Week 3: Demand and Innovation

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Econ 220C: Topics in Industrial Organization

Innovation responds to incentives

"...invention is largely an economic activity, which, like other economic activities, is pursued for gain." – Schmookler (1966)

Or, more explicitly: "The amount of invention is governed by the extent of the market" – Schmookler (1966)

The empirical relationship between market size and innovation

- You could imagine trying to correlate the amount / quality of innovation with demand / market size, but market size is endogenous
  - Better (more innovative) products will have more demand
- Broad idea: want shifters of market size that are uncorrelated with innovation
  - Unexpected changes to vaccine policy
  - Changing weather patterns due to climate change

Market size and innovation

- Finkelstein (2004)
- Moscona and Sastry (2023)

Market design for innovation

- Kremer and Williams (2010)

Static & Dynamic Effects of Health Policy: Evidence from Vaccines

- Key idea: policies designed for a "static" purpose of increasing utilization of an existing technology may also have a "dynamic" effect on developing new technologies
- More specifically, the paper studies the effect of public health policies designed to increase vaccination rates (of existing vaccines)
- These policies stimulated the development of *new* vaccines

Static framework

Vaccines yield positive consumption externalities. Thus $SMB > D_0$. Current equilibrium is (Q_0, P_0) where $MR_0 = MC$

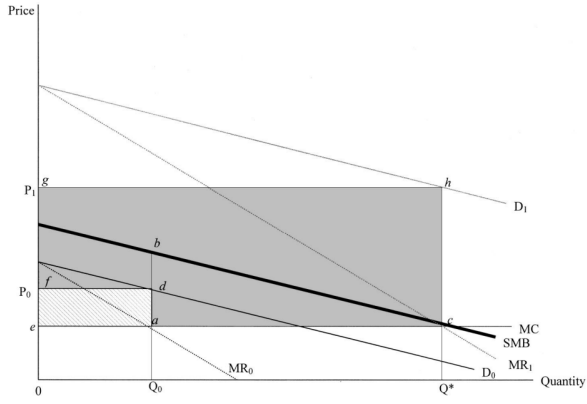

FIGURE I

Static framework

In a static world, we would simply subsidize demand to D_1 to arrive at the socially optimal equilibrium Q^*. This increases total welfare by *abc* (why?)

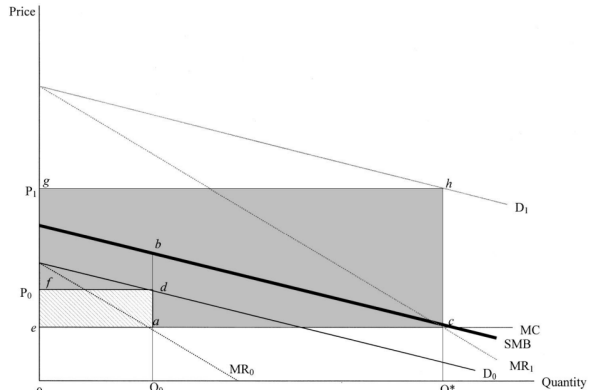

FIGURE I

However, it also increases monopolist profits from *efda* to *eghc*...

Incentives to innovate

- If the potential profits are larger, the returns to innovation are higher $\rightarrow$ firms will innovate more
- If the innovation is actually higher quality (either increased social marginal benefits or lower marginal costs), then this induced innovation further improves welfare
- On the other hand, if the innovation is pure business stealing, then the induced innovation harms welfare (excess R&D expenditure)

Dynamic framework with positive innovation

The static subsidy moves us from $Q_0 \rightarrow Q_1$ but still below Q^*. This yields a static benefit of *abij*

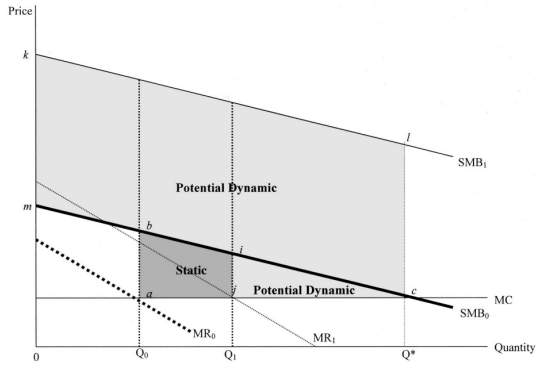

FIGURE II

Dynamic framework with positive innovation

However, innovation may also do two things:

1. Further shift private demand, getting us to Q^* (adding *jic*)
2. Shift the *SMB* curve out, adding *mjlc*

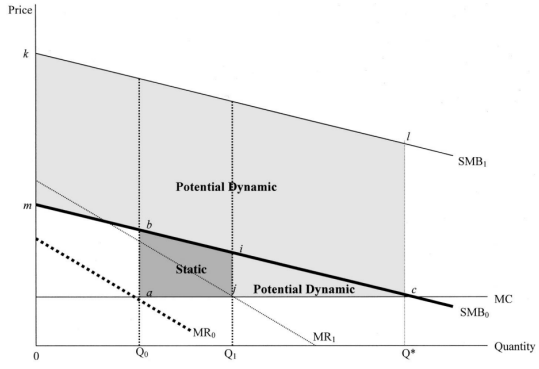

FIGURE II

Vaccine policy and vaccine development

Four features that the policy changes should have:

1. Occur at a discrete time with no anticipation
2. Have a substantial effect on the return to vaccine development
3. Should effect only some vaccines (so others can be used as a control)
4. Policies should not be prompted by technological developments

Policies in detail

The paper leverages three different vaccine policies (affecting six different vaccines)

1. 1991 CDC recommendation to vaccinate all infants against Hepatitis B
2. 1993 Medicare decision to cover flu vaccines
3. 1986 introduction of the Vaccine Injury Compensation Fund (protected manufacturers from lawsuits from adverse reactions to polio, DT, MMR, and pertussis vaccines)

Objective of these policies was to increase vaccination rates, but they also increased the returns to developing vaccines for these diseases

Innovation outcomes

Measure the innovation response at four sequential stages in the R&D pipeline:

1. Basic research (via patents)
2. Preclinical (animal) trials (via the business publication *The NDA Pipeline*)
3. Clinical (human) trials (via the *The NDA Pipeline*)
4. FDA approvals (via the *The NDA Pipeline*)

Descriptive results immediately visible

An increase in innovation is immediately visible by simply looking at clinical trial starts

TABLE I
NUMBER OF NEW VACCINE CLINICAL TRIALS PER YEAR

	Year clinical trial started																
Disease	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99
Affected diseases																	
Pertussis	1	1	0	0	**0**	**5**	**4**	**5**	**1**	**1**	**3**	**4**	**5**	**1**	**0**	**2**	**6**
Measles-Mumps-Rubella	0	0	1	0	**0**	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**
Diphtheria-Tetanus	1	0	0	0	**0**	**3**	**1**	**3**	**0**	**1**	**2**	**1**	**5**	**2**	**0**	**2**	**7**
Polio	0	0	0	2	**1**	**2**	**1**	**0**	**0**	**0**	**1**	**0**	**1**	**1**	**0**	**0**	**2**
Hepatitis B	1	0	3	1	0	1	0	1	0	**0**	**2**	**2**	**5**	**3**	**1**	**5**	**5**
Flu	0	0	0	0	0	0	0	2	1	0	1	**2**	**1**	**3**	**2**	**4**	**3**
Control diseases																	
"Any clinicals"	0.04	0.00	0.12	0.19	0.04	0.42	0.15	0.19	0.04	0.19	0.35	0.46	0.38	0.42	0.42	0.81	0.73
"Early clinicals"	0.14	0.00	0.43	0.71	0.14	1.29	0.57	0.57	0.14	0.42	0.14	0.71	1.00	0.71	0.43	0.29	0.70
"Prior approvals"	0.00	0.00	0.00	0.43	0.00	0.14	0.00	0.00	0.00	0.29	0.86	0.71	0.29	0.57	0.29	0.71	0.71
"Technology"	0.11	0.00	0.22	0.11	0.11	0.56	0.11	0.44	0.11	0.33	0.22	0.44	0.89	0.56	0.44	0.56	0.78

The switch from gray to white background demarcates the start of a new policy. Entries for control groups represent average number of new clinical trials per year. Table II provides a list of the diseases included in each of the control groups; see text for further details.

Key regression

For disease i in year t:

$$\text{NewTrials}_{it} = \alpha_i + \delta_t + \lambda \text{Adopt}_{it} + \varepsilon_{it}$$

where:

- NewTrials_{it} is the number of new clinical trials for disease i in year t
- Adopt_{it} is an indicator for whether a policy is in place
- Much care is taken in selecting appropriate control diseases with no vaccine policy

