Protecting Intellectual Property

Fabian Waldinger (University of Warwick)

Topics in Applied Microeconomics

- Course Lecturers:
  - Fabian Waldinger (Weeks 2-5)
  - Sascha Becker (Weeks 6-10)
- E-mail address: f.waldinger@warwick.ac.uk
- Office hour: Tuesdays: 11-12 in S.2.92.
- Please come to the office hour if you want to discuss questions on the course material.
- Most importantly: ask questions during the lectures starting today!

Assessment

- Written examination in May (weight 70%)
- 2 referee reports: - Each worth 15%
  - Due in weeks 6 and 10
  - (Extensions of deadline almost impossible)
  - You will get advice on how to write reports

Lecture Structure Part 1

1. Intellectual Property Rights
2. Knowledge Spillovers
3. Peer Effects
4. Migration

Course Design

- Papers discussed in the lecture cover areas in economics of innovation, labour economics, and economic history
- New methodologies will be introduced before discussing a paper
- We go very much in detail into a number of papers per week
- Please read the papers (even if it is hard)

Knowledge - Leaks Easily

- Ideas/intellectual property are special because they are
  - non-rival (i.e. the use of an idea by somebody does not prevent others from using it)
- Once you share it everyone can in principle copy your idea
- Non-rival nature of ideas is at the heart of endogenous growth models
- If ideas are non-excludable, innovation will not take place in perfect competition

The Value of Innovation in a Partial Equilibrium Model

- Model based on Acemoglu 2008, pp. 542
- N firms in a certain industry can produce a product at marginal cost $\psi > 0$
- They face a strictly decreasing demand curve:

$$Q = D(p)$$

- With perfect competition there will be no innovation.
- Suppose one of the firms (firm 1) can innovate (process innovation):
  - reduce marginal cost of production to $\frac{\psi}{\lambda}$ with $(\lambda > 1)$
  - cost of innovation $\mu > 0$

The Equilibrium without Innovation

- As there are a large number (N) of firms that all have access to the same technology with marginal cost ψ the equilibrium price without innovation will be (superscript N denotes no innovation):

$$p^N = \psi$$

- Total quantity demanded will be $D(\psi) > 0$ and can be distributed among the N firms in any arbitrary fashion
- Profits of firm 1:

$$\begin{aligned} \pi_1^N &= (p^N - \psi) q_1^N \\ &= 0 \end{aligned}$$

- Where q_1^N denotes the amount supplied by this firm

What Happens if Firm 1 Innovates?

- If firm 1 innovates the innovation can be used by all other firms (because of non-rivalry and non-excludability)
- The equilibrium price in the case of innovation will therefore be:

$$p^I = \frac{\psi}{\lambda}$$

- Total quantity supplied by all firms will be $D(\frac{\psi}{\lambda}) > D(\psi)$
- Profits of firm 1:

$$\begin{aligned} \pi_1^I &= (p^I - \tfrac{\psi}{\lambda}) q_1^I - \mu \\ &= -\mu < 0 \end{aligned}$$

- As a result, the firm has no incentive to innovate under perfect competition if ideas are non-excludable (even if λ is arbitrarily large and/or μ is arbitrarily small)

How Can Innovation Occur?

- How does one ensure that firm 1 innovates nonetheless?
- The firm has to find ways to protect its intellectual property
- There are potentially several ways of doing that:
  - Secrecy
  - Only engage in innovations that are useful for firm 1
  - Monopolies on other factors of production
  - Lead times/Beating other firms to the market
  - More formal ways of protecting intellectual property: most importantly: patents

Patenting vs. Secrecy

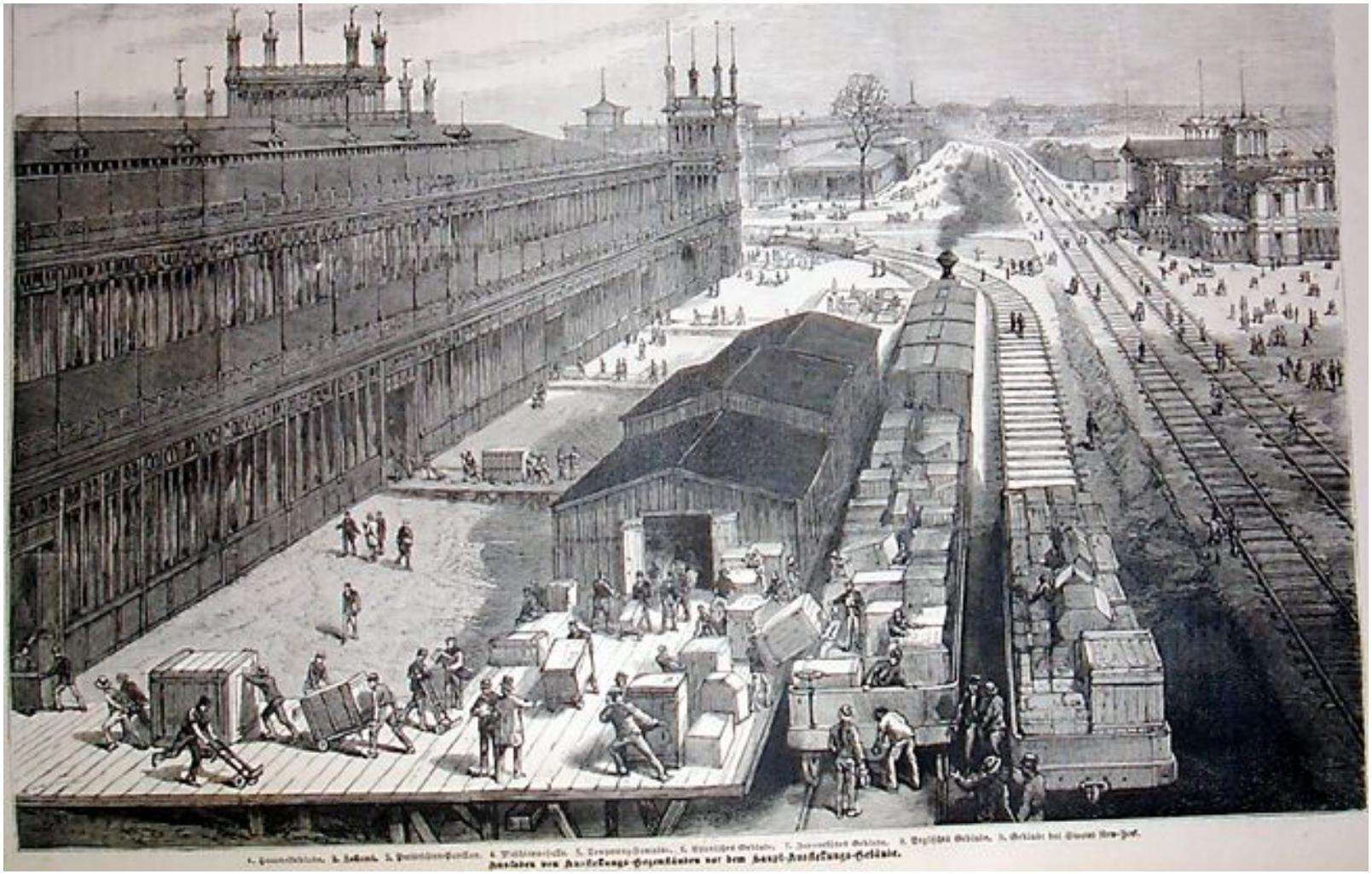
- The vast majority of the economics literature on intellectual property protection focuses on patents
- Patents are easily observable
- Non-patented innovations, however, are very hard to observe
- It is hard to study how patents affect incentives to innovate because non-patented innovations are difficult to observe
- Creative idea by Petra Moser (2005): Look at two 19th century world fairs (when these exhibitions actually showed the newest innovations)
- She compares industries of inventors in countries with and without patent protection
- Main research question: Do inventors in countries without patent protection focus on industries that allow other mechanisms to protect intellectual property (e.g. secrecy)?

Patent Laws Differed Across Countries in the 19th Century

	Patent length		Population	
Country	1851	1876	1851	1876
Austria	15	15	3,950	4,730
Bavaria	15	—	4,521	—
Belgium	15	20	4,449	5,303
Britain	14	14	25,601	30,662
Denmark	0	5	1,499	1,973
France	15	15	36,350	38,221
Germany	—	15	—	24,023
Netherlands	15	0	3,095	3,822
Prussia	12	—	16,331	—
Saxony	12	—	1,894	—
Norway & Sweden	15	—	4,875	—
Norway	—	3	—	1,803
Sweden	—	3	—	4,363
Switzerland	0	0	2,379	2,750
Württemberg	10	—	1,745	—

