

Health Insurance Expansion and New Technology Adoption: Evidence from U.S. Medicare Part D

*Chuanzi Yue** *Qiyuan Zhan* *Marisa Miraldo*

Imperial College London

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Introduction

- ▶ Health insurance expansion can have a profound effect on firms' expected profit.
- ▶ The change in profit will impact the marginal profit gain from adopting productivity-enhancing technologies.
- ▶ Thus, health insurance expansion can increase/decrease the adoption of new technology depending on its profit increasing/decreasing effect.
- ▶ Leverage US Medicare Part D, we document the impact of social health insurance on the DHTs adoption in pharmaceutical trials.

What is DHT?

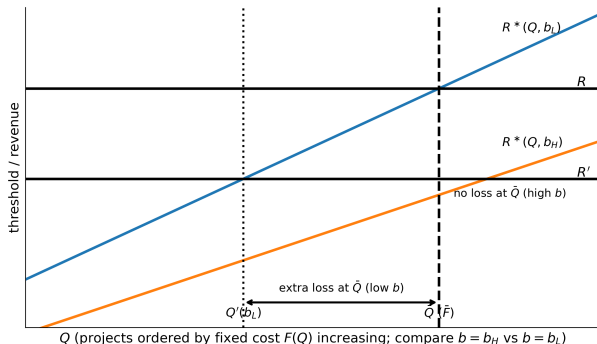
- ▶ Digital Health Technology (DHT) refers to digital tools used to manage illness, mitigate health risks, and promote wellness (NLM, 2026).
- ▶ In this paper, DHT adoption is measured from trial text and grouped into three main functions:
 - ▶ **Digital trial operations and data capture:** electronic systems, databases, remote follow-up, mobile apps, and telecare.
 - ▶ **Computerized instruments and digital measurement tools:** sensors, actigraphy, ambulatory monitoring, telemetry, and wearable devices.
 - ▶ **Algorithmic or AI-enabled analytics:** algorithms, simulations, diagnostic analytics, and machine-assisted trial-support tools.
- ▶ The focus is on DHT as a **trial-support technology**, rather than as the treatment itself. [Examples](#)

What is Medicare Part D?

- ▶ Medicare Part D is the U.S. prescription drug insurance programme for Medicare beneficiaries.
- ▶ Enacted in 2003 and implemented in 2006, it expanded outpatient drug coverage mainly for older Americans.
- ▶ It shifted previously uninsured senior drug demand into private Part D plans.
- ▶ This matters for pharmaceutical firms through two channels:
 - ▶ **Market-size channel:** broader coverage increases insured demand.
 - ▶ **Buyer-power channel:** Part D plans and PBMs bargain over formularies, rebates, and net prices (consumer concentration).

DHT adoption under revenue compression

- ▶ Fixed investments in validation, data integration, staff training, and workflow redesign.
- ▶ Revenue compression lowers the expected return to these investments.



How we do this

- ▶ Using ClinicalTrial.gov data in the period 1996-2010 (DHT adoption) and MEPS data between 2000-2010 (Part-D market share).
- ▶ Baseline:
 - ▶ Population: U.S. based trials reported to ClinicalTrial.gov.
 - ▶ Outcome: DHT adoption in pharmaceutical trials
 - ▶ Compare disease area with different level of exposure: pre-2003 disease-level reliance on uninsured senior drug demand.

Group/Years	1996-2002	2003-2010
Medicare Part D	No	Yes
Diseases with high Part-D share	Not targeted/more exposed	Targeted/more exposed
Diseases with low Part-D share	Not targeted/less exposed	Targeted/less exposed

Preview of results

- ▶ DHT adoption:
 - ▶ A 10 percentage-point increase in Part-D exposure reduces DHT adoption by about 0.1 percentage points.
 - ▶ This corresponds to around 14 to 17 percent of the baseline adoption rate.
- ▶ Mechanism:
 - ▶ The decline is concentrated in more competitive disease markets.
 - ▶ The effect is concentrated among smaller commercial sponsors; top-25 pharmaceutical firms show little reduction.
 - ▶ Revenue falls more in exposed competitive disease markets, consistent with margin compression.
- ▶ Operational consequence:
 - ▶ One-standard-deviation increase in exposure increases trial duration by around 3.3 days.

