

The Endless Frontier?
Innovation, Sustainability and Tragic Choices in the Treatment of Cancer Diseases

Fabio Pammolli

DIG and CADS, Politecnico di Milano Fondazione CERM

Cancer Real World. Milan, January 25, 2019



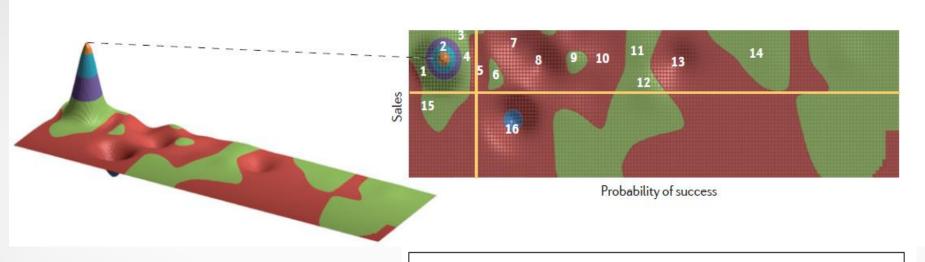
- The Endless Frontier
- Innovation, Sustainability and Pricing
- Targeting and Impact Analysis in the Wild



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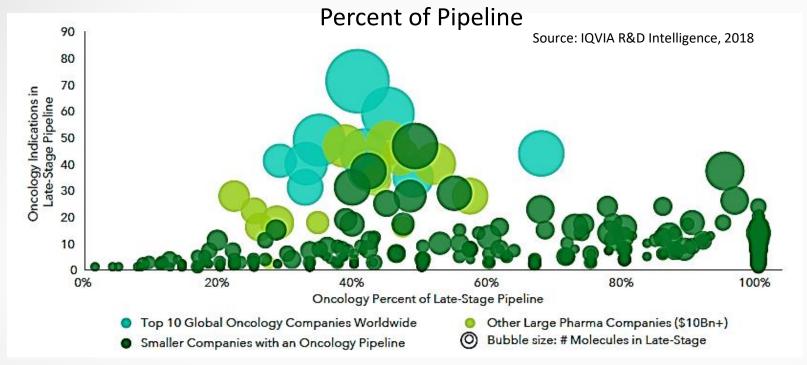
- 1 A08A: Anti-obesity
- 2 L01X: Cancer, monoclonal antibodies
- 3 N07D: Anti-Alzheimer's drugs
- 4 M01C: Specific antirheumatics
- 5 C01B: Anti-arrhythmics
- 6 A10B: Diabetes, excluding insulin
- 7 J05C: Anti-HIV
- 8 C01D: Vasodilators
- 9 N04A: Anti-Parkinson's drugs

- 10 C04A: Peripheral vasodilators
- 11 J05B: Antivirals, others
- 12 N02B: Analgesics
- 13 C02A: Anti-adrenergic agents
- **14** G04D: Urinary incontinence; B02D: Blood fractions
- 15 A16A: Other alimentary tract and metabolism products
- 16 C06A: Cardiovascular, others

F. Pammolli, L. Magazzini, M. Riccaboni, (2011), "The productivity crisis in pharmaceutical R&D", Nature Reviews Drug Discovery volume 10, pages 428–438



