in many settings, including studies of social effects (Manski, 1993) and medical treatments (Miguel and Kremer, 2004). In those other contexts, a few authors have also suggested estimation strategies that can account for certain types of indirect effects (Hudgens and Halloran, 2008; Aronow and Samii, 2012). However, the issue remains largely ignored in studies of innovation induced by environmental regulation.

In what follows, I analyze the potential for regulation to indirectly induce innovation by downstream unregulated firms using a mix of theory and empirical approaches. On the theoretical side, I first employ Rubin's (1974) potential outcomes framework to demonstrate the potential for bias in standard estimators that ignore downstream responses to regulation. Then, I use a two-period model that captures both spillover channels outlined above to illustrate why downstream firms might respond to a change in regulation by innovating more. Regulated firms innovate in response to regulation, thereby increasing knowledge stocks, and the pass-through of regulatory costs into the price of regulated firm outputs emerges as an equilibrium outcome. The magnitude of these indirect effects of any one policy on innovation will, of course, depend upon the strength of the hypothesized channels. For example, when regulated firms are able to pass through costs because of a lack of unregulated competition, the effects are likely to be larger. In contrast, sectors whose competitiveness may be threatened by regulation due to the presence of competition from an unregulated sector (e.g. foreign firms) are less likely to pass through costs, providing fewer incentives for innovation by consumers of that sector's output. Similarly, the strength of intellectual property rights in the jurisdiction of a particular environmental policy will impact the degree of knowledge spillovers, which will influence the way in which higher patent output by regulated firms affects the productivity of R&D for unregulated firms.

After establishing the potential for such indirect effects of regulation, I quantify the importance of those effects for the EU ETS by estimating dynamic count models with a panel dataset of firm-level low-carbon patenting. The EU ETS provides a useful test of the relative importance of indirect effects for two primary reasons.[3] First, as previously mentioned, regulated power producers are indeed passing along permit costs into the price of electricity.[4] The first empirical approach I take pairs existing estimates of pass-through with my own estimates of the elasticity of patenting with respect to electricity prices. Second, the potential for cost pass-through all the way to retail electricity prices varies geographically due to differences in generation mix, market concentration, and retail price regulation, giving rise to variation in exposure to indirect innovation incentives.[5] With that variation in mind, my second empirical approach makes use of the contrast between mostly market-based retail pricing in several EU countries with the still high degree of retail price regulation in France. If carbon cost pass-through does indeed induce innovation among unregulated firms, there should be a stronger response in other countries as compared to France.

In the context of the European carbon market, my estimates suggest that the total effect of environmental regulation on innovation is 71% larger than the direct effect on regulated firms alone. As such, consideration of indirect effects may be important for accurate estimation of effects of environmental policy on innovation. While the total effect of that policy on low-carbon innovation remains modest in absolute terms, the primary purpose of that empirical exercise and this paper as a whole is to illustrate relative effect sizes. As I show theoretically, the indirect effects of policy on innovation by unregulated firms are likely to scale with the size of direct effects on regulated firms. As such, if the total policy effect can be substantially larger than the direct effect, in

[3]I highlight features of the ETS that I think make indirect effects both relevant and estimable. There are plenty of other benefits to studying the ETS, including its size, quality of available data, and the existence of a carefully constructed estimate of the *direct* innovation effect from Calel and Dechezleprêtre (2014) that can act as a reference point.

[4]A consistent but indirect source of evidence of pass-through is a positive link between CO2 prices and stock performance of large, ETS-regulated electric utilities (Veith et al., 2009; Oberndorfer, 2009; Bushnell et al., 2013).

[5]While wholesale markets are increasingly connected across markets, retail prices remain localized.

settings where the direct effect of a policy is larger, the bias of studies that consider only direct effects may be economically significant.

The remainder of this paper is organized as follows. The next section more formally presents the standard approaches taken in estimating induced innovation, highlighting the prevalence of the assumption that unregulated firms do not innovate in response to regulation, and the consequences when that assumption is violated. The third section uses simple models to illustrate two common channels through which regulation is likely to have indirect effects on innovation by unregulated firms: knowledge spillovers and cost pass-through. The fourth section presents the empirical application to the EU ETS, including development of an alternative estimation approach using dynamic count models that account for both indirect channels, as well as a description of the data used for estimation. Section five presents the results of estimation, and the final section concludes.

3.2 Estimation of policy effects and potential bias

To illustrate why innovation by unregulated firms in the EU or elsewhere might pose a problem for assessment of policy effects, it is useful to review the objectives of and assumptions underlying most studies of induced innovation. Many empirical studies of environmental policy effects, including those on innovation, seek to quantify the effect of regulation on a particular outcome of interest. From a policy perspective, the relevant outcome of interest is typically an aggregate quantity, such as total low-carbon patenting across all firms. To get at that total policy effect (TPE), most studies first estimate firm-level average responses, such as the average treatment effect (ATE) or average treatment effect on the treated (ATT), then sum those effects across regulated firms. There are two potential problems with this approach when unregulated firms respond to policy, which may result in biased estimates of the TPE. The first is that unregulated firms do not form a suitable counterfactual for regulated firm behavior in the absence of a policy. The second is that the responses by unregulated firms go uncounted. This section briefly illustrates these issues in the treatment effects framework introduced by Rubin (1974).

To fix ideas, suppose that the outcome of interest is aggregate innovation in a particular technological field and the total policy effect of interest is the change in such innovation (as measured by patents) caused by new environmental regulation. The TPE can theoretically be calculated by comparing the total patenting under the actual policy regime with total patenting in the absence of the policy. The key challenge in such studies is construction of a credible counterfactual: how many patents would have been generated if the policy had not been implemented?

To answer that question, the treatment effects literature makes use of the idea of potential outcomes. Suppose that firm i's regulatory status is $T_i \in \{0, 1\}$, with $T_i = 1$ if firm i is subject to environmental regulation and $T_i = 0$ if not. Let $R \in \{0, 1\}$ be a binary indicator of whether or not any firms are regulated, i.e. $R = \mathbb{1}(\sum_i T_i > 0)$.[6] Finally, let patenting by firm i with regulatory status T within overall policy regime R be denoted y_{iTR}. For example, i's patent output if regulated under a policy is y_{i11}, while that same firm would output y_{i00} patents if it not regulated and no other firms were regulated.

This notation permits a concise expression of the total policy effect, defined here as the change in total patenting caused by the introduction of regulation. Note that the introduction of regulation changes R from 0 to 1 for all firms, while it changes T_i from 0

[6] This could be extended to allow T_i, R, or both to be continuous variables measuring the intensity of treatment/regulation. More generally, R could even be an N-dimensional vector capturing the treatment status for all firms. For practical purposes, and looking ahead to the empirical application to the EU ETS, the largest firms in covered sectors are regulated, such that a binary indicator for R should be a useful approximation. I use a binary treatment T at the firm-level for comparison with existing studies.

to 1 only for firms directly subject to regulation. As a result, we may write the TPE as

$$TPE = \sum_i y_{iT1} - y_{i00}, \tag{3.1}$$

where the sum is over all firms that might be affected in some way by the policy, not just firms directly subject to regulation.[7] For each firm, the TPE compares patenting given a firm's actual treatment status and the presence of regulation (y_{iT1}) with what that firm's patenting output would have been in if it were not regulated and no other firm were regulated (y_{i00}). For firms actually regulated, this difference corresponds to $y_{i11} - y_{i00}$, while for unregulated firms it corresponds to $y_{i01} - y_{i00}$.

The principal practical challenge in estimating the TPE is that we only observe one outcome for each firm at a given point in time. When regulation is in place, we observe y_{i11} for regulated firms, but we do not observe y_{i01} or y_{i00}, both of which enter into (3.3). Similarly, for unregulated firms, we do not observe y_{j00}. Since we cannot estimate such unobserved outcomes for a single individual, a natural approach is to replace firm-level potential outcomes with their population averages, frequently after conditioning on covariates, e.g. to replace y_{iTR} with $E[y_{iTR}|x_i]$. Here, the expectation is be taken over unobserved components of the potential outcome. Making these replacements yields:

$$TPE = \sum_i E[y_{iT1} - y_{i00}|x_i] \tag{3.2}$$

where, to save on notation, I simply re-define TPE to refer to this new expression.

The total policy effect can be usefully decomposed into direct and indirect effects on

[7]This sum should include all entities that could potentially respond to the policy in some way. This may include individuals, or universities, and may include firms outside of the jurisdiction of the policy in question. For practical purposes, in the empirical application to the EU ETS I consider the universe of responding entities to be those falling within a particular country, regardless of regulatory status.

both regulated and unregulated firms. In particular, we may rewrite (3.2) as:

$$TPE = \underbrace{\sum_{i:T_i=1} E[y_{i11} - y_{i01}|x_i]}_{\substack{\text{Direct Effect on} \\ \text{Regulated Firms} \\ \gamma^R_{Direct}}} + \underbrace{\sum_{i:T_i=1} E[y_{i01} - y_{i00}|x_i]}_{\substack{\text{Indirect Effect on} \\ \text{Regulated Firms} \\ \gamma^R_{Indirect}}} + \underbrace{\sum_{j:T_j=0} E[y_{j01} - y_{j00}|x_j]}_{\substack{\text{Indirect Effect on} \\ \text{Unregulated Firms} \\ \gamma^U_{Indirect}}}. \tag{3.3}$$

The total policy effect thus consists of three components, corresponding to the three sums above. The first (γ^R_{Direct}) is the direct effect of regulation on regulated firms: what are the consequences of regulating a firm given that some regulation of other firms is in place (i.e. holding R fixed at 1)? The second term ($\gamma^R_{Indirect}$) is the indirect effect of regulation on regulated firms, capturing ways in which decisions made by other regulated firms might impact firm i even if firm i were not regulated. The final term ($\gamma^U_{Indirect}$) captures a similar indirect effect on firms that are actually unregulated. This decomposition of the TPE into direct and indirect effects is similar to that in Hudgens and Halloran (2008); I further decompose the indirect effects into those on regulated firms and those on unregulated firms. Doing so emphasizes the two potential pitfalls of focusing only on direct effects: part of the response by regulated firms goes uncounted, and any response by unregulated firms is ignored.

From (3.3) we can begin to see how standard estimators relate to the total policy effect. Most studies of induced innovation seek to quantify the Average Treatment Effect (ATE) or Average Treatment Effect on the Treated (ATT) (e.g. Lanjouw and Mody (1996); Jaffe and Palmer (1997); Brunnermeier and Cohen (2003)). The ATE conditioned on x_i is defined as:

$$ATE(x_i) = E[y_{i11} - y_{i01}|x_i], \tag{3.4}$$

while the ATT conditioned on x_i is

$$ATT(x_i) = E[y_{i11} - y_{i01}|x_i, T_i = 1]. \tag{3.5}$$

The summand in the first sum in (3.3) corresponds to the ATE, which is also equal to the ATT if the treatment effect is constant across the population.[8,9] As such, estimators that seek to estimate the ATE or ATT are useful in estimating the direct effect γ^R_{Direct} of a policy on the outcomes of regulated firms. To make progress, it is common to assume that potential outcomes are conditionally mean-independent of a firm's regulatory status given some vector of covariates x. In particular, this implies that if i is regulated, j is unregulated, and $x_i = x_j$, then $E[y_{i01}|x_i] = E[y_{j01}|x_j]$. In other words, after conditioning on covariates, the expected outcome a firm would have if it were not regulated but some regulation were in place is the same for all firms, regardless of their actual regulatory status. That assumption allows unbiased estimation of $ATE(x_i)$, and by summing over regulated firms, unbiased estimation of γ^R_{Direct}. Regression and matching estimators, including difference-in-difference and propensity score approaches, take this general approach to estimating the ATE.

Since estimators of the ATE and ATT quantify the *direct* effects of policy, a key question is whether those same estimators provide unbiased estimates of the *total* policy effect. Mathematically, we wish to know when $TPE = \gamma^R_{Direct}$. From (3.3) a sufficient condition for $TPE = \gamma^R_{Direct}$ is for there to be no indirect effects of any kind. That condition corresponds to the Stable Unit Treatment Value Assumption (SUTVA), under which the regulatory status of other firms has no effect on firm i's patent output. Thus,

[8] In the decomposition of the TPE, I have, in fact, assumed homogenous treatment effects by omitting conditioning on T_i.

[9] Standard ATE and ATT definitions often are written under SUTVA and thus do not include the R subscript on potential outcomes, and would simply be written as $E[y_{i1} - y_{i0}|x_i]$. Practically speaking, though, most ATE estimators are implemented to estimate (3.4) since they use outcomes for unregulated firms in the presence of regulation to estimate $E[y_{i0}|x_i]$.

if SUTVA holds, average treatment effect estimators provide an unbiased estimate of the total policy effect (when scaled by the number of regulated firms). If SUTVA does not hold, an estimator of the direct effect may still provide an unbiased estimate of the total policy effect, but only in the extreme case where the indirect effects on regulated and unregulated firms exactly cancel. A secondary issue arising from the presence of indirect effects is that the total effect of the policy on regulated firms, $TPE^R = \gamma^R_{Direct} + \gamma^R_{Indirect}$, cannot be derived from the ATE or ATT alone. Estimators of the ATE or ATT only capture the differential (direct) effect of a policy on regulated vs unregulated firms, which may not be the same as the total effect on regulated firms.

By this logic, prior studies of regulation-induced innovation that estimate only direct effects on regulated firms will provide biased estimates of the total policy effect unless the indirect policy effects are zero. Those studies may still provide unbiased estimates of the direct effects they set out to quantify, but they offer an incomplete picture of the total innovation effects of environmental policy. Further, as I will illustrate theoretically, in many environmental policy settings, SUTVA is indeed likely to fail: both cost pass-through and knowledge spillovers give rise to indirect effects of regulation on innovation by regulated firms, unregulated firms, or both.

The direction of bias in standard estimators depends upon the sign of the indirect effects. If both of those indirect effect terms are positive, estimators corresponding to the direct effect alone will underestimate the total policy effect. In the empirical setting of the EU ETS, the estimated net indirect effect is in fact positive, implying that prior studies under-estimate the patenting effects of that policy. To provide motivation for why that might be the case, I next develop a simple theoretical framework that incorporates cost pass-through and spillovers into a model of induced innovation.

3.3 Theoretical framework

To understand why environmental regulation might induce innovation in downstream, unregulated sectors, I present a stylized model of regulation, innovation, knowledge spillovers, and cost pass-through. Consider a two-sector economy in which one of the sectors is subject to environmental regulation, and that sector produces a good used by the unregulated sector. The N^R regulated firms use a number of primary inputs to produce a single output good X^R, and in the process, generate a harmful pollutant e. The regulated sector is subject to an emissions permit scheme with permit price τ, which regulated firms take as given.[10] The N^U unregulated firms use the regulated sector's output as an input to production of a final good X^U. A simple example of this is a regulated sector producing electricity and an unregulated sector using electricity to produce textiles.

In this two-period model, firms have two decisions to make. In the second period, a firm must choose how much of its output to produce, with firms competing in Cournot fashion. In the first period, each firm may invest in R&D to alter its production technology for the second period. In particular, regulated firms may invest in R&D that lowers emissions, while unregulated firms may invest in R&D that reduces the use of X^R. R&D is costly, and to maintain focus, considered to be deterministic.

The primary purpose of the model is to demonstrate how the presence of τ alters R&D by unregulated firms through the indirect channels of knowledge spillovers and cost pass-through. For a related treatment of R&D without such indirect channels, focusing on the effects of τ on R&D by regulated firms only, see Baker and Shittu (2006). For a general theoretical treatment of cost pass-through (tax incidence) without discussion of R&D,

[10] Even if regulated firms have market power in their output market, imagine that the permit scheme covers other firms that are economically and technologically disconnected from the two sectors considered here such that each firm considers the permit price to be exogenous.

see Weyl and Fabinger (2013). Knowledge spillovers have been studied extensively in the broader R&D literature; see, for example, Leahy and Neary (1997). The model here combines elements of all of these approaches to highlight the role that indirect effects may play in R&D responses to environmental policy.

I begin by considering firms' second-period output decisions, taking first period knowledge investment decisions (and thus second period knowledge stocks) as given. The analysis then turns to the first period R&D decisions, effectively working backwards.