Defining the control groups

TABLE II
DESCRIPTION OF THE DISEASES IN THE VACCINE SAMPLE

Disease name	Included in restricted control groups? "Early clinicals"	"Prior approvals"	"Technology"	Average number of new clinical trials per year per vaccine 1983–1986	1996–1999	Year vaccine first approved
Treated Diseases						
Hepatitis B	√	√	√	1.25	3.25	1981
Influenza		√	√	0	3	1945
Polio	√	√		0.5	0.75	1955
Diphtheria, Tetanus (DT)	√	√		0.25	2.75	1949
Measles, Mumps, Rubella (MMR)	√	√		0.25	0.25	1971
Pertussis	√	√	√	0.5	2.25	1914
Control diseases ("Any clinicals")						
Varicella (Chicken Pox)	√			0.25	0.75	1995
Malaria	√			0.25	1	Not yet
Cholera	√	√		0.25	0	1914
Haemophilus Influenza B (HIB)	√		√	0.5	1.25	1985
Parainfluenza	√		√	0.25	0.5	Not yet
Gonorrhea	√		√	0.25	0	Not yet
Typhoid	√	√		0.5	0.5	1914
Tuberculosis (BCG)		√		0	0	1950
Meningitis		√		0	2	1974
Yellow Fever		√		0	0.25	1953
Streptococcus		√	√	0	1	1952
Pneumonia		√		0	0.25	1977
Hepatitis A			√	0	0.25	1995
Herpes			√	0	0.25	Not yet
Rotavirus			√	0	0.25	1988
Cytomagalovirus			√	0	0	Not yet
Respiratory Syncytial Virus			√	0	1.5	Not yet
Hepatitis C				0	0.75	Not yet
Lyme Disease				0	0.5	1998
Chlamydia				0	0.25	Not yet
Japanese Encephalitis				0	0.5	1992
Epstein-Barr Virus				0	0.25	Not yet
E. Coli				0	0.75	Not yet
Helicobacter pylori				0	0.5	Not yet
Human Papilloma Virus				0	0.75	Not yet
Otitis Media				0	1.25	Not yet

Listed control diseases consist of all 26 diseases included in the "any clinicals" control group. The first three columns show which of these diseases meet the more restricted control group definitions; for the treated diseases they indicate which of the treated diseases would also meet these definitions. "Early clinicals" consists of diseases that have at least one new clinical trial prior to 1987. "Prior approvals" consists of diseases for which an approved vaccine exists prior to 1983 (the start of the data). "Technology" consists of diseases that are listed by the Institute of Medicine [1985a] as having the potential to develop new or improved vaccine within the decade that would convey substantial health benefits within the United States. Data source for all columns but the last one is *The NDA Pipeline*. Hoyt [2002] provided the approval dates.

Results suggest massive effects

- The policies are associated with 1.2-1.3 additional clinical trials (a 2.5x increase over the mean of affected diseases prior to the policies).
- Alternatively, the estimates imply that these policies accounted for 1/3 of the total 260 new vaccine trials for all diseases in the post-period
- Back-of-the-envelope: every $1 increase in expected market revenue → industry will spend an additional $0.06 on R&D

TABLE III
EFFECT OF POLICIES ON NUMBER OF NEW CLINICAL TRIALS

	Any clinicals	Early clinicals	Prior approvals	Technology	Propensity score weighting
ADOPT	**1.210*** (0.184)**	**1.307*** (0.273)**	**1.233*** (0.263)**	**1.212*** (0.242)**	**1.192*** (0.248)**
Unadjusted p-value	<0.01	<0.01	<0.01	<0.01	<0.01
Adjusted p-value	<0.01	<0.01	<0.01	<0.01	<0.01
Mean dependent variable	0.48	0.87	0.75	0.73	0.54
Number of diseases	32	13	13	15	32
N	544	221	221	255	544

Results are from OLS estimates of equation (1). Top row indicates the control group used; these are defined in Table II. All regressions include year and disease fixed effects. Unadjusted standard errors are in parentheses. Adjusted p-values are calculated using the randomized inference approach of Bertrand, Duflo, and Mullainathan [2004]. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively, using the unadjusted p-values.

Dynamics

- Dynamics suggest no anticipation
- Also suggest not just a "pulling forward" of planned investment, but rather new investment

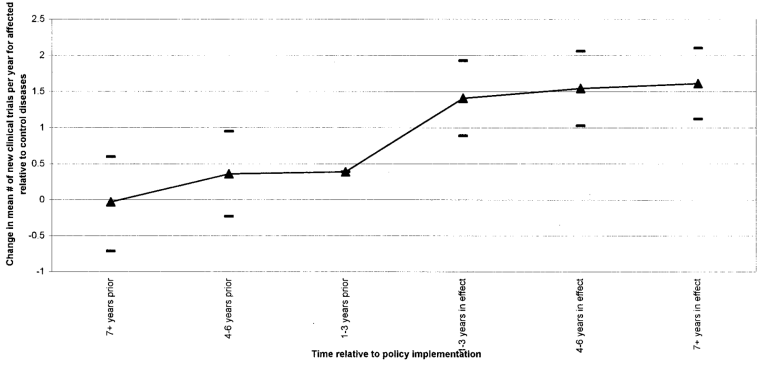

FIGURE III

Timing of Effect of Policies on New Clinical Trials

Figure III graphs the coefficients on the ADOPT variables from estimating equation (2) using the "any clinicals" control group; the regression includes year and disease fixed effects. The reference period (1–3 years prior to adoption) is set at the mean of the dependent variable for the affected diseases in that period. The dotted lines represent the 95 percent confidence intervals for these coefficients, based on the unadjusted standard errors. The adjusted and unadjusted p-values (not shown) are comparable.