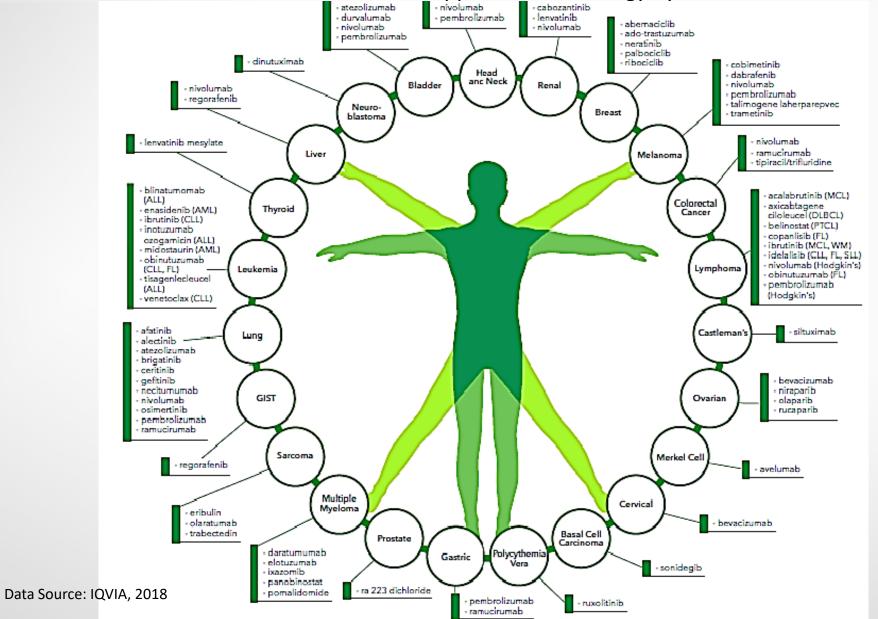
Company Late-Stage Pipelines, Number of Oncology Indications and Oncology



- CAR T (Chimeric Antigen Receptor T-cell) Immunotherapy 50 projects in clinical trials.
- Cell therapy, carrier cell therapy and stem cell therapy 529 projects in clinical development
- Conjugated monoclonal antibodies 188 projects in clinical development

