

Week 11: 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)

Market size and innovation

Acemoglu and Linn (2004)

Finkelstein (2004)

Moscona and Sastry (2022)

Market design for innovation

Kremer and Williams (2010)

Market size and innovation in the pharmaceutical industry

- ▶ 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
- ▶ Key idea: demographic changes represent exogenous shifts in demand for treatments of certain diseases
 - ▶ As a population ages, heart disease becomes a relatively bigger market than childhood leukemia (for example)
 - ▶ The aging of the baby boomer generation was a particularly large demographic shift
 - ▶ Identifying assumption: demographic shifts are orthogonal to confounders such as scientific feasibility

Key regression

The key regression is straightforward. For drug category c in time period t the authors estimate a variant of the following Poisson regression:

$$E[N_{ct}] = \exp(\alpha \ln M_{ct} + X'_{ct}\beta + \zeta_c + \mu_t)$$

where

- ▶ N_{ct} is the number of drugs approved in category c during time period t (5-year periods)
- ▶ M_{ct} is the potential market size
- ▶ X' is a vector of time-varying controls
- ▶ ζ_c is a category FE
- ▶ μ_t is a year FE

Challenge: timing

- ▶ Drugs take a long time from development to approval – seems reasonable to expect a long lag after the initial demographic shift
- ▶ On the other hand, demographic shifts are potentially easy to anticipate – maybe there will be no lag
- ▶ Approach is to include leads and lags
 - ▶ Include one lead and one lag of market size (5-year periods)

Measuring potential market size

- ▶ u_{ca} is the age-specific expenditure share on drugs in category c
 - ▶ Age is grouped into 5-year bins
 - ▶ If 40-44 year olds spend 2% of their income on statins, $u_{statins,40} = 0.02$
 - ▶ Not time-varying
- ▶ i_{at} is the total income of individuals aged a in year t
- ▶ Thus, market size is given by:

$$M_{ct} = \sum_a u_{ca} i_{at}$$

- ▶ All variation comes from change in i_{at} 's over time
- ▶ Note that this is income-based (rather than purely population-based). Does this make sense in a world with insurance? Results are robust to a population-based measure

Demographic shifts (population)

Demographic data comes from the CPS

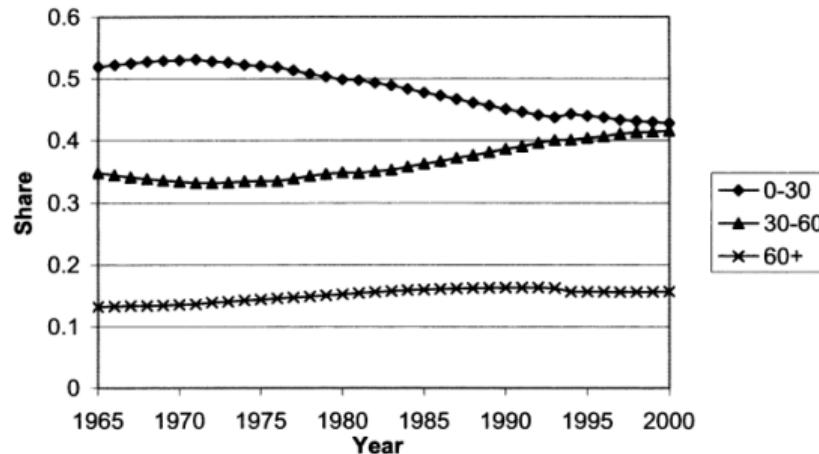


FIGURE I

Share of Population by Age Group from CPS, 1965–2000

Share of population is the population of the corresponding age group divided by total population, computed from the March CPS.

Demographic shifts (income-weighted population i_{at})