Crystal Palace London 1851

Centennial Exhibition Philadelphia 1876



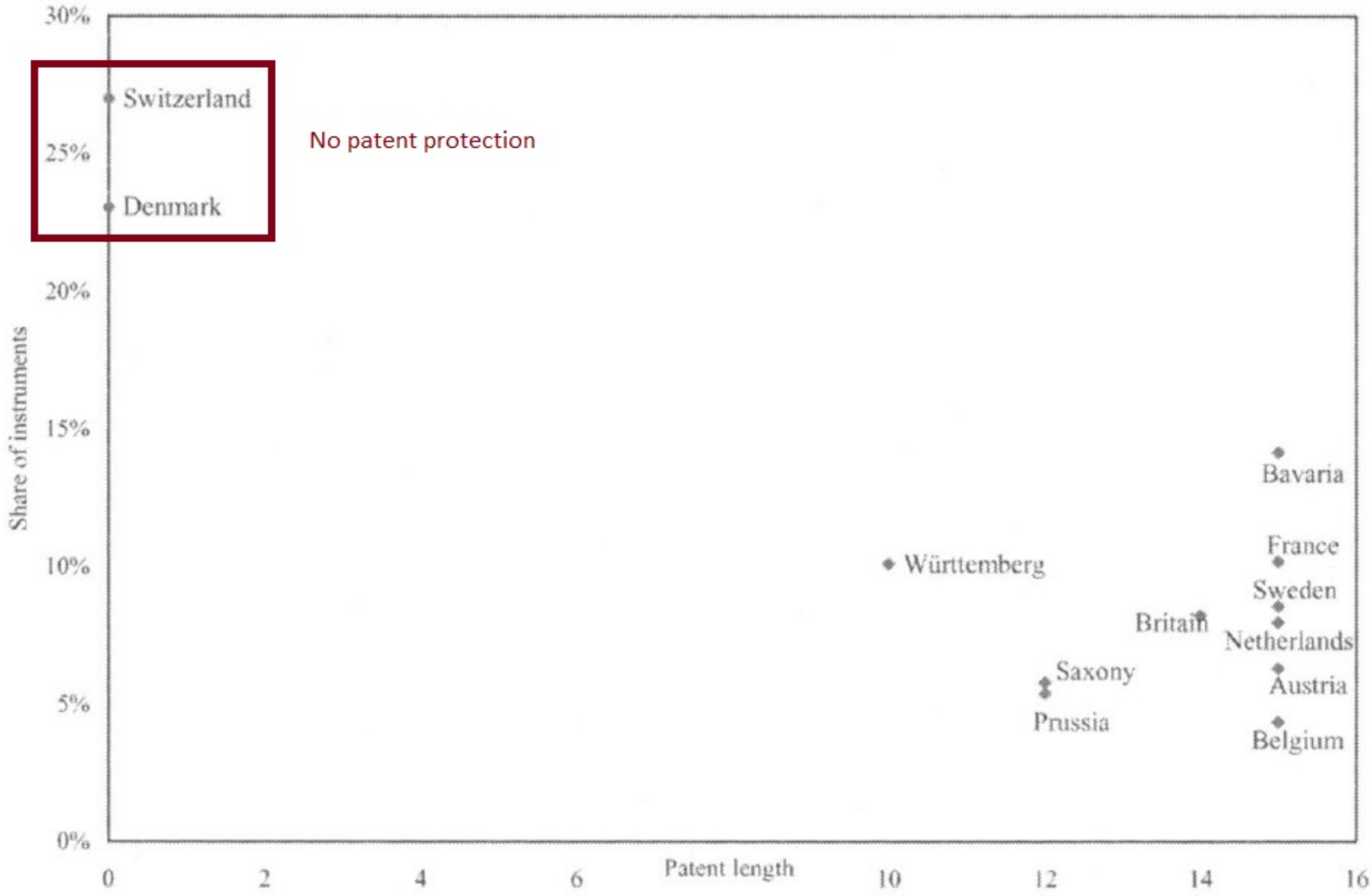
Exhibition Data

- Exhibition data are useful because they measure innovations regardless of patenting status.
  - Slight concern: innovations that can be easily copied will have a lower probability of being exhibited (unless they are protected by enforceable patents)
- To protect secrecy, inventors could exhibit the final product (instead of the machine producing it)

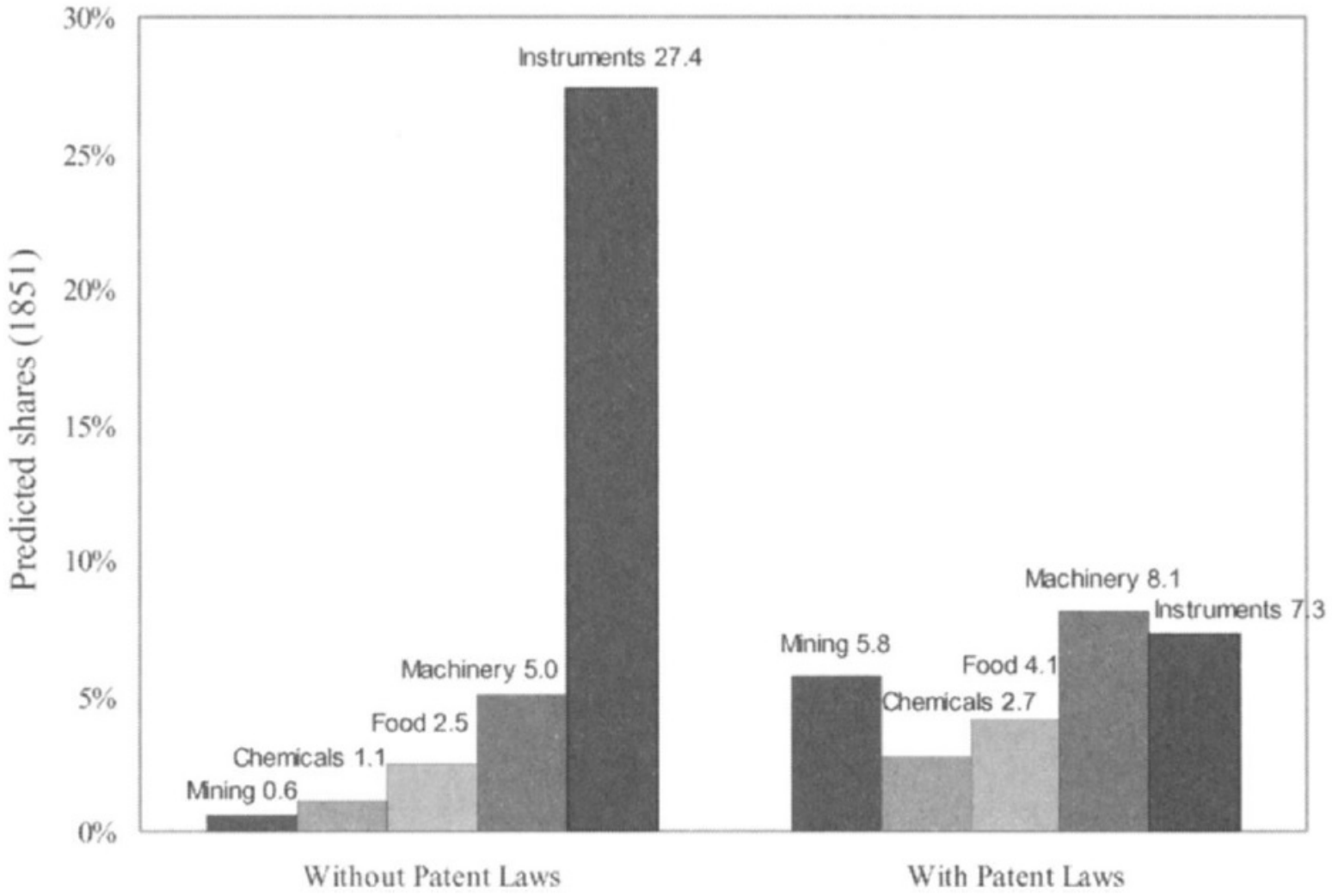
Summary Statistics

	Exhibition	
	Crystal Palace	Centennial
Location	London	Philadelphia
Year	1851	1876
Countries		
Total	40	35
N. Europe	12	10
Exhibitors		
Total	17,062	30,864
N. Europe	11,610	6,482
Visitors	6,039,195	9,892,625
Area (in acres)	25.7	71.4