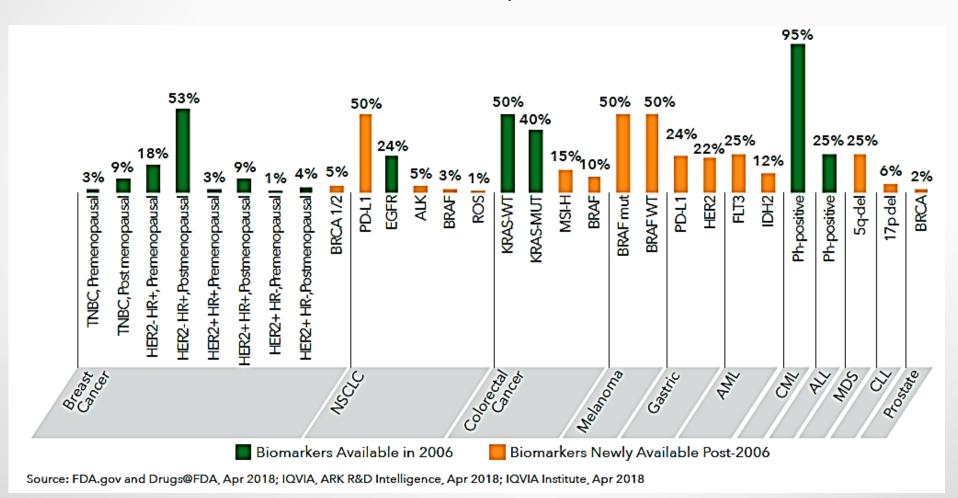


New Active Substance Approvals in Oncology by Indication, 2013—2017



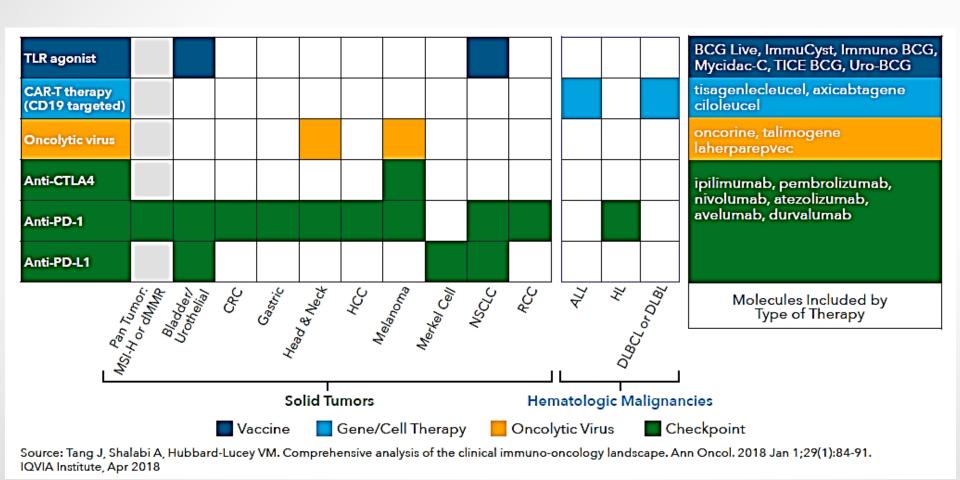


Patient Incidence of Positive Biomarker Results Per Cancer by Biomarker Availability, 2017





Approved Checkpoint Inhibitors and Next-Generation Biotherapeutics by Mechanism of Action and Tumor Type Approvals



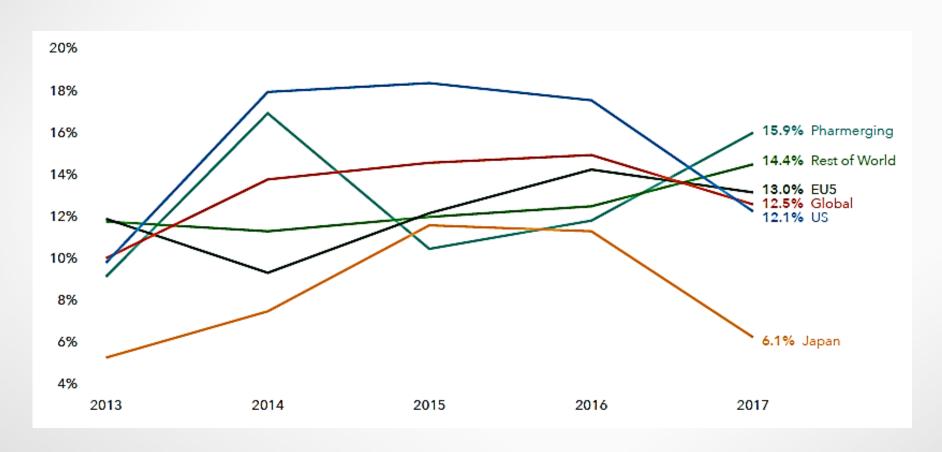


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Innovation, Sustainability and Pricing

Growth Rates for Global Oncology Therapeutic Medicines Spending, 2013—2017

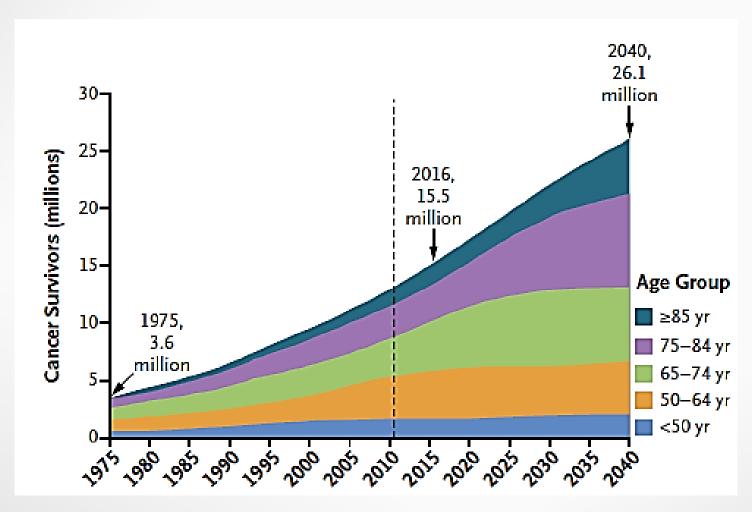


Data Source: IQVIA, MIDAS, Dec 2017



Innovation, Ageing, and the Welfare System

Cancer Survivors by Age Cohort



Innovation and Ageing: The Macro Constraints

Population 65+:

2017: 22.3% (Germany: 21.2%, France:19.2%)

2040: 32.1% (Germany: 28.7%, France: 25.6%)