Results for earlier-stage R&D

Don't see strong evidence for increases in earlier-stage R&D (though not sure how good the patent data is...why not use academic papers?)

TABLE V

EFFECT OF POLICIES ON INVESTMENT AT EARLIER STAGES OF THE R&D PIPELINE

	Number of new preclinical trials		Number of new patents filed by for-profit companies		Number of new patents filed by nonprofit entities	
	Any clinicals (1)	Propensity score (2)	Any clinicals (3)	Propensity score (4)	Any clinicals (5)	Propensity score (6)
ADOPT	**0.115**	**0.184**	**0.198**	**0.260**	**0.120**	**0.097**
	(0.173)	**(0.234)**	**(0.126)**	**(0.205)**	**(0.103)**	**(0.142)**
Unadjusted p-value	0.51	0.44	0.12	0.21	0.25	0.50
Adjusted p-value	0.56	0.68	0.11	0.12	0.40	0.41
Mean dependent variable	0.46	0.47	0.27	0.29	0.19	0.19
Number of diseases	32	32	32	32	32	32
N	544	544	672	672	672	672

The dependent variable is given in the top row; the next row indicates the control group used. Results are from OLS estimation of equation (1). See notes to Table III for more details.

Results for later-stage R&D

See effects for vaccine approvals, though these take time to appear

TABLE IV
EFFECT OF POLICIES ON NUMBER OF NEW APPROVED VACCINES

	Any clinicals	Early clinicals	Prior approvals	Technology	Propensity score weighting
$ADOPT_{(1-6)}$ (Policy in place 1–6 years)	**−0.051**	**−0.081**	**−0.050**	**−0.083**	**−0.057**
	(0.072)	**(0.101)**	**(0.092)**	**(0.102)**	**(0.060)**
Unadjusted p-value	0.48	0.42	0.59	0.42	0.34
Adjusted p-value	0.41	0.40	0.38	0.48	0.32
$ADOPT_{(7+)}$ (Policy in place 7+ years)	**0.364*****	**0.346*****	**0.409*****	**0.305****	**0.348****
	(0.084)	**(0.127)**	**(0.115)**	**(0.126)**	**(0.136)**
Unadjusted p-value	<0.01	<0.01	<0.01	0.02	0.02
Adjusted p-value	<0.01	0.01	<0.01	0.05	0.02
Mean dependent variable	0.07	0.12	0.10	0.11	0.08
Number of diseases	32	13	13	15	32
N	576	234	234	270	576

Dependent variable is number of approved vaccines against a given disease in a given year. Results are from OLS estimates of equation (1) but where the indicator ADOPT has been replaced by two mutually exclusive indicator variables for a policy being in effect for 1–6 years ($ADOPT_{(1-6)}$) and for a policy being in effect 7 or more years ($ADOPT_{(7+)}$). Top row indicates the control group used. See notes to Table III for more details.

Interpreting up the results

- The quick initial response of new trials suggests there is a "substantial reservoir" of technology sitting on the shelf, but whether this turns into a clinical trial is highly responsive to incentives
- Consistent with this, most of the quick response is driven by established firms, who are more likely to have technology "sitting around"
- The later response is driven by less established firms

Estimating the static effects

Since new approvals take 7-8 years, a reasonable way to estimate the static effect is to look at the increase in vaccination rates over the first 8 years after the policy:

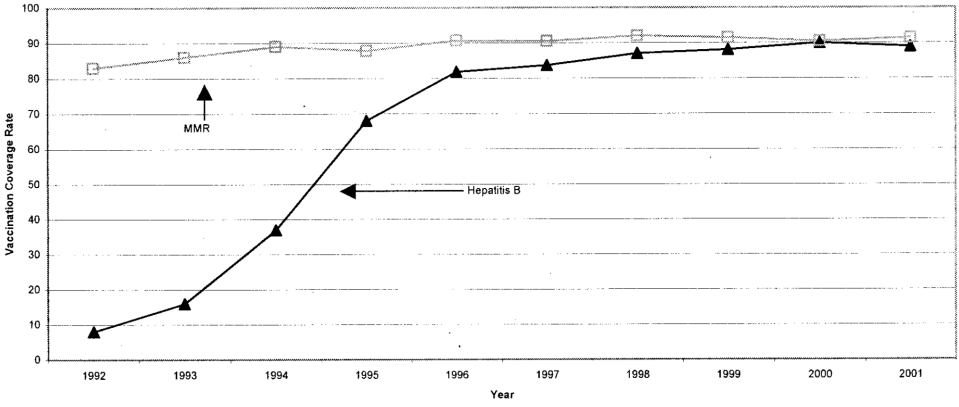

FIGURE IV

Vaccination Coverage Levels among Children 19–35 Months

Data on vaccination rates are from National Health Interview Surveys as reported in CDC [1995a, 1997, 1998, 2001, 2002c].