3.3.1 Output decisions

Let profits for representative regulated and unregulated firms be written as π^R and π^U, with

$$\pi^R = P^R\left(X^R\right)x_i^R - c^R(x_i^R, w) - \tau e(x_i^R, k_i^R), \tag{3.6}$$

$$\pi^U = P^U\left(X^U\right)x_j^U - c^U(x_j^U, w) - w^R D^R(x_j^U, k_j^U, w). \tag{3.7}$$

Here, $P^S(X^S)$, $S \in \{R, U\}$ is the inverse demand facing a firm in sector S, x_i^S is the output quantity chosen by that firm (with sector-wide total output $X^S = \sum_i x_i^S$), and production costs for firms in sector S are $c^S(x_i^S, w)$. Factor prices are denoted by w, with the endogenously determined price of the regulated firm's output separated out as w^R. Emissions $e(x_i^R, k_i^R)$ depend upon both output and the firm's knowledge k_i^R. Unregulated firms do not emit, but use production technology with conditional factor demand for X^R denoted by $D^R(x_i^U, k_i^U, w)$, which depends on the unregulated firm's output x_i^U and knowledge k_i^U and factor prices w, which include w^R. I make standard assumptions that demand is non-negative and downward sloping ($P^{U'} < 0$, $P^U(X^U) \geq 0$) and costs are increasing and convex in output ($c_x^S > 0, c_{xx}^S > 0$). Emissions are increasing in output ($e_x > 0$) and decreasing and convex in knowledge ($e_k < 0, e_{kk} > 0$), and marginal emissions are decreasing in knowledge ($e_{xk} < 0$). Finally, the production technology for unregulated firms is such that conditional factor demand for the regulated firm output is increasing in output ($D^R_x > 0$) and decreasing and convex in knowledge ($D^R_k < 0, D^R_{kk} > 0$), and marginal demand for regulated firm output is decreasing in knowledge ($D^R_{xk} < 0$).

Both regulated and unregulated firms choose output to maximize profits, taking prices, knowledge, and actions of other firms as given. Equilibrium output choices (assumed interior) are defined by the first order conditions for maximization of (3.6) and (3.7). Specifically:

$$P^{R'}(X^R)x_i^{R*} + P^R(X^R) = c^R_x(x_i^{R*}, w) + \tau e_x(x_i^{R*}, k_i^R), \tag{3.8}$$

$$P^{U'}(X^U)x_j^{U*} + P^U(X^U) = c^U_x(x_j^{U*}, w) + w^R D^R_x(x_j^{U*}, k_j^U, w). \tag{3.9}$$

Let the equilibrium output of an unregulated firm implicitly defined by those first order conditions be denoted x_j^{U*}. Focusing on symmetric equilibrium, total demand for X^R facing regulated firms is then $N^U D^R(x_j^{U^*}, k_j^U, w)$, and the inverse demand function $P^R(\cdot)$ is defined such that $P^R(N^U D^R(x_j^{U^*}, k_j^U, w)) = w^R$. Similarly, first order conditions for regulated firms yield implicitly defined output choices x_i^{R*}.

As in Weyl and Fabinger (2013), the first order conditions defining equilibrium output by regulated firms can be implicitly differentiated to yield the rate at which regulated firms pass-through the costs of regulation (τ) into the price of their output (w^R). In particular, it can be shown (see Appendix) that

$$\frac{\partial w^R}{\partial \tau} = P^{R'} N^R \frac{e_x}{N^R P^{R''} x_i^{R*} + (N^R + 1)P^{R\prime} - c^R_{xx} - \tau e_{xx}}, \tag{3.10}$$

where all derivatives are evaluated at equilibrium output levels. The fraction corresponds to the change in a firm's equilibrium output in response to a marginal increase in the tax, which, when multiplied by $P^{R'}(X^{R*})N^R$, yields the resulting change in the price w^R. That change in output is determined by the relative size of the two effects a tax increase has on the marginal profit of output. First, holding output constant, a higher tax directly alters marginal profits in proportion to marginal emissions, as captured in the numerator. Second, a tax increase will cause all firms to alter their output decisions, which will affect both prices and the firm's own marginal costs, as represented by the denominator. The ratio of the direct tax effect and the output effect determines how much output will change in response to a tax increase.

The pass through effect described in (3.10) will, in general, depend on both market characteristics and technology, as is often discussed in the literature on tax incidence. Note in particular that market power is not required for cost pass-through to occur. As the market becomes competitive, i.e. $N \to \infty$ and consequently $x_i^{R*} \to 0$, the pass-through rate from (3.10) converges to a constant e_x, which depends upon regulated firm production technologies (often in the literature unit choices and technology with constant emissions per unit output imply $e_x = 1$). If there were a third, unregulated production sector competing with regulated firms, then prospects for pass-through begin to erode. In such a case, $P^{R'}$ could be seen as a residual demand facing the regulated sector, and the larger that competing sector is, the flatter that residual demand would be ($P^{R'} \to 0$), driving pass-through to zero. As such, the regulated sector as a whole must possess power in its output market, but firms within that sector need not possess market power for cost pass-through to occur.

Provided that the equilibrium is stable in the sense of Seade (1980),[11] $\frac{\partial w^R}{\partial \tau} > 0$ and the effect of a tax increase on the price of regulated firm output is positive (see Appendix). Thus, for a given level of knowledge k_i^R, regulated firms facing a cost increase via τ

[11] Essentially, reaction functions must be downward sloping.

will choose output such that w^R increases, and unregulated firms will thus face a higher relative price for X^R. It is intuitive that this higher price may affect R&D decisions for unregulated firms in earlier periods; I turn to this next.

3.3.2 Innovation decisions

In the first period, firms choose R&D investment with a goal of maximizing the sum of profits across the two periods. I ignore discounting given the short time horizon of the model; adding it offers little additional insight. R&D by a firm in sector S is denoted r^S, with each unit of R&D having unit cost. Such investment generates new knowledge according to knowledge production function $f^S(r_i^S, R^S, R^{-S}, k_i)$, where R^S captures total investment by other firms in i's sector, R^{-S} is total investment by firms in the other sector, and k_i is the firm's current knowledge stock. Knowledge production is assumed to be increasing and concave in both own R&D ($f_r^S > 0, f_{rr}^S < 0$) and own knowledge ($f_k^S > 0, f_{kk}^S < 0$). In general, $f^S(\cdot)$ may either increase or decrease in both R^S and R^{-S}. An increasing relationship reflects positive R&D spillovers ($f_R^S > 0$), while a decreasing one may reflect technological saturation ($f_R^S < 0$). The theory below does not depend on the sign of f_R^S, but when making predictions regarding the direction of expected effects for the empirical application, I assume $f_R^S > 0$ since the low-carbon technologies of interest are not yet mature enough that saturation should be an issue. New knowledge generated via these functions increments the knowledge stock additively:

$$k_i^S = k_{i0}^S + f^S(r^S, R^S, R^{-S}, k_{i0}^S), \tag{3.11}$$

where k_{i0}^S is firm i's initial knowledge stock.

With this notation, the first-period problems facing firms can be written as follows:

$$\max_{r_i^R} \left\{ -r_i^R + \pi^{R*}(k_i^R, w, \tau, K^R, K^U) \right\} \tag{3.12}$$

$$\max_{r_j^U} \left\{ -r_j^U + \pi^{U*}(k_i^U, w, \tau, K^U, K^R) \right\}. \tag{3.13}$$

Here, π^{S*} represents the equilibrium payoffs a firm in sector S will earn in the second period. Those future payoffs will depend upon both future prices (including the emissions price) and future knowledge stocks of all firms (K^R, K^U), which are affected by current period investments in R&D via (3.11). When choosing R&D, each firm takes the R&D decisions of all other firms as given. Further, consistent with the price-taking behavior described earlier, unregulated firms assume that their R&D will have no effect on future input prices. However, unregulated firms do recognize that their R&D decisions may affect future output choices by other unregulated firms, due both to knowledge spillovers and the strategic nature of second period output decisions.

First order conditions corresponding to the problems above again implicitly define equilibrium firm choices r_i^{R*} and r_j^{U*}. I focus solely on first period R&D choices by unregulated firms, since the purpose of the theoretical framework is to highlight channels for induced innovation outside the regulated sector. Still, due to the parallel structure of (3.12) and (3.13), the analysis for regulated firms is analogous. Adapting the methods in Leahy and Neary (1997) (see Appendix), in a symmetric equilibrium the first order condition defining r_j^{U*} can be written:

$$-w^R D_k^R f_r^U \left(\underbrace{1}_{\text{R\&D cost effect}} \underbrace{+ (N^U - 1) P' x_j^{U*} \frac{\pi_{jj}^{Uj} \left(\frac{\pi_{lj}^{Uj}}{\pi_{jj}^{Uj}} - \frac{f_{R^U}^U}{f_r^U} \right)}{\left(\pi_{jj}^{Uj} - \pi_{lj}^{Uj} \right) \left(\pi_{jj}^{Uj} + (N^U - 1) \pi_{lj}^{Uj} \right)}}_{\text{R\&D strategic effect}} \right) = 1, \tag{3.14}$$

where the notation π_{lj}^{Uj} is used to denote a second order partial derivative of firm j's profits with respect to output decisions by unregulated firms j and l. This condition equates the marginal benefit of R&D, which consists of a (direct) cost effect and a strategic effect via impacts to other firms' output decisions, with the (constant) marginal cost of R&D. Note that the sign of the strategic effect on optimal R&D depends on the strength of knowledge spillovers, captured here by $f_{R^U}^U$. Once $f_{R^U}^U$ grows larger than a threshold level, the strategic effect changes sign. The intuition is straightforward: if spillovers are small, R&D enables j to increase output, causing a strategic reduction in output by other firms, and providing additional marginal benefits of R&D to firm j. As spillovers get larger, however, R&D by j also reduces costs for other firms, causing them to increase output and reduce the marginal benefits to firm j. Above a spillover threshold, the net impact of those effects is negative.

This condition provides useful insight into the determinants of R&D by unregulated firms in equilibrium. First, and of greatest interest, the price of regulated firm output will clearly impact R&D decisions. Thus, any factor affecting the price of that good will, in turn, impact R&D by unregulated firms. In particular, pass through of τ into w^R and R&D by regulated firms R^R (which affects regulated firm output X^R) will both impact w^R, and ultimately R&D by unregulated firms. Second, through $f_{R^U}^U$ and f_r^U, R&D by one unregulated firm is likely to depend upon R&D choices by other unregulated firms

R^U. Thus, determinants of R^U and R^R, including the knowledge stocks of other firms K^U and K^R, will also affect the equilibrium value of r_j^{U*}. Finally, the marginal benefits of R&D scale with D_k^R, which corresponds to the (negative of the) marginal rate of technical substitution (MRTS) between X^R and k in an unregulated firm's production of its output X^U. If knowledge is a poor substitute for X^R, then D_k^R is small in magnitude, and regardless of the magnitude of cost pass-through, the marginal benefits of R&D will be small, and we should expect to see little R&D in that unregulated sector. The MRTS will be small in magnitude if past investment in R&D is high (so that k is large) since $D_k^R < 0$ and $D_{kk}^R > 0$. Similarly, the MRTS will be small if little or no X^R is required in the production of X^U in the first place. That is, for a given level of pass-through (and hence a fixed w^R), we should expect to see the most innovation in a sector that is intensive in its use of X^R and immature with respect to technological advances to reduce use of X^R.

Determining the sign of the effect of τ on r_j^{U*} becomes quickly intractable: τ impacts the price w^R, R&D by regulated firms and other unregulated firms, and output choices of all unregulated firms, all of which affect r_j^{U*} via (3.14). Some additional insight can be gained if the unregulated sector is a monopoly ($N^U = 1$), in which case the strategic effect of R&D disappears ($N^U - 1 = 0$).[12] In that case, differentiation of (3.14) with respect to τ yields

$$\frac{\partial r_j^{U*}}{\partial \tau} = \frac{\partial w^R}{\partial \tau}\frac{\partial r_j^{U*}}{\partial w^R} = \frac{\partial w^R}{\partial \tau}\frac{f_r^U}{w^R}\frac{\left(-D_k^R - w^R D_{kx}^R \frac{\partial x_j^{U*}}{\partial w^R} - w^R D_{kw^R}^R\right)}{D_k^R f_{rr}^U + D_{kk}^R (f_r^U)^2}. \tag{3.15}$$

Casual inspection of this expression suggests that the change in R&D by unregulated firms due to regulation will depend upon the pass-through of the permit price $\frac{\partial w^R}{\partial \tau}$. Any market characteristics or policies (e.g. price regulation) that limit cost pass-through

[12] The strategic term also vanishes in perfect competition, since $x_j^{U*} \to 0$.

should therefore reduce the level of indirectly induced innovation.

The sign of the effect in (3.15) hinges upon the numerator of the final fraction, which captures the way in which a change in w^R impacts the marginal benefit of knowledge at a given knowledge level. The first effect ($-D_k^R$) simply reflects that as X^R becomes more expensive, technology that helps reduce use of X^R is more valuable. However, the unregulated firm has two other ways to reduce its use of X^R: it can reduce its own output or substitute away from X^R toward other inputs. The second ($-w^R D_{kx}^R \frac{\partial x_j^{U*}}{\partial w^R}$) and third ($-w^R D_{kw^R}^R$) terms capture those possibilities. Both of those effects counteract the first term, since they limit the marginal benefit of knowledge. Which force dominates depends on the production technology that gives rise to D^R in the first place. As in Acemoglu (2002), if other factors are a poor substitute for X^R, the price increase will tend to increase innovation leading to reduced use of X^R. In contrast, if other factors are good substitutes, the firm may substitute away from X^R enough so that R&D related to use of X^R actually declines.

Pulling this all together, we may write equilibrium R&D by an unregulated firm as a function of variables that firm treats as exogenous (w^R is endogenous, but unregulated firms are price takers):

$$r_j^{U*} = r^{U*}(w^R, w, \tau, k_{i0}^U, K_0^U, K_0^R). \tag{3.16}$$

These dependencies will be important in translating the theoretical framework to an empirical specification for the application to the EU ETS. As noted above, it is difficult to definitively sign the effect of changes in determinants of R&D on equilibrium levels of innovation without further restrictions on the primitive functions defining production of both output and knowledge.

I conclude this section by summarizing the expectations about what will impact innovation by unregulated firms based on the discussion above. The first two hypotheses follow directly from assumptions about the properties of the knowledge production function $f^U(\cdot)$:

H1 *Innovation by unregulated firms increases in own knowledge.*

H2 *Innovation by unregulated firms increases in total knowledge for newer technologies.*

While these knowledge effects do not directly pertain to unregulated firms' response to regulation, they apply in general and thus will mediate some of the indirect effects of regulation on unregulated firms.

The remaining hypotheses address unregulated firm patenting responses to regulation more directly. First, while the sign of $\frac{\partial r_j^{U*}}{\partial \tau}$ cannot be determined in general, relatively inelastic short-run demand for electricity suggests that for many production technologies, substitution possibilities are limited. Therefore, we should expect to see more innovation due to cost pass-through:

H3 *Innovation by unregulated firms increases with higher costs of inputs produced by regulated firms.*

Further, the discussion of condition (3.14) includes additional hypotheses about market characteristics and technology. Specifically:

H4 *Innovation by unregulated firms is higher in sectors that are intensive in their use of regulated firm output and are technologically immature.*

H5 *Innovation by unregulated firms is higher in markets facing higher cost pass-through from regulated firms (larger $\frac{\partial w^R}{\partial \tau}$).*

To test these hypotheses, I turn to an empirical application involving low-carbon innovation and the emissions trading program in the EU.

3.4 Empirical Application: EU ETS

The European Union launched its permit market for greenhouse gas emissions in 2005 covering a subset of CO2 emitting installations across several industries; currently over 11,000 installations in 31 countries are regulated under the scheme.[13] As the largest emissions permit market in the world, the EU ETS is under intense scrutiny for its ability to meet a variety of objectives. One important metric on which the EU ETS is being evaluated is its ability to stimulate low-carbon innovation, both in patentable product form and process innovations. As discussed earlier, studies to date have found little evidence of a strong impact of the EU ETS on product innovation. In this empirical application, I revisit those findings in light of the potential for indirect effects as outlined in the preceding theoretical framework.