Welfare expenditure, Italy

Demographics: higher life expectancy (+2 years)

AWG Risk: Higher health expenditure due to technological

drivers

Innovation, Ageing: The Macro Constraints

PAYGO Burden, baseline (Demography: EUROPOP2015 base scenario, AWG Reference scenario)

Italy: Current: 64.2% (*21.8% health+ltc*) 2040: 80.0% (26.4% health+ltc)

Demographic stress scenario (higher life expectancy)

2040: 80.2% (24.5% health+ltc)

Innovation intensive stress scenario (Health)

2040: 81.4% (27.8% health+ltc)



Innovation and Ageing: The Macro Constraints

Total Health Expenditure as a function of GDP:

8.9% (OECD) (of which 71% funded through public expenditure, i.e. 6.3% GDP).

We project public health expenditure using age-class cost profiles and population projections and compute the average benefit cut required to keep the expenditure at the current level (as a % of GDP).

Costs are assumed to grow at the GDP growth rate.

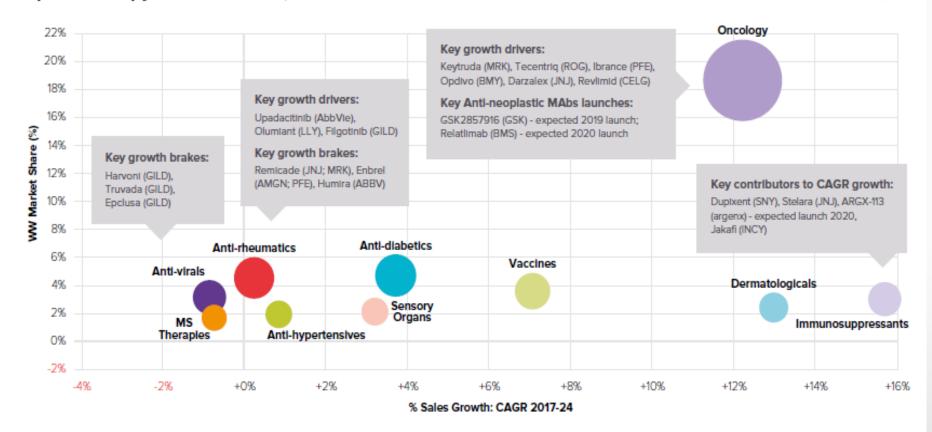
	2020	2030	2040
Coverage Cut	2.9%	9.5%	15.3%



Back to Innovation and Sustainability

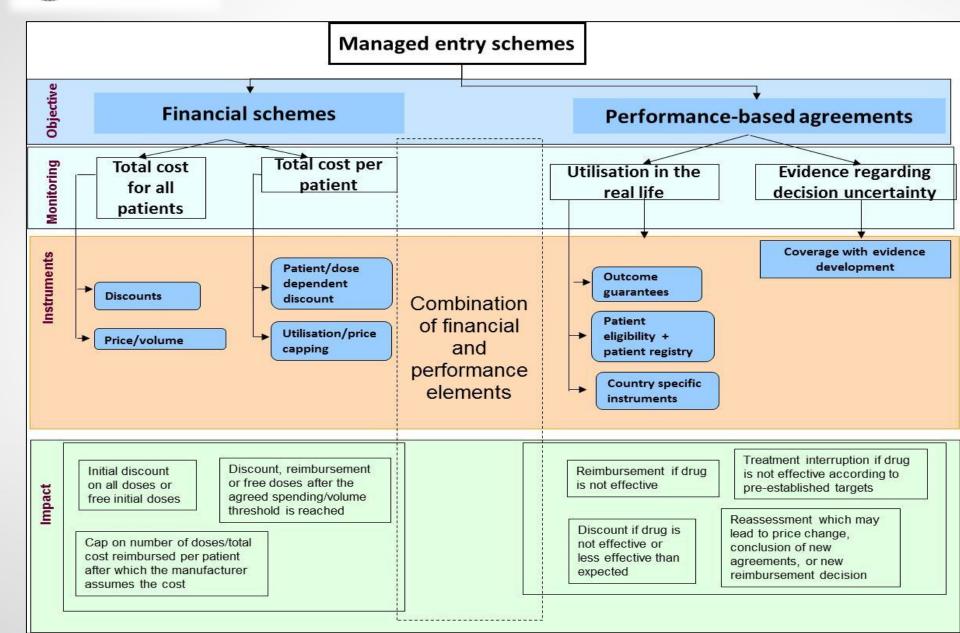
Top 10 Therapy Areas in 2024, Market Share & Sales Growth

