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Technology adoption and diffusion with uncertainty in a commons

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HIGHLIGHTS

- We model technology adoption in a commons with uncertainty in the resource stock.
- Firms use their own resource extraction to update priors on the value of technology.
- Initial adoption and diffusion rates are greater when the resource stock is larger.
- Diffusion is faster when competition for the resource is stronger.

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ABSTRACT

We model adoption and diffusion in a commons under uncertainty about a technology's value. Technological resource stock externalities make technology less valuable with depleted stocks, but transmit information about a new technology's value, causing faster adoption of high-value technologies.

1. Introduction and motivation

Do firms have different incentives to adopt resource extraction technologies when the resource is held in common? Zero steady state rents would suggest the value of technology adoption is limited, yet adoption of new technology may increase one's share of the resource. Several empirical studies have documented rapid adoption in open access fisheries and an emerging literature examines the impact of technological change on renewable resource abundance and welfare (Squires, 1992; Hannesson et al., 2010; Fissel and Gilbert, 2010; Gordon and Hannesson, 2011; Murray, 2012; Squires and Vestergaard, forthcoming). To this end, Squires and Vestergaard (forthcoming) find a normative relationship between technological change specific to the commons. The consequences for common resources may be large; Murray (2012) shows that ignoring technical change when assessing resource stock size can lead to sudden collapse of the resource and the industry, and Fissel and Gilbert (2010) show that technical change can cause boom and bust cycles and exacerbate excess entry. This literature has not studied adoption and diffusion incentives. The problem is important for other common pool resources such as forests and groundwater.

A new technology's productivity is typically uncertain to market participants. The potential profitability and the spread of information about the new technology are two key determinants of adoption and diffusion (Sunding and Zilberman, 2001). In resource extraction industries in particular, uncertain harvest conditions

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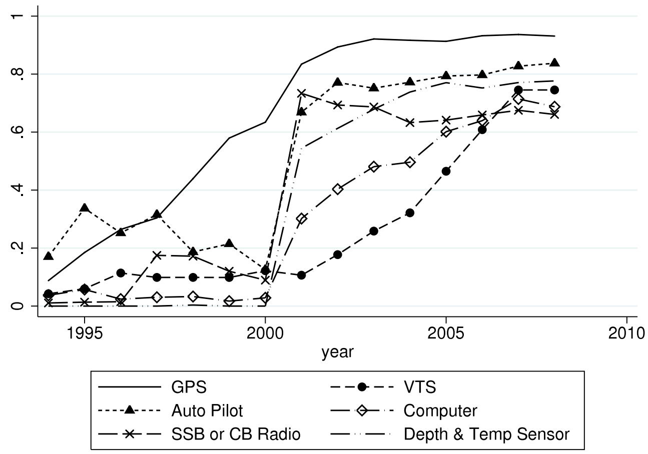

Fig. 1. Technology diffusion for various electronics in the NEGF.

make identification of the marginal effect of a new technology on productivity difficult. In this paper we develop a simple model of technology adoption specific to the commons. In the model, the quality of a new technology is uncertain. The contribution of this paper is to identify how uncertainty over the quality of the new technology manifests in a common pool resource.

As motivation, consider the New England groundfish fishery (NEGF), a multispecies, multi-gear fishery targeting cod, haddock, pollock, hake, and flounder. After being essentially open access through 1999, the NEGF underwent two important management changes in 2000 and 2004. Regulations in 2000 created new definitions of overfishing resulting in tighter caps, more closures within seasons, and a limited number of firms participating. One way of interpreting these changes is that the fishery went from a de facto open access fishery to one managed with an annual cap on time and total harvest.

In 2004 the fishery underwent another change. The Northeast Fisheries Management Council (NEFMC) further tightened limits on fishing time and implemented a formal quota sharing agreement with Canada with annual harvest caps for each country and monitoring of US catch. It is possible that the restrictions imposed in 2000 and 2004 increased harvest competition within fishing seasons. However, resource stocks did not markedly recover.

Fig. 1 shows diffusion rates for a variety of equipment for individual vessels surveyed between 1994 and 2008. The data presented are from individual surveys of vessels given by federal on-board observers. The figure shows a distinct increase in the uptake of new technologies in 2000 as the fishery went from open access to a more constrained form of a common pool in which externalities between boats within a season may have been greater.[1] These graphs are shown for motivation of the model in the next section and caution should be taken in drawing any strong conclusions considering the short time period and lack of a comparison group.