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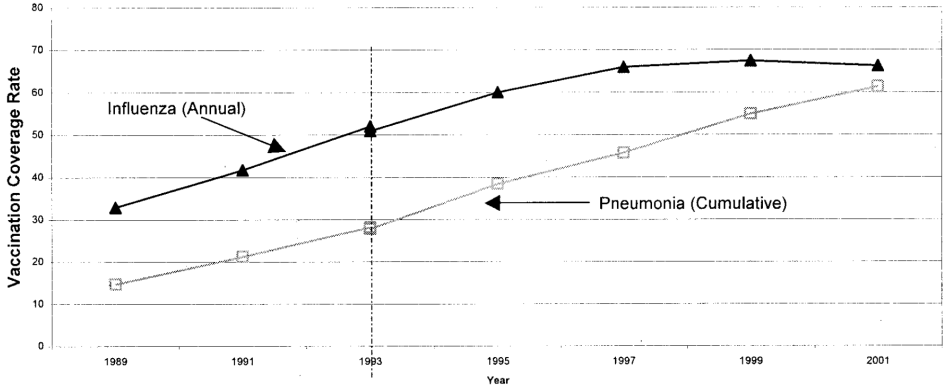


FIGURE V

Trends in Vaccination Rates for Ages 65+

1989–1993 data are from National Health Interview Surveys as reported in CDC [1995b].

1993–1999 data are from Behavioral Risk Factor Surveillance System and reported in CDC [2002b].

Valuing the static effects

Back-of-the-envelope estimates of the dollar value of these policies multiplies (change in vaccination rate)×(maximal efficacy of available vaccine)×($ value of elimination of disease)

TABLE VI
DOLLAR VALUE OF HEALTH BENEFITS FROM STATIC IMPACT OF POLICIES

	Estimated static impact on vaccination rate (1)	Dollar value of static impact on vaccination rate (2)	Costs of static policy impact (3)	Dollar value of *net* static impact on vaccination rate (4)
Hepatitis B recommendation	0.90	$7,524	$326	$7,198
Medicare covers Flu	0 to 0.15	0 to $2,775	$60 to $111	−$60 to $2,664

All estimates are annual and all dollar amounts are in millions. See text for more details.

Bounding the dynamic effects

Recall from the dynamic framework that there are two sources of dynamic benefits:

1. Increasing private demand, thus increasing Q (vaccine rates)
   - Assume this maxes out at 90%
2. Increasing the SMB of vaccines (efficacy rate)
   - Assume Hep B had already attained maximum efficacy
   - Assume flu vaccine had scope to increase (from 58% $\rightarrow$ 85%)

Costs are based on the estimated costs of new clinical trials

Estimates of dynamic effects

Upper and lower bounds:

- Hep B: 90% vaccination rate, very effective vaccine → no room for dynamic improvement! But still see R&D spending...
- Flu: 67% vaccination rate, 63% efficacy rate → room for dynamic improvement

TABLE VII
DOLLAR VALUE OF HEALTH BENEFITS FROM DYNAMIC IMPACT OF POLICIES

	Increase in vaccination rate (1)	Dollar value of increase in vaccination rate (2)	Increase in efficacy (3)	Dollar value of increase in efficacy (4)	Costs of dynamic policy impact (5)	Dollar value of *net* dynamic impact (6)
Upper-bound estimate (maximum potential benefit)						
Hepatitis B recommendation	0	0	0	0	$20	−$20
Medicare covers Flu	0.23	$3,395	0.27	$6,104	$20	$9,479
Lower-bound estimate (actual benefits to date)						
Hepatitis B recommendation	0	0	0	0	$20	−$20
Medicare covers Flu	0	0	0.27	$4,307	$20	$4,287

All estimates are annual, and all dollar amounts are in millions. Dollar value of dynamic benefits are discounted using a 3 percent annual discount rate. See text for more details.

Value of talking to actual experts

Cited Interviews

Doctors

Dr. George Grady, physician and vaccine researcher (Massachusetts Public Health Biologics Laboratories), telephone conversation, November 2000.

Individuals in the pharmaceutical industry

Deborah Alfona, Merck, telephone conversation, June 2001, Director of health policy for vaccines.