Source: Evaluate, May 2018





Back to Innovation: Pricing, Reimbursement and MEAs





Back to Innovation: Pricing, Reimbursement and MEAs

Financial Sustainability, Risk Sharing, Payments by Results,

....but...

Real World Challenges

- Accelerated Adaptive pathways, Micro-level heterogeneity,
 Clinical guidelines vs. usage in specific patient cohorts
- Adjunctive therapies, Multiple indications, Combined therapies (e.g. ipilinumab + nivolumab in metastatic melanoma), Entry of new drugs
- Percentage of long term survivors (unknown ex ante)
- Duration of drug responses (unknown ex ante)
- Local and national formulary listing decisions; Off-labeling

Back to Innovation: Pricing, Reimbursement and MEAs

Alternative solutions

Master and Margarita (Bulgakov) (e.g. broad equivalency classes, denial of breakthrough designations, rationing/coverage restrictions, delays ...)

OR ...

Data repositories to support ML+Causal modelling in real world to sustain payment by results, adaptive reimbursement, outcome based refund agreements, protocols in real world, socio-economic impact

AND ...

Drugs Looking for Diseases, Medical Decision Making, Tragic Choices



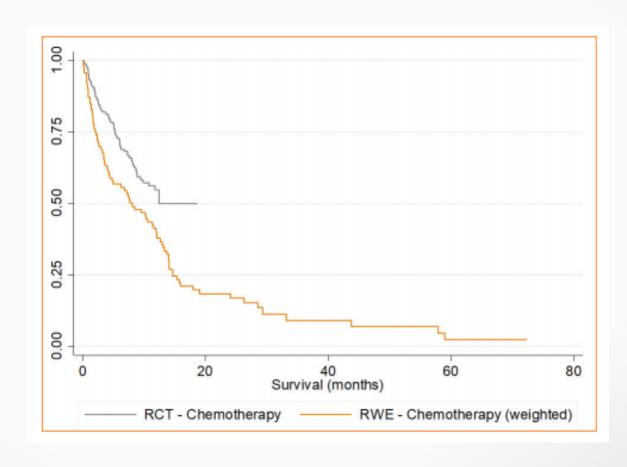
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Causality in the wild:

- Age groups
- Ethnicity and gender variances
- Co-morbidity
- Concomitant drugs
- Lifestyle variances
- Differences in disease severity
- Varying levels of compliance





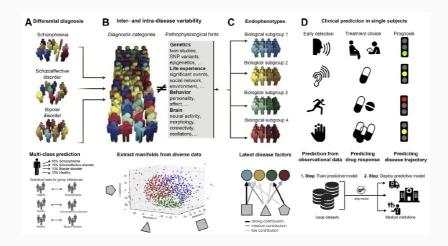
X. Huang et al., 2018, "Revealing Alzheimer's disease genes spectrum in the whole-genome by machine learning", BMC Neurology

S. Mueller et al., 2017, "Overall Survival In Patients With Non-small Cell Lung Cancer: A Comparison Of Clinical Trial Versus Real-world Outcomes Using A Propensity Score Reweighting Approach", INGRESS



Inferences in the wild

- Clusterization of patients based on multiple features (comorbidity, disease intensity, etc.)
- Machine Learning and **RWE** to support therapy choice and dosage