Graphical Evidence - Instruments



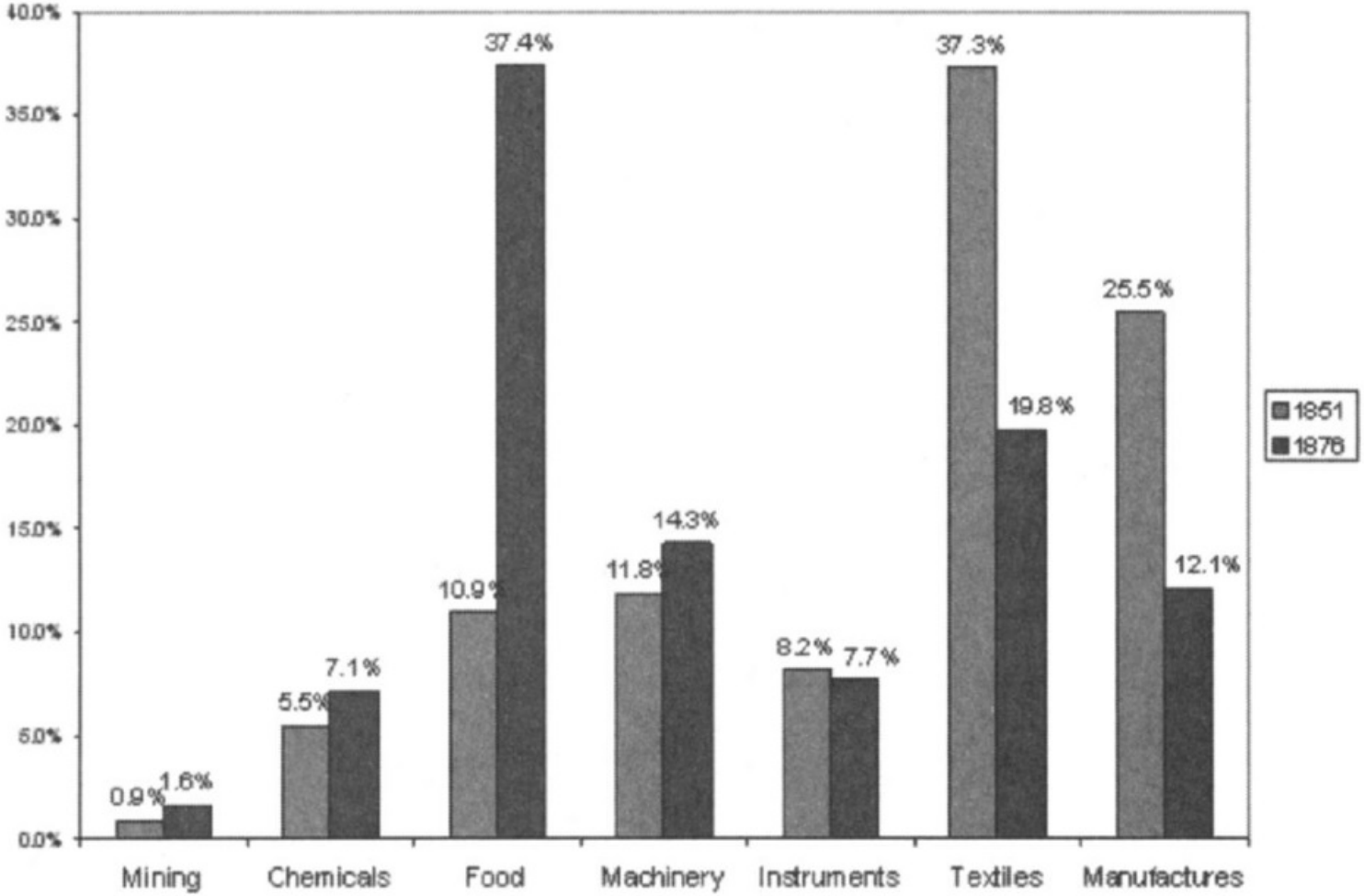
Predicted Shares Multinomial Logit - 1851



Are the Differences Really Driven by Patenting Incentives?

- There could be other unobserved factors that drive the correlation between innovation industry and patent laws
- Ideally one would investigate a situation where countries abolishe or introduce patent protection
- The Netherlands did just that and abolished patent protection in 1869
- We would expect that inventors moved into different industries after that
- Inventors:
  - moved into food processing (secrecy important)
  - stayed in instruments (despite the fact that other countries reduced their share in instruments)

Dutch Abolition of Patent Protection



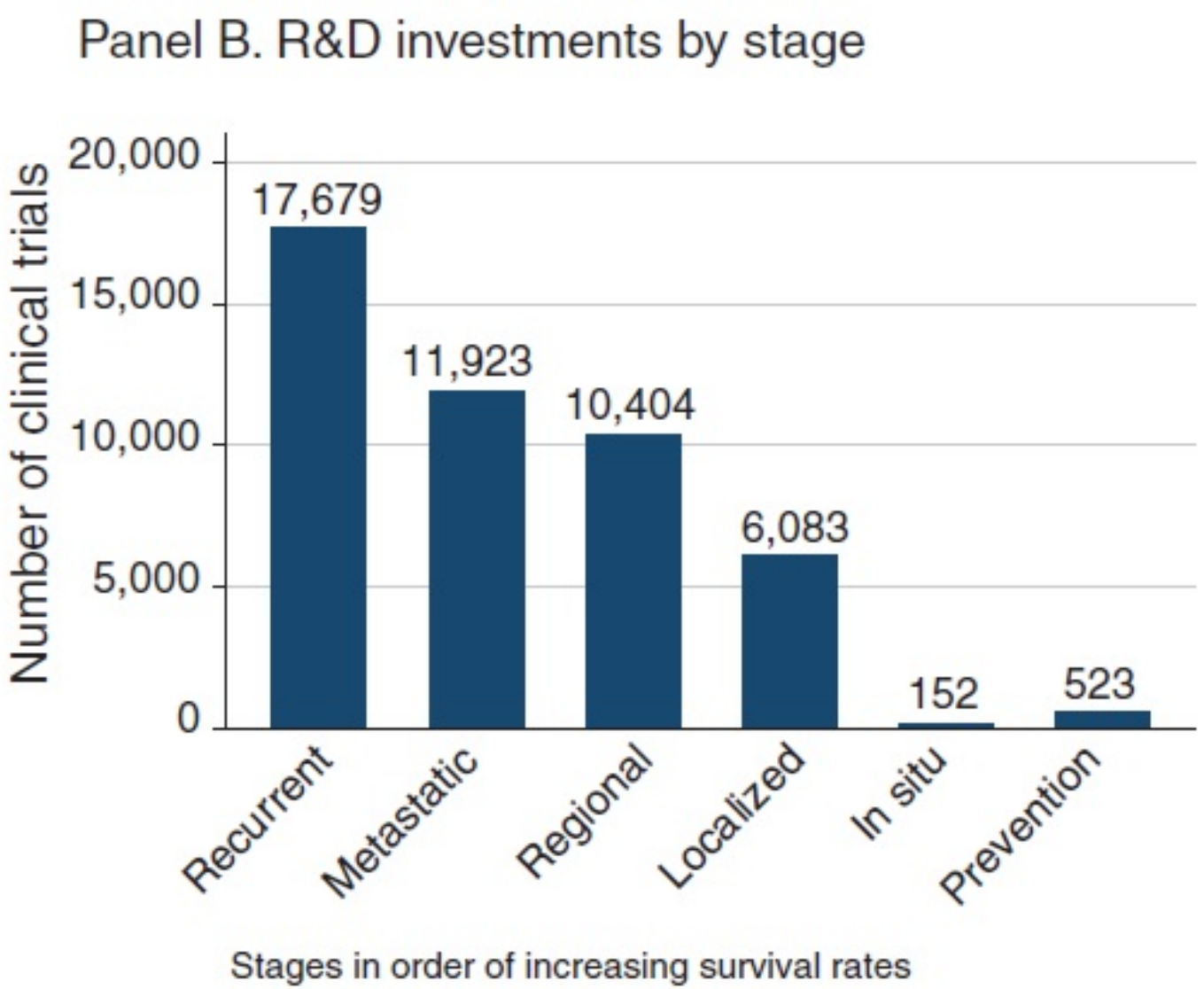
The Effect of Intellectual Property Rights on Innovation

- Intellectual property rights affect innovation in various ways:
  1. Temporary monopoly rights incentivize people to innovate (overcoming the problems highlighted in the simple model above)
  2. Once an intellectual property right has been granted it may reduce follow-on innovation
- Budish, Roin, and Williams (2015) investigate how patent length affects innovation incentives
- Heidi Williams (2013) investigates the second channel by looking at research using the human genome

Effective Patent Protection and Innovation

- Budish, Roin and Williams (2015) investigate how effective patent protection time affects innovation incentives
- In many industries firms patent at time of invention rather than first sale
  $\Rightarrow$ effective patent protection depends on the time it takes to commercialize an invention
- The authors investigate clinical trials for cancer drugs
- In most cases, firms have to show that a new drug increases survival
  $\Rightarrow$ underinvestment in drugs for conditions with longer survival times (because clinical trials last longer and effective patent protection is shorter)

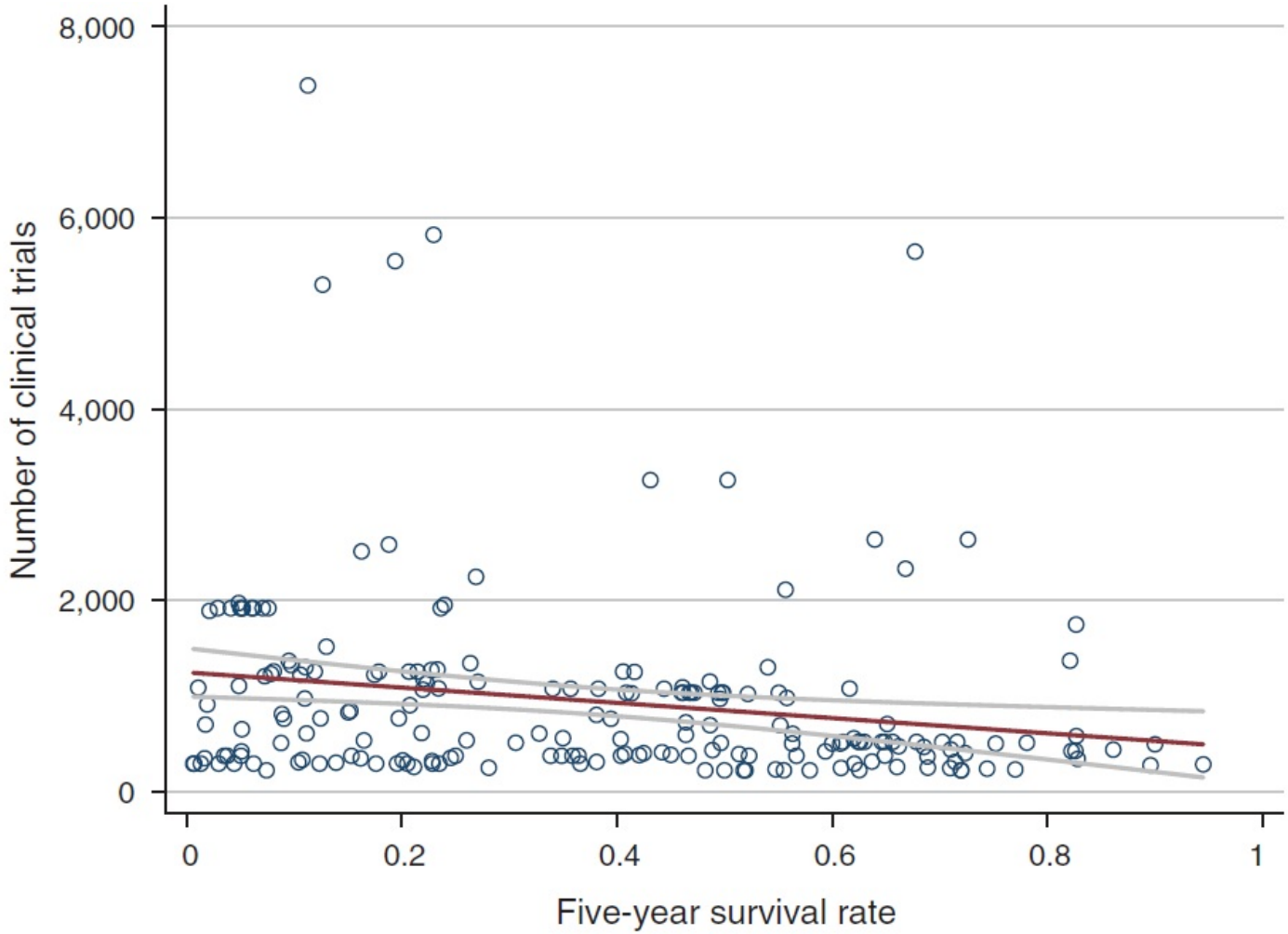
More Clinical Trials for Cancers with Shorter Survival