Harry Greenberg, Aviron, Mountain View, CA, February 2001.

Bronwen Kaye, American Home Products, telephone interview, December 2000.

Richard Manning, Pfizer, telephone conversation, September 2000.

Lorri Michael, Merck, telephone conversation, June 2001.

Courtney Piron, American Home Products, telephone conversation, October 2000.

Mark Sanyour, Merck, several phone and email correspondences.

Jan Wolters, Merck, Cambridge, MA, June 2001.

Public Sector

Bob Snyder, CDC, several phone and email correspondences.

Market size and innovation

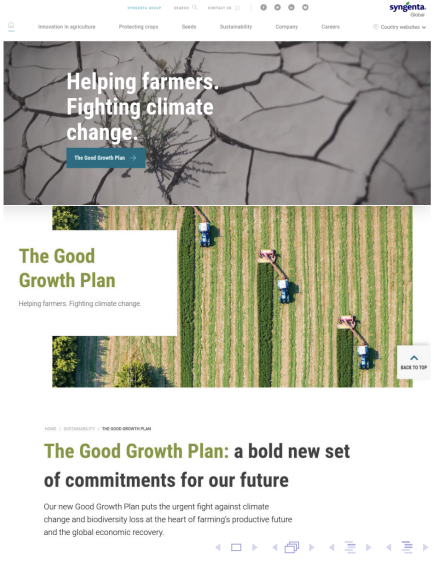
- Finkelstein (2004)
- Moscona and Sastry (2023)

Market design for innovation

- Kremer and Williams (2010)

Does Directed Innovation Mitigate Climate Damage? Evidence from US Agriculture

- In the face of global warming, has innovation redirected toward the most affected crops and the technologies best suited for helping?
- If yes, how has this affected agriculture's resilience to climate change?



Climate change and innovation incentives

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Climate change and innovation incentives

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- If innovation *complements* favorable climate conditions (for example, developing higher yield seeds that need more precise climactic conditions), then climate change will lead to less innovation for the most affected crops. Innovation can exacerbate the effects of climate change

Climate change and innovation incentives

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Ultimately the authors argue this is an empirical question

Innovation and resilience

A few more subtleties:

- Two objects of interest
  1. Amount of innovation
  2. Climate resilience ($-\partial \text{ farm profit}/\partial \text{ climate}$)
     - High resilience value $\rightarrow$ same climate shock has a *smaller* absolute value effect on farm profits
- Price effects will also matter – a negative climate shock will reduce crop yields which will increase prices of the final crop. Higher prices should induce more innovation. This is therefore a countervailing force when firms face a bad climate shock

Putting it all together

Summary of model predictions:

In a sector damaged by climate change...

	Climate-Substituting Technology	Climate-Complementing Technology
Price Effects Weak	(a) Innovation ↑ and Resilience ↑	(b) Innovation ↓ and Resilience ↑
Price Effects Strong		(b) Innovation ↑ and Resilience ↓

FIGURE I

Summary of Model Cases

Data requirements

Need to measure three things:

1. Exposure to damaging climate change
2. Crop-specific innovation
3. Local agricultural outcomes (profitability)

Measuring climate change exposure I

- Use daily grid-level (2.5 mile $\times$ 2.5 mile) temperature data from 1950 to present, obtained from the PRISM Climate Group
  - Argue that extreme values are what is relevant (hence daily data is critical)
  - Use crop-level upper temperature thresholds from EcoCrop
  - These thresholds vary from 15°C to 35°C (SD = 5°C)
- Define a variable ExtremeExposure which integrates the temperature in excess of each crop's threshold during the April-October growing season
  - For example, for a crop with a threshold of 30°C, one day at 35°C counts as 5 days.
  - In the same example, five days at 31°C also counts as five days
- Validate this measure against crop yields

Measuring climate change exposure II

- The ExtremeExposure measure is unique at the county (i), crop (k), decade (t) level
- Want to aggregate up to the k, t level (since innovation happens at the crop-year level). Weight by each county's share of the crop's total planted area:

$$\text{ExtremeExposure}_{k,t} = \sum_i \left[\frac{\text{Area}_{i,k}^{Pre}}{\sum_j \text{Area}_{i,k}^{Pre}} \cdot \text{ExtremeExposure}_{i,k,t} \right]$$

where $\text{Area}_{i,k}^{Pre}$ is the area devoted to crop k in county i prior to the sample period (in 1959)

Measuring innovation

Innovation is measured a few ways:

- Innovation measured using the digitized USDA *Variety Name List* (easy to link innovation to individual crops)
- Patent data (more difficult to link innovation to individual crops)

