

Accelerating vaccine innovation for emerging infectious diseases via parallel discovery

Joseph Barberio, Jacob Becraft, Zied Ben Chaouch, Dimitris Bertsimas, Tasuku Kitada, Michael L. Li, Andrew W. Lo, Kevin Shi, Qingyang Xu

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MIT

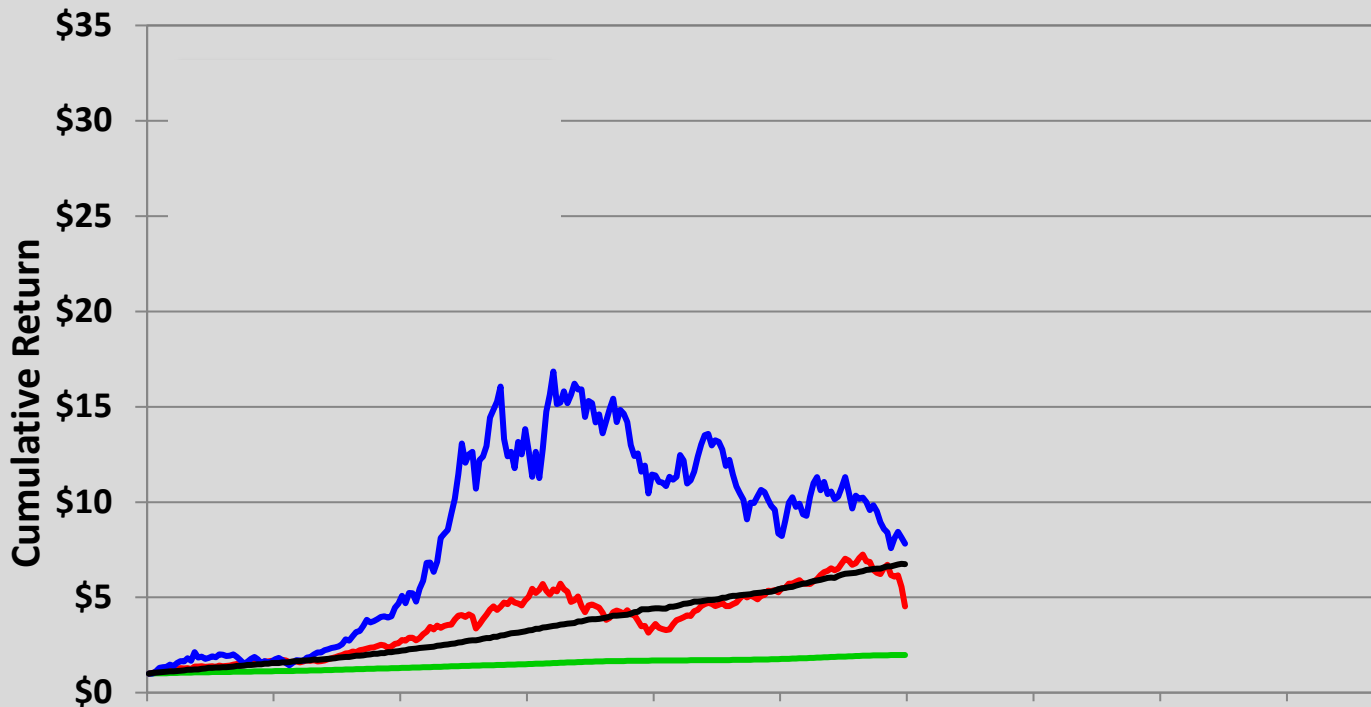
Laboratory for
Financial Engineering

The Business of Vaccines

- Business model for vaccines is challenging
- Non-profits like CEPI, WHO, CARB-X, Gates Foundation are helping
- But philanthropy is not enough
- Is it possible to attract more private-sector investment to address emerging infections diseases?