Data

- The authors use a data set that reports cancer trials from the US National Cancer Institute
- For each clinical trial the data contain
  1. the cancer type (e.g. breast cancer)
  2. the stage of cancer (localized, regional, metastatic)
- The authors combine these data with data on expected survival times for each cancer type and stage (main survival measure: 5-year survival)

Relationship Between Clinical Trials and Survival Time



Note: An observation is a cancer type - stage combination

Regression Results

	Number of clinical trials (mean = 945)		
	(1)	(2)	(3)
Five-year survival rate	−0.868***	−1.113***	−0.930***
	(0.319)	(0.286)	(0.286)
log(Market size)	—	0.243***	—
		(0.055)	
log(Life-years lost)	—	—	0.282***
			(0.068)

Drivers of Correlation Between Effective Patent Length and Trials?

- The negative correlation between effective patent length and the number of trials may not only be driven by a causal effect of commercialization lags on invention incentives
- The correlation may alternatively be driven by:
  - Scientific opportunities: i.e. it may be the case that it is harder to invent a drug for cancer prevention or we may already know how to treat certain "in situ" cancers
  - Demand: maybe demand affects the level of research
  - Even if commercialization lags are relevant, the social planner may want to engage in trials with faster results

Cancers with Surrogate Endpoints

- Historically some cancers predominantely use non-mortality endpoints to show drug effectiveness
- Drugs against hematological cancers (leukemias and lymphomas) have traditionally been evaluated with other endpoints (e.g. white blood cell counts for leukemia)
- Use of surrogate endpoints of FDA-approved drugs:
  - 92% for hematological cancers
  - 53% for other cancers
- This institutional setup and their theoretical model gives them two testable predictions:
  - No negative relationship between expected survival and the number of drug trials for hematological cancer
  - The number of drug trials should be similar between hematological and other cancers if expected survival is very low (as effective patent length is very similar)

Hematological vs. Other Cancers

- The authors test this predictions with the following regression:

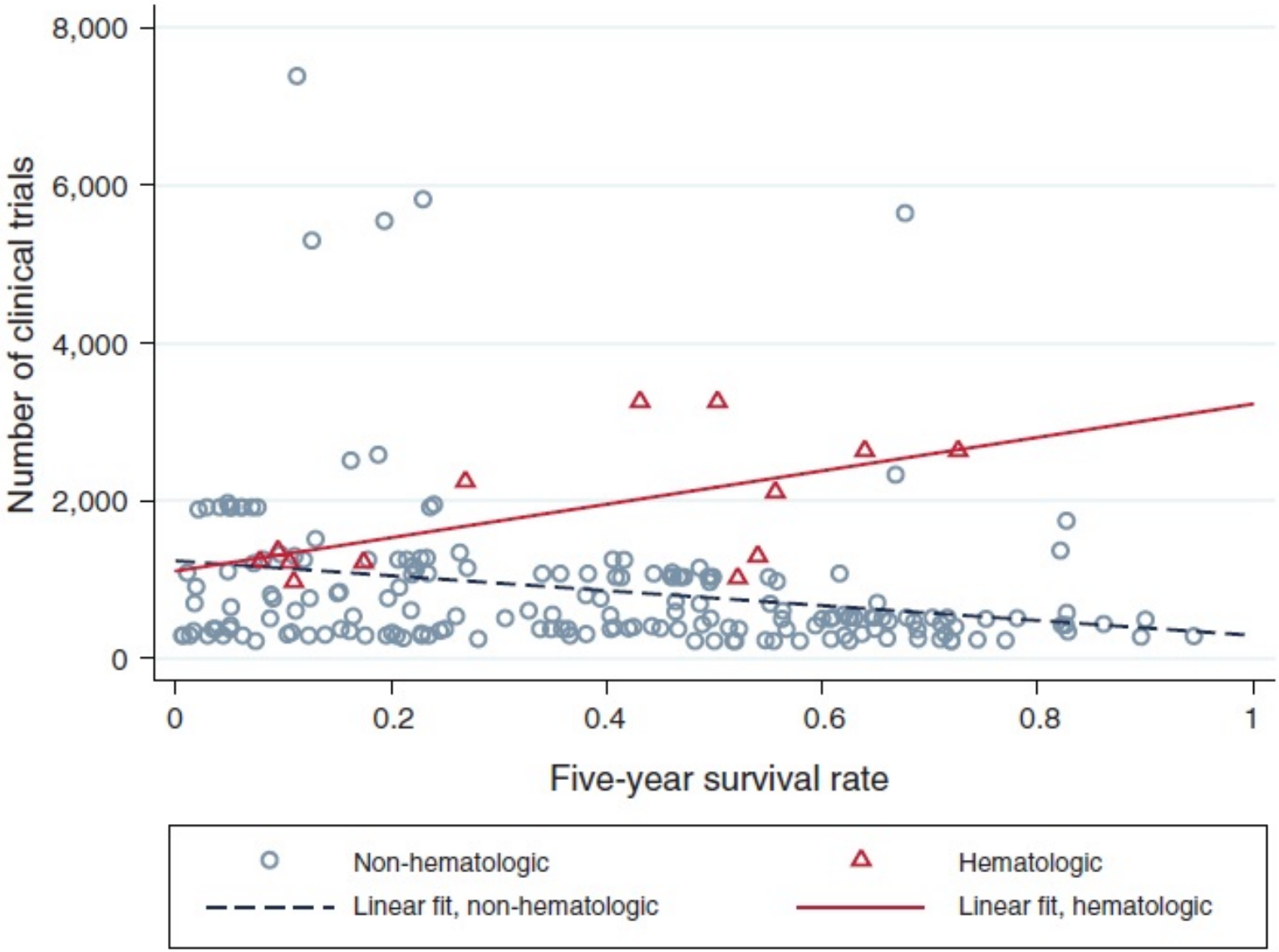
$$Trials_{cs} = \alpha + \beta\, Survival_{cs} * Hema_c + \gamma Hema_c + \delta Survival_{cs} + X_{cs} + \varepsilon_{cs}$$

- Which signs do they expect on β, γ, and δ?

Hematological vs. Other Cancers

Panel B. Composition of R&D, dependent variable: number of clinical trials (mean = 945)			
(Five-year survival rate) × (0/1: hematologic)	2.266***	2.140***	1.963***
	(0.408)	(0.541)	(0.613)
Five-year survival rate	−1.122***	−1.309***	−1.133***
	(0.343)	(0.297)	(0.303)
(0/1: hematologic)	−0.077	−0.216	−0.261
	(0.189)	(0.228)	(0.252)
log(Market size)	—	0.226***	—
		(0.056)	
log(Life-years lost)	—	—	0.253***
			(0.073)