Demographic data comes from the CPS

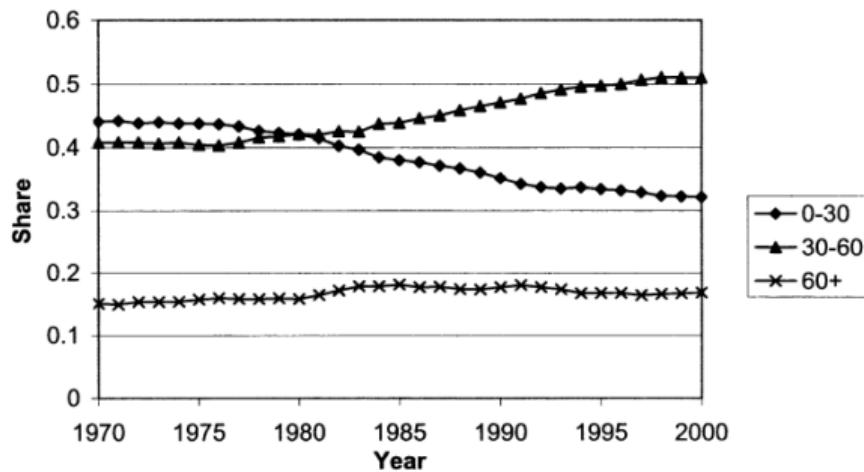


FIGURE II

Share of Income by Age Group from CPS, 1970–2000

Share of income is income of the corresponding age group divided by total income, computed from the March CPS. Individual income is obtained by dividing total family income equally among family members.

Age-specific drug spending u_{ca}

APPENDIX 2: SUMMARY OF DISEASE CLASSIFICATION AND DRUG EXPENDITURE
BY AGE GROUP

- ▶ Divide conditions into 33 categories
- ▶ Data comes from the Medical Expenditures Panel Survey (MEPS)
- ▶ Survey data that includes age, income, drug spending

Class	Description	Expenditure share × 1000 [Share of expenditure by age group in total expenditure in brackets]			Age group with largest expenditure
		0–30	30–60	60+	
1	Antibiotics	0.95 (0.41)	0.62 (0.40)	0.90 (0.19)	0–30
		0.03	0.36	0.05	
2	Antivirals	(0.05)	(0.91)	(0.04)	30–60
		0.01	0.05	0.08	
3	Antiparasitics	(0.10)	(0.60)	(0.29)	30–60
		0.26	0.23	0.38	
4	Antifungals	(0.32)	(0.44)	(0.24)	30–60
		0.00	0.00	0.01	
5	Anemia	(0.07)	(0.47)	(0.47)	60+
		0.00	0.06	0.77	
6	Anticoagulants	(0.01)	(0.19)	(0.80)	60+
		0.00	0.03	0.58	
7	Glaucoma	(0.01)	(0.14)	(0.85)	60+
		0.17	0.89	2.87	
8	Acid/Peptic Disorders	(0.06)	(0.46)	(0.49)	60+
		0.00	0.01	0.03	
9	Antidiarrheals, Laxatives	(0.07)	(0.45)	(0.49)	60+
		0.03	0.72	4.68	
10	Cardiac	(0.01)	(0.32)	(0.67)	60+
		0.12	1.24	7.00	

Descriptive evidence

Use FDA approval data to compute share of drugs targeted at each age group:

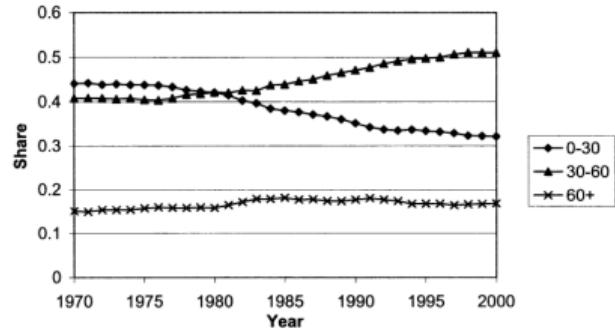


FIGURE II

Share of Income by Age Group from CPS, 1970–2000

Share of income is income of the corresponding age group divided by total income, computed from the March CPS. Individual income is obtained by dividing total family income equally among family members.

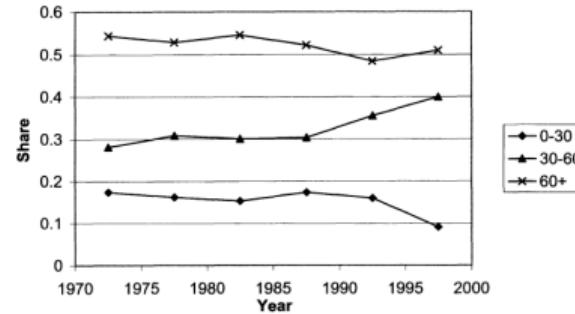


FIGURE III

Share of FDA Approvals by Age Group, 1970–2000

Share of FDA approvals is computed as approvals of drugs in the corresponding broad age group divided by total approvals in that period, calculated from the FDA data set of New Drug Approvals. Each of the 33 drug categories is assigned to one of the three broad age groups according to which broad age group has the largest expenditure (see Appendix 2).

Regression results (all drugs)

Lead market size seems to matter most (firms anticipate?)