Investment Pop Quiz #1

$$\text{Sharpe Ratio} \equiv \frac{E[R] - R_f}{SD[R]}$$



Investment Pop Quiz #2

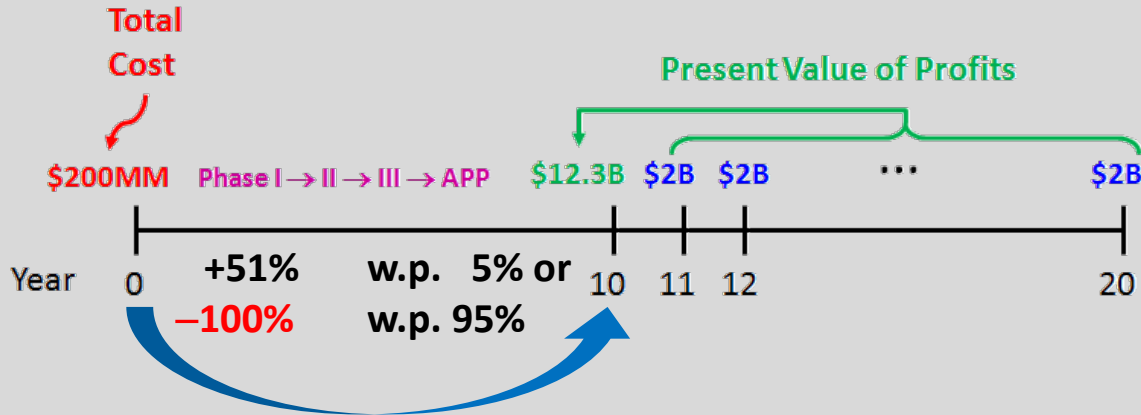
Would You Invest In This Project?

- \$200MM investment, 10-year horizon
- Probability of positive payoff is 5%
- If successful, annual profits of \$2B for 10 years

$$E[R] = 11.9\%$$

$$SD[R] = 423.5\%$$

$$SR = 0.03$$



Financial Engineering Can Help

What If We Invest In 150 Programs Simultaneously?:

- Requires \$30B of capital
- Assume programs are IID (can be relaxed)
- Diversification changes the economics of the business:

$$E[R] = 11.9\%$$

$$SD[R] = 423.5\% / \sqrt{150} = 34.6\% \Rightarrow \mathbf{SR = 0.33}$$

- But can we really raise \$30B??
- It depends on the portfolio's risk/reward profile (correlations?)

Challenges of Vaccine Development

Why did big pharma leave vaccine development (before the COVID-19 pandemic)?

Plotkin et al. (2015):

- Declining and highly uncertain **revenues**
- Lack of **funding** in the absence of an imminent threat
- Vaccines for uncommon but deadly infectious diseases are not as **profitable** as the seasonal flu

Challenges of Vaccine Development

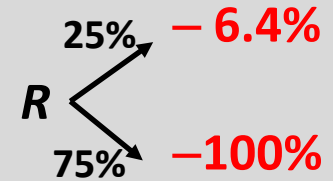
How has the pandemic changed vaccine development?

- **Innovations** in biomedical technology (e.g., mRNA vaccines)
- Unprecedented acceleration for **clinical development**
- Unprecedented **collaboration** among stakeholders
- Increased **public awareness** of the importance to prevent future pandemic outbreaks of emerging infectious diseases (EID)

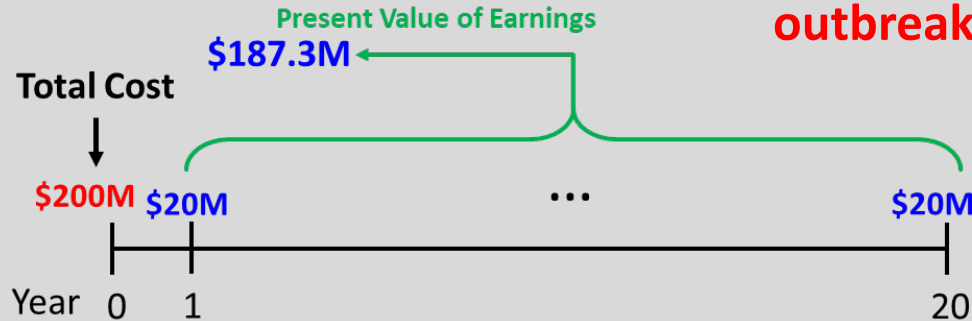
Investment Pop Quiz #3

Would You Invest In This Project?

- \$200M investment, 1-year horizon
- Probability of success is 25%
- If successful, \$187.3M = $PV_{20}(10\% \times \text{price} \times \text{doses} \times \text{prob. of outbreak})$



SR = ???