While cost pass-through is possible for any output produced by regulated firms, I focus only on electricity, given its prevalence as an input used by unregulated firms and existing documentation of cost pass-through. From an empirical perspective, electricity markets offer two sources of variation that will prove useful in identification of cost pass-through as a driver of indirectly induced innovation. First, prices within a country vary across time for a variety of reasons, setting up panel estimation of the relationship between electricity prices and low-carbon patenting. Those estimates of the elasticity of low carbon patenting with respect to electricity can be paired with estimates of cost pass-through to give a picture of how low-carbon patenting by electricity users responded to the introduction of the ETS. I rely on existing estimates of cost pass-through for this first approach, focusing empirical efforts only on the relationship between electricity prices and low-carbon patenting.

The relationship between the emissions permit price and electricity price is also likely

[13] For detailed background on the ETS, the reader is referred to any of the prior studies referenced earlier.

to vary geographically. Power producers face different emissions costs due to the use of different technologies, and geographic variation in price regulation and market characteristics will influence those firms' ability to pass through emission costs into the price of electricity. Although the EU as a whole has made strides toward market-based pricing for electricity, there is still substantial variation in scope for carbon price pass-through all the way to end users. Such variation in cost pass-through should, in turn, influence the strength of the hypothesized indirect effects of regulation on innovation.

Based on that observation, the second estimation approach I take in the paper is a difference-in-difference style estimation comparing the change in low-carbon patenting that occurred with the introduction of the ETS across markets with different pass-through potential. In particular, retail electricity markets in France are somewhat unique in that the prospects for pass-through are extremely limited as compared to the rest of the EU. On the generation side, France's large nuclear capacity means that the bulk of domestic electricity generation generates few carbon emissions (though the marginal technology may still be carbon-intensive). In terms of price regulation, many French firms have the option (and most take it) to buy electricity under a regulated tariff scheme. Because regulated tariffs are set on a cost-recovery basis and not on the marginal costs of production as in a market system, the large nuclear capacity means that the retail price faced by many firms will contain a relatively small carbon component. In other countries in the EU, the more liberalized retail markets and smaller nuclear capacity will mean the retail market price will contain more carbon costs.[14] As such, downstream, unregulated firms in countries other than France should exhibit a stronger low-carbon

[14]This intuition is reflected in early model-based estimates of pass-through rates by Sijm et al. (2006), which suggest carbon costs of 20 €/ton should increase electricity prices in Germany by 13-19 €/MWH but only by 1-5 €/MWH in France. In practice, the carbon price has been below that absolute level, but the modeling exercise hints at substantively different pass-through rates in the two countries. In a later study, Sijm et al. (2008) and co-authors explicitly model the French market differently in that they assume the dominant utility, EdF, does not pass-through its costs due to regulatory threats.

patenting response to the introduction of the ETS than their French counterparts.

To operationalize these ideas, I next detail my estimation strategy.

3.4.1 Empirical Model

We can use the theoretical framework outlined earlier to define an estimation strategy for studying the effects of the EU ETS on low-carbon patenting. In particular, the knowledge production functions from (3.11), evaluated at equilibrium levels of output and investment, provide the basis for estimation. In light of the discrete nature of patent counts generated via those knowledge production functions, all models considered are count models. All of the estimated models include both direct and indirect effects from (3.3). The latter effect is identified through variation in the electricity price, knowledge stock, and patenting over time, relying upon inclusion of other time-varying variables to control for other factors which might include patenting output.

To make these count models operational, it is necessary to specify functional forms for the knowledge production functions $f^R(\cdot)$ and $f^U(\cdot)$. I assume both take a Cobb-Douglas form, as is common in many models of innovation (e.g. Griliches (1979); Popp (2002)). Evaluating the knowledge production function at equilibrium levels of R&D as defined by (3.14) yields

$$pats_{it}^S = \alpha_i^0 \alpha_{ct} (r_{it}^{S*})^{\alpha_r^S} (R_t^{S*})^{\alpha_S^S} (R_t^{-S*})^{\alpha_{-S}^S} k_{it}^{\alpha_k^S} \nu_{it}, \tag{3.17}$$

where $\nu_{it} \geq 0$ is a shock to patenting productivity. Recall that R_t^{S*} captures R&D by other firms within i's sector, while R_t^{-S*} captures R&D by firms outside i's sector. The α parameters capture various aspects of innovative productivity: α_i^0 represents firm-specific productivity, α_{ct} is a time-varying patenting productivity parameter that varies at the country level c,[15] α_r^S is the productivity of own R&D, α_S^S is the productivity of within-sector other R&D, and α_{-S}^S is the productivity of cross-sector other R&D. Thus, α_S^S and α_{-S}^S capture spillovers within and across sectors. The superscripts on coefficients indicate that the effects of determinants on patent output may vary with regulatory status.

This equation can be re-expressed in a form more familiar in count models with exponential mean:

$$pats_{it}^S = \alpha_i^0 \alpha_{ct} exp\left(\alpha_r^S ln(r_{it}^{S*}) + \alpha_S^S ln(R_t^{S*}) + \alpha_{-S}^S ln(R_t^{-S*}) + \alpha_k^S ln(k_{it})\right) \nu_{it}. \tag{3.18}$$

Unfortunately, since relevant R&D investments at the firm and industry level are not observed, I cannot estimate this equation as part of a structural approach. Instead, I employ a reduced-form approach by replacing the terms involving $ln(r_{it}^{S*})$, $ln(R_t^{S*})$, and $ln(R_t^{-S*})$ with predicted determinants based on (3.14) and (3.16) and the analogous condition for regulated firms. Those determinants include the price of regulated firm output w^R, other factor prices w, own knowledge k_i, and knowledge stocks from other firms, K. Further, to reflect the fact that equilibrium and R&D in the regulated sector will differ once regulation is introduced, I allow R&D investment to depend upon a treatment status dummy variable T_{it}, which takes the value one if a firm is in the regulated sector and the policy is active, and zero otherwise (i.e. $T_{it} = \mathbb{1}(S_i = R \ \& \ t \geq \tilde{t})$, where $\tilde{t}$ is the first year the policy is in effect).

Substituting these determinants yields the following reduced-form specification:

$$\begin{aligned} pats_{ict} = \beta_i \beta_{ct} exp(&\beta_R^S T_{it-1} + \beta_k^S ln(k_{it}) + \beta_{K^S}^S ln(K_t^S) + \beta_{K^{-S}}^S ln(K_t^{-S}) \\ &+ \sum_{m \in M} \beta_m^S ln(w_{ct-1}^m) + \beta_{elec}^S ln(w_{ct-1}^{elec}))u_{it}. \end{aligned} \tag{3.19}$$

[15] Note a firm may operate in several countries. For the purposes of analysis, a firm operating in multiple countries is treated as multiple firms.

Here, w^m_{ct-1} is the lagged price for factor m in country c (with the set of all factors included denoted M). The factors I focus on for estimation are the prices of coal and natural gas. Both are commonly used as inputs to production processes in conjunction with electricity, and may be thought of more generally as capturing the effect of movements in other input prices. T_{it-1} is a (lagged) dummy variable taking the value 1 if firm i is regulated under the ETS, and 0 if that firm is not regulated. I use one year lags of prices and regulatory status to allow for prices to affect R&D with some delay (later I explore alternative lag structures). K^S and K^{-S} reflect the overall knowledge stocks in the firm's own sector and the other sector.

Before this equation can be estimated, a few practical considerations must be dealt with. First, knowledge stocks cannot be measured directly, and so I proxy for a firm's knowledge stock with that firm's past patenting output. To account for firms with no prior patenting history, I replace $ln(k_{it})$ with a combination of a dummy variable indicating if the firm has not patented in the past, and the log of past patents if the firm has a nonzero patent history (as in Aghion et al. (2012)). Second, because one of the variables of interest, electricity price, is only observed at the country by year level, estimating β_{ct} using a standard dummy variable approach would preclude identification of β^S_{elec}. Since β^S_{elec} is a coefficient of interest, I instead proxy for β_{ct} with observed total patenting rates $Pats_{ct}$ at the country level across all technology types. Third, other government intervention besides emissions regulation may affect the costs or benefits of R&D, such as demand-side policies (e.g. feed-in-tariffs) or R&D subsidies via public-private partnerships. While the stylized model presented earlier omitted such complications for clarity, I allow for them in the empirics with additional country-year controls Z_{ct}. Finally, I assume that the industry knowledge stocks K^S_t and K^{-S}_t are truly public, such that they can be considered a single public knowledge stock K_t. Making these substitutions yields the main model for estimation:

$$
\begin{aligned}
pats_{ict} = \beta_i exp(\beta_R T_{it-1} + & & \textit{Treatment effect} \\
& \beta_{k,0}\mathbb{1}(k_{it}=0) + \beta^S_{k,>0}\mathbb{1}(k_{it}>0)ln(k_{it}) + & \textit{Own knowledge effect} \\
& \beta_K s\, ln(K_t) + & \textit{Knowledge spillover effect} \\
& \beta^S_{elec} ln(w^{elec}_{ct-1}) + & \textit{Electricity price effect} \\
& \beta_{Pats} ln(Pats_{ct}) + & \\
& \sum_{m \in M} \beta^S_m ln(w^m_{ct-1}) + & \\
& \beta_g Z_{ct}) u_{it}. & \qquad (3.20)
\end{aligned}
$$

Taking the expectation of equation (3.20) defines the conditional mean number of patents for firm i, which forms the basis for count model estimation. In particular, I estimate three quasi-poisson variants of this model via quasi-maximum likelihood, relaxing the strong mean-variance equality assumption in poisson models to allow for over-dispersion. The three variants differ in their approach to handling unobserved heterogeneity β_i. The preferred model uses the pre-sample mean estimator introduced by Blundell et al. (1995), which uses pre-sample information on patenting by firms in the data set to proxy for unobserved heterogeneity. I also contrast this approach with a standard fixed effects poisson model (estimated via concentrated maximum likelihood) and a simple pooled poisson estimator that ignores unobserved heterogeneity. The former alternative will produce biased estimates in light of the dynamic nature of the model, while the latter is likely to do the same on account of ignoring persistent firm-level heterogeneity (Cameron and Trivedi, 1998).

Note that this specification does not directly include the price of emissions permits τ. The treatment dummy variable T_{it-1} captures a discrete effect of regulation on regulated firms. I use that dummy variable rather than a price for direct comparison with existing studies which use binary treatment status. Further, per the theoretical framework, any indirect effects operate through both knowledge stocks and the electricity price, both of which are included in the model. As a result, the evidence for indirect effects in this model is itself partly indirect, requiring combination of the parameter estimates from (3.20) and prior evidence of cost pass-through.

To provide a more direct test of the presence of indirect effects, I also estimate a modified version of (3.20) that includes the permit price. Since one of the key hypothesized channels for indirect effects is pass-through of the emissions price into the electricity price, a natural step is to replace the electricity price with its determinants, including the emissions price and the already included prices of coal and natural gas. The resulting model provides a reduced form estimate of the impact of the emissions price on low-carbon patenting. As discussed earlier, this effect is expected to be much stronger for firms outside of France due to that country's uniquely limited prospects for cost pass-through.

The resulting model is

$$
\begin{aligned}
pats_{ict} = \beta_i exp(\beta_R T_{it-1} + & \qquad \textit{Treatment effect} \\
& \beta_{k,0}\mathbb{1}(k_{it}=0) + \beta^S_{k,>0}\mathbb{1}(k_{it}>0)ln(k_{it}) + \qquad \textit{Own knowledge effect} \\
& \beta_K ln(K_t) + \qquad \textit{Knowledge spillover effect} \\
& \beta^{Sc}_{\tau}\tau_{t-1} + \qquad \textit{Emissions price effect} \\
& \beta_{Pats} ln(Pats_{ct}) + \\
& \sum_{m\in M}\beta_m ln(w^m_{ct-1}) + \\
& \beta_g Z_{ct})u_{it},
\end{aligned}
\tag{3.21}
$$

where the per-country coefficient β_{τ}^{Sc} captures the effect of interest. If the emissions price has little influence on the retail electricity price (as in France) and there are no other channels through which the ETS impacts low-carbon patenting by unregulated firms, β_{τ}^{Sc} should be near zero. In other countries with greater prospects for cost pass-through, if the increase in electricity price due to the permit price leads to more low-carbon patenting, β_{τ}^{Sc} should be positive.

While the coefficient estimates from both (3.20) and (3.21) provide evidence as to the presence or absence of indirect effects, they do not correspond directly to the direct and indirect policy effects in (3.3) that are of most interest. With that in mind, I next describe the two approaches I use to construct estimates of the direct and indirect policy effects using estimated coefficients.

3.4.2 Constructing Estimated Direct and Indirect Policy Effects

To construct estimates of the direct and indirect effects of policy in (3.3), I employ a simulation approach combining my fitted models with estimates of cost pass-through rates from the literature. Because both (3.20) and (3.21) are dynamic specifications, computing policy effects requires simulation using each fitted model rather than simply interpreting coefficients. The estimate of β_T, for example, provides insight into the sign and significance of the direct effect of regulation on regulated firms, but the magnitude of that effect depends on a combination of that coefficient and knowledge effects. In particular, to construct estimates for both $E[y_{is1}]$ and $E[y_{i01}]$, it is necessary to compute expected patent output for the first year in which regulation could have impacted patent output, use those fitted outputs to update the knowledge stocks for the second year, and so on. I next describe these simulations in more detail, beginning with computation of direct effects, then describing adaptations to compute indirect effects. The steps are written with reference to (3.20), but I use the same procedure for (3.21) except where noted.

Estimates of the direct effect

To estimate the direct effect of regulation on regulated firms (γ^R_{Direct}), I perform two related simulations. The first is designed to provide an estimate $\hat{y}_{iT1}$ of $E[y_{iT1}]$, while the second provides an estimate $\hat{y}_{i01}$ of $E[y_{i01}]$.

The steps for producing $\hat{y}_{iT1}$ are as follows:

S1. For the first year of regulation, simulate patent output per firm using (3.20) and estimated parameters.

S2. Update knowledge stocks for $t+1$ using the simulated patent output in year t.

S3. Repeat steps S1 and S2 for each year of regulation in sequence.

S4. Sum the patent output per firm from S1 across all years of regulation.

Denote the sum produced in $S4$ by $\hat{y}_{iT1}$. These steps compute predicted patent output per firm, and sum over the years of regulation such that $\hat{y}_{iT1}$ represents an estimate of total expected patent output under the actual policy and regulatory status of firms.

To compute $\hat{y}_{i01}$, I simulate a regulated firm's i's patent output if it were not regulated by setting its regulatory status to unregulated and simulating in a similar fashion to above. For this simulation, I hold estimated output by other firms $j \neq i$ fixed at the levels simulated during computation of $\hat{y}_{iT1}$. This reflects the fact that the direct effect is intended to capture only the effect of a firm's own regulatory status on its own patent output. This process is then repeated for all regulated firms. In particular, I perform the following steps to compute $\hat{y}_{i01}$:

D1. Simulate patent output under observed regulation according to S1-S4 above.

D2. For firm i, set $T_{it} = 0$ for all t.

D3. For the first year of regulation, simulate patent output for firm i only using the modified data and estimates from (3.20).

D4. Update firm i's knowledge stock and total knowledge stocks for year $t+1$.

D5. Repeat steps D3 and D4 for each year of regulation in sequence.

D6. Sum the patent output computed in step D3 for each firm across all years of regulation, and denote the sum by $\hat{y}_{i01}$.

D7. Repeat steps D2-D6 for each regulated firm i.

Once estimates of $\hat{y}_{is1}$ and $\hat{y}_{i01}$ have been computed according to the simulations above, the estimate $\hat{\gamma}^R_{Direct}$ of the direct effect γ^R_{Direct} is computed as:

$$\hat{\gamma}^R_{Direct} = \sum_{i:T_i=1} (\hat{y}_{iT1} - \hat{y}_{i01}). \tag{3.22}$$

Estimates of the indirect effects

Estimation of the indirect effects of the ETS on patenting combines each fitted model with existing estimates of cost pass-through rates from prior studies. Both of the indirect effects in (3.3) contain the expected change in patenting when a given firm remains unregulated but regulation is introduced for other firms. To construct an estimate $\hat{y}_{i00}$ of the counterfactual patent output in which a firm is unregulated and no regulation exists ($E[y_{i00}]$), I use the estimated model to simulate patenting output when the electricity price is modified according to previously estimated pass-through rates, the regulatory status of all firms is unregulated, and, for the alternative specification (3.21), the emissions permit price is set to zero.