2. The model

We model adoption in the context of resource stock uncertainty when the productivity of the new technology is also not known. Consider a group of fishing vessels or firms supplying unit effort E inelastically (we consider a vessel to be a firm and will use the terms interchangeably) such that the relationship between effort and harvest is entirely determined by the resource stock size X, the stock elasticity α (assumed to be one[2]) and the level of technology θ: $y = \theta X^{\alpha} E = \theta X$. Assume that a new technology is available for a fixed cost F that could be a high productivity technology (θ_H) or a low productivity technology (θ_L) such that $\theta_H > \theta_L \geq \theta$. This formulation of the production function constrains signals of the technology's productivity to the resource stock. Thus, the harvests of other firms carry information about the technology's productivity through the resource stock. Note that this is true even if the harvests and profits of other firms are not directly observable.

Firms are homogeneous except in their initial belief $\tau_{i0} \in (0, 1)$ about the probability that the technology is of type θ_H. An alternative model could have heterogeneous initial productivity θ_i so the value of the marginal increase in θ_i is different across firms. Note, though, that the results of this model of idiosyncratic beliefs about the productivity of the new technology would not change if firms have heterogeneous productivity.[3]

Non-adopting firms receive signals about the productivity of the new technology through the stock's effect on their own harvest. Information accrues according to the following process within each period: There is a stock or level of escapement that is carried over from the previous period, X_{t-1}. At the beginning of the period, recruitment to the stock (or growth) occurs as an unobserved draw from a time independent distribution[4] $\epsilon_t \sim U[\underline{\epsilon}, \overline{\epsilon}]$. For notational simplicity define the expected recruitment as $E[\epsilon] = \mu$. Fishing occurs by all vessels simultaneously and every firm observes its harvest y_{it}. Beliefs are then updated according to Bayes Rule. Adoption decisions are then made at time t before the start of the next time period.

First, consider the initial decision of a firm to adopt the technology as a function of some initial belief τ_{i0} that the technology is of type θ_H. For simplicity, assume that there are two ex ante homogeneous vessels each with full knowledge of the previous period's escapement, X_{t-1}. The expected yields from adopting the new technology assuming the other vessel does not adopt are:

$$\begin{aligned} E(y_{it}|\tau_{i0}) &= \tau_{i0}\,[\theta_H(X_{t-1} + \mu - k\theta(X_{t-1} + \mu))] \\ &\quad + (1 - \tau_{i0})\,[\theta_L(X_{t-1} + \mu - k\theta(X_{t-1} + \mu))] \\ &= \tau_{i0}\theta_H(1 - k\theta)(X_{t-1} + \mu) \\ &\quad + (1 - \tau_{i0})\theta_L(1 - k\theta)(X_{t-1} + \mu). \end{aligned} \tag{1}$$

Here k can be thought of as the average effect of other firms' harvest on a firm's own harvest within a season. By withdrawing from the same stock, all other vessels leave a smaller effective stock $(1 - k\theta)(X_{t-1} + \mu)$ available for an individual vessel to harvest in that season. Assume $k < 1$ and $k\theta < 1$ so that k represents the intensity of the externality between firms in the common pool within a given time period.[5]

Given the form of Eq. (1), the expected benefit of adopting the new technology is the difference between expected profits with

[1] The composition of sampled vessel types changed somewhat during the sample period, but the diffusion patterns shown are consistent within each category of vessel size and gear type.

[2] We assume $\alpha = 1$ for simplicity. This assumption does not change the qualitative results although $\alpha < 1$ would reduce the magnitude of the effects found in Propositions 1 and 2 because harvest would be less sensitive to available stock and convey less information about technology. $\alpha < 1$ is typically true in fish that swim in schools, although even in these cases $\alpha > 0$.

[3] Without heterogeneous θ, this model informs the initial adoptions rates as opposed to the initial adoption levels. Changes in initial adoption levels could be layered onto this model.

[4] The uniform distribution is assumed for clarity but all results hold for a more general distribution. This includes density dependent innovations or growth under mild assumptions. More critical is the assumption that innovations to the stock must be observable, perhaps with error.