TABLE II
EFFECT OF CHANGES IN MARKET SIZE ON NEW DRUG APPROVALS

	(1)	(2)	(3)	(4)
Panel A: QML for Poisson model, dep var is count of drug approvals				
Market size	6.15 (1.23)	6.84 (4.87)	-2.22 (4.12)	
Lag market size		-0.61 (3.85)		
Lead market size			10.16 (4.28)	7.57 (1.99)

Regression results (new drugs)

Less anticipation for more innovative drugs?

Panel B: QML for Poisson model, dep var is count of nongeneric drug approvals

Market size	3.82 (1.15)	6.72 (7.63)	2.91 (5.31)
Lag market size		-2.49 (5.97)	
Lead market size			-1.77 (6.94) 1.73 (2.02)

Panel C: QML for Poisson model, dep var is count of new molecular entities

Market size	3.54 (1.19)	5.79 (6.66)	-1.38 (5.16)
Lag market size		-1.99 (5.28)	
Lead market size			7.35 (5.11) 5.75 (2.37)

Regression results (generics)

Large effects for generics that the authors decline to explain

Panel D: QML for Poisson model, dep var is count of generic drug approvals

Market size	11.81 (3.30)	8.55 (6.85)	1.28 (7.17)
Lag market size		3.12 (5.94)	
Lead market size			13.24 (8.66) 14.65 (3.71)
Number of observations	198	198	165 165

Market size and innovation

Acemoglu and Linn (2004)

Finkelstein (2004)

Moscona and Sastry (2022)

Market design for innovation

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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 $MR_0 = MC$

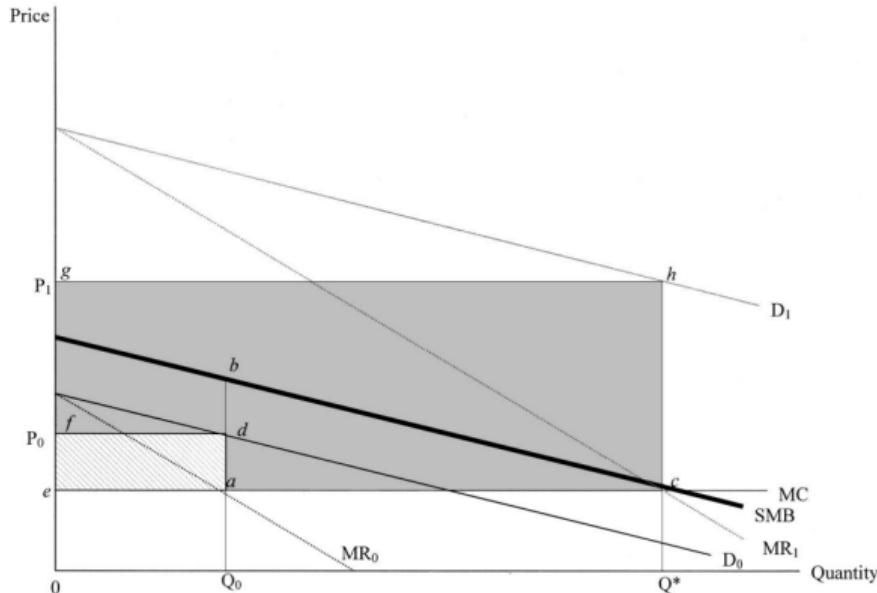


FIGURE I

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?)