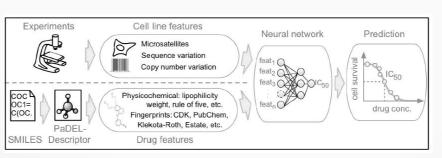


Polymorphic (36.5K) Functional impact score (FIS) Reva et al., 201

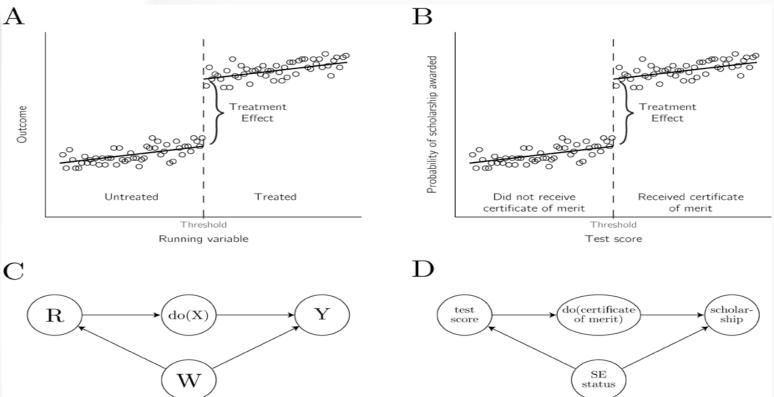
Disease-associated (19.2K)

methods ML to classify protein mutations as cancerassociated as opposed to common polymorphisms

Oncogenetic cell profiles and drug features: ML to assess drug efficacy in inhibiting tumoral cells







A) Schematic of a Regression Discontinuity Design analysis. The treatment is only administered if the running variable is above the threshold. The outcome (y-axis) is plotted as a function of a running variable (x-axis). The magnitude of the treatment effect, the difference in outcome at the threshold, is estimated using regression. B) Schematic figure representing the analysis performed in (Thistlethwaite D.L., Campbell D.T., 1960, "Regression-Discontinuity Analysis: An Alternative to the Ex-Post Facto Experiment", *The Journal of Educational Psychology*. 1960;51:309-17). Academic outcome (probability of scholarship) is plotted as a function of test score, and a discontinuity is seen at the cutoff for receiving a certificate of merit. Note that this figure is stylized and does not use the data used in the original analysis; it is intended only to demonstrate the approach. C) Graphical model of Regression Discontinuity Design. W are confounding variables; R is the running variable which determines the treatment along with the threshold; X is the treatment (independent variable) which is either administered (do(X)) or not administered (do(not X)) depending on R; and Y is the outcome (dependent variable) of interest. D) Graphical model representing this analysis. Socioeconomic status (for example) is likely to affect both test score and the probability of receiving a scholarship. Test score determines whether a certificate of merit is awarded, which in turn affects the probability of receiving a scholarship.



Venkataramani, Atheendar & Bor, Jacob & B Jena, Anupam. (2016), Regression discontinuity designs in healthcare

to initiate early antiretroviral treatment in South

Infants with birth weights <1500 g (designated very

low birth weight) recommended for intensive care in

Infants with birth weights <1500 g (designated very

low birth weight) recommended for intensive care in

10 year cardiovascular risk >20% as a guideline to

efficacy of caesarean section starting 21 October

Changes in information and guidelines about

William William Control of the Contr	, , , , , , , , , , , , , , , , , , , ,			
	research. BMJ. 35	52.		
		Type of assignment		
Studies	Exposures	variables	Threshold rules	Outcomes
Clinical:				
Bor et al 2014, 2015 ⁷¹⁶	HIV antiretroviral therapy	Therapeutic	Patients with CD4 counts < 200 cells/mm3 eligible	Mortality, immune

Africa

United States

Chile and Norway

2000 in Denmark

initiate statins

c	li	n	ic	a	ŀ	
	7	8/	nr.	0		al

Bor et al 2014, 2015

HIV antiretroviral therapy

Almond et al 2010¹³

Geneletti et al 201515

Jensen and Wust 201519

Prevention and public health:

Ludwig and Miller 200722

De La Mata et al 201224

Wherry et al 201525

Sood et al 201426

Almond et al 201127

Smith et al 2015²⁰

Callaghan 201321

Chen et al 201323

Health policy:

Neonatal intensive care

Bharadwai et al 201314

Neonatal intensive care

Statins

Caesarean section

Minimum drinking age

Head Start program

HPV vaccine

Air pollution

Health insurance

Health insurance

Health insurance

Length of hospital stay

Therapeutic

Age

Geographic

Program eligibility

Calendar time

Geographic

Clock time

Therapeutic

Therapeutic

Calendar time

Calendar time 1 January 1994 Program eligibility

consume alcohol in United States

Counties ranked <300 based on historic poverty

changes

rates were eligible to receive federal Head Start

Households north of China's Huai River received subsidies for high emission coal to heat homes People in households below a specific income

neighboring districts were not

more years of Medicaid coverage owing to rule

People living in predesignated districts were

eligible to receive insurance, whereas those in

Patients admitted after 12 am were allowed longer

threshold were eligible for Medicaid People born after 1 October 1983 were eligible for Child mortality Mortality Healthcare utilization

Hospital admissions among

Maternal and newborn

Vaccines were available for select age groups after Cervical dysplasia and anogenital warts Adults aged 21 or older can legally purchase and Mortality

among children

adolescents

Mortality

for neonates

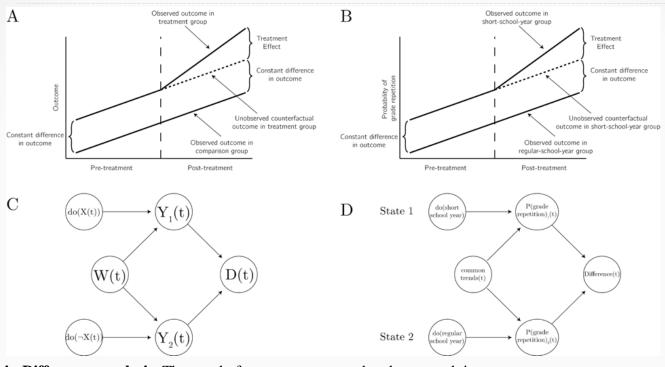
cholesterol Apgar score, physician visits, hospital admissions

recovery, retention in clinical care Infant mortality

Child cognitive development, academic

achievement Low density lipoprotein

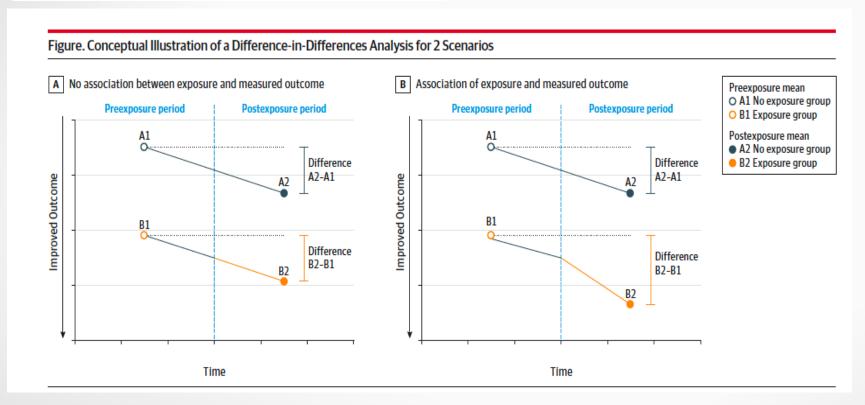




A) Schematic of a Difference-in-Differences analysis. The trend of two groups, treated and untreated, is plotted as a function of time. Before the treatment, the trends of the two groups should be parallel (a constant difference-in-differences). The treatment effect is estimated by the degree to which the trends diverge after the treatment is administered. B) Schematic figure representing the analysis performed in (Pischke J.S., 2007, "The impact of length of the school year on student performance and earnings: Evidence from the German short school years", Economic Journal, 117, 1216-42). Outcome (probability of grade repetition) is plotted as a function of time, before and after the implementation of the short school year in some states. The difference between State outcomes changes after the change in school year (i.e., there is an increase in difference in differences). Note that this figure is stylized and does not use the data used in the original analysis; it is intended only to demonstrate the approach. C) Graphical model for Difference-In-**Differences.** All variables are considered as a function of time, t. W are confounding variables; X is the treatment (independent variable) which is administered (do(X)) to population 1, and not administered (do(not X)) to population 2; Y1 and Y2 are the outcomes (dependent variables) for populations 1 and 2, respectively; D is the difference between Y1 and Y2 and is tracked over time. D) Graphical model representing the analysis performed. Common trends such as federal taxes and economic conditions are likely to affect the two States similarly. The short school year is implemented only in one State. The difference in outcome is calculated from the two States' outcomes.