Hematological vs. Other Cancers Graphical Evidence



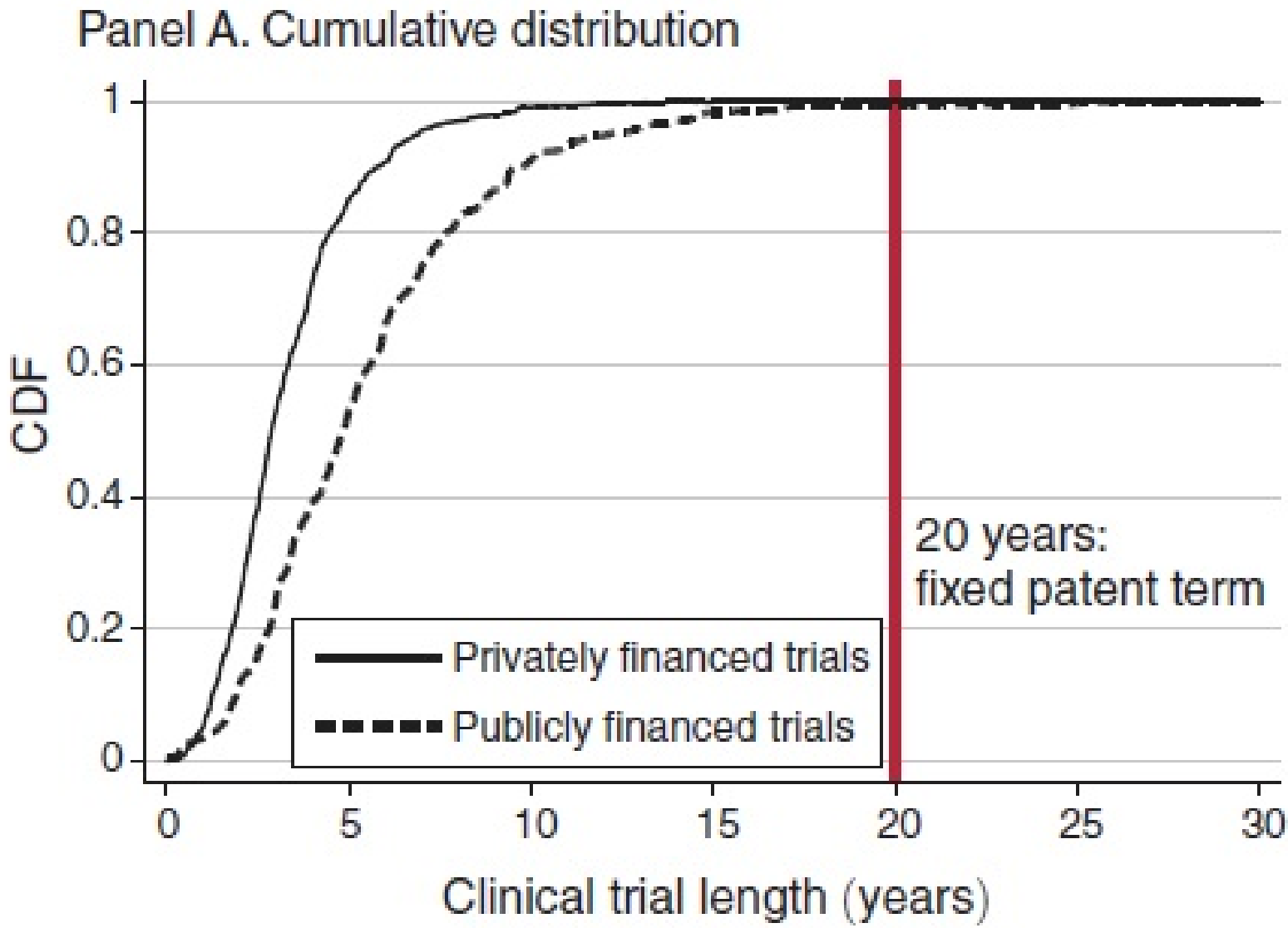
Hematological vs. Other Cancers

- Very nice evidence that cancers with surrogate endpoints do not seem to show the same distortions
- Could this relationship be driven by other factors?
  - maybe research on hematological cancers is older and research moves from late-stage to early stage?

Public vs. Private Trials

- Commercialization length should affect both publicly and privately funded trials (because even public social planners presumably want faster results)
- Privately funded trials, however, should have a stronger incentive to focus on trials with short expected survival (i.e. long expected patent protection)

Public vs. Private Trials

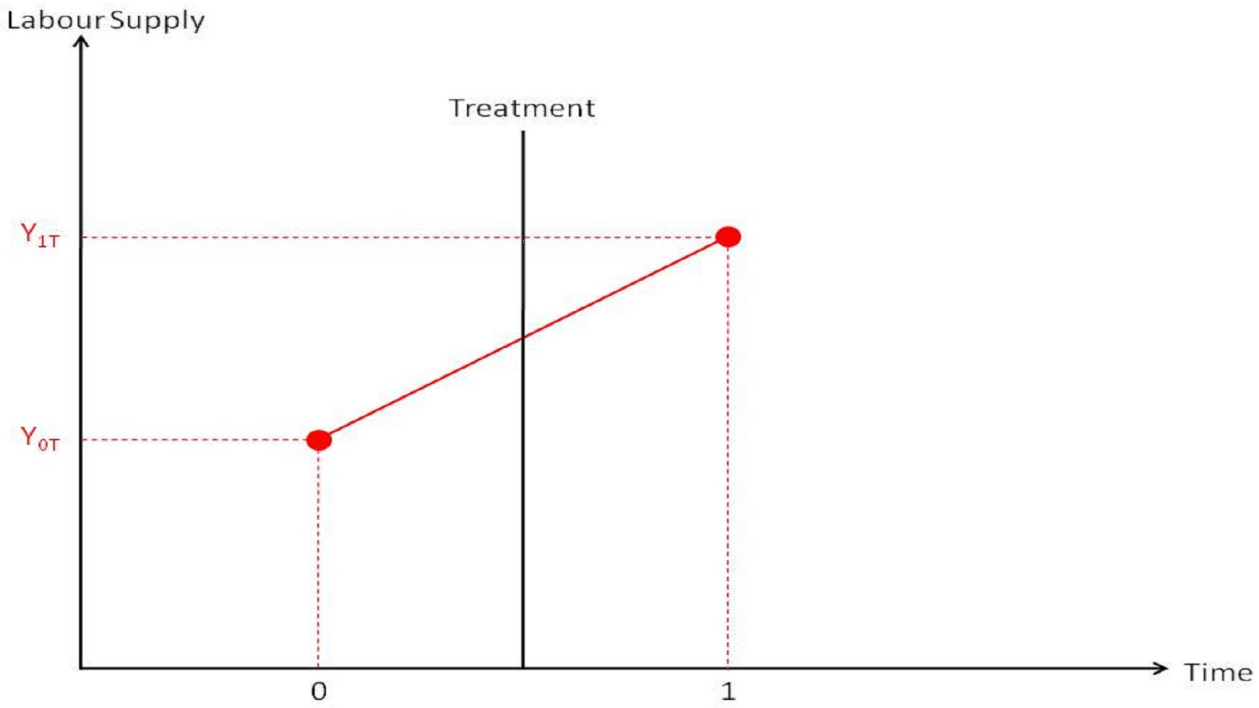


Summary

- Very nice evidence that effective patent length (as measured by expected survival) affects innovation incentives
- Cancers that allow non-survival (i.e. earlier) endpoints do not face these distortions
- Innovation incentives affect both publicly and privately funded research but has stronger effects on privately funded research

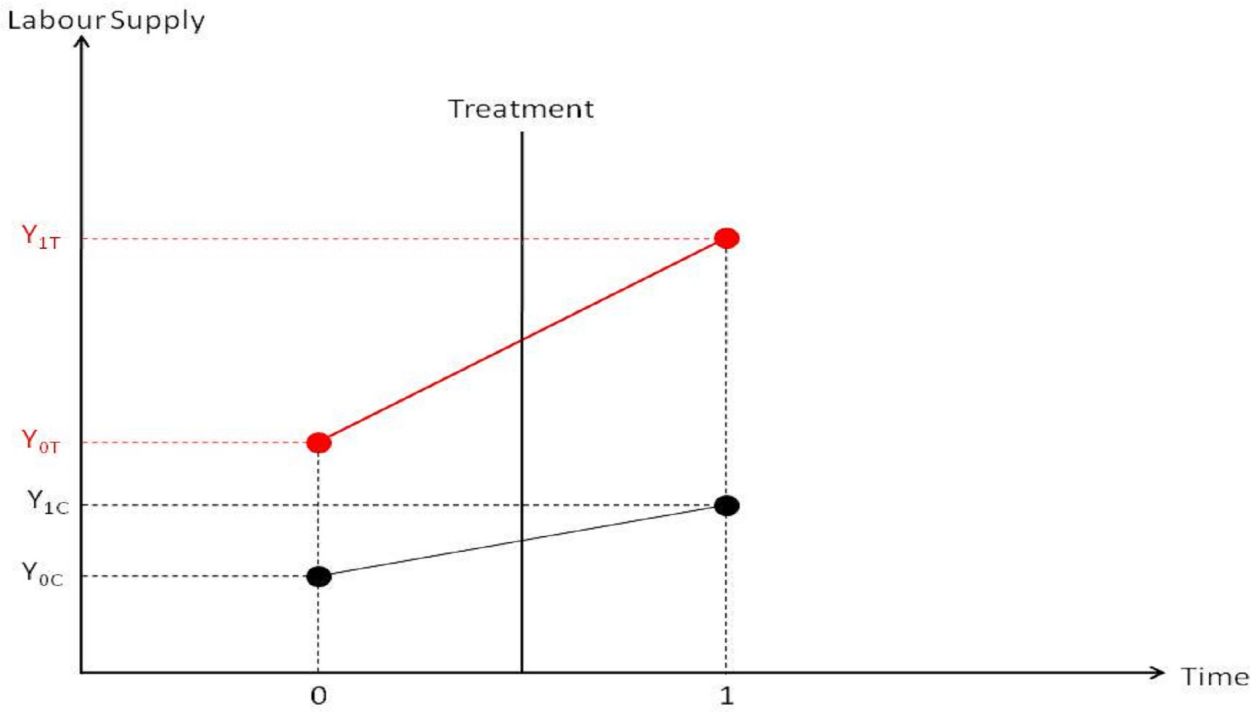
Methodology: Differences-in-Differences

- We often want to evaluate the effect of a certain programme using pre and post-treatment data
- Common problem: other factors (which affect treatment outcomes) also change from the pre to the post period (e.g. changes in the business cycle).