Measuring agricultural outcomes

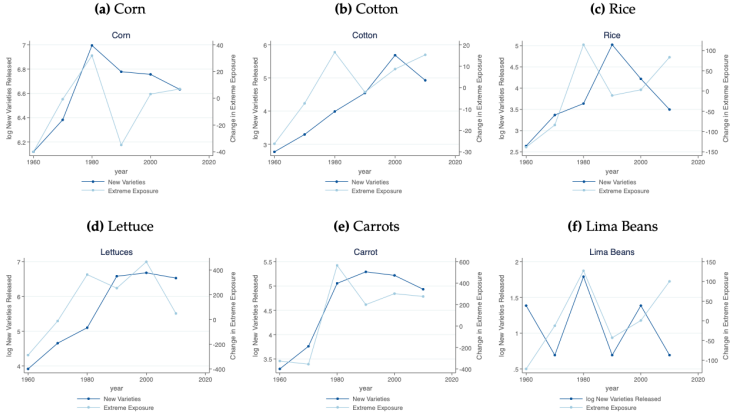
Argue that land values are a sufficient statistic for crop profitability

- Measure the value of land per acre
- Data comes from the US Census of Agriculture
- Also collect data on crop revenue, non-crop revenue, and profits for robustness checks

Descriptive results

New varieties track climate change exposure:

Figure 2: Changes in Extreme Exposure and Variety Releases Across Decades: Examples



Notes: Each graph reports the change in $\text{ExtremeExposure}_{k,t}$ (light line, left y-axis) and the change in the (log of the number of) new varieties released (dark line, right y-axis) across decades.

Key regression

The authors estimate the following long-difference regression:

$$y_k = \exp\{\delta \cdot \Delta\text{ExtremeExposure}_k + \Gamma X_k' + \varepsilon_k\}$$

where:

- y_k is the number of seed varieties developed during the 1960-2016 sample period
- $\Delta\text{ExtremeExposure}_k$ is the change in crop-level extreme exposure between 1960-2016
- X_k is a vector of crop-level controls

Recall that $\delta > 0$ implies that innovation is directed toward crops that have been exposed to more extreme temperatures, while $\delta < 0$ implies the opposite Thoughts on identification?

Regression results

More innovation for more climate-exposed crops. A one standard deviation increase in climate distress led to a 0.2 standard deviation increase in new varieties

Table 1: Temperature Distress Induces Crop Variety Development

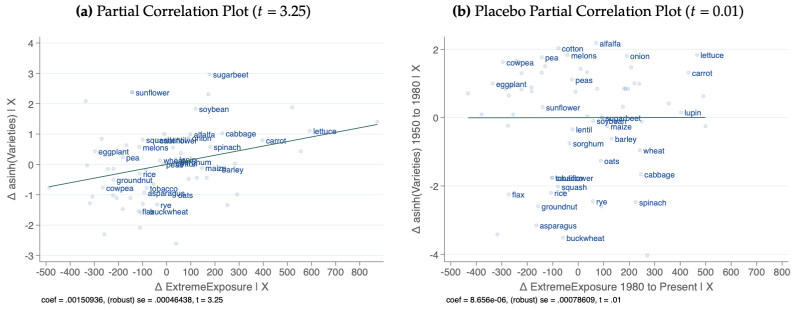
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is New Crop Varieties					
Sample Period	1950-2016					1980-2016
Δ ExtremeExposure	0.0167***	0.0171***	0.0136***	0.0184***	0.0226***	0.0338***
	(0.00424)	(0.00436)	(0.00372)	(0.00541)	(0.00668)	(0.00745)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	Yes	Yes
Pre-period varieties	No	No	Yes	Yes	Yes	Yes
Cut-off temp. and cut-off temp sq.	No	No	No	Yes	Yes	Yes
Average Temperature Change	No	No	No	No	Yes	No
Observations	69	69	69	69	69	69

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released and the sample period for each specification is listed at the top of each column. The controls included in each specification are noted at the bottom of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Regression results

No evidence of anticipation or pre-trends:

Figure 3: Extreme Exposure and Variety Development: Partial Correlation Plot (OLS)



Notes: The unit of observation is a crop and the full set of baseline controls are included on the right hand side in each specification, including log of pre-period area, pre-period temperature, pre-period precipitation, and (asinh of) pre-period variety releases. The coefficient estimate, standard error, and t-statistic are reported at the bottom of each graph.