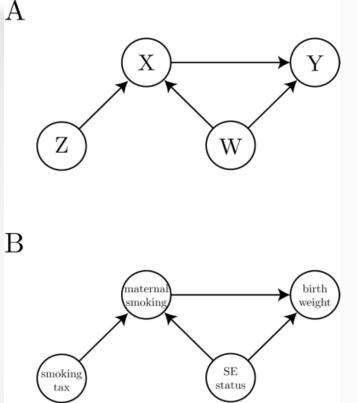






Designing Difference in Difference Studies: Best Practices for Public Health Policy Coady Wing, Kosali Simon, Ricardo A. Bello-Gomez Annual Review of Public Health 2018 39:1, 453-469





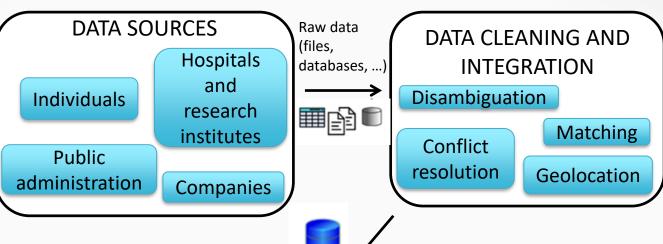
An instrumental variable (IV) is a variable, generally found in administrative data, that is assumed to randomize a treatment to estimate cause and effect relationships, thus controlling for known and unknown patient characteristics affecting health outcomes. An important (often heroic) assumption is that the IV randomizes treatment but does not directly affect the patient outcome.

A) Graphical model for Instrumental Variables. W are confounding variables; X is the independent variable; Y is the outcome (dependent variable); Z is the instrument which only affects Y through its effect on X. B) Graphical model representing the analysis performed. Graphical model representing this analysis performed in (Evans W.N., Ringel J.S., 1999, "Can higher cigarette taxes improve birth outcomes?", *Journal of Public Economics*, 72, 135-54. Maternal smoking is thought to affect birth weight. But socioeconomic status (for example) likely affects both a mother's decision to smoke as well as the child's birth weight. A tax on cigarette smoking could affect maternal smoking but is unlikely to directly influence the birth weight, except through an effect on maternal smoking. Such a tax is therefore a good instrument to examine the effect of smoking on birth weight without being confounded by socioeconomic status

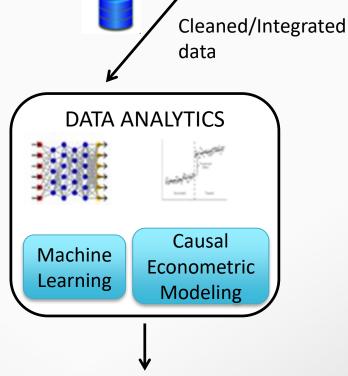


POLITECNICO Inferences in the Wild: The Organization of Research

Micro and population data from heterogeneous sources



- Combination of ML and causal models in real world quasi experimental settings
- Multidisciplinary data analytics factories



Decision Making, Targeting and Impact Evaluation



Summing Up

- The Endless Frontier: Innovation, ageing, sustainability and tragic choices in health.
- Looking for a Selective Universalism, designed around the evolution of individual needs over the life cycle
- Causal inferences in real world to sustain Risk Sharing and Outcome-Based Dynamic Pricing Schemes. Data: A Tragedy of the Anticommons (M. Heller)?
- Adaptive Precision Therapies call for ... Adaptive Precision Policies.
- ML and causal modelling for targeting and impact evaluation. The organizational challenge for research