[5] A more precise model would perhaps look like $\int_0^T \theta(X + \epsilon - \theta_{-i}(X + \epsilon)s)sds$. However, Eq. (1) is a good first approximation.

and without the new technology less any fixed costs F of adoption, where we normalize output prices to 1:

$$\Delta_\pi = E(y_{it}|\tau_{i0}) - \theta(1 - k\theta)(X_{t-1} + \mu) - F. \quad (2)$$

When $\Delta_\pi > 0$ then the firm will adopt the new technology. As a result, for non-trivial technological innovations, the parameters in (2) implicitly define a critical belief $\tau^\star$ such that every vessel with a belief at or above $\tau^\star$ adopts and those below do not. This critical belief $\tau^\star$ is defined as:

$$\tau^\star = \frac{F}{(1 - k\theta)(X_{t-1} + \mu)(\theta_H - \theta_L)} - \frac{\theta_L - \theta}{\theta_H - \theta_L}. \quad (3)$$

The first term in $\tau^\star$ is the cost-benefit ratio of getting a high vs. a low technology. The second term is an adjustment for the productivity of the low technology relative to the status quo. If the low technology is also much more productive than the status quo then one's belief about the probability of getting a high technology does not need to be very strong in order to adopt. Eq. (3) does not necessarily describe beliefs over the long-run such as those that might be derived as the solution to the social planner's problem over an infinite horizon. Future work could extend this model beyond the myopic short-run solutions considered here by examining the evolution of beliefs as the long-run trajectory of the stock is incorporated into harvesters decisions.

2.1. Initial adoption of the technology

We now consider the updating process of non-adopters with $\tau_{i0} < \tau^\star$. Conditional on other firms adopting, the non-adopting firm can use their own harvest as a noisy signal to infer the quality of the new technology, given that recruitment ϵ_t is not observed but escapement X_{t-1} is observed. Non-adopting firms Bayesian update their belief that the new technology is highly productive. To perform this exercise, they must find the relative probability of their realized harvest conditional on the adoption behavior of other fishermen.

This process is illustrated in Fig. 2. Assume that there are only two firms in the fishery and consider the non-adopter's yield conditional on only one other firm adopting.[6] Potential harvests of the non-adopting firm share the same support except for two places where the new technology of the adopting firm is either high or low productivity. If the highest possible recruitment $\overline{\epsilon}$ occurs and the technology is θ_L, then yields of the non-adopting firm will be higher than they could possibly be if the new technology had been θ_H, leading the non-adopting firm to update their belief that the new technology must be θ_L with probability one. Similarly, when recruitment is very low and the adopting firm's technology is θ_H, then the non-adopter's take is lower than it could possibly be if the new technology were θ_L leading the non-adopting firm to update their belief that the new technology must be θ_H with probability one.

Given that there is an upper and lower bound for what the non-adopting firm's take can be, there is a closed support for which the non-adopting firm's belief is updated to neither zero nor one. The absorbing state bounds for updating beliefs are found by calculating the recruitment range for which the high and low productivity technologies have common support. The lower bound

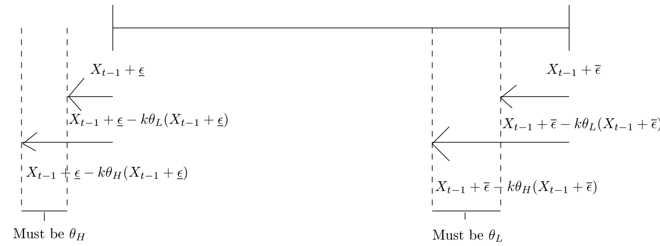

Fig. 2. Updating with uncertain stock size.

for recruitment in the low technology state is dictated by the following equation:

$$\theta\left(X_{t-1} + \underline{\epsilon} - k\theta_L(X_{t-1} + \underline{\epsilon})\right) \le \theta\left(X_{t-1} + \epsilon - k\theta_H(X_{t-1} + \epsilon)\right). \quad (4)$$

A similar expression dictates the upper bound for recruitment in the high technology state. The resulting solutions can be expressed as

$$\underline{\epsilon_H} = \frac{\underline{\epsilon}(1 - k\theta_L) + X_{t-1}(k\theta_H - k\theta_L)}{1 - k\theta_H} \le \epsilon \quad (5)$$

$$\overline{\epsilon_L} = \frac{\overline{\epsilon}(1 - k\theta_H) - X_{t-1}(k\theta_H - k\theta_L)}{1 - k\theta_L} \ge \epsilon. \quad (6)$$