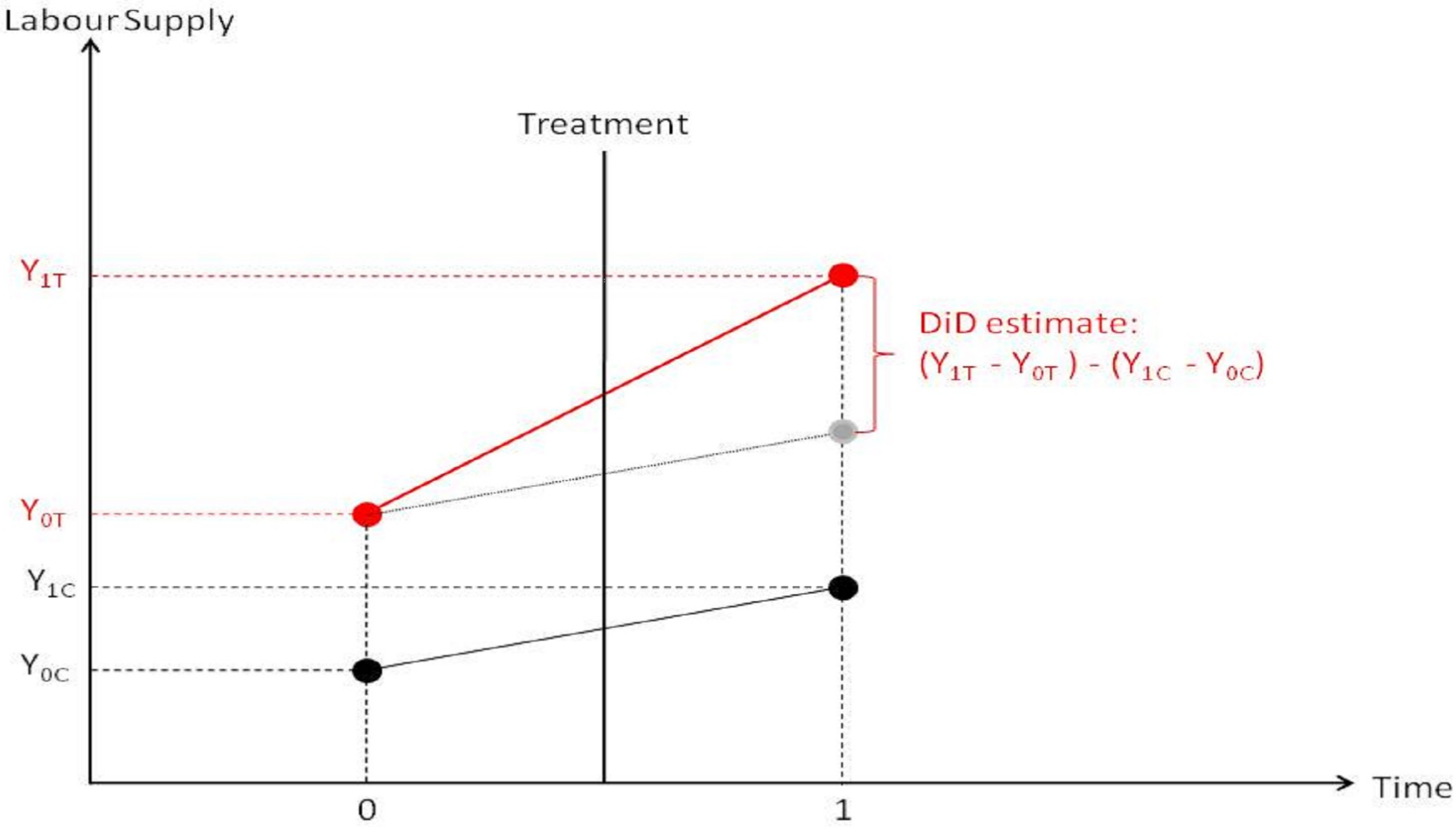


Methodology: Differences-in-Differences

- Solution: find a control group that is unaffected by the treatment but otherwise behaves exactly the same.
- In that case we control for other changes between the pre-and the post period using the changes in the in the control group.

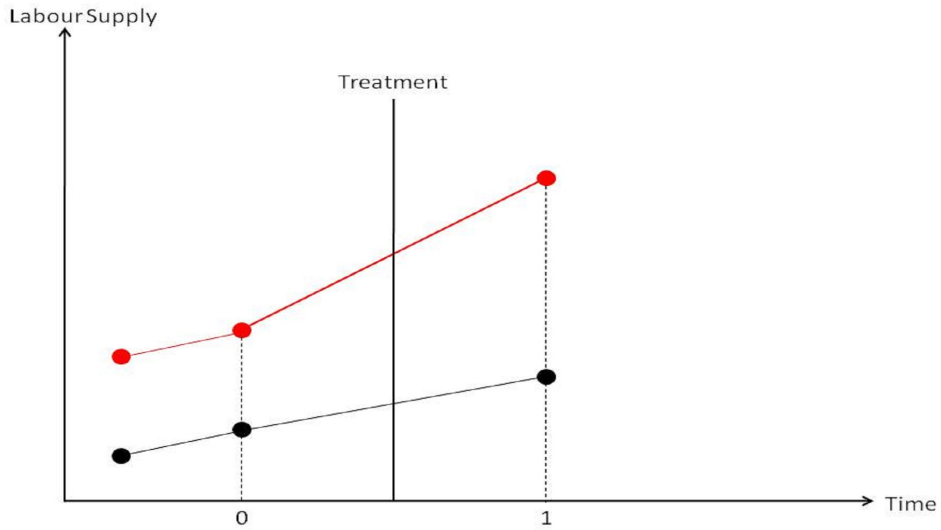


Methodology: DiD - Estimator



Methodology: DiD - Assumption

- The key assumption is that treatment and control group would have the same time trend in the absence of the treatment
- This does not mean that they have to have the same mean of the outcome!
- Difficult to verify but one usually uses pre-treatment data to show that the trends are the same (This is no proof!)



Methodology: DiD - Regression

- We can estimate the differences-in-differences estimator in a regression framework
- Advantages:
  - It is easy to calculate standard errors
  - We can control for other variables which may reduce the residual variance (reduces standard errors)
  - It is easy to include multiple periods
  - We can study treatments with different treatment intensity. (e.g. varying increases in the marginal tax rate for different people)
- Simplest DiD regression model:

$$Outcome_{it} = \beta_1 + \beta_2 Treatment_i + \beta_3 Post_t + \beta_4 (TreatmentPost)_{it} + \varepsilon_{it}$$

  - Treatment: dummy variable = 1 if individual in treatment group.
  - Post: dummy variable = 1 after treatment.

Methodology: DiD - Regression

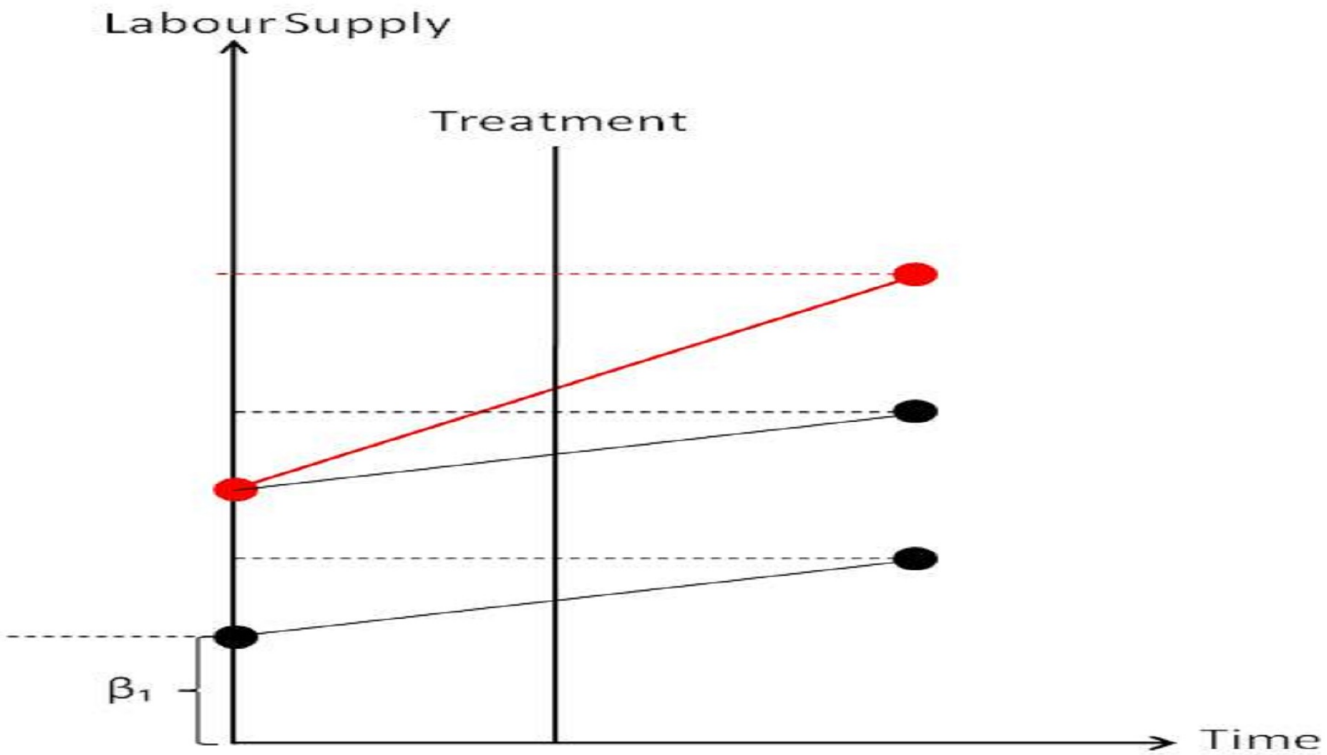
$$Outcome_{it} = \beta_1 + \beta_2 Treatment_i + \beta_3 Post_t + \beta_4 (Treatment Post)_{it} + \varepsilon_{it}$$