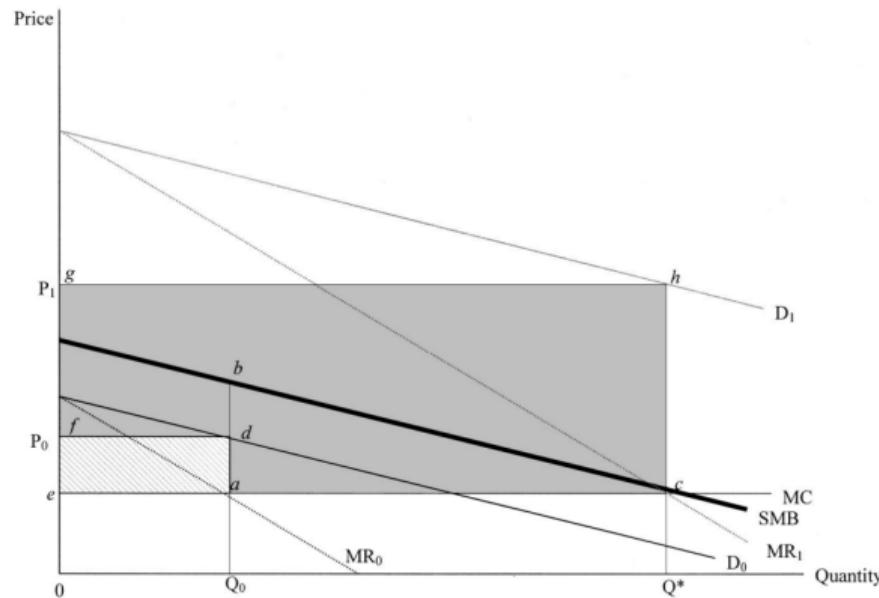


FIGURE I

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 → 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 $abij$

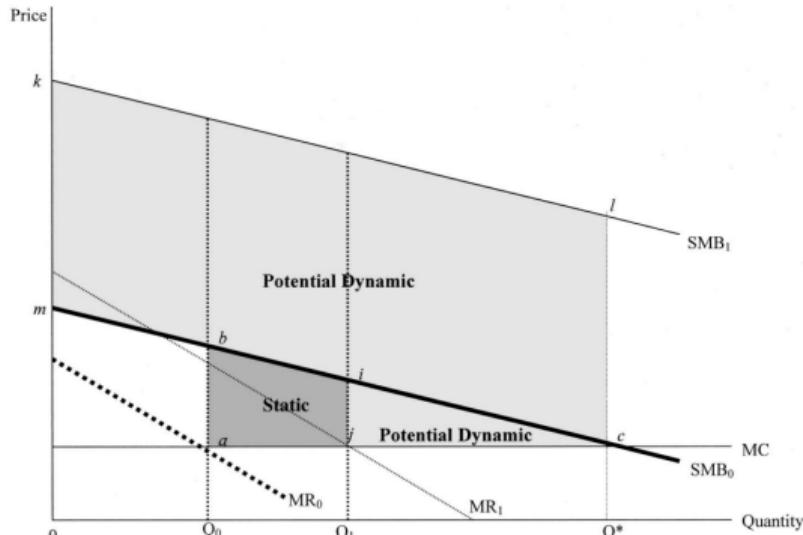


FIGURE II

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 mjc

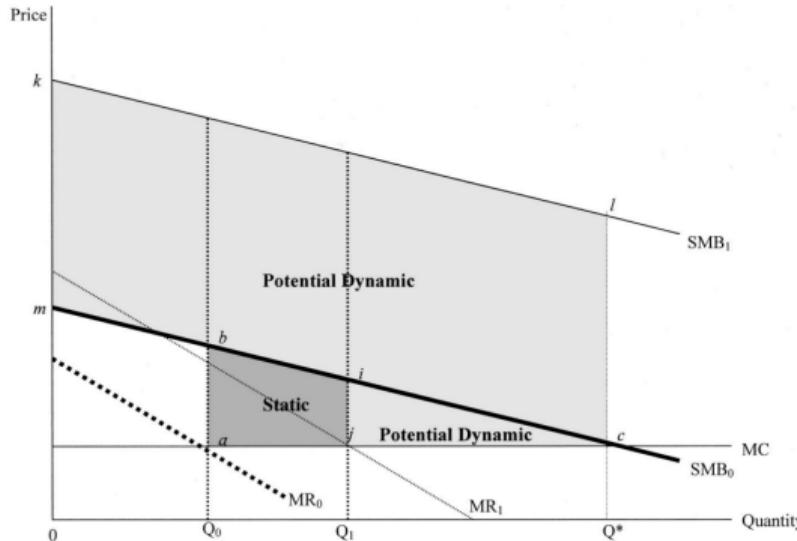


FIGURE II

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

Disease	Year clinical trial started																
	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	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

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 <i>p</i> -value	<0.01	<0.01	<0.01	<0.01	<0.01
Adjusted <i>p</i> -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