Given that a harvest does not perfectly reveal information about the nature of the new technology, the non-adopting firm updates their prior belief τ_0 according to the following updating equation:

$$\tau_1 = \frac{\tau_0 \frac{1}{\overline{\epsilon} - \underline{\epsilon_H}}}{\tau_0 \frac{1}{\overline{\epsilon} - \underline{\epsilon_H}} + (1 - \tau_0)\frac{1}{\overline{\epsilon_L} - \underline{\epsilon}}}. \quad (7)$$

Note that (7) summarizes the relative probability that a non-revealing yield would have occurred given the uniform pdf dictating the stock recruitment's distribution.[7] Given that other firms' adoption decisions affect an individual firm's yields, there is a new threshold belief which determines adoption decisions for firms that did not adopt in the first period. The expected yield is now

$$E(y_{it}|\tau_{i0}) = \tau_{i0}\theta_H(1 - k\theta_H)(X_{t-1} + \mu) + (1 - \tau_{i0})\theta_L(1 - k\theta_L)(X_{t-1} + \mu). \quad (8)$$

Again, assuming a fixed adoption cost F and price of yield at numeraire, the resultant threshold belief to spur adoption is

$$\tau^\star = \frac{F - (E[y_{it}|\theta_L, Adopt] - E[y_i|\theta_L, \neg Adopt])}{E[y_i|\theta_H, Adopt] - E[y_i|\theta_H, \neg Adopt] - (E[y_i|\theta_L, Adopt] - E[y_i|\theta_L, \neg Adopt])}, \quad (9)$$

where $\neg$ denotes "not". Interpretation of Eq. (9) is intuitive. The magnitude of the threshold belief is determined by the relative yields based on technological adoption in the low state relative to the magnitude of the difference in yields based on technological adoption in the high versus low technology productivity states.

It is helpful to examine (9) explicitly given the functional forms assumed above. After some algebraic manipulation, Eq. (9) can be expressed as

$$\tau^\star = \frac{\frac{F}{X_{t-1} + E[\epsilon]} - (\theta_L - \theta)(1 - k\theta_L)}{(\theta_H - \theta)(1 - k\theta_H) - (\theta_L - \theta)(1 - k\theta_L)}. \quad (10)$$

6 Most of the exposition here assumes two vessels for purposes of clarity and simplicity. The model is easily extended to the case of many firms. The only additional implication will be that if non-adopters do not know what percentage of the rest of the industry has adopted, the absorbing states described in Fig. 2 will be a relatively smaller portion of the overall support.

7 The more general expression is $\tau_1 = \frac{\tau_0 * Pr(y_t|\theta_H)}{\tau_0 * Pr(y_t|\theta_H) + (1 - \tau_0) * Pr(y_t|\theta_L)}$.

Proposition 1. *Higher common resource stock levels lead to higher initial rates of technological adoption (lower $\tau^\star$). For a given resource stock, greater externalities in the common pool (larger values of k) lead to lower initial rates of technological adoption (higher $\tau^\star$).*

Proof. By inspection, Eq. (10) clearly shows that $\frac{d\tau^\star}{dX_{t-1}} < 0$. Let the numerator of (10) equal $A > 0$ and the denominator equal $B > 0$. Then

$$\frac{d\tau^\star}{dk} = \frac{\theta_L(\theta_L - \theta) \cdot B + [\theta_H(\theta_H - \theta) - \theta_L(\theta_L - \theta)] \cdot A}{B^2} > 0. \quad \square$$

Eq. (10) shows that the only difference in the technology adoption threshold that might change after the initial period is the stock size. Specifically, for a given technology the threshold belief needed for adoption $\tau^\star$ varies only with X_{t-1}. Thus, by inspection, low stock levels dictate a higher threshold belief $\tau^\star$ and fewer initial adopters. Conversely, higher stock levels dictate a lower threshold belief $\tau^\star$ and many initial adopters. The implication is that if the stock is depleted under open access there will be few initial adopters. If a new governance regime increases expected stock size, such as with harvest restrictions or property rights management, there should be an increase in initial adoption rates.

One important caveat is the interplay between the expected recruitment, stock size, and the common pool externality k. In most commercial fisheries managers and harvesters consider recruitment to be independent of stock size. However, if recruitment does vary with stock size then the entire denominator $X_{t-1} + E[\epsilon]$ takes the form $X_{t-1} + E[\epsilon(X_{t-1})]$. However, so long as the total derivative $\frac{d\,(X_{t-1}+E[\epsilon(X_{t-1})])}{d\,X_{t-1}} > 0$ then the implications hold. Similarly, it is possible that k would also increase as the stock decreases $\frac{\partial k}{\partial X_{t-1}} < 0$, but because $\frac{d\tau^\star}{dk} > 0$, then the total derivative $\frac{d\tau^\star}{dX_{t-1}} < 0$.