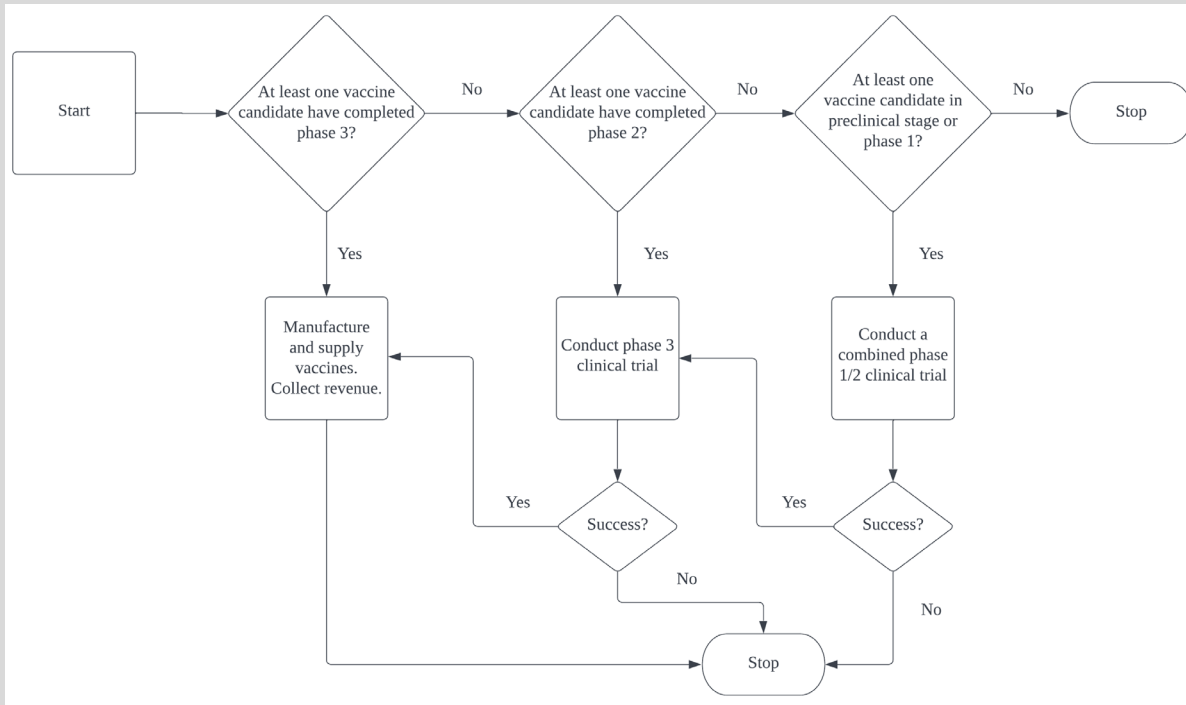


Simulating a Vaccine Fund

| Disease | # Vaccine Candidates | Annual Probability of Outbreak (%) |
|---------------------------------|----------------------|------------------------------------|
| Disease X | 10 | 1.0 |
| Chikungunya | 16 | 10.8 |
| Zika Virus | 18 | 4.3 |
| Lassa Fever | 7 | 100.0 |
| Rift Valley Fever | 3 | 10.5 |
| SARS-CoV-1 | 2 | 7.1 |
| West Nile Virus | 23 | 10.0 |
| MERS-CoV | 8 | 40.0 |
| Crimean-Congo Hemorrhagic Fever | 7 | 12.5 |
| Nipah Virus | 20 | 15.8 |
| Marburg Virus | 6 | 12.0 |

- Adapted from CEPI and Vu et al. (2022)
- 10 vaccine candidates for “disease X” (pandemic)
- Simulate outbreaks over 20 years

Simulating a Vaccine Fund



- Simulate epidemics each year
- For each occurrence, follow flowchart

Simulating a Vaccine Fund

| Category | Item | Unit Cost (USD) | Quantity |
|----------------|-----------------|--------------------------------------|---|
| Fixed cost | Production line | \$58M | 1 bioreactor of 30L working volume |
| Variable costs | Raw materials | \$456.6M/(year · production line) | 29,162 grams of mRNA per production line per year |
| | Consumables | \$150M/(year · production line) | |
| | Labor | \$20/hour | 113,186 labor hours per production line per year |
| | Quality control | \$10/hour | |
| | Fill-and-finish | \$0.27/dose | |
| | | Lab, utility, waste management, etc. | <1% total cost |

Sources: Kis & Rizvi (2021), Kis et al. (2021)