- β_4 is the differences-in-differences estimate
- In control group:
  - Pre-treatment: $Outcome_{it} = \beta_1$
  - Post-treatment: $Outcome_{it} = \beta_1 + \beta_3$
- In treatment group:
  - Pre-treatment: $Outcome_{it} = \beta_1 + \beta_2$
  - Post-treatment: $Outcome_{it} = \beta_1 + \beta_2 + \beta_3 + \beta_4$
- Differences-in-Differences: $[y_{1T} - y_{0T}] - [y_{1C} - y_{0C}]$

$$= [(\beta_1 + \beta_2 + \beta_3 + \beta_4) - (\beta_1 + \beta_2)] - [(\beta_1 + \beta_3) - (\beta_1)] = \beta_4$$

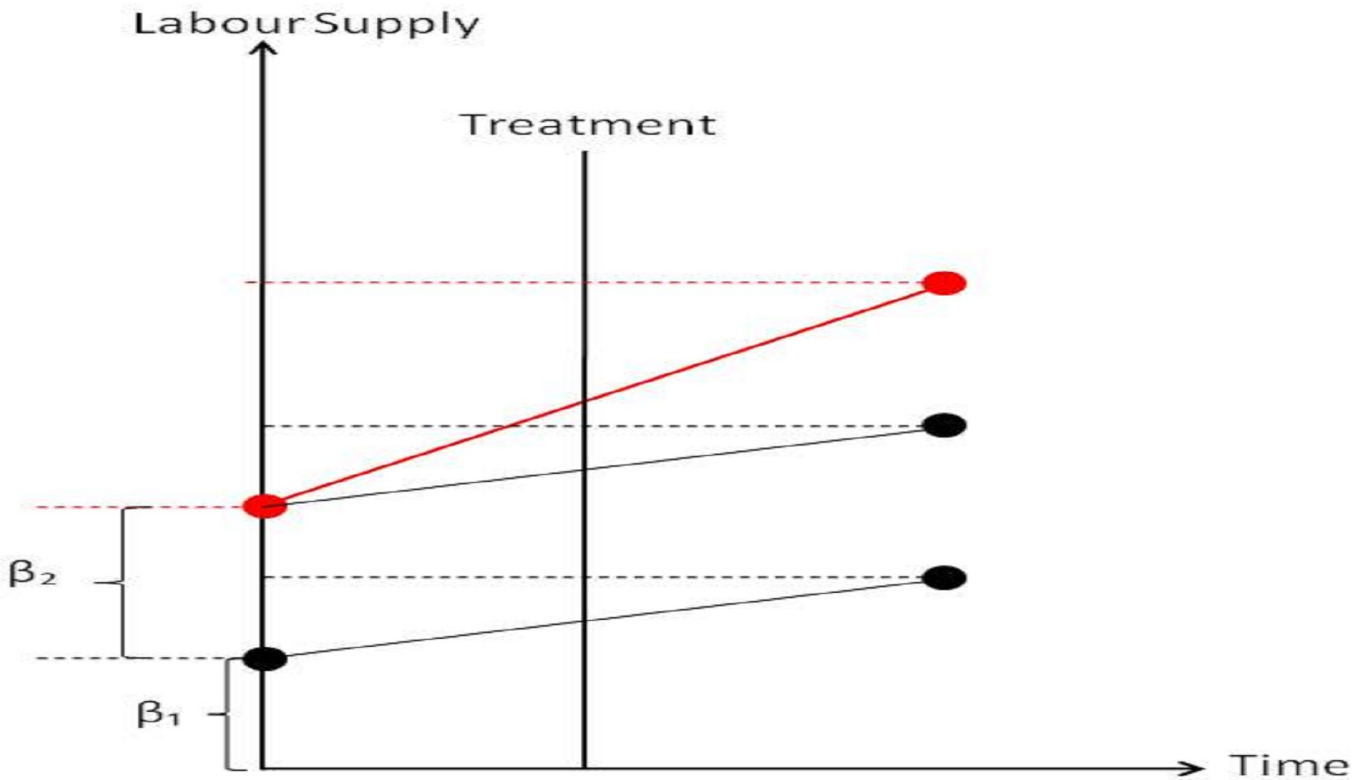
Methodology: Differences-in-Differences

$$Outcome_{it} = \beta_1 + \beta_2 Treatment_i + \beta_3 Post_t + \beta_4 (Treatment Post)_{it} + \varepsilon_{it}$$



Methodology: Differences-in-Differences

$$Outcome_{it} = \beta_1 + \beta_2 Treatment_i + \beta_3 Post_t + \beta_4 (Treatment\,Post)_{it} + \varepsilon_{it}$$



Methodology: Differences-in-Differences

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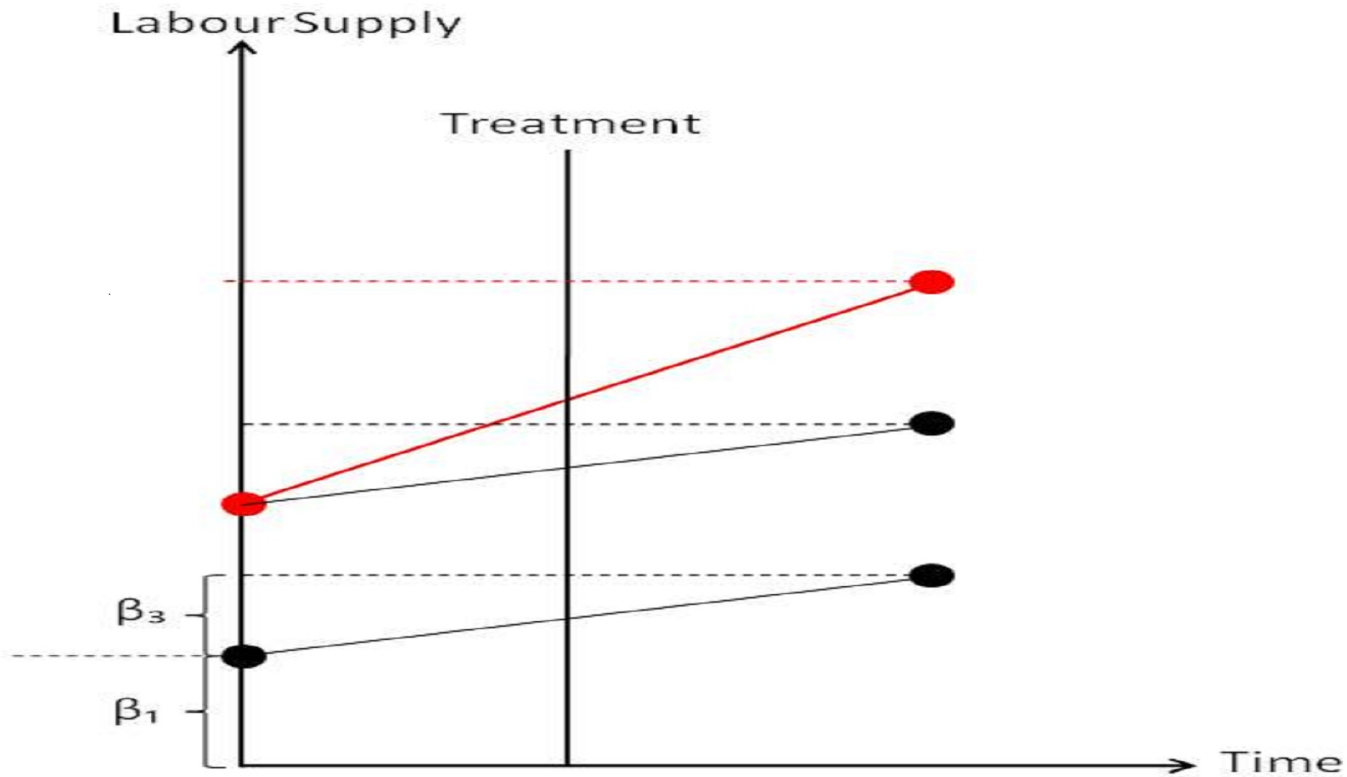