Climate vs. non-climate innovation

Effects appear to be driven by climate-related innovation. Mine patent text for mentions of patents to code patents as climate-related or non-climate related

Table 2: Temperature Distress and Climate-Related Patenting

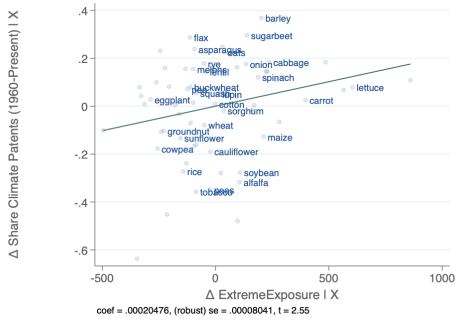
Dependent Variable:	(1) Patents *not* related to the climate	(2) Patents related to the climate
Δ ExtremeExposure	0.00335	0.0118**
	(0.00458)	(0.00552)
All Baseline Controls	Yes	Yes
Observations	69	69

Notes: The unit of observation is a crop and both columns report Poisson pseudo-maximum likelihood estimates. The outcome variables are the number of crop-specific agricultural patents that are not related to the climate (column 1) and the number of crop-specific agricultural patents related to the climate (column 2). All baseline controls are included in both specifications. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Climate vs. non-climate innovation

Effects appear to be driven by climate-related innovation. Mine patent text for mentions of patents to code patents as climate-related or non-climate related

Figure 5: Temperature Distress and the Share of Climate-Related Patents

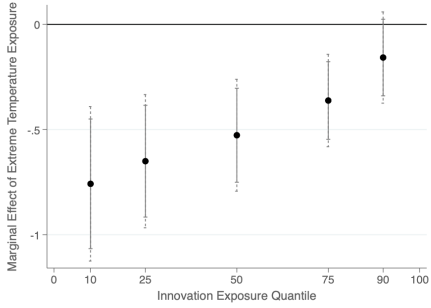


Notes: This figure reports the partial correlation plot between $\Delta\text{ExtremeExposure}_k$ and the share of crop-specific patented technologies released since 1960 that are related to the climate. The full set of baseline controls are included, including the relevant pre-period dependent variable in this context: the share of climate-related patented technologies developed between 1900-1960. The coefficient estimate, standard error, and t-statistic are reported at the bottom of the figure.

Estimating resilience

Land values fall less in areas with more innovation (holding the amount of extreme temperature exposure constant) – consistent with innovation leading to increased resilience in the substitutes case

Figure 6: Marginal Effect of County-Level Extreme Exposure as a Function of Innovation Exposure



Notes: This figure reports marginal effect of extreme-temperature exposure on (log of) agricultural land values for quantiles of the innovation exposure distribution. The solid and dashed lines are 90% and 95% confidence intervals respectively.

Damage mitigation due to innovation

- Model land values as a function of ExtremeExposure, InnovationExposure, interaction. Use these coefficients to predict land values under two scenarios:
  1. No climate change: ExtremeExposure and InnovationExposure are fixed at t_0 values
  2. Yes climate change, no innovation: InnovationExposure is fixed at t_0 value
- Aggregate up to the national level to estimate the total value of US agricultural land under each scenario
- Compare these to actual fitted values (yes climate change, yes innovation case)
- Exercise suggests that about 20% of climate damage as measured by land values has been mitigated by innovation

Market size and innovation

- Finkelstein (2004)
- Moscona and Sastry (2023)

Market design for innovation

- Kremer and Williams (2010)

Can we do better than patents?

- Seen lots of evidence in the past two lectures that innovation responds to incentives
- Patents provide ex-ante incentives to innovate
- But they generate ex-post efficiency costs due to monopoly power
- Can we do better?

Prizes

- Reward inventors who meet a set of technical specifications laid out in advance (typically the first inventor)
- Example: the X-Prize Foundation regularly promises and awards prizes. First offered a $10 million price for the first non-governmental organization to launch a reusable, manned spacecraft into space (prize was awarded in 2004 to a team lead by aircraft designer Burt Rutan financed by Microsoft cofounder Paul Allen)
- Challenge: what "counts?"
- In general, there are tradeoffs between ex-ante commitment and ex-post discretion

Example of the "what counts" problem

- Board of Longitude prize offered in the 1700s for a tool that would determine longitude
- John Harrison (a clockmaker) developed a chronometer which used time to determine longitude – very different from what the committee was expecting
- It took 12 years and much testing before they were willing to award the prize

Advance market commitments

- Similar to a prize, but condition payout on market use
- Sponsors commit in advance to underwrite a guaranteed price for a maximum number of units if the innovation meets some technical specifications
- Key point: payment only occurs if item is purchased! Removes some of the need for squishy judgement as to "what counts"
- This mechanism was used by GAVI to help bring COVID-19 vaccines to low-income countries

Patent buyouts

- Ex-post, buy the patent rights from the innovating firm and place the invention in the public domain, allowing competition
- Example: In 1839, the French government purchased the patent for Daguerreotype photography. This sped the adoption and increased follow-on innovation
- Key challenge: what is the right price to pay? Kremer (1998) proposes an auction-type system that would incentivize firms to truthfully reveal their valuations