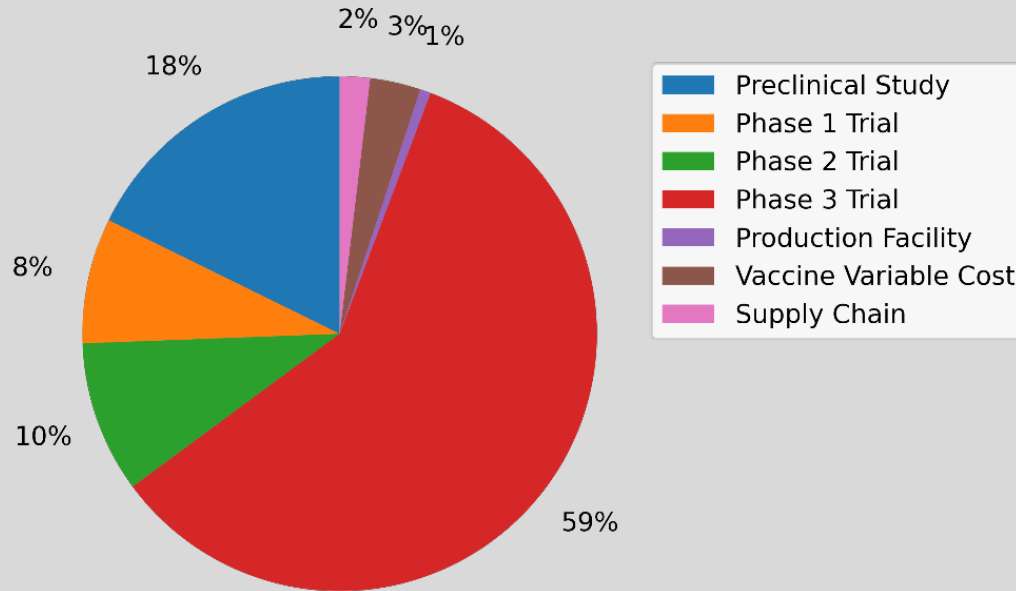
Results

| Metric | Mean | Std Dev | Median |
|-------------------------|-------|---------|--------|
| Annualized Return (%) | -6.0 | 6.7 | -5.7 |
| NPV (\$ billion) | -9.5 | 4.1 | -9.9 |
| Investment (\$ billion) | 17.7 | 5.3 | 17.8 |
| Revenue (\$ billion) | 7.5 | 7.7 | 5.8 |
| Profit (\$ billion) | -10.0 | 7.4 | -11.5 |
| # Epidemics Prevented | 31 | 13 | 34 |

- Needs \$9.5 billion to break even
- Prevents 31 epidemic outbreaks on average in the next 2 decades

Results

Costs of Vaccine Development and Delivery



- 94% of costs are clinical trials (59% in Phase 3)
- mRNA technology does not save much in costs (but reduces time!)

Sensitivity Analysis: Price

- Expected annual return is **negative** unless price per dose > \$69.00
- Expected NPV is **negative** unless the price per dose > \$78.00
- 12 common adult vaccines have list prices above \$100.00 in US*

| Price Per Dose | $E[R_a]$ | $SD[R_a]$ | $E[NPV]$ (\$B) | $SD[NPV]$ (\$B) |
|-----------------------|----------|-----------|-------------------|--------------------|
| \$20.00 (baseline) | -6.0% | 6.7% | -9.5 | 4.1 |
| \$69.00 | 0.0% | 7.1% | -1.4 | 11.9 |
| \$78.00 | 0.7% | 7.1% | 0.0 | 13.5 |
| \$100.00 | 1.9% | 7.2% | 3.6 | 17.4 |

*US CDC (Jan. 1, 2022)

What Can Be Done?

- Pricing policy innovation:
 - AMCs, subscription model, etc.
- More generally, government policy is key
- Is healthcare a privilege or a right? Ethics?
- Should vaccine and anti-infective companies be considered “regulated utilities”?
- Finance can play a **positive** role in facilitating public health

What Can Be Done?