Letting PTR_c denote the pass-through rate for carbon and electricity prices in the EU ETS, the simulation of the counterfactual proceeds as follows:

I1 Set $T_{it} = 0$ for all i and all t

I2 Modify w_t^{elec} to be $w_t^{ALTelec} = w_t^{elec}/(1 + PTR_c)$ for all t.

I3 If the specification is (3.21), set $\tau_t = 0$ for all t.

I4 Simulate patent output according to steps S1-S4 above using the modified data, and denote the sum from S4 as $\hat{y}_{i00}$

The simulation procedure produces an estimate $\hat{y}_{i00}$ of $E[y_{i00}]$, the patent output of firm i if no regulation existed. That estimate can be subtracted from estimates of $\hat{y}_{i10}$ and $\hat{y}_{i00}$ computed in S1-S4 and D1-D7 to produce the desired estimates of indirect effects. In particular:

$$\hat{\gamma}^{R}_{indirect} = \sum_{i:T_{it}=1} \left(\hat{y}_{i01} - \hat{y}_{i00}\right), \tag{3.23}$$

$$\hat{\gamma}^{U}_{indirect} = \sum_{i:T_{it}=0} \left(\hat{y}_{i01} - \hat{y}_{i00}\right). \tag{3.24}$$

On a final note, interpretation of the estimates $\hat{\gamma}^{R}_{indirect}$ and $\hat{\gamma}^{U}_{indirect}$ requires some care. As discussed above, β_τ^{Sc} in the alternative model (3.21) captures a joint effect of simultaneous changes in the permit price and other determinants of the electricity price such that the electricity price remains unchanged. Since other factor prices in the model are likely to positively influence the electricity price, those factor prices would have to simultaneously decline, meaning the change captured by β_τ^{Sc} involves a larger relative price increase for emissions than a standard *ceteris paribus* price increase. As a result, I interpret estimates $\hat{\gamma}^{R}_{indirect}$ and $\hat{\gamma}^{U}_{indirect}$ derived from that model as upper bounds. That alternative model is quite useful in pinning down the role that cost pass-through plays in innovation, but I focus my discussion of the estimated magnitude of indirect and total effects on those derived from the main specification (3.20).

3.4.3 Data

In line with the specifications presented above, I construct a panel dataset of low-carbon patenting in the EU at the firm level. The study period ranges from 1995 to 2010, covering activity both before the EU ETS (1995-2004) and during (2005-2010). While patent data exist beyond 2010, I do not include those years in order to avoid well-documented problems of truncation in patent counts (due to delays in processing of patent applications). For the pre-sample mean estimator, I also use patent data going back to 1985, allowing for a full decade of data to be used for that purpose.

The primary outcome of interest is low-carbon patenting activity at the European Patent Office (EPO). I obtained patent records from the Worldwide Patent Statistical Database (PATSTAT), with patents pertaining to reduction of carbon emissions identified using the Cooperative Patent Classification (CPC) categories associated with each patent. As in Calel and Dechezleprêtre (2014), I consider any patent labeled with a CPC category beginning with *Y02* to be a low-carbon invention. Knowledge stocks based on these patent counts are constructed using one, two, and three year lags of patent output.

Price and other control data come from several different sources. Emissions allowance prices are from the European Energy Exchange (EEX), and represent the price (in €) of a year-ahead future contract for a permit granting the right to emit one ton of CO2. Coal prices come from the International Energy Agency (IEA)[16] and represent the annual

[16]Table 4 of http://www.iea.org/media/training/presentations/statisticsmarch/CoalInformation.pdf

average per-ton price of Colombian coal. Electricity and natural gas prices are from Eurostat and represent within-year average prices for those commodities by country. The natural gas prices used are those for mid-size industrial consumers.[17] Controls for other factors affecting the profitability of low-carbon R&D come from the IEA, and include both installed renewable energy capacity (as a proxy for demand side-policies such as feed-in tariffs) and public R&D investment in renewable energy (as a proxy for supply-side interventions).

Regulatory status per firm is based on matching of patent data to the European Union Transaction Log (EUTL) associated with the EU ETS. To match firms, I apply the name harmonization process used in PATSTAT (Magerman et al., 2006) to account operator names from the EUTL. Firms are then matched between datasets using the harmonized name and country from both datasets.

Calculation of estimated effect sizes requires specification of a pass-through rate relating the emissions permit price to the *retail* electricity price. Very few estimates of the retail pass-through rates exist; most studies concern wholesale electricity prices due to the frequency and availability of the data. In one of the only studies attempting to quantify retail pass-through rates, Sijm et al. (2008) offer several such estimates for Germany and the Netherlands (excluded here due to missing data), but none for France. I use their estimates that are based on the assumption that the level of costs passed through to the retail price is the same as the level passed through to the wholesale price. To ensure my estimates are conservative, I use the lowest such estimate, which equates to 4.8 €/MWh. Further, that pass-through level is also smaller than the average pass-through level for Germany estimated via either of the other two approaches in Sijm et al. (2008). For France, due to retail price regulation and in keeping with my desire to pro-

[17] Specifically, gas prices are from tables nrg_pc_203 and nrg_pc_203_h. Data up to 2007 are from nrg_pc_203_h, and data from 2008-2010 are from nrg_pc_203. Prices are for band I3, which is for customers using between 10,000 and 100,000 GJ.

vide conservative estimates, I assume that while wholesale pass-through rate estimates are positive, there will be no pass-through to retail prices (0%). Because no published estimates exist for retail pass-through rates in other countries, I restrict effect size calculations to Germany and France. That choice implicitly assumes the ETS has no effect on low-carbon patenting in other countries, thereby ensuring that estimated effect sizes remain conservative.

To motivate the empirical analysis, Table 3.1 provides brief summary statistics of low-carbon, electricity related patent output broken out by country, ETS status, and period (1995-2004 vs 2005-2010). A number of observations emerge from these summary statistics. First, the average number of low-carbon patents per firm per year increases during years in which the ETS is active. This is consistent with the idea of induced innovation. Second, the increase in patenting among unregulated firms that occurs with the introduction of the ETS is smallest in France (as a percent of pre-ETS patenting), which is consistent with the hypothesis that indirect innovation effects will be weakest in France. That pattern is more easily seen graphically; Figure 3.2 presents the low-carbon patent output in the UK, Germany, and France, normalized to 2004 levels. The increase in France is notably lower. However, attributing any of these observations to the introduction of regulation is complicated by a number of factors. Both electricity and fuel prices increase, and the patent rate for regulated firms differs from that for unregulated firms even prior to the introduction of regulation. Thus, any estimation strategy must account for both unobserved heterogeneity and the impact of factors other than the ETS on low-carbon patenting. The preferred specification does both.

3.5 Results and Discussion

3.5.1 Models with electricity price only

I first estimate (3.20) using the three estimation strategies outlined earlier, then compute estimates of the direct, indirect, and total policy effects according to Sections 3.4.2 and 3.4.2. The results in Table 3.2 indicate that being subjected to ETS regulation increases patent output, higher electricity prices lead to additional patents, and that lagged own knowledge increases patent output. Evidence for strong cross-firm knowledge spillovers in this context is mixed; patent stocks from the previous year have no significant impact on current patenting, but longer lags exhibit significant effects of opposite signs. I return to interpretation of these estimates in the discussion section below.

Estimates of the direct, indirect, and total policy effects computed according to Sections 3.4.2 and 3.4.2 are reported at the bottom of Table 3.2. For the preferred presample mean specification, the estimated direct effect of the ETS on patenting, captured by $\hat{\gamma}^R_{Direct}$ is 649 additional patents. The estimates of $\hat{\gamma}^R_{Indirect}$ and $\hat{\gamma}^U_{Indirect}$ are of greater interest, as those indirect effects are the central focus of this paper. The estimated indirect effect on regulated firms $\hat{\gamma}^R_{Indirect}$ is 100 additional patents, while the indirect effect on unregulated firms $\hat{\gamma}^U_{Indirect}$ is 361 additional patents, for a total indirect effect of 461 patents. These results suggest that indirect effects are 71% the size of the estimated direct effects, such that the total effect of regulation on innovation may be substantially larger than frequently reported estimates of direct effects.

3.5.2 Models including emissions permit price

The results in the previous section provide a two-part argument that the EU ETS has increased low-carbon patenting by unregulated firms: the ETS increased electricity price, and an increased electricity price leads to more low-carbon patenting. Estimates of (3.21) should offer more direct evidence of such an effect, since the carbon price appears directly in the model. Estimates of three variants of that model (pooled, fixed effects, and presample mean) are reported in Table 3.3, with standard errors again adjusted for over-dispersion.

The results in Table 3.3 suggest that again, own knowledge and ETS regulatory status are important determinants of patent output. In addition, the estimates provide evidence that the degree to which passed-through carbon costs contribute positively to patent output varies by country. The estimates indicate no significant effect in France, but a significant and positive effect in several other countries. This discrepancy in effects across the two countries is consistent with the hypothesis that permit prices impact innovation through cost pass-through, since the scope for pass-through is much higher in the more liberalized retail markets outside of France. If permit prices were to affect innovation through a channel other than the electricity price, we should still see an effect of the permit price on patenting in France. If, instead, permit prices do not affect innovation outside the regulated sector, we should see a zero effect across all countries. The fact that we see no permit price effect in France but a positive effect elsewhere is consistent with the hypothesis that indirectly induced innovation is mediated by cost pass-through.

3.5.3 Additional tests

While the main results presented above are consistent with the ETS having indirect effects on low-carbon innovation, it is possible they reflect some other driver of innovation. To address that possibility, I attempt to falsify the results through estimation of variants of (3.20). First, since the stylized theoretical framework is based on unregulated firms being users of the output produced by regulated firms (i.e. electricity), I estimate

(3.20) on the subset of firms that are unregulated. Doing so yields the results in Table 3.4, which still suggests a positive and significant elasticity of patenting with respect to electricity price; the primary results are not driven by behavior of regulated firms. I also estimate a variant of (3.20) allowing β_{elec} to vary by industrial sector. Lending credibility to the specification, firms in electricity-dependent sectors, such as those devoted to the manufacture of chemicals, metals, electronic components, energy machinery, and telecommunications exhibit strong, positive patenting responses to higher electricity prices and pass-through.

Further exploration of the relation between electricity prices and low-carbon patenting suggests that cost pass-through may impact innovation through multiple channels. The preceding results are consistent with the theoretical setup in which firms innovate to reduce their own production costs in response to a factor price increase. However, suppliers of technology to downstream firms would view such cost increases as a market opportunity for more electrically efficient machinery or distributed power generation. Similarly, just as firms are exposed to higher electricity prices via pass-through, so too are household users. To investigate whether pass-through stimulates innovation via these alternate channels, I estimate variants of (3.20) that include foreign electricity prices and domestic household electricity prices. The results in Tables 3.5 and 3.6 suggest that cost pass-through could be affecting innovation by downstream, unregulated firms via all of those mechanisms.

Third, I examine the sensitivity of the results to how both knowledge stocks and expectations for future electricity prices are measured. In the primary specification, knowledge stocks are based upon one, two, and three year lags of patent output, with effects falling off quickly after the first lag. Estimation of a model that includes only that first lag does not substantively change coefficient estimates (Table 3.7). Similarly, the returns to innovation depend upon future electricity prices, and using only one-year lags of electricity prices as a proxy for expected future prices may be imperfect. As such, I estimate an alternative specification including first, second, and third lags of electricity prices. The results (Table 3.8) indicate that the effects of more than one year lags of electricity prices fall off quickly, and the first lag retains its positive and significant impact on patenting. Interestingly, the coefficient on the second lag of electricity price is negative (though not significant), which could indicate that firms look at trends in prices when forecasting future electricity costs. A higher second lag holding the first lag fixed would indicate a declining electricity price trend and, if that trend were to continue, lower future electricity costs and lower demand for innovation.

Finally, I also conduct a placebo test to examine whether patent outcomes that should not respond to the electricity price in fact show no response. In particular, I examine whether low-carbon patenting responds to *future* electricity price increases. As expected, changes in electricity prices do not have a retroactive impact on patenting (Table 3.9).

3.5.4 Discussion

Several questions follow from the preceding empirical results, which suggest that unregulated, downstream firms responded to the introduction of the EU ETS by increasing low-carbon patenting. First, why does such a response appear here but not in carefully done studies such as that by Calel and Dechezleprêtre (2014)? Second, are the indirect effects estimated here due to the hypothesized channel of cost pass-through and downstream firms innovating to reduce their own costs, or some other channel? Third, are patents an appropriate measure of innovation?

Comparison with prior studies

The results here differ from prior studies for several reasons. First and foremost, the current study emphasizes downstream spillovers, whereas prior studies either ignore spillovers or focus onupstream spillovers involving suppliers of technology to regulated firms. Downstream spillovers entail a different and much broader set of firms and a larger set of technologies than the traditional focus on upstream spillovers. For example, the vast majority of firms use electricity in their daily activities, yet most of them are not regulated, not suitable matches for regulated firms, and not technology suppliers to regulated firms. Thus any estimator focused on innovation that directly reduces emissions is likely to miss any response by those electricity users. This suggests a broader definition of low-carbon innovation to include technology related to efficient use of goods produced by regulated firms (e.g. electrical efficiency). The concept of "embedded carbon" is familiar in lifecycle analysis but it merits more careful consideration in studies of induced innovation.

The estimates here also indicate a larger direct effect than that found in Calel and Dechezleprêtre (2014) in the ETS context, which demands explanation. That study uses a matched difference in difference estimator, finding a treatment effect of 2 additional patents per regulated firm. Applied to their matched sample, that corresponds to a direct effect of 84 additional patents, and 188 additional patents for the full set of ETS firms (including firms for which no suitable match was found). In contrast, the direct effect estimated here for the full set of ETS firms is 649 additional patents.

The difference in the estimated direct effects here and in Calel and Dechezleprêtre (2014) stems from differing assumptions about whether treatment effects are homogenous or heterogeneous across firms. In Calel and Dechezleprêtre (2014), each firm subjected to regulation is assumed to increase patenting by a fixed *number* of patents, with the caveat that patent output is censored at zero. In contrast, the dynamic count model here assumes that treatment has a multiplicative effect, such that regulated firms increase patenting by a fixed *percentage* rather than a fixed number of patents. The two assumptions imply very different patenting responses to regulation for more innovative firms, while they may have similar predictions for firms that produce no more than a few patents. To illustrate the point, I use estimates in Table 3.2 to compute direct effects for a set of firms with patent output comparable to the matched sample used in Calel and Dechezleprêtre (2014). Since their matched sample accounted for only 14.4% of patenting by ETS firms during the 2005-2009 period but 61.6% of ETS firms, the matched sample must consist of less innovative firms. This exercise yields a direct effect of 82 patents, which is in line with the matched sample effect from Calel and Dechezleprêtre (2014). The primary difference between the direct effects estimated in the two studies then seems to be the different assumptions about how treatment impacts the more innovative, unmatched firms.

Alternative channels

The question of whether the estimated effect of the ETS on low-carbon patenting by unregulated firms is due to the modeled mechanism is more difficult to answer. The empirical results are certainly consistent with unregulated firms responding to higher electricity prices, and I have attempted to account for the influence of other drivers of low carbon patenting (e.g. demand-side policies and public R&D investment) and conduct appropriate placebo and robustness checks.[18] None of the results provide evidence against the hypothesis that cost pass-through leads to increased low-carbon patenting by

[18] To the extent that public R&D is funded by revenue recycling from permit auctions, controlling for public R&D may artificially remove some of the effect of the ETS on downstream innovation that occurs via public-private R&D partnerships. I thank Dallas Burtraw for that observation. To the extent revenue recycling provides a substantive component of R&D funding, the estimates presented here should then be interpreted as lower bounds.

downstream, unregulated firms.