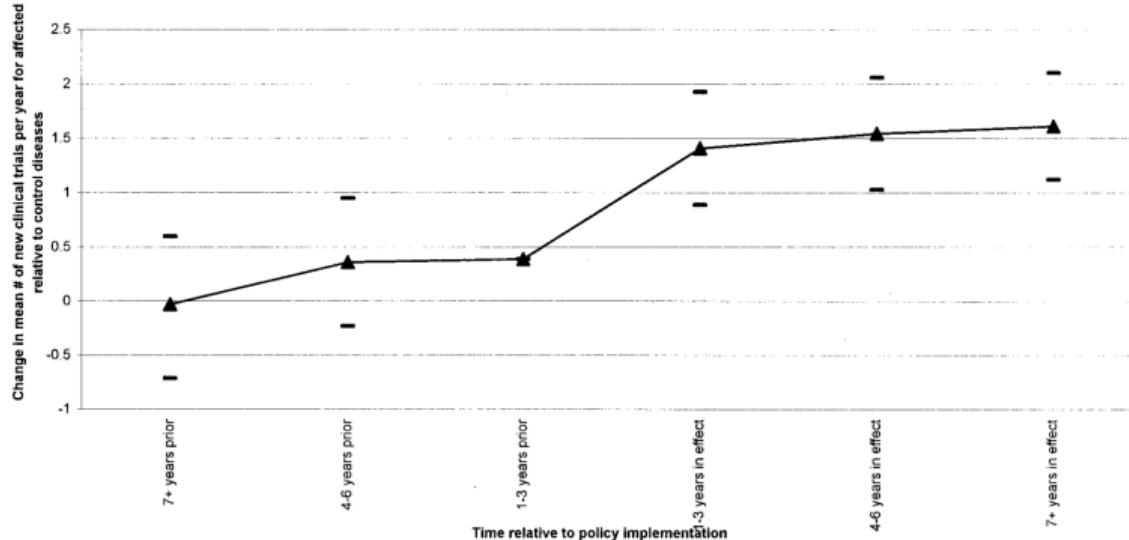


FIGURE III
Timing of Effect of Policies on New Clinical Trials

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 (0.173)	0.184 (0.234)	0.198 (0.126)	0.260 (0.205)	0.120 (0.103)	0.097 (0.142)
Unadjusted <i>p</i> -value	0.51	0.44	0.12	0.21	0.25	0.50
Adjusted <i>p</i> -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₎	-0.051	-0.081	-0.050	-0.083	-0.057
(Policy in place 1-6 years)	(0.072)	(0.101)	(0.092)	(0.102)	(0.060)
Unadjusted <i>p</i> -value	0.48	0.42	0.59	0.42	0.34
Adjusted <i>p</i> -value	0.41	0.40	0.38	0.48	0.32
ADOPT₍₇₊₎	0.364***	0.346***	0.409***	0.305**	0.348**
(Policy in place 7+ years)	(0.084)	(0.127)	(0.115)	(0.126)	(0.136)
Unadjusted <i>p</i> -value	<0.01	<0.01	<0.01	0.02	0.02
Adjusted <i>p</i> -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 ($\text{ADOPT}_{(1-6)}$) and for a policy being in effect 7 or more years ($\text{ADOPT}_{(7+)}$). 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:

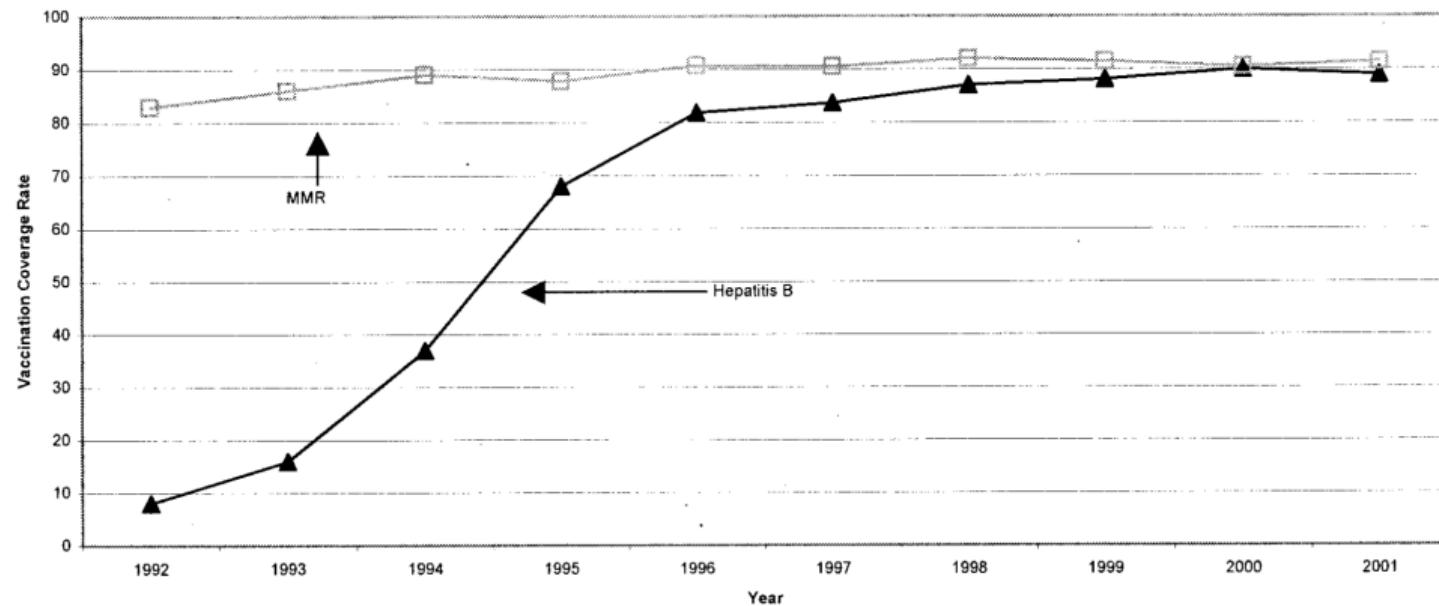


FIGURE IV

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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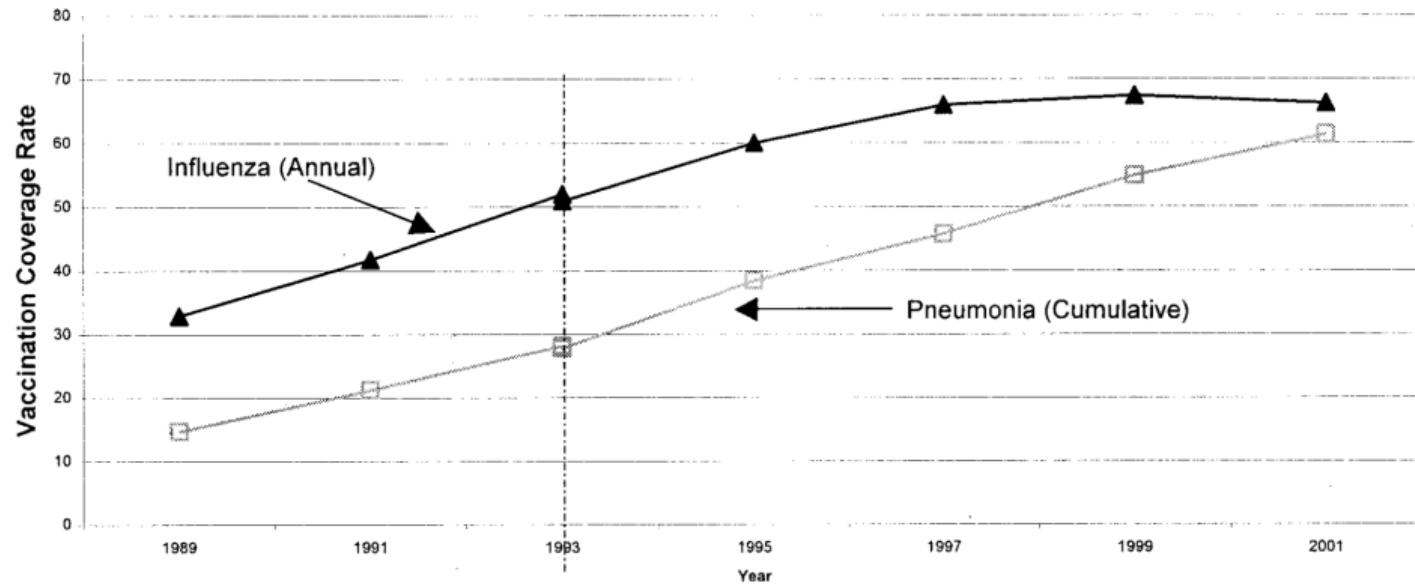


FIGURE V

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) \times (maximal efficacy of available vaccine) \times (\$ 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 <i>net</i> 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% → 85%)

Costs are based on the estimated costs of new clinical trials

Estimates of dynamic effects

Upper and lower bounds:

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.

Market size and innovation

Acemoglu and Linn (2004)

Finkelstein (2004)

Moscona and Sastry (2022)

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?