Government involvement is essential when:

1. The investment **horizon** is long (over a decade)
2. The **capital** required is significant (~ \$200 million)
3. The **probability of success** is low (~ 25% overall)
4. Potential **benefits** to the society are large

“Long Shot”
Hull, Lo, Stein
(2019)

$$\text{Sharpe Ratio} = \frac{\text{Private-Sector Reward}}{\text{Risk}}$$

- Risk-based “market failure” (Lo, 2022)

**Thank
You!**

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Supplementary Materials

Simulating a Vaccine Fund

- Probability of success (PoS)
- Correlation of trial outcomes
- Clinical trial duration and cost

| Param. | Preclinical | Phase 1 | Phase 2 | Phase 3 |
|-------------------|-------------|---------|---------|---------|
| PoS (%) | 60.0 | 83.6 | 65.8 | 80.9 |
| Duration (months) | 18.0 | 24.0 | 18.0 | 14.0 |
| Cost (\$ million) | 26.0 | 14.0 | 28.0 | 150.0 |

Gouglas et al., 2018; Project ALPHA, 2021

| | Chikun. | SARS | MERS | Marburg | RVF | Lassa | Nipah | CCHF | WNV | Zika |
|---------|---------|------|------|---------|------|-------|-------|------|------|------|
| Chikun. | 1.00 | 0.30 | 0.30 | 0.37 | 0.27 | 0.39 | 0.38 | 0.29 | 0.38 | 0.33 |
| SARS | 0.30 | 1.00 | 0.58 | 0.32 | 0.21 | 0.25 | 0.28 | 0.26 | 0.29 | 0.28 |
| MERS | 0.30 | 0.58 | 1.00 | 0.33 | 0.20 | 0.25 | 0.28 | 0.26 | 0.29 | 0.28 |
| Marburg | 0.37 | 0.32 | 0.33 | 1.00 | 0.27 | 0.37 | 0.46 | 0.37 | 0.36 | 0.35 |
| RVF | 0.27 | 0.21 | 0.20 | 0.27 | 1.00 | 0.48 | 0.29 | 0.52 | 0.27 | 0.26 |
| Lassa | 0.39 | 0.25 | 0.25 | 0.37 | 0.48 | 1.00 | 0.36 | 0.35 | 0.40 | 0.40 |
| Nipah | 0.38 | 0.28 | 0.28 | 0.46 | 0.29 | 0.36 | 1.00 | 0.32 | 0.39 | 0.39 |
| CCHF | 0.29 | 0.26 | 0.26 | 0.37 | 0.52 | 0.35 | 0.32 | 1.00 | 0.29 | 0.28 |
| WNV | 0.38 | 0.29 | 0.29 | 0.36 | 0.27 | 0.40 | 0.39 | 0.29 | 1.00 | 0.64 |
| Zika | 0.33 | 0.28 | 0.28 | 0.35 | 0.26 | 0.40 | 0.39 | 0.28 | 0.64 | 1.00 |

Correlation matrix of vaccine trial outcomes calibrated by biomedical similarity of pathogens

Sensitivity Analysis: mRNA Technology

- Increasing probability of success for mRNA technology increases both the number of approved vaccines and total investment
- Revenue of vaccine sales increases less significantly

| Price Per Dose | $E[R_a]$ | $SD[R_a]$ | $E[NPV]$ (\$B) | $E[Inv]$ (\$B) |
|-------------------------------------|----------|-----------|-------------------|-------------------|
| $\alpha_{tech} = 1.0$ | -6.7% | 11.9% | -8.1 | 15.2 |
| $\alpha_{tech} = 1.1$ | -6.2% | 9.1% | -8.8 | 16.4 |
| $\alpha_{tech} = 1.2$ (baseline) | -6.0% | 6.7% | -9.5 | 17.7 |
| $\alpha_{tech} = 1.3$ | -5.8% | 4.8% | -9.9 | 18.7 |

Estimating Clinical Trials Success Rates

Biostatistics (2019) 20, 2, pp. 273–286
doi:10.1093/biostatistics/kxx069
Advance Access publication on January 31, 2018

Estimation of clinical trial success rates and related parameters

CHI HEEM WONG, KIEN WEI SIAH

MIT Computer Science and Artificial Intelligence Laboratory & Department of Electrical Engineering and Computer Science, Cambridge, MA 02139, USA and MIT Sloan School of Management and Laboratory for Financial Engineering, Cambridge, MA 02142, USA