However, in light of positive firm responses to both foreign industrial electricity prices and domestic household electricity prices, cost pass-through may be influencing patenting decisions of downstream, unregulated firms via multiple pathways. The theory presented earlier suggests that firms facing higher electricity prices due to pass-through will view investment in R&D as more profitable, and will alter R&D decisions accordingly. In a similar fashion, both firms and households facing higher electricity prices due to pass-through will view investment in electricity-saving technology provided by other firms as more profitable than before. As such, some of the increase in low-carbon patenting by unregulated firms may reflect increased patent output by technology suppliers reacting to a market opportunity created by the electricity price increase rather than their own cost increases. For example, downstream firms could be innovate to offer a differentiated, more energy efficient good to consumers facing higher electricity prices (in the spirit of Romer (1990)). Regardless, all of those mechanisms imply that pass-through of emissions permit costs led to increased low-carbon patenting by unregulated firms. Disentangling the different sub-mechanisms is an interesting avenue for further research.

Measuring innovation

This study and all others using patents as a measure of innovation are subject to the caveats that come with such data. Other than the practical considerations (e.g. truncation due to delays in patent processing), two primary issues are worth addressing here. First, not all innovations result in patents. As documented elsewhere (e.g. Hoffmann (2007)), the EU ETS spurred many process changes that helped lower emissions without the production of a patent. Similarly, some inventors of patentable innovations may choose not to apply for protection, instead keeping the invention as a trade secret. As such, the estimates presented here are likely to still underestimate the total impact of the

ETS on innovation. Second, patent counts are a noisy measure of what is economically relevant for the costs of regulation like the EUETS, which is the adoption of those new technologies. Data do exist for some specific technologies (e.g. air conditioners – see Newell et al. (1999)), but not across the full spectrum of technologies considered here. Still, related pieces of evidence may shed some light on the topic. Patents filed just after the introduction of the EU ETS had comparable family sizes to those filed just before, providing no evidence that the additional induced patents were of any lower quality than those filed before the introduction of the permit market. Since patent application is a costly activity, we might interpret this as suggestive evidence that any induced innovations are as likely to be brought to market as others.

3.6 Conclusions

Increasingly, a stated objective of environmental policy is to stimulate the development of new technology that will make achievement of environmental goals less costly. This is especially true for climate policy, for which the social costs of not achieving environmental targets may be quite large. Traditional policy analysis seeks to quantify the innovation effects of a particular environmental policy by estimating a treatment effect on firms regulated under that policy. This paper has argued that the total effects of a policy may diverge from the direct effects, using both a simple modeling framework and an empirical application to the European Union Emissions Trading System. In that empirical application, estimates suggest that the total effect of the EU ETS on low-carbon patents is 71% larger than the direct effect that would be estimated via standard methods based upon the treatment effects framework. The absolute size of the impact of the EU ETS on low-carbon innovation remains small, but the relative size of the direct and total policy effects suggests that for policies imposing higher costs on regulated firms, failure to account for indirectly induced innovation may have more important consequences.

Further, I argue the general mechanism for indirect effects is likely to apply to a broad array of environmental policies. As seen in the simplified theoretical model, pass-through of policy-imposed costs is likely to occur whenever regulated firms face little unregulated competition in their output market(s). This can occur when all firms are regulated, or when only some firms are regulated, but those firms possess market power. The latter scenario is quite common in environmental policies. Firms with market power are often included in environmental regulation: they are frequently large emitters, and the concentration of emissions among a smaller number of firms may lower monitoring costs for the regulator. As a result, the mechanisms presented here may be more broadly applicable to a large number of environmental policies, though the strength of the indirect policy effects on innovation will differ by policy, industry, and market conditions.

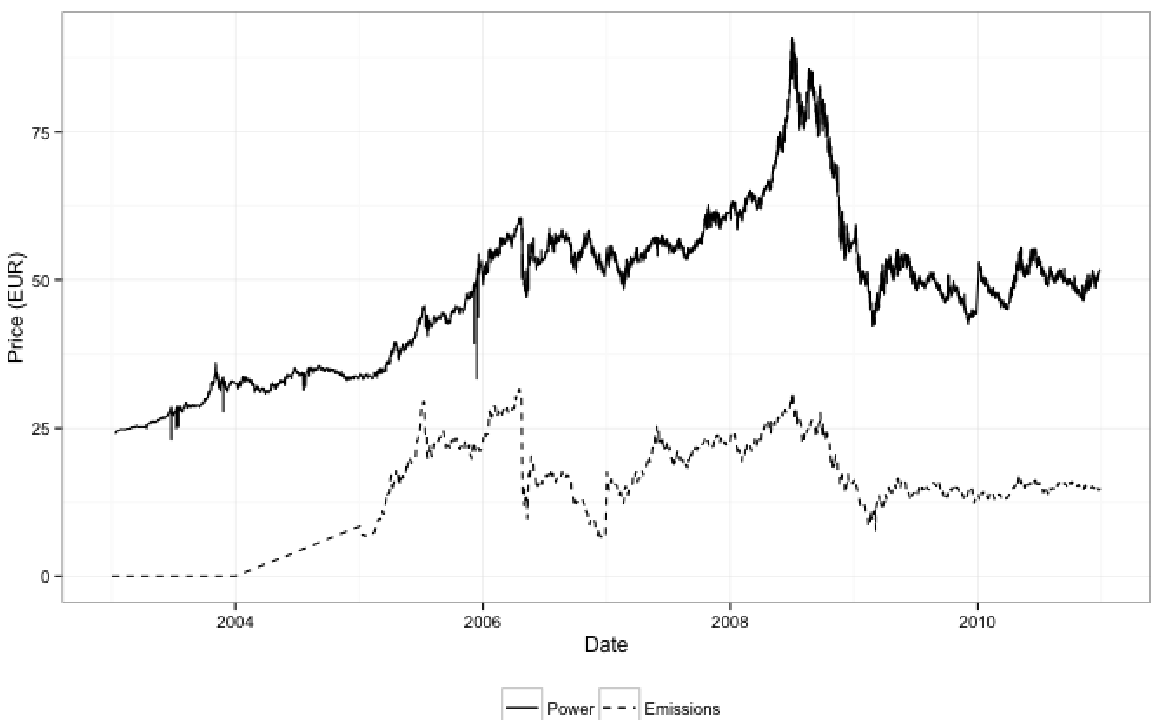

Figure 3.1: Prices over time for year-ahead power futures and year-ahead emissions permit futures. All prices are nominal and in EUR. Source: European Energy Exchange (EEX).

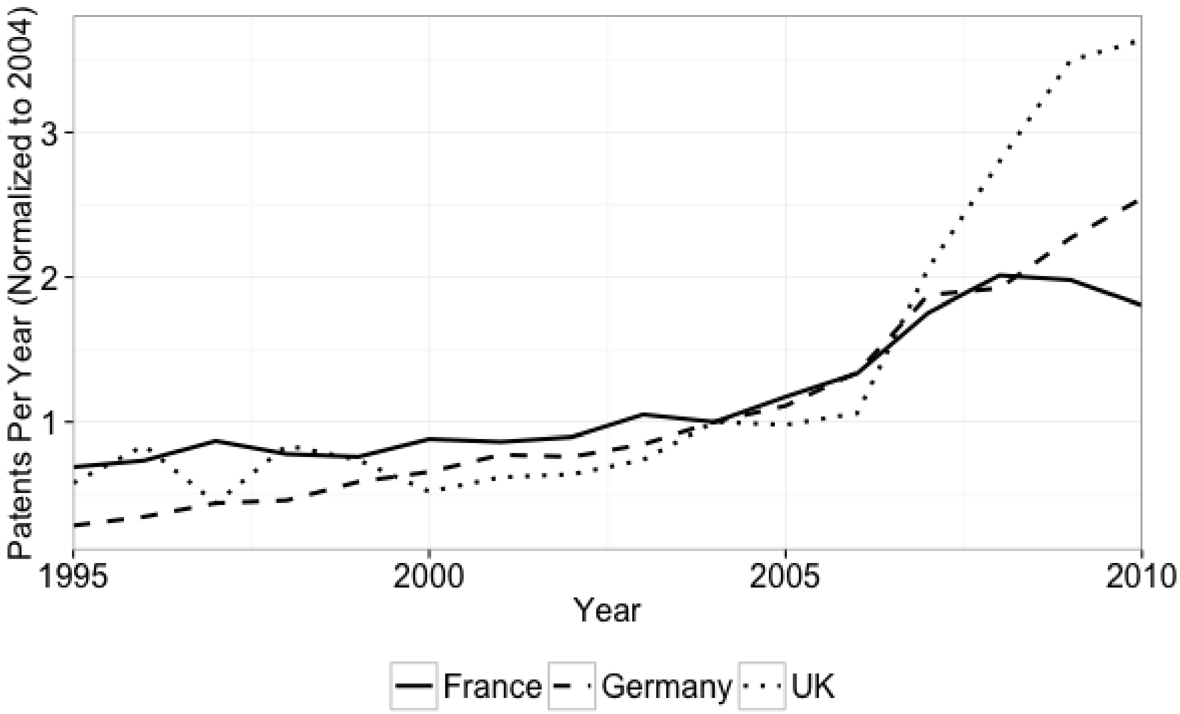

Figure 3.2: Low-carbon patents by country per year in France, Germany, and UK, normalized to 2004 levels for each country. Source: European Patent Office (EPO).

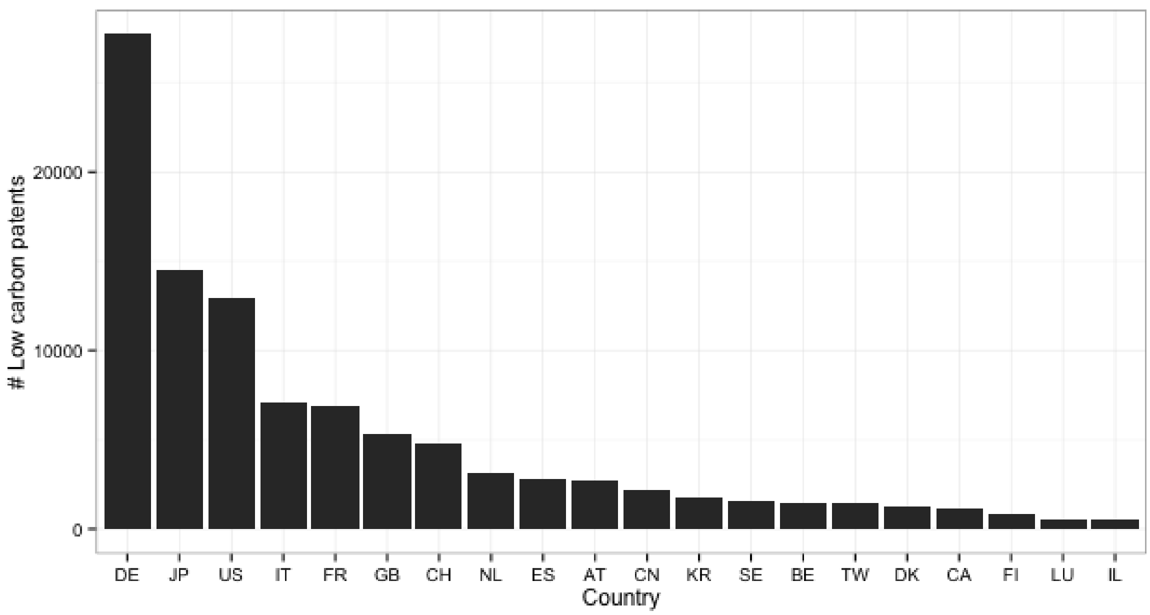

Figure 3.3: Number of low-carbon patents by country during 2000-2010 for the top 20 low-carbon patenting countries. Source: EPO.

Table 3.1: Summary statistics.

	Total Pats		Avg Pats		Elec Price		Gas Price		Firms
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	
Belgium	129	309	0.1	0.39	91.62	119.8	5.62	9.32	133
Non-ETS	98	298	0.08	0.39	–	–	–	–	128
ETS	31	11	0.62	0.37	–	–	–	–	5
Germany	6056	10884	0.24	0.72	94.77	132.82	7.36	13.36	2518
Non-ETS	5016	8852	0.2	0.6	–	–	–	–	2470
ETS	1040	2032	2.17	7.06	–	–	–	–	48
Denmark	143	506	0.13	0.77	93.74	168.19	5.94	14.33	110
Non-ETS	119	468	0.11	0.74	–	–	–	–	105
ETS	24	38	0.48	1.27	–	–	–	–	5
Spain	101	493	0.04	0.33	74.31	107.53	4.57	8.36	252
Non-ETS	101	482	0.04	0.32	–	–	–	–	250
ETS	0	11	0	0.92	–	–	–	–	2
France	1323	1560	0.21	0.41	69.43	75.7	5.38	10.18	627
Non-ETS	1173	1341	0.19	0.37	–	–	–	–	606
ETS	150	219	0.71	1.74	–	–	–	–	21
Italy	607	727	0.09	0.19	107.25	152.28	5.66	9.54	642
Non-ETS	532	660	0.08	0.17	–	–	–	–	629
ETS	75	67	0.58	0.86	–	–	–	–	13
UK	348	702	0.07	0.24	69.87	108.18	4.53	9.48	482
Non-ETS	247	467	0.05	0.17	–	–	–	–	468
ETS	101	235	0.72	2.8	–	–	–	–	14

Table 3.2: Main regression results: low-carbon patents as a function of predictors including electricity price. Estimates of coefficients corresponding to other covariates, including factor prices, presample mean, country effects, and total patent rate are omitted for emphasis on the effects of interest. All standard errors are adjusted for overdispersion by fitting a quasipoisson model.

		Pooled	FE	Presample
Log total knowledge	$ln(K_t)$	-0.293.	0.041	-0.270
		(0.169)	(0.059)	(0.167)
	$ln(K_{t-1})$	0.699**	0.456***	0.708**
		(0.243)	(0.096)	(0.240)
	$ln(K_{t-2})$	-0.488**	-0.273***	-0.479**
		(0.170)	(0.070)	(0.168)
No own knowledge	$\mathbb{1}(k_{it} = 0)$	-1.226***	-0.529***	-1.221***
		(0.032)	(0.016)	(0.031)
	$\mathbb{1}(k_{it-1} = 0)$	-0.812***	-0.226***	-0.831***
		(0.033)	(0.015)	(0.032)
	$\mathbb{1}(k_{it-2} = 0)$	-0.464***	-0.009	-0.515***
		(0.032)	(0.014)	(0.032)
Log own knowledge	$ln(k_{it})$	0.780***	0.387***	0.754***
		(0.017)	(0.005)	(0.017)
	$ln(k_{it-1})$	0.099***	0.009	0.087***
		(0.020)	(0.007)	(0.019)
	$ln(k_{it-2})$	0.071***	-0.079***	0.009
		(0.017)	(0.006)	(0.018)
Log elec price	$ln(w^{elec}_{t-1})$	0.757***	0.816***	0.718***
		(0.131)	(0.024)	(0.129)
Regulatory status	T_{it-1}	0.100**	0.004	0.138***
		(0.034)	(0.011)	(0.034)
Policy effect estimates:	# additional patents			
Direct effect	$\hat{\gamma}^R_{Direct}$	502	13	649
		(340,683)	(-44,122)	(466,854)
Indirect effect (reg)	$\hat{\gamma}^R_{Indirect}$	116	106	100
		(107,122)	(68,158)	(93,106)
Indirect effect (unreg)	$\hat{\gamma}^U_{Indirect}$	397	426	361
		(379,422)	(279,649)	(349,370)

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

Table 3.3: Regression results: low-carbon patents on predictors including emissions permit price. Direct and indirect effect size estimates omitted for brevity.