The image shows a screenshot of the Syngenta Global website. At the top, there is a navigation bar with links for "Innovation in agriculture", "Protecting crops", "Seeds", "Sustainability", "Company", "Careers", and "Country websites". The main headline on the page reads "Helping farmers. Fighting climate change." with a "The Good Growth Plan" button below it. Below this, there is a large image of a dry, cracked landscape. To the right of the headline, there is a smaller image of agricultural machinery in a field. The text "The Good Growth Plan" is displayed above this image. Below the machinery image, the text "Helping farmers. Fighting climate change." is repeated. At the bottom of the page, there is a section titled "The Good Growth Plan: a bold new set of commitments for our future" with a subtext about fighting climate change and biodiversity loss. The footer of the website includes links for "HOME", "SUSTAINABILITY", and "THE GOOD GROWTH PLAN".

Climate change and innovation incentives

Should we expect to see more or less innovation in crops that are the most impacted by climate change?

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- ▶ If innovation *substitutes* for favorable climate conditions (for example, making seeds more heat resistant), then climate change leads to more innovation for the most affected crops. Innovation will blunt the impact of climate change

Climate change and innovation incentives

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- ▶ If innovation *substitutes* for favorable climate conditions (for example, making seeds more heat resistant), then climate change leads to more innovation for the most affected crops. Innovation will blunt the impact of climate change
- ▶ 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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- ▶ 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

Ultimately the authors argue this is an empirical question

Innovation and resilience

A few more subtleties:

- ▶ Two objects of interest
 1. Innovation
 2. Climate resilience ($-\partial\pi/\partial$ climate)
- ▶ 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

Putting it all together

Summary of model predictions:

Figure 1: Summary of Model Cases

In a sector damaged by climate change...

		Climate-Substitute Technology	Climate-Complement Technology
		(a) Innovation ↑ and Resilience ↑	(b) Innovation ↓ and Resilience ↑
Price Effects Weak	Weak		
	Strong		(c) Innovation ↑ and Resilience ↓

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 × 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)

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

where $\text{Area}_{i,k}^{\text{Pre}}$ 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

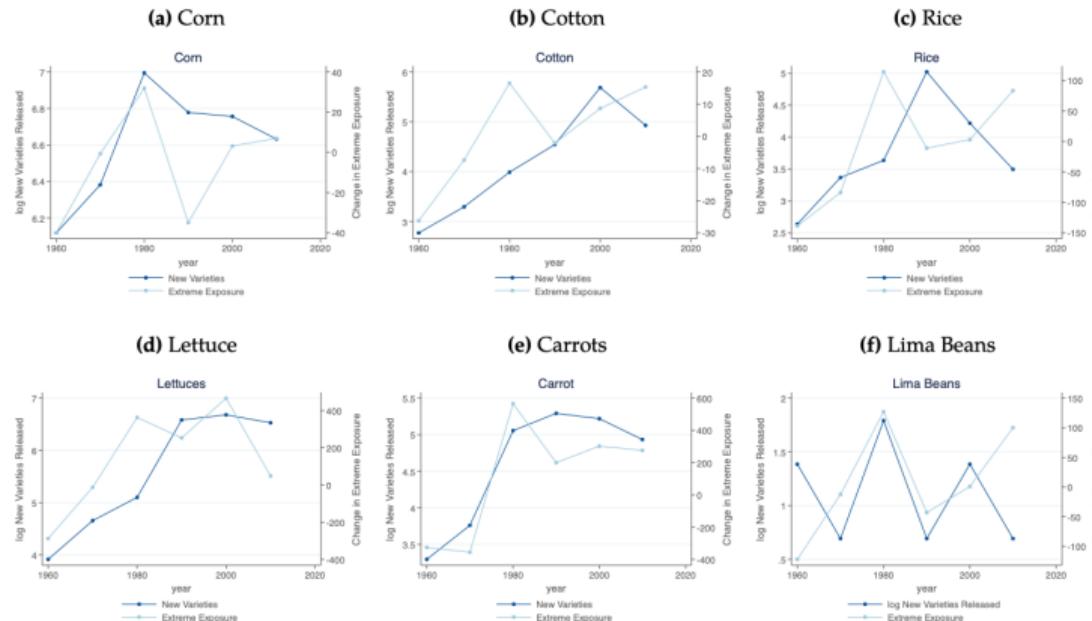
Argue that land values are a sufficient statistic for crop profitability

- ▶ 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 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