Methodology: Differences-in-Differences

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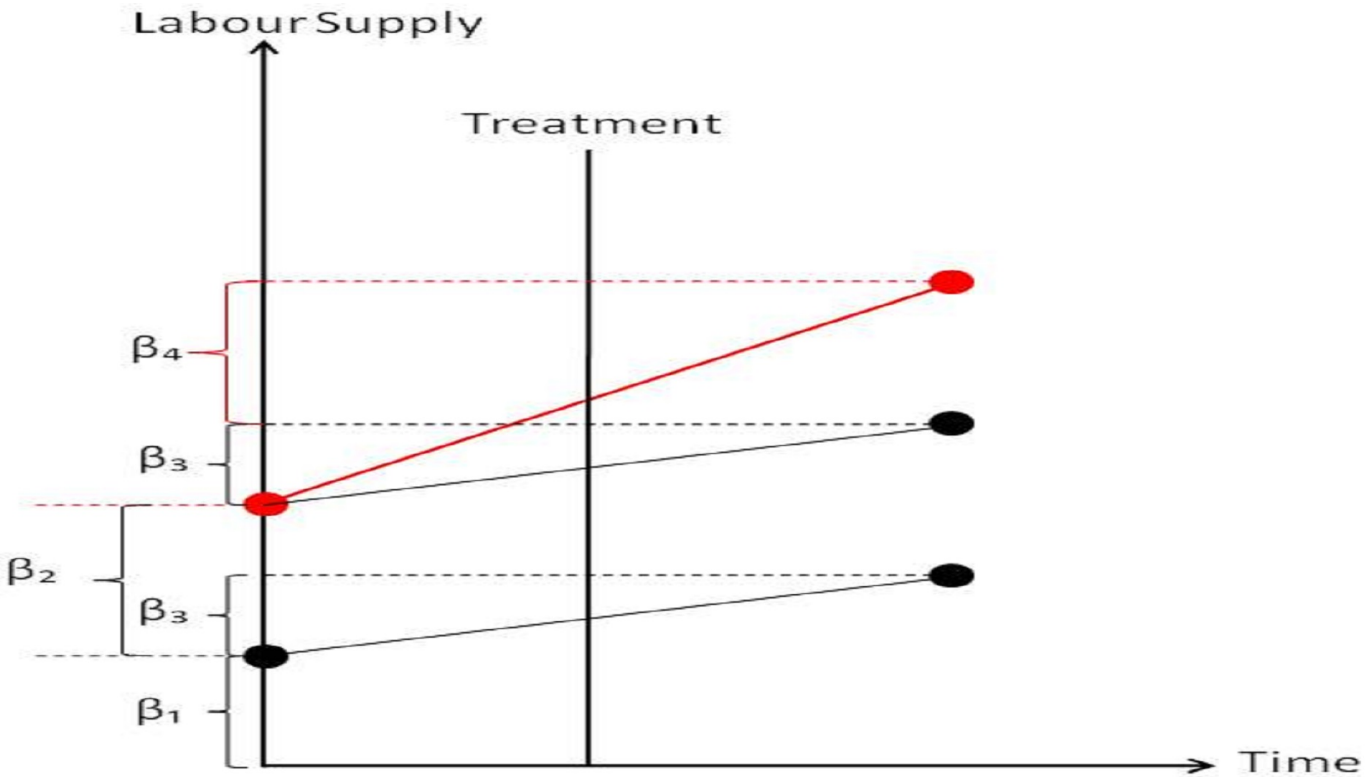


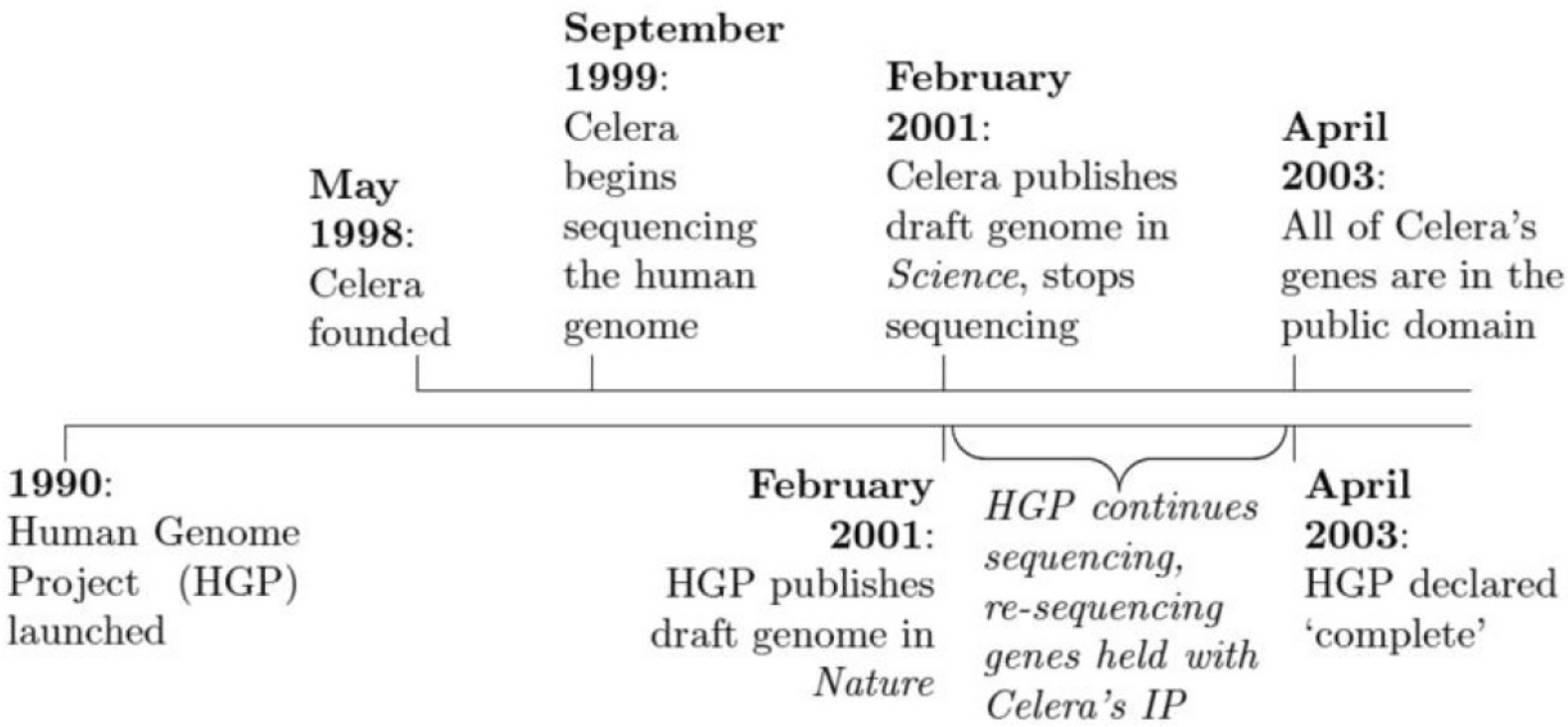
How Do Intellectual Property Rights Affect Follow-on Innovation?

- As discussed above, intellectual property rights do not only affect the incentives of the "first" inventor
- They may also affect how much follow-on innovation happens
- In a world with perfect contracting follow-on inventors would pay a license fee to compensate the intellectual property right holder but market imperfections often prevent such transactions
- Heidi Williams (2013) investigates how intellectual property rights affect follow-on innovation by looking at research building on gene sequencing of the human genome

The Human Genome

- The human genome was fully sequenced by two groups:
  1. Public *Human Genome Project*
  2. Private firm *Celera* (Craig Venter)
- For up to 2 years, genes that were sequenced by *Celera* were protected by a contract law-based form of intellectual property:
  - individuals could use the Celera sequenced genes but could not commercialize products based on those genes
  - there was uncertainty of whether Celera-held genes could be patented (eventually most genes could not be patented)

Timeline


May 1998: Celera founded
September 1999: Celera begins sequencing the human genome
February 2001: Celera publishes draft genome in *Science*, stops sequencing
April 2003: All of Celera's genes are in the public domain
1990: Human Genome Project (HGP) launched
February 2001: HGP publishes draft genome in *Nature*
HGP continues sequencing, re-sequencing genes held with Celera's IP
April 2003: HGP declared 'complete'

Basic OLS Comparison

- The most basic results estimate the following regression equation:

$$outcome_g = \alpha + \beta\, celera_g + \lambda\, controls_g + \varepsilon_g$$

- Just comparing genes sequenced by the HGP and Celera is problematic because the HGP initially targeted genes with suggested medical applications
- To control for positive selection in sequencing by the HGP she estimates the following regression:

$$outcome_{gy} = \alpha + \beta\, celera_{gy} + \delta_g + \gamma_y + \varepsilon_{gy}$$

- She controls for gene and time FE and uses the fact that some genes switch from being exclusively sequenced by Celera (celera = 1) to also being sequenced by the HGP (celera = 0)
- Basically a differences-in-differences specification

Baseline Results

A. Publications in 2001–9 (mean = 2.197):			
Celera	−.877	−.328	−.264
	(.177)***	(.099)***	(.107)***
B. 1(known, uncertain phenotype) (mean = .453)			
Celera	−.162	−.158	−.128
	(.015)***	(.015)***	(.017)***
C. 1(known, certain phenotype) (mean = .081)			
Celera	−.027	−.017	−.014
	(.007)***	(.006)***	(.007)**
D. 1(used in any diagnostic test) (mean = .060)			
Celera	−.023	−.014	−.013
	(.006)***	(.005)***	(.006)**
Indicator variables for year of disclosure	Yes	Yes	Yes
Number of publications in each year 1970–2000	No	Yes	Yes
Detailed cytogenetic and molecular covariates	No	No	Yes
Observations	27,882	27,882	16,485

Differences-in-Differences Results

	(1)	(2)	(3)
A. Publications (mean = .244)			
Celera	−.160	−.121	−.109
	(.017)***	(.011)***	(.011)***
B. **1**(known, uncertain phenotype) (mean = .381)			
Celera	−.163	−.160	−.083
	(.009)***	(.008)***	(.008)***
Year fixed effects	Yes	Yes	Yes
Indicator variables for year of disclosure	Yes	Yes	No
Number of publications in each year 1970–2000	No	Yes	No
Gene fixed effects	No	No	Yes
Observations	250,938	250,938	250,938

Event Study Graph - Publications