		Pooled	Presample
Log total knowledge	$ln(K_t)$	0.089	0.083
		(0.124)	(0.122)
	$ln(K_{t-1})$	-0.032	0.011
		(0.173)	(0.170)
	$ln(K_{t-2})$	0.061	0.066
		(0.126)	(0.124)
No own knowledge	$\mathbb{1}(k_{it} = 0)$	-1.220***	-1.216***
		(0.032)	(0.031)
	$\mathbb{1}(k_{it-1} = 0)$	-0.807***	-0.826***
		(0.033)	(0.032)
	$\mathbb{1}(k_{it-2} = 0)$	-0.463***	-0.514***
		(0.033)	(0.032)
Log own knowledge	$ln(k_{it})$	0.780***	0.754***
		(0.017)	(0.017)
	$ln(k_{it-1})$	0.102***	0.090***
		(0.020)	(0.019)
	$ln(k_{it-2})$	0.072***	0.012
		(0.017)	(0.018)
Permit price	τ_{t-1}	0.005	0.003
		(0.004)	(0.004)
Permit price x Belgium	$\tau_{t-1} * \mathbb{1}(Belgium)$	0.021**	0.020**
		(0.008)	(0.008)
Permit price x Germany	$\tau_{t-1} * \mathbb{1}(Germany)$	0.004	0.004
		(0.003)	(0.003)
Permit price x Denmark	$\tau_{t-1} * \mathbb{1}(Denmark)$	0.030***	0.032***
		(0.008)	(0.007)
Permit price x Spain	$\tau_{t-1} * \mathbb{1}(Spain)$	0.024**	0.023**
		(0.008)	(0.007)
Permit price x Italy	$\tau_{t-1} * \mathbb{1}(Italy)$	0.011*	0.009.
		(0.005)	(0.005)
Permit price x UK	$\tau_{t-1} * \mathbb{1}(UK)$	0.036***	0.036***
		(0.006)	(0.005)
Regulatory status	T_{it-1}	0.089*	0.129***
		(0.035)	(0.034)

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

Table 3.4: Regression results: low-carbon patents on predictors, with sample restricted to unregulated firms. All estimates use presample mean estimator to account for unobserved heterogeneity.

		Presample
Log total knowledge	$ln(K_t)$	-0.093
		(0.131)
	$ln(K_{t-1})$	0.300
		(0.195)
	$ln(K_{t-2})$	-0.190
		(0.140)
No own knowledge	$\mathbb{1}(k_{it} = 0)$	-1.210***
		(0.031)
	$\mathbb{1}(k_{it-1} = 0)$	-0.841***
		(0.032)
	$\mathbb{1}(k_{it-2} = 0)$	-0.500***
		(0.032)
Log own knowledge	$ln(k_{it})$	0.782***
		(0.018)
	$ln(k_{it-1})$	0.064**
		(0.021)
	$ln(k_{it-2})$	0.019
		(0.019)
Log elec price	$ln(w^{elec}_{ct-1})$	0.574***
		(0.126)

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

Table 3.5: Regression results: low-carbon patents on predictors, including cross-country electricity price effects. All estimates use presample mean estimator to account for unobserved heterogeneity.

		Presample
Log total knowledge	$ln(K_t)$	-0.078
		(0.124)
	$ln(K_{t-1})$	0.508**
		(0.192)
	$ln(K_{t-2})$	-0.440**
		(0.142)
No own knowledge	$\mathbb{1}(k_{it} = 0)$	-1.218***
		(0.031)
	$\mathbb{1}(k_{it-1} = 0)$	-0.829***
		(0.032)
	$\mathbb{1}(k_{it-2} = 0)$	-0.512***
		(0.032)
Log own knowledge	$ln(k_{it})$	0.755***
		(0.017)
	$ln(k_{it-1})$	0.087***
		(0.019)
	$ln(k_{it-2})$	0.011
		(0.018)
Log own elec price	$ln(w^{elec}_{ct-1})$	0.625***
		(0.121)
Log other elec price	$ln(w^{elec}_{c't-1})$	0.469**
		(0.152)
Regulatory status	T_{it-1}	0.140***
		(0.034)

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

Table 3.6: Regression results: low-carbon patents on predictors, including household electricity price effects. All estimates use presample mean estimator to account for unobserved heterogeneity.

		Presample
Log total knowledge	$ln(K_t)$	-0.054
		(0.124)
	$ln(K_{t-1})$	0.318.
		(0.186)
	$ln(K_{t-2})$	-0.221
		(0.136)
No own knowledge	$\mathbb{1}(k_{it} = 0)$	-1.227***
		(0.032)
	$\mathbb{1}(k_{it-1} = 0)$	-0.839***
		(0.033)
	$\mathbb{1}(k_{it-2} = 0)$	-0.505***
		(0.032)
Log own knowledge	$ln(k_{it})$	0.754***
		(0.017)
	$ln(k_{it-1})$	0.084***
		(0.020)
	$ln(k_{it-2})$	0.011
		(0.018)
Log own elec price	$ln(w_{ct-1}^{elec,Industry})$	0.401*
		(0.166)
Log household elec price	$ln(w_{ct-1}^{elec,Household})$	0.469*
		(0.213)
Regulatory status	T_{it-1}	0.138***
		(0.034)

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

Table 3.7: Regression results: low-carbon patents on predictors, including one year lag of patent output as knowledge stock proxy. All estimates use presample mean estimator to account for unobserved heterogeneity.

		Presample
Log total knowledge	$ln(K_t)$	-0.044
		(0.058)
No own knowledge	$ln(K_{t-1})$	-1.672***
		(0.027)
Log own knowledge	$\mathbb{1}(k_{it} = 0)$	1.006***
		(0.010)
Log elec price	$ln(k_{it})$	0.552***
		(0.113)
Regulatory status	$ln(w^{elec}_{ct-1})$	0.107**
		(0.035)

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

Table 3.8: Regression results: low-carbon patents on predictors, including multiple lags of electricity price. All estimates use presample mean estimator to account for unobserved heterogeneity.

		Presample
Log total knowledge	$ln(K_t)$	-0.006
		(0.128)
	$ln(K_{t-1})$	0.363.
		(0.187)
	$ln(K_{t-2})$	-0.324*
		(0.139)
No own knowledge	$\mathbb{1}(k_{it} = 0)$	-1.222***
		(0.031)
	$\mathbb{1}(k_{it-1} = 0)$	-0.830***
		(0.032)
	$\mathbb{1}(k_{it-2} = 0)$	-0.514***
		(0.032)
Log own knowledge	$ln(k_{it})$	0.754***
		(0.017)
	$ln(k_{it-1})$	0.088***
		(0.019)
	$ln(k_{it-2})$	0.009
		(0.018)
Log own elec price	$ln(w^{elec}_{ct-1})$	0.816***
		(0.184)
	$ln(w^{elec}_{ct-2})$	-0.254
		(0.203)
	$ln(w^{elec}_{ct-3})$	0.064
		(0.146)
Regulatory status	T_{it-1}	0.138***
		(0.034)

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

Table 3.9: Regression results: low-carbon patents on predictors, including future electricity price. All estimates use presample mean estimator to account for unobserved heterogeneity.

		Presample
Log total knowledge	$ln(K_t)$	-0.177
		(0.126)
	$ln(K_{t-1})$	0.170
		(0.145)
No own knowledge	$\mathbb{1}(k_{it} = 0)$	-1.372***
		(0.031)
	$\mathbb{1}(k_{it-1} = 0)$	-1.071***
		(0.031)
Log own knowledge	$ln(k_{it})$	0.751***
		(0.018)
	$ln(k_{it-1})$	0.134***
		(0.018)
Log elec price	$ln(w^{elec}_{ct-1})$	0.594***
		(0.135)
Log future elec price	$ln(w^{elec}_{ct+1})$	-0.027
		(0.135)
Regulatory status	T_{it-1}	0.131***
		(0.038)

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

Appendix A

Appendix

A.1 Appendix - Chapter 1

The following lemma will be useful in the proofs of multiple results and propositions:

Lemma 1 *Let $n^*(\omega)$ be the largest integer n_t satisfying*

$$ln(n_t) \leq \omega\, ln\left(1 + \frac{1}{\omega + N - n_t}\right).$$

Then $n^*(\omega)$ is non-decreasing in ω, i.e. $n^*(\omega_2) \geq n^*(\omega_1)$ for $\omega_2 > \omega_1$.

Proof: First, fix n_t at the largest integer which satisfies the inequality, and consider the partial derivative of the right hand side of the inequality with respect to ω:

$$\frac{\partial}{\partial\omega}\omega\, ln\left(1 + \frac{1}{\omega + N - n_t}\right) = ln\left(1 + \frac{1}{\omega + N - n_t}\right) - \frac{\omega}{(\omega + N - n_t)(\omega + N - n_t + 1)}$$

An established bound for the natural log is $ln(1+x) \geq \frac{x}{1+x}$. Applying this to the partial derivative yields:

$$\frac{\partial}{\partial\omega}\omega\, ln\left(1 + \frac{1}{\omega + N - n_t}\right) \geq \frac{\frac{1}{\omega+N-n_t}}{1 + \frac{1}{\omega+N-n_t}} - \frac{\omega}{(\omega + N - n_t)(\omega + N - n_t + 1)}.$$

Algebra on the right side yields

$$\frac{\partial}{\partial\omega}\omega\, ln\left(1 + \frac{1}{\omega + N - n_t}\right) \geq \frac{1}{\omega + N - n_t + 1}\left(1 - \frac{\omega}{\omega + N - n_t}\right)$$

Both terms on the right hand side are positive, yielding $\frac{\partial}{\partial\omega}\left(1 + \frac{1}{\omega+N-n_t}\right)^{\omega} > 0$. Thus, if $n^*(\omega_1)$ satisfies the inequality at ω_1, it will satisfy the inequality at $\omega_2 > \omega_1$. Since $n^*(\omega_2)$ is the largest integer satisfying the inequality at ω_2, $n^*(\omega_2)$ can be no smaller than $n^*(\omega_1)$, i.e. $n^*(\omega_2) \geq n^*(\omega_1)$. ■

Proof of Result 1

Proof: (i) Consider the stability condition (1.18). It can be shown that $ln(1+x) \leq x$ (use the concavity of $ln(\cdot)$). As a result, $ln\left(1 + \frac{1}{\delta A_L + N - n_t + 1}\right) \leq \frac{1}{\delta A_L + N - n_t + 1}$. Use this result to bound the right hand side of (1.18):

$$ln(n_t) \leq (1 + \delta A_L)\, ln\left(1 + \frac{1}{\delta A_L + N - n_t + 1}\right) \leq \frac{1 + \delta A_L}{\delta A_L + N - n_t + 1}$$

Since $N \geq n_t$, the rightmost fraction is necessarily less than or equal one. However, since $ln(n_t) > 1$ for $n_t \geq 3$, the stability condition is violated for $n_t \geq 3$. As a result, $n_t^* \leq 2$.

(ii) Stability condition (1.18) can be rewritten as

$$n_t \leq \left(1 + \frac{1}{1 + \delta A_L + N - n_t}\right)^{1+\delta A_L},$$

which is of the form of the inequality in Lemma 1, with $\omega = 1 + \delta A_L$. Note that

$$\frac{\partial}{\partial b_L}(1 + \delta A_L) = \frac{\partial}{\partial b_L}\frac{\delta}{1 - \delta(1 - b_L)} = -\frac{\delta^2}{(1 - \delta(1 - b_L))^2} < 0.$$

Applying Lemma 1, an increase in b_L causes a decrease in ω, which can only destabilize the coalition. As a result, n_L^* is non-increasing in b_L. ■

Proof of Proposition 1

Proof: The proof is analogous to that for Result 1, with A_L replaced by $\bar{A}$. Consider the stability condition (1.28). Note that the term $ln\left(1 + \frac{1}{\delta \bar{A} + N - n_t + 1}\right)$ is again of the form $ln(1 + x)$. It can be shown that $ln(1 + x) \leq x$ (use the concavity of $ln(\cdot)$). As a result, $ln\left(1 + \frac{1}{\delta \bar{A} + N - n_t + 1}\right) \leq \frac{1}{\delta \bar{A} + N - n_t + 1}$. Use this result to bound the right hand side of (1.28):

$$ln(n_t) \leq \left(1+\delta\bar{A}\right) ln\left(1+\frac{1}{\delta\bar{A}+N-n_t+1}\right) \leq \frac{1+\delta\bar{A}}{\delta\bar{A}+N-n_t+1}$$

Since $N \geq n_t$, the rightmost fraction is necessarily less than or equal one. However, since $ln(n_t) > 1$ for $n_t \geq 3$, the stability condition is violated for $n_t \geq 3$. As a result, $n_t^* \leq 2$. ■

Proof of Proposition 2

Proof: We show first that (i) an increase in $\bar{\rho}$ cannot destabilize a stable coalition, and then that (ii) there exist some increases in $\bar{\rho}$ that cause the n_H^* to increase.
(i) The stability condition (1.28) is again of the form in Lemma 1, with $\omega = 1+\delta\bar{A}$. We are interested in the sign of $\frac{\partial\omega}{\partial\bar{\rho}}$. Using the definitions of A_H and A_L, and $\bar{A}$, we can write $\bar{A}$ as

$$\bar{A} = \frac{1-\delta(1-b_L)+\bar{\rho}\left(\frac{b_H-b_L}{1-b_H}+\delta(1-b_L)\right)}{1-\delta(1-\bar{\rho})(1-b_H)}\frac{1-b_H}{1-\delta(1-b_L)}$$

The sign of $\frac{\partial\omega}{\partial\bar{\rho}}$ is the same as the sign of $\frac{\partial\bar{A}}{\partial\bar{\rho}}$. Since the second fraction in the expression for $\bar{A}$ is constant with respect to $\bar{\rho}$, we consider only the partial of the first fraction. Applying the quotient rule and rearranging the numerator, we are interested in the sign of

$$\frac{\left[\delta(1-b_L)+\frac{b_H-b_L}{1-b_H}\right]\left[1-\delta(1-b_H)\right]-\left[\delta(1-b_H)\right]\left[1-\delta(1-b_L)\right]}{(1-\delta(1-\bar{\rho})(1-b_H))^2}.$$

The denominator is clearly positive, so we need only determine the sign of the numerator. Since $b_H > b_L$, $\delta(1-b_L) > \delta(1-b_H)$, and the first term is larger than the third. Similarly, $b_H > b_L \Rightarrow 1 - \delta(1 - b_H) > 1 - \delta(1 - b_L)$, and the second term is larger than the fourth. As a result, the entire expression is positive, and thus $\frac{\partial \omega}{\partial \bar{\rho}} > 0$. Applying Lemma 1, this implies that an increase in $\bar{\rho}$ cannot destabilize the coalition, and thus an increase in $\bar{\rho}$ will never decrease the stable coalition size.

(ii) To demonstrate that the introduction of exogenous threat can indeed make a coalition of size 2 stable when it would not be in the absence of threat, consider the case where $N = 3, b_H = 0.9, b_L = 0.1$, and $\delta = 0.95$. At $\bar{\rho} = 0$, the coalition of size 2 is not internally stable. When $\bar{\rho} = 0.5$, the coalition of size 2 is stable. ■

Proof of Proposition 3

Proof: Denote by n_H^*, h_{jt}, and h_{it} the equilibria coalition size, harvest rate for a non-member, and harvest rate for a member obtained under the threat of regime shift. Clearly, the outcome of the no-shift case is given by $\tilde{n}_H^* = n_{H|\bar{\rho}=0}$, $\tilde{h}_{jt} = h_{jt|\bar{\rho}=0}$, and $\tilde{h}_{it} = h_{it|\bar{\rho}=0}$. In addition, as long as the second condition in (1.31) holds, we have $\tilde{n}_H^* = 1$, $n_H^* = 2$, and $N \geq 3$.

Using (1.24) and (1.25), we derive

$$h_{jt} - \tilde{h}_{jt} = \frac{g(S_t, H)(1 + \delta(\tilde{A}_H - \bar{A}))}{(\delta \tilde{A}_H + N)[N - 1 + \delta \bar{A}]}, \tag{A.1}$$

$$h_{it} - \tilde{h}_{it} = \frac{g(S_t, H)(2 - N + \delta(\tilde{A}_H - 2\bar{A}))}{(\delta \tilde{A}_H + N)[N - 1 + \delta \bar{A}]}, \tag{A.2}$$

where $\tilde{A}_H = \bar{A}_{H|\bar{\rho}=0}$. Since $\tilde{A}_H, \bar{A} > 0$, then (A.1) suggests that $h_{jt} > \tilde{h}_{jt}$ if and only if $1 + \delta(\tilde{A}_H - \bar{A}) > 0$. It can be shown that $1 > \delta(\tilde{A}_H - \bar{A})$ if and only if $\bar{\rho} < \bar{\rho}^R$, where $\bar{\rho}^R$ is given in (1.32).