ANDREW W. LO*

MIT Computer Science and Artificial Intelligence Laboratory & Department of Electrical Engineering and Computer Science, Cambridge, MA 02139, USA, MIT Sloan School of Management and Laboratory for Financial Engineering, Cambridge, MA 02142, USA, and AlphaSimplex Group, LLC, Cambridge, MA 02142, USA

alo-admin@mit.edu

SUMMARY

Previous estimates of drug development success rates rely on relatively small samples from databases curated by the pharmaceutical industry and are subject to potential selection biases. Using a sample of 406 038 entries of clinical trial data for over 21 143 compounds from January 1, 2000 to October 31, 2015, we estimate aggregate clinical trial success rates and durations. We also compute disaggregated estimates across several trial features including disease type, clinical phase, industry or academic sponsor, biomarker presence, lead indication status, and time. In several cases, our results differ significantly in detail from widely cited statistics. For example, oncology has a 3.4% success rate in our sample vs. 5.1% in prior studies. However, after declining to 1.7% in 2012, this rate has improved to 2.5% and 8.3% in 2014 and 2015, respectively. In addition, trials that use biomarkers in patient-selection have higher overall success probabilities than trials without biomarkers.



Estimating Probabilities of Success of Vaccine and Other Anti-Infective Therapeutic Development Programs

by Andrew W. Lo, Kien Wei Siah, and Chi Heem Wong

Published: May 14, 2020



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Table 2. The POS by therapeutic group, using data from January 1, 2000, to October 31, 2015. We computed this using the path-by-path method. SE denotes the standard error

| Therapeutic group | All indications (industry) | | | | | | | |
|-------------------------------------|----------------------------|-----------------------------------|--------------------|-----------------------------------|-------------------------------------|---------------------|-------------------------------------|-------------------|
| | Phase 1 to Phase 2 | | Phase 2 to Phase 3 | | | Phase 3 to Approval | | Overall |
| | Total paths | POS _{1,2} , % (SE, %) | Total paths | POS _{2,3} , % (SE, %) | POS _{2,APP} , % (SE, %) | Total paths | POS _{3,APP} , % (SE, %) | POS, % (SE, %) |
| Oncology | 17 368 | 57.6 (0.4) | 6533 | 32.7 (0.6) | 6.7 (0.3) | 1236 | 35.5 (1.4) | 3.4 (0.2) |
| Metabolic/ Endocrinology | 3589 | 76.2 (0.7) | 2357 | 59.7 (1.0) | 24.1 (0.9) | 1101 | 51.6 (1.5) | 19.6 (0.7) |
| Cardiovascular | 2810 | 73.3 (0.8) | 1858 | 65.7 (1.1) | 32.3 (1.1) | 964 | 62.2 (1.6) | 25.5 (0.9) |
| CNS | 4924 | 73.2 (0.6) | 3037 | 51.9 (0.9) | 19.5 (0.7) | 1156 | 51.1 (1.5) | 15.0 (0.6) |
| Autoimmune/ Inflammation | 5086 | 69.8 (0.6) | 2910 | 45.7 (0.9) | 21.2 (0.8) | 969 | 63.7 (1.5) | 15.1 (0.6) |
| Genitourinary | 757 | 68.7 (1.7) | 475 | 57.1 (2.3) | 29.7 (2.1) | 212 | 66.5 (3.2) | 21.6 (1.6) |
| Infectious disease | 3963 | 70.1 (0.7) | 2314 | 58.3 (1.0) | 35.1 (1.0) | 1078 | 75.3 (1.3) | 25.2 (0.8) |
| Ophthalmology | 674 | 87.1 (1.3) | 461 | 60.7 (2.3) | 33.6 (2.2) | 207 | 74.9 (3.0) | 32.6 (2.2) |
| Vaccines (Infectious Disease) | 1869 | 76.8 (1.0) | 1235 | 58.2 (1.4) | 42.1 (1.4) | 609 | 85.4 (1.4) | 33.4 (1.2) |
| Overall | 41 040 | 66.4 (0.2) | 21 180 | 58.3 (2.3) | 35.1 (2.2) | 7532 | 59.0 (0.6) | 13.8 (0.2) |
| All without oncology | 23 672 | 73.0 (0.3) | 14 647 | 27.3 (0.4) | 27.3 (0.4) | 6296 | 63.6 (0.6) | 20.9 (0.3) |

Vaccine Success Rates

Harvard Data Science Review

Estimating Prob Success of Vacc Other Anti-Infe Therapeutic De Programs

Andrew W. Lo¹, Kien Wei Siah², Chi Heer

¹MIT Sloan School of Management & Laboratory for Finan

²MIT Department of Electrical Engineering and Comput
Artificial Intelligence Lab (CSAIL)

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