2.2. The rate of technology adoption

Initial adoption rates are only one component of overall adoption and diffusion, however. Eq. (7) describes updating behavior for harvests that do not perfectly identify the technology type. However a potentially significant portion of the harvest support given by $\underline{\epsilon_H} - \underline{\epsilon}$ in (5) and $\overline{\epsilon} - \overline{\epsilon_L}$ in (6) will be perfectly revealing about the technology type. Furthermore the range of perfectly revealing harvests also depends on the resource stock size and the common pool externality.

The probabilities that harvest perfectly reveals a high technology given θ_H or low technology given θ_L, respectively, are given by:

$$P(\epsilon \le \underline{\epsilon_H}|\theta_H) = \frac{k(\theta_H - \theta_L)(X_{t-1} + \underline{\epsilon})}{(1 - k\theta_H)(\overline{\epsilon} - \underline{\epsilon})} \tag{11}$$

and

$$P(\epsilon \ge \overline{\epsilon_L}|\theta_L) = \frac{k(\theta_H - \theta_L)(X_{t-1} + \overline{\epsilon})}{(1 - k\theta_L)(\overline{\epsilon} - \underline{\epsilon})}. \tag{12}$$

From these expressions we can derive the following proposition:

Proposition 2. *Higher common resource stock levels lead to higher probabilities that beliefs are in an absorbing state and the technology type is perfectly identified. For a given resource stock, greater externalities in the common pool (larger values of k) also lead to higher probabilities that beliefs are in an absorbing state and the technology type is perfectly identified. The probability of perfectly identifying θ increases at an increasing rate in k.*

Proof. By inspection, Eqs. (11) and (12) clearly show that $\frac{dP(\underline{\epsilon_H}|\theta_H)}{dX_{t-1}} > 0$ and $\frac{dP(\overline{\epsilon_L}|\theta_L)}{dX_{t-1}} > 0$. Taking derivatives and some algebraic manipulation leads to

$$\frac{dP(\underline{\epsilon_H}|\theta_H)}{dk} = \frac{(\theta_H - \theta_L)(X_{t-1} + \underline{\epsilon})}{(1 - k\theta_H)^2(\overline{\epsilon} - \underline{\epsilon})} > 0$$

which is also increasing in k, and

$$\frac{dP(\overline{\epsilon_L}|\theta_L)}{dk} = \frac{(\theta_H - \theta_L)(X_{t-1} + \overline{\epsilon})}{(1 - k\theta_L)^2(\overline{\epsilon} - \underline{\epsilon})} > 0$$

which is also increasing in k. $\square$

3. Conclusion

This model explains differing rates of technological adoption and diffusion in common pool resource industries. A key feature is that the resource stock size is uncertain, which is an accurate assumption in fisheries. In a commons, initial adoption rates are greater when resource stocks are abundant and stock externalities – how one firm's harvest affects the cost of harvesting for another firm – are low. Subsequent diffusion rates, however, depend critically on firms' ability to identify a technology's usefulness based on uncertain signals obtained via harvesting practices. Sorting between good and bad technologies is easier with more abundant resource stocks, but also with more intense stock externalities between firms that arise in the common pool. This finding can explain the rapid adoption of certain technologies that has been documented empirically in commercial fisheries. Policies that increase the stock may cause a negative "rebound" as the industry is better equipped to extract more, whereas policies that reduce commons externalities will slow the diffusion of inventions.

Our model offers a useful framework to address a number of unanswered questions in this area. For example additional technology signals not unique to common resource industries can be incorporated and compared, such as the effect of shifting cost curves on equilibrium output prices or direct communication with or observation of competitors. Future theoretical research must explore whether different governance rules for common resources might distort both information and incentives for adoption and diffusion. Further, additional theoretical and empirical work is needed to identify how technology diffuses as a function of more nuanced characteristics of both the resource itself and the technology. For example, many common resources involve the extraction of multiple species or resource types; the choice of species to harvest can be discrete, mutually exclusive and paired with specific technologies at one extreme versus nonseparable and jointly produced at the other extreme. Technology adoption may affect substitution possibilities between potentially interconnected resource stocks as well as between conventional inputs. There is also an intertemporal tradeoff between information accumulation and stock depletion that can influence optimal resource management.

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OMB disclaimer:

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