As shown in the proof of Proposition 2, we have $\frac{\partial \bar{A}}{\partial \bar{\rho}} > 0$, which implies $\bar{A} > \tilde{A}_H =$

$\bar{A}_{|\bar{\rho}=0}$. Using this result along with (A.2) and the fact that $N \geq 3$, we get $h_{it} < \tilde{h}_{it}$. ■

Proof of Result 2

Proof: We are interested in the sign of $\frac{\partial H_t(S_t,H)}{\partial \bar{\rho}} = \frac{\partial}{\partial \bar{\rho}}\left(n_H^* h_{it}^* + (N - n_H^*)h_{jt}^*\right) = \frac{\partial}{\partial \bar{\rho}}(N - n_H^* + 1)\frac{g(S_t,H)}{\delta \bar{A} + N - n_H^* + 1}$. Since $g(S_t, H)$ is independent of $\bar{\rho}$, we need only consider the sign of $\frac{\partial}{\partial \bar{\rho}}\frac{N - n_H^* + 1}{\delta \bar{A} + N - n_H^* + 1}$. By the quotient rule,

$$\begin{aligned}\frac{\partial}{\partial \bar{\rho}}\frac{N - n_H^* + 1}{\delta \bar{A} + N - n_H^* + 1} =& \frac{-\frac{\partial n_H^*}{\partial \bar{\rho}}\left(\delta \bar{A} + N - n_H^* + 1\right) - (N - n_H^* + 1)\left(\delta \frac{\partial \bar{A}}{\partial \bar{\rho}} - \frac{\partial n_H^*}{\partial \bar{\rho}}\right)}{\left(\delta \bar{A} + N - n_H^* + 1\right)^2} \\ =& - \delta \frac{\frac{\partial n_H^*}{\partial \bar{\rho}}\bar{A} + (N - n_H^* + 1)\frac{\partial \bar{A}}{\partial \bar{\rho}}}{\left(\delta \bar{A} + N - n_H^* + 1\right)^2}\end{aligned}$$

By Result 1, $\frac{\partial n_H^*}{\partial \bar{\rho}} \geq 0$. Similarly, from the proof of Result 1, $\frac{\partial \bar{A}}{\partial \bar{\rho}} > 0$. Since all other terms in the fraction are positive, the entire fraction is positive, and as such the right hand side is negative, and thus $\frac{\partial H}{\partial \bar{\rho}} < 0$. ■

Proof of Proposition 5

Proof: The stability condition in the doomsday scenario can be written as

$$n_H^{*DD} \leq \left(1 + \frac{1}{\frac{1}{1-\delta(1-\bar{\rho})(1-b_H)} + N - n_H^{*DD}}\right)^{\frac{1}{1-\delta(1-\bar{\rho})(1-b_H)}}. \tag{A.3}$$

This condition is again of the form used in Lemma 1, with $\omega = \frac{1}{1-\delta(1-\bar{\rho})(1-b_H)}$. In this case, ω is clearly decreasing in $\bar{\rho}$, and by Lemma 1, $n_H^{*DD}(\bar{\rho})$ is non-increasing in $\bar{\rho}$. ■

Proof of Proposition 6

Proof: (*i*) The second part of condition (1.35) corresponds directly to the stability conditions for the doomsday and no-shift cases, and requires that the coalition of size two is stable in the no-shift case and full non-cooperation prevails in the doomsday scenario. (*ii*) Denote by $\tilde{h}_{jt}$ the harvest rate obtained under the no-shift case. Using (1.25) and result (*i*), we derive

$$h_{jt} - \tilde{h}_{jt} = \frac{g(S_t, H)[-1 + \delta(\tilde{A}_H - \bar{A}^{DD})]}{(\delta\bar{A} + N)(\delta\tilde{A}_H + N - 1)}.$$

It can be shown that $-1+\delta(\tilde{A}_H - \bar{A}^{DD}) < 0$ if and only if the first condition in (1.35) holds. The result then follows. ■

Proof of Result 3

Proof: Total harvest prior to the occurrence of a doomsday event can be written

$$H_H^* = (N - n_H^*)h_j^* + n_H^* h_i^* = \frac{(N - n_H^* + 1)\, g(S_t, H)}{\delta\bar{A} + N - n_H^* + 1}$$

By Proposition 5, we know $n_H^*(0) > n_H^{*DD}(\bar{\rho})$ for $\bar{\rho} > 0$. This reduction in coalition size tends to increase total harvest. The other difference between the no-threat case and the doomsday scenario is the change in $\bar{A}$. In particular, we may compare $\bar{A}^{DD}$ at $\bar{\rho}$ and $\rho = 0$. $\bar{A}^{DD}$ can be written

$$\bar{A}^{DD} = (1 - \bar{\rho})\frac{1 - b_H}{1 - \delta(1 - \bar{\rho})(1 - b_H)}$$

The right hand side is clearly decreasing in $\bar{\rho}$, such that $\bar{A}^{DD}(\bar{\rho}) < \bar{A}^{DD}(0)$. Further, H_H^* is decreasing in $\bar{A}^{DD}$, so that an increase in $\bar{\rho}$ (including from 0 to $\bar{\rho} > 0$) causes H_H^* to increase.

Since both effects act in the same direction, total harvest is higher under the doomsday scenario than the productivity shift scenario. ■

A.2 Appendix - Chapter 2

A.2.1 Representing Trip Limits in Spatial Effort Model

As explained in the text, the probability that a trip limit will constrain harvester i's effort in patch j depends: negatively on the actual catch limits that the regulation imposes for each species; positively on i's harvests of each species in other patches; and positively on the density of each species in patch j. In turn, the density of each species in patch j depends positively on the stock densities in the absence of fishing and negatively on the effort other fishers apply there. Finally, the probability a trip limit will constrain fishing effort must lie in the unit interval. The following function, Ψ_{jt}, has each of the desired properties:

$$\Psi_{jt} = (1 - IFQ_t)e^{-\alpha q \bar{T}_{jt}}, \tag{A.4}$$

where

$$\bar{T}_{jt} = \min_s \frac{n_{jt}\bar{Q}_{jst}}{CPUE^0_{jst}}. \tag{A.5}$$

$\bar{Q}_{jet}$ is the species s trip limit for each harvester, $\alpha > 0$, q was defined earlier, n_{jt} is the number of vessels with experience fishing in patch j, and IFQ_t is an indicator variable taking the value 1 if the fishery is under IFQ management in period t. (Recall that trip limits for most species were removed with the introduction of IFQs).

To see the intuition for this proxy, consider a special case in which n_{jt} identical fishers visit patch j in period t and these harvesters catch species s only in patch j. In this case the trip limit prohibits the group's aggregate catch of species s from exceeding $n_{jt}\ \bar{Q}_{jet}$. Dividing this by catch per unit effort for species s on patch j translates the aggregate catch limit into an aggregate effort limit that is linked to the trip limit for species s. However, there are trip limits for several species and the individual must cease fishing if any of these binds. Accordingly, the implied effort limit is the minimum of these species-specific limits. The proxy function Ψ_{jt} in equation (A.4) scales this maximal effort limit by the parameter α and maps it to the unit interval. If $\alpha < 1$ the scaling spreads maximal effort level across several cells, relaxing the assumption that all species with trip limits are caught only in patch j.

The variable $\bar{T}_{jt}$ is computed from (A.5) for each data point and the result is incorporated into (A.4), the proxy for the probability that a trip limit binds for patch j. The estimating equation is expressed in terms of the probability that a trip limit does not bind, $(1 - \Psi_{jt})$. Inserting this into equation (2.5) yields

$$T_{jt} = \frac{1}{q} ln \left(\frac{(p_t - c_t)(1 - \Psi_{jt}) \cdot E\left[CPUE^0_{jt}\right]}{VC_{jt} + \bar{\pi}_t} \right) + \frac{1}{q}\epsilon_{jt}. \tag{A.6}$$

This is the equation actually estimated. The parameter α is estimated along with other parameters in the model. The proxy is viewed less as a literal probability than as a general indicator of the likely severity of trip limits for fishing decisions on each patch. Equation (A.6) is estimating equation used to examine spatial avoidance of bycatch.

A.2.2 Estimation Strategy for Spatial Effort Model

We estimate a variant of equation (2.5) in the text, with trip limits incorporated as given by equations (A.4), (A.5), and (A.6) above. As mentioned in the text, the outcome variable T_{jt} is necessarily non-negative, suggesting a censored data estimation approach similar to Tobit. Let the first term on the right hand side of (A.6) be denoted T^*_{jt}. Then the likelihood of T_{jt} is simply

$$L(T_{jt}) = \left[P(T^*_{jt} > 0) f(T_{jt} | T^*_{jt} > 0)\right]^{\mathbf{1}(T_{jt}>0)} \left[P(T^*_{jt} \leq 0\right]^{\mathbf{1}(T_{jt}=0)}, \tag{A.7}$$

where $\mathbf{1}(\cdot)$ denotes an indicator function. As with a standard Tobit, the component probabilities and densities in this likelihood are based on the normal distribution (recall our assumption that the error term is normally distributed). The difference between this and a standard Tobit is that the relevant normal distributions do not have means that are a linear function of parameters. Instead, the means are a nonlinear function of parameters as given by the first term in equation (A.6). Regardless, the sum across all observations of the log of (A.7) can be maximized numerically as with a standard Tobit.

A.2.3 Corrections to Expected Catch Per Unit Effort for 2011, 2012

The baseline proxy we use for expected catch per unit effort in patch j in period t is based on actual catch per unit effort in j during the same two-month season in the prior two years. Our evidence on non-spatial adjustments indicates that fishers can influence CPUE in response to IFQs. If fishers anticipate such changes in CPUE, then our baseline proxy in 2011 and 2012 must be adjusted to better reflect fishers' expectations. In particular, we require a way to identify systematic changes in CPUE that fishers could anticipate at the start of a period in 2011 and 2012 and update our CPUE proxy based on those expected changes to CPUE. Based on equation (2.3), changes to expected CPUE under IFQs come from changes to vulnerability f under a new fishing method a_{kjt}. We are interested in the effect of that change in vulnerability on the start-of-period CPUE for each combination of species, patch, and period under IFQs. The ratio of start-of-period CPUE for species s under IFQs to that under pre-IFQ management can be written

$$\frac{CPUE^0_{ksjt}}{CPUE^0_{k'sjt}} = \frac{qf_s(a_{kjt})X^0_{jst}}{qf_s(a_{k'jt})X^0_{jst}} = \frac{f_s(a_{kjt})}{f_s(a_{k'jt})} \tag{A.8}$$

where k represents the optimal fishing method under IFQs, and k' represents the optimal method prior to IFQs. If fishers anticipate these changes, then we may replace CPUEs with their expectations and rearrange (A.8) to give

$$E[CPUE^0_{ksjt}] = \frac{f_s(a_{kjt})}{f_s(a_{k'jt})} E[CPUE^0_{k'sjt}] \tag{A.9}$$

Equation (A.9) forms the basis for our expected CPUE proxy adjustment in 2011 and 2012. The expectation on the right hand side is our baseline proxy that uses lagged data. The ratio of vulnerabilities is a correction factor that we seek to estimate. To do so, we regress actual CPUE under IFQs against our baseline proxy, doing so separately for 2011 and 2012. The estimated coefficient on our proxy variable in that regression represents the expected CPUE correction factor we seek. We multiply those coefficients by our original proxy to get an updated proxy for expected CPUE for 2011 and 2012.

It is important to note that we only apply this updating process for coefficient estimates that are significant in the regression based on (A.9). Significant coefficients represent systematic changes to CPUE, and we argue it is those changes to vulnerability that fishers might have anticipated when making location decisions. Insignificant coefficients indicate that fishers could not reliably alter their CPUE of that species in response to IFQs. Given that fishers could not actually achieve systematic CPUE changes, we have no reason to believe that fishers would have expected to achieve CPUE changes. As such, for those species, we leave our baseline expected CPUE proxy untouched.

A.3 Appendix - Chapter 3

A.3.1 Deriving cost pass-through

Since w^R is an endogenously determined price that depends upon regulated firm output, the effect of τ on w^R acts solely through output decisions of regulated firms. Further, since $w^R = P(X^{R*})$, we may write

$$\frac{\partial w^R}{\partial \tau} = \sum_{i:S_i=R} \frac{\partial w^R}{\partial x_i^{R*}} \frac{\partial x_i^{R*}}{\partial \tau} = N^R P'(X^{R*}) \frac{\partial x_i^{R*}}{\partial \tau}. \tag{A.10}$$

Next, we can derive an expression for $\frac{\partial x_i^{R*}}{\partial \tau}$ through total differentiation of (3.8). Rearranging the result of that differentiation yields $\frac{\partial x^{R*}}{\partial \tau}$, which can be substituted into (A.10) to yield (3.10).

A.3.2 Signing cost pass-through

Differentiate (3.8) with respect to the output of some other firm j:

$$P''(X^{R*})x_i^{R*} + P'(X^{R*})\frac{\partial x_i^{R*}}{\partial x_j^R} + P'(X^{R*}) = c_{xx}(x_i^{R*}, w)\frac{\partial x_i^{R*}}{\partial x_j^R} + \tau e_{xx}(x_i^{R*}, k_i^R)\frac{\partial x_i^{R*}}{\partial x_j^R}$$

and solve for $\frac{\partial x_i^{R*}}{\partial x_j^R}$:

$$\frac{\partial x_i^{R*}}{\partial x_j^R} = -\frac{P''(X^{R*})x_i^{R*} + P'(X^{R*})}{P'(X^{R*}) - c_{xx}(x_i^{R*}, w) - \tau e_{xx}(x_i^{R*}, k_i^R)}$$

Equilibrium stability requires the entire expression to be negative: reaction functions should be downward sloping (see Seade (1980)). Since the denominator is negative under the maintained assumptions, stability requires $P''(X^{R*})x_i^{R*} + P'(X^{R*}) < 0$.

Similarly, the firm's second-order condition for output requires for a maximum that

$$P''(X^{R*})x_i^{R*} + 2P'(X^{R*}) - c_{xx}(x_i^{R*}, w) - \tau e_{xx}(x_i^{R*}, k_i^R) < 0 \tag{A.11}$$

Summing $(N-1)$ times the stability condition plus the second order condition yields the denominator in (3.10). Since it is the sum of negative components, that denominator is negative. As a result, cost pass-through is positive provided that the equilibrium is stable. Note that the denominator captures the change in marginal profits that occur from a simultaneous marginal increase in quantity by all firms. If marginal profits increased in such a case at some equilibrium profile of quantity choices, the equilibrium could not be stable.

A.3.3 Derivation of optimal R&D choices

Derivation of R&D incentives follows Leahy and Neary (1997). The first-order condition for R&D by unregulated firm j is then

$$\frac{\partial \pi_j^{U*}}{\partial k_j^U}\frac{\partial k_j^U}{\partial r_j^U} + \sum_{l \neq j} \frac{\partial \pi_j^{U*}}{\partial x_l^{U*}}\frac{\partial x_l^{U*}}{\partial r_j^U} = 1. \tag{A.12}$$

Thus, the unregulated firm accounts for the direct effect of augmented knowledge on its own profits, but must also account for the effect of its R&D on second period output choices of other unregulated firms. Note, however, that this expression does not include an effect of r_j^U on profits through output choices of regulated firms. In keeping with the assumption that unregulated firms are price takers, unregulated firms assume that their R&D will not impact output decisions of regulated firms (and hence the equilibrium price w^R).