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

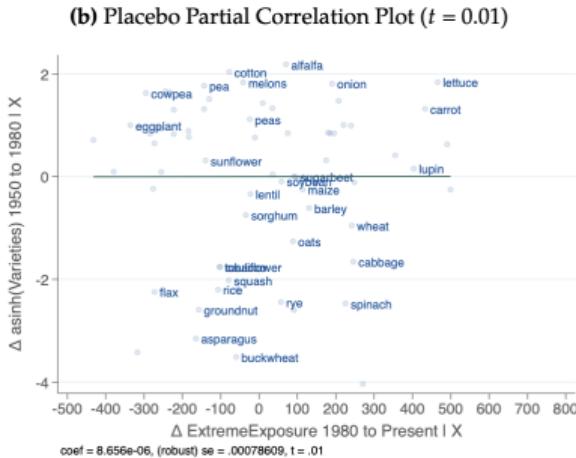
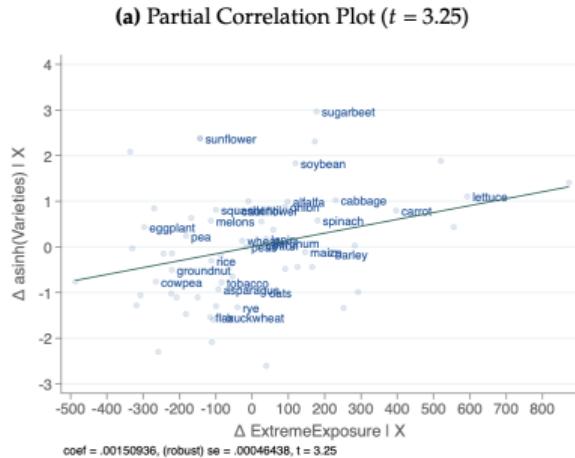
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable is New Crop Varieties						
Sample Period	1950-2016				1980-2016	
Δ ExtremeExposure	0.0167*** (0.00424)	0.0171*** (0.00436)	0.0136*** (0.00372)	0.0184*** (0.00541)	0.0226*** (0.00668)	0.0338*** (0.00745)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period 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

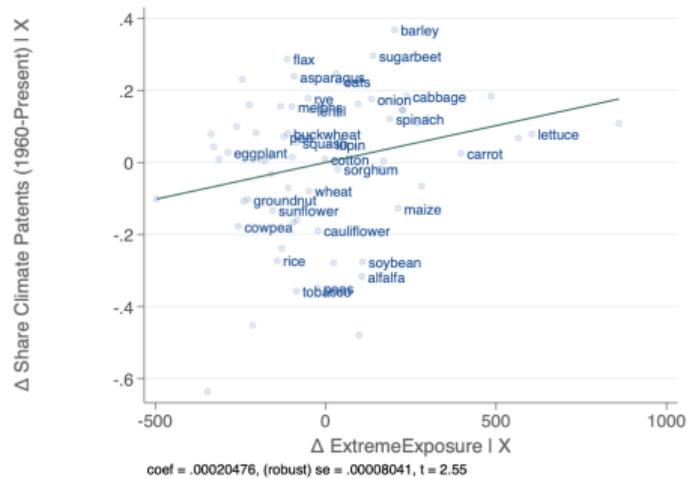
Dependent Variable:	(1) Patents <i>not</i> related to the climate	(2) Patents related to the climate
Δ ExtremeExposure	0.00335 (0.00458)	0.0118** (0.00552)
All Baseline Controls	Yes	Yes
Observations	69	69

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

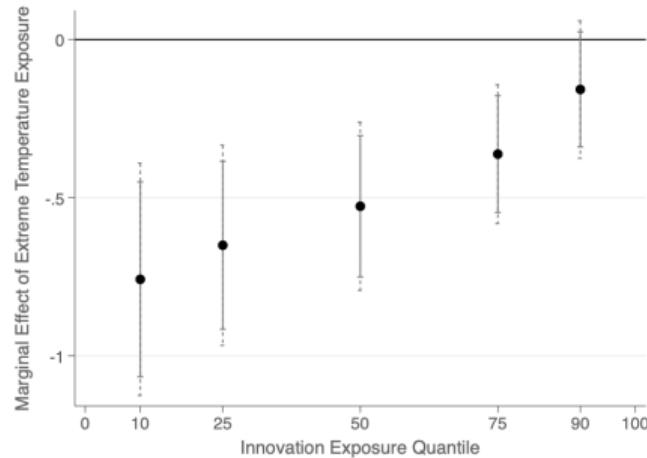


Notes: This figure reports the partial correlation plot between $\Delta \text{ExtremeExposure}_k$ and the share of crop-specific patented technologies released since 1960 that are related to the climate. The full set of baseline controls are included, including the relevant pre-period dependent variable 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.

Market size and innovation

Acemoglu and Linn (2004)

Finkelstein (2004)

Moscona and Sastry (2022)

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 prize 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