Note that by the envelope theorem, $\frac{\partial \pi_j^{U*}}{\partial k_j^U} = -w^R D_k^R$, and by the knowledge dynamics, $\frac{\partial k_j^U}{\partial r_j^U} = f_r^U$. In addition, $\frac{\partial \pi_j^{U*}}{\partial x_l^{U*}} = P' x_j^{U*}$. For a symmetric equilibrium, we may rewrite (A.12) as

$$-w^R D_k^R f_r^U + (N^U - 1) P' x_{j2}^{U*} \frac{\partial x_l^{U*}}{\partial r_j^U} = 1. \tag{A.13}$$

To derive $\frac{\partial x_l^{U*}}{\partial r_j^U}$, we start with the first order conditions defining x_l^{U*} and x_j^{U*}, and consider a shock that affects output decisions of all unregulated firms and R&D of unregulated firm j. Totally differentiate both first order conditions(except hold r_l^U, $l \neq j$, and w^R constant), substitute for x_j^{U*} from the differentiation of x_j^{U*} into the result for x_l^{U*}, and rearrange. Letting π_{lj}^{Uj} denote the second order partial derivative of profits by firm j with respect to output of unregulated firms l and j, differentiation yields:

$$\begin{aligned} \pi_{jj}^{Uj} dx_j^U + (N^U - 1)\pi_{lj}^{Uj} dx_l^U + \frac{\partial \pi_j^{Uj}}{\partial k_j^U} f_r^U dr_j^U &= 0, \\ \pi_{ll}^{Ul} dx_l^U + \pi_{jl}^{Ul} dx_j^U + (N^U - 2)\pi_{l'l}^{Ul} dx_{l'}^U + \frac{\partial \pi_l^{Ul}}{\partial k_j^U} f_{R^U}^U dr_j^U &= 0. \end{aligned}$$

Assuming symmetry of the equilibrium prior to the shock (i.e. $dx_l^U = dx_{l'}^U$, $\pi_{l'l}^{Ul} = \pi_{jl}^{Ul} = \pi_{lj}^{Uj}$, $\pi_{jj}^{Uj} = \pi_{ll}^{Ul}$, and $\frac{\partial \pi_j^{Uj}}{\partial k_j^U} = -w^R D_k^R$), solving these two equations and rearranging yields:

$$\frac{dx_l^U}{dr_j^U} = \frac{\pi_{jj}^{Uj}\left(f_{R^U}^U - \frac{\pi_{lj}^{Uj}}{\pi_{jj}^{Uj}} f_r^U\right) w^R D_k^R}{\left(\pi_{jj}^{Uj} - \pi_{lj}^{Uj}\right)\left(\pi_{jj}^{Uj} + (N^U - 1)\pi_{lj}^{Uj}\right)}. \tag{A.14}$$

Substituting (A.14) into (A.13) and factoring out $-f_r^U w^R D_k^R$ yields (3.14).

Bibliography

Acemoglu, D., 2002. Directed technical change. The Review of Economic Studies 69 (4), 781–809.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., Reenen, J. V., December 2012. Carbon taxes, path dependency and directed technical change: Evidence from the auto industry. Working Paper 18596, National Bureau of Economic Research.
URL `http://www.nber.org/papers/w18596`

Arnason, R., 2012. Property rights in fisheries: How much can individual transferable quotas accomplish? Review of Environmental Economics and Policy 6 (2), 217–236.

Aronow, P. M., Samii, C., 2012. Estimating average causal effects under general interference. In: Summer Meeting of the Society for Political Methodology, University of North Carolina, Chapel Hill, July. Citeseer, pp. 19–21.

Baker, E., Shittu, E., 2006. Profit-maximizing r&d in response to a random carbon tax. Resource and Energy Economics 28 (2), 160–180.

Bellman, M. A., Heery, E., Hastie, J., 2008. Estimated discard and total catch of selected groundfish species in the 2007 us west coast fisheries. Online report available at: http://www. nwfsc. noaa. gov/research/divisions/fram/observer/datareport/docs/TotalMorta lity_update2007. pdf.

Blundell, R., Griffith, R., Reenen, J. V., 1995. Dynamic count data models of technological innovation. The Economic Journal 105 (429), 333–344.
URL `http://www.jstor.org/stable/2235494`

Boyce, J. R., 1996. An economic analysis of the fisheries bycatch problem. Journal of Environmental Economics and Management 31 (3), 314–336.

Breen, P. A., Sykes, D. R., Starr, P. J., Kim, S., Haist, V., 2009. A voluntary reduction in the commercial catch of rock lobster (jasus edwardsii) in a new zealand fishery. New Zealand Journal of Marine and Freshwater Research 43 (1), 511–523.
URL `http://www.tandfonline.com/doi/abs/10.1080/00288330909510018`

Brunnermeier, S. B., Cohen, M. A., 2003. Determinants of environmental innovation in {US} manufacturing industries. Journal of Environmental Economics and Management 45 (2), 278 – 293.
URL http://www.sciencedirect.com/science/article/pii/S009506960200058X

Burtraw, D., Palmer, K., Bharvirkar, R., Paul, A., 2001. Cost-effective reduction of nox emissions from electricity generation. Journal of the Air & Waste Management Association 51 (10), 1476–1489.

Bushnell, J. B., Chong, H., Mansur, E. T., 2013. Profiting from regulation: Evidence from the european carbon market. American Economic Journal: Economic Policy 5 (4), 78–106.

Calel, R., Dechezleprêtre, A., 2014. Environmental policy and directed technological change: Evidence from the european carbon market. Review of economics and statistics(Forthcoming).

Cameron, A. C., Trivedi, P. K., 1998. Regression analysis of count data. No. 53. Cambridge university press.

Cheung, S. N., 1970. The structure of a contract and the theory of a non-exclusive resource. Journal of Law and Economics, 49–70.

Clark, C. W., Kirkwood, G. P., 1986. On uncertain renewable resource stocks: Optimal harvest policies and the value of stock surveys. Journal of Environmental Economics and Management 13 (3), 235–244.
URL http://www.sciencedirect.com/science/article/pii/0095069686900240

Clarke, H. R., Reed, W. J., 1994. Consumption/pollution tradeoffs in an environment vulnerable to pollution-related catastrophic collapse. Journal of Economic Dynamics and Control 18, 991–1010.

Collie, J. S., Richardson, K., Steele, J. H., 2004. Regime shifts: Can ecological theory illuminate the mechanisms? Progress in Oceanography 60 (2?4), 281 – 302.
URL http://www.sciencedirect.com/science/article/pii/S0079661104000321

Convery, F., Ellerman, A. D., De Perthuis, C., 2008. The european carbon market in action: Lessons from the first trading period interim report. Tech. rep., MIT Joint Program on the Science and Policy of Global Change.

Costello, C., Adams, R. M., Polasky, S., 1998. The value of el niño forecasts in the management of salmon: A stochastic dynamic assessment. American Journal of Agricultural Economics 80 (4), 765–777.

Costello, C., Gaines, S. D., Lynham, J., 2008. Can catch shares prevent fisheries collapse? Science 321 (5896), 1678–1681.

Costello, C., Polasky, S., 2008. Optimal harvesting of stochastic spatial resources. Journal of Environmental Economics and Management 56 (1), 1 – 18.
URL http://www.sciencedirect.com/science/article/pii/S0095069608000235

Cowan, S., 1993. Regulation of several market failures: the water industry in england and wales. Oxford Review of Economic Policy, 14–23.

Cox, D. R., 1958. Planning of experiments.

Cropper, M., 1976. Regulating activities with catastrophic environmental effects. Journal of Environmental Economics and Management 3 (1), 1 – 15.
URL http://www.sciencedirect.com/science/article/pii/0095069676900097

d'Aspremont, C., Jacquemin, A., Gabszewicz, J. J., Weymark, J. A., 1983. On the stability of collusive price leadership. Canadian Journal of economics 16 (1), 17–25.

de Zeeuw, A., Zemel, A., 2012. Regime shifts and uncertainty in pollution control. Journal of Economic Dynamics and Control 36 (7), 939–950.

Delarue, E., Voorspools, K., D'haeseleer, W., 2008. Fuel switching in the electricity sector under the eu ets: Review and prospective. Journal of Energy Engineering 134 (2), 40–46.

Fabra, N., Reguant, M., November 2013. Pass-through of emissions costs in electricity markets. Working Paper 19613, National Bureau of Economic Research.
URL http://www.nber.org/papers/w19613

Fesselmeyer, E., Santugini, M., 2013. Strategic exploitation of a common resource under environmental risk. Journal of Economic Dynamics and Control 37 (1), 125–136.
URL http://www.sciencedirect.com/science/article/pii/S0165188912001467

Fischer, C., Newell, R. G., 2008. Environmental and technology policies for climate mitigation. Journal of environmental economics and management 55 (2), 142–162.

Fischer, C., Parry, I. W., Pizer, W. A., 2003. Instrument choice for environmental protection when technological innovation is endogenous. Journal of Environmental Economics and Management 45 (3), 523–545.

Folke, C., Carpenter, S., Walker, B., Scheffer, M., Elmqvist, T., Gunderson, L., Holling, C. S., 2004. Regime shifts, resilience, and biodiversity in ecosystem management. Annual Review of Ecology, Evolution, and Systematics 35, 557–581.
URL http://www.jstor.org/stable/30034127

Gianessi, L. P., Peskin, H. M., Wolff, E., 1979. The distributional effects of uniform air pollution policy in the united states. The Quarterly Journal of Economics, 281–301.

Grafton, R. Q., Nelson, H. W., Turris, B., 2005. How to resolve the class ii common property problem? the case of british columbia's multi-species groundfish trawl fishery.Australian National University Economics and Environment Network Working Paper EEN0506.

Grafton, R. Q., Squires, D., Fox, K. J., 2000. Private property and economic efficiency: A study of a common-pool resource. The Journal of Law and Economics 43 (2), 679–714.

Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. The Bell Journal of Economics 10 (1), pp. 92–116.
URL http://www.jstor.org/stable/3003321

Hicks, J. R., 1932. The theory of wages. and 245, 117.

Hoffmann, V. H., 2007. Eu ets and investment decisions:: The case of the german electricity industry. European Management Journal 25 (6), 464 – 474, business, Climate Change and Emissions Trading.
URL http://www.sciencedirect.com/science/article/pii/S0263237307000837

Holland, D. S., 2010. Markets, pooling and insurance for managing bycatch in fisheries. Ecological Economics 70 (1), 121–133.

Hudgens, M. G., Halloran, M. E., 2008. Toward causal inference with interference. Journal of the American Statistical Association 103 (482).

Jaffe, A. B., Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Review of economics and statistics 79 (4), 610–619.

Johnstone, N., Haščič, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environmental and Resource Economics 45 (1), 133–155.

Judd, K. L., 1998. Numerical methods in economics. MIT press, Cambridge, MA.

Kwon, O. S., 2006. Partial international coordination in the great fish war. Environmental and Resource Economics 33 (4), 463–483.
URL http://dx.doi.org/10.1007/s10640-005-4994-x

Lanjouw, J. O., Mody, A., 1996. Innovation and the international diffusion of environmentally responsive technology. Research Policy 25 (4), 549 – 571.
URL http://www.sciencedirect.com/science/article/pii/0048733395008535

Leahy, D., Neary, J. P., 1997. Public policy towards r&d in oligopolistic industries. The American Economic Review 87 (4), 642–662.
URL http://www.jstor.org/stable/2951367

Levhari, D., Mirman, L. J., 1980. The great fish war: an example using a dynamic cournot-nash solution. The Bell Journal of Economics 11 (1), 322–334.

Lindegren, M., Diekmann, R., Möllmann, C., 2010. Regime shifts, resilience and recovery of a cod stock. Marine Ecology Progress Series 402, 239–253.
URL http://www.int-res.com/abstracts/meps/v402/p239-253/

Magerman, T., Van Looy, B., Song, X., 2006. Data production methods for harmonized patent statistics: Patentee name harmonization. K.U. Leuven FETEW MSI Research report 0605, 1–88.

Manski, C. F., 1993. Identification of endogenous social effects: The reflection problem. The Review of Economic Studies 60 (3), pp. 531–542.
URL http://www.jstor.org/stable/2298123

Miguel, E., Kremer, M., 2004. Worms: identifying impacts on education and health in the presence of treatment externalities. Econometrica 72 (1), 159–217.

Milliman, S. R., Prince, R., 1989. Firm incentives to promote technological change in pollution control. Journal of Environmental economics and Management 17 (3), 247–265.

Newell, R. G., Jaffe, A. B., Stavins, R. N., 1999. The induced innovation hypothesis and energy-saving technological change. Quarterly Journal of Economics, 941–975.

Newell, R. G., Sanchirico, J. N., Kerr, S., 2005. Fishing quota markets. Journal of Environmental Economics and Management 49 (3), 437–462.

Nkuiya, B., 2012. The effects of the length of the period of commitment on the size of stable international environmental agreements. Dynamic Games and Applications 2 (4), 411–430.

Nkuiya, B., Costello, C., 2014. Pollution control under a possible shift in system capacity.

Nkuiya, B., Marrouch, W., Bahel, E., 2014. International environmental agreements under endogenous uncertainty. Journal of Public Economic Theory, forthcoming.

Oberndorfer, U., 2009. {EU} emission allowances and the stock market: Evidence from the electricity industry. Ecological Economics 68 (4), 1116 – 1126, participation and Evaluation for Sustainable River Basin Governance.
URL http://www.sciencedirect.com/science/article/pii/S0921800908003492

Polasky, S., de Zeeuw, A., Wagener, F., 2011. Optimal management with potential regime shifts. Journal of Environmental Economics and Management 62 (2), 229–240.
URL http://www.sciencedirect.com/science/article/pii/S0095069611000556

Popp, D., 2002. Induced innovation and energy prices. American Economic Review 92 (1), 160–180.
URL http://www.aeaweb.org/articles.php?doi=10.1257/000282802760015658

Porter, M. E., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. Journal of Economic Perspectives 9 (4), 97–118.
URL http://www.aeaweb.org/articles.php?doi=10.1257/jep.9.4.97

Radovich, J., 1981. The collapse of the california sardine fishery. what have we learned? In: Glantz, M., Thompson, J. (Eds.), Resource Management and Environmental Uncertainty: Lessons from Coastal Upwelling Fisheries. Wiley, New York, NY, pp. 107–136.

Reed, W. J., 1988. Optimal harvesting of a fishery subject to random catastrophic collapse. Mathematical Medicine and Biology 5 (3), 215–235.

Reid, P. C., Edwards, M., Hunt, H. G., Warner, A. J., 1998. Phytoplankton change in the north atlantic. Nature 391 (6667), 546–546.

Ren, B., Polasky, S., 2014. The optimal management of renewable resources under the risk of potential regime shift. Journal of Economic Dynamics and Control 40 (0), 195 – 212.
URL http://www.sciencedirect.com/science/article/pii/S0165188914000153

Requate, T., Unold, W., 2003. Environmental policy incentives to adopt advanced abatement technology:: Will the true ranking please stand up? European Economic Review 47 (1), 125–146.

Romer, P. M., 1990. Endogenous technological change. Journal of Political Economy 98 (5 pt 2).

Rubin, D. B., 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. Journal of educational Psychology 66 (5), 688.

Sakamoto, H., 2014. Dynamic resource management under the risk of regime shifts. Journal of Environmental Economics and Management 68 (1), 1–19.

Seade, J., 1980. The stability of cournot revisited. Journal of Economic Theory 23 (1), 15–27.

Sethi, G., Costello, C., Fisher, A., Hanemann, M., Karp, L., 2005. Fishery management under multiple uncertainty. Journal of Environmental Economics and Management 50 (2), 300 – 318.
URL http://www.sciencedirect.com/science/article/pii/S0095069605000057

Sijm, J., Hers, S., Lise, W., Wetzelaer, B., 2008. The impact of the eu ets on electricity prices. Final report to DG Environment of the European Commission. ECN-E-08-007.

Sijm, J., Neuhoff, K., Chen, Y., 2006. Co2 cost pass-through and windfall profits in the power sector. Climate Policy 6 (1), 49–72.

Toft, J. E., Punt, A. E., Little, L. R., 2011. Modelling the economic and ecological impacts of the transition to individual transferable quotas in the multispecies us west coast groundfish trawl fleet. ICES Journal of Marine Science: Journal du Conseil 68 (7), 1566–1579.

Tsur, Y., Zemel, A., 1998. Pollution control in an uncertain environment. Journal of Economic Dynamics and Control 22, 961–975.

Veith, S., Werner, J., Zimmermann, J., 2009. Economic consequences of emission trading schemes: Evidence from the european power sector. Energy Economics 31 (4), 605–613.

Vukina, T., 2003. The relationship between contracting and livestock waste pollution. Review of Agricultural Economics 25 (1), 66–88.

Weyl, E. G., Fabinger, M., 2013. Pass-through as an economic tool: principles of incidence under imperfect competition. Journal of Political Economy 121 (3), 528–583.

Worm, B., Hilborn, R., Baum, J. K., Branch, T. A., Collie, J. S., Costello, C., Fogarty, M. J., Fulton, E. A., Hutchings, J. A., Jennings, S., et al., 2009. Rebuilding global fisheries. science 325 (5940), 578–585.