Outline

Data set

Summary statistics

Regression specifications

Results

Data sets

- ▶ **Medical Expenditure Panel Survey (MEPS):**
 - ▶ Survey data of a representative sample of the U.S. non-institutionalised population.
 - ▶ Contains prescription consumption by **NDC**, disease classification, age, insurance status, and prescription spending.
 - ▶ Used to construct disease area's Part-D exposure, HHI, and revenue per firm.
- ▶ **ClinicalTrial.gov:**
 - ▶ Contains clinical trial records with titles, summaries, interventions, outcomes, conditions, phases, and sponsor information.
 - ▶ Trial text is used to detect DHT adoption; trial sponsor is used to measure firm size.
- ▶ Combine via disease classification (ICD-10 category) and obtain clinical trial and DHT adoption information at **trial-disease-year** level.

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DHT keywords and frequency

Category	Keywords matched	Frequency
Digital trial operations, data capture, and follow-up platforms	computer; digital; electronic; database; databases; integration; app; mobile; off-site; portable; remote; smart; telecare	937
Computerized instruments and digital measurement tools	analytics; actigraph; actiwatch; ambulatory monitoring; biofeedback; robotic; sensor; telemetry; telemedicine; virtual reality; wearable	1,001
Algorithmic or AI-enabled analytics	algorithm; diagnostics; AI; intelligence; simulations	256
Total		2,194

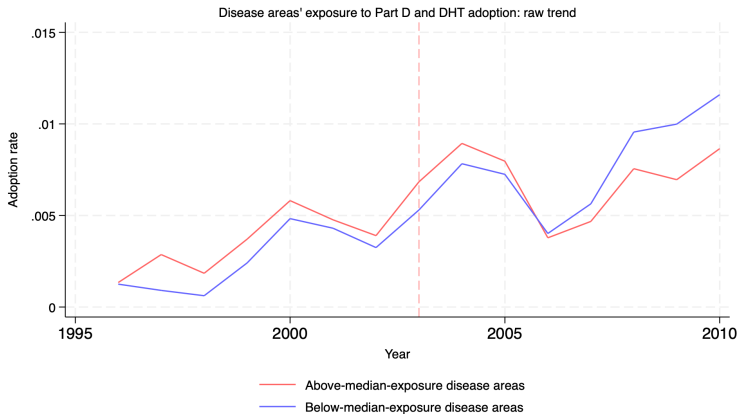
- ▶ The frequency of matched keywords is broadly consistent with the relative adoption of these trial technologies during the study period.
- ▶ Manual review show that some keywords generate more false positives, while others capture more regulatory-facing technologies.

Key variables before and after the announcement of Medicare Part D

	(1996–2002)		(2003–2010)	
	Mean	Std. dev.	Mean	Std. dev.
<i>DHT adoption rate</i>	0.003	0.051	0.006	0.080
<i>Revenue per firm (million USD)</i>	56.2	239	88.8	357
<i>Trials per disease area</i>	13.6	-	41.9	-
<i>Exposure</i>	0.086	0.121	-	-
<i>HHI</i>	0.341	0.216	-	-
<i>Obs (Trial-disease-year)</i>	36,076		228,333	

- ▶ DHT adoption remains rare, but increases from around 0.3 percent to 0.6 percent.
- ▶ Rich variation in Part-D exposure and HHI.

Part D exposure and DHT adoption: raw trend



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Part-D effect on DHT adoption

$$Y_{jdt} = \beta_1 PD_t * Exposure_d + \epsilon_t + \epsilon_d + \epsilon_f + \epsilon_{jdt}$$

$$Y_{jdt} = \beta_{11} HHI_d * PD_t * Exposure_d + \beta_{12} PD_t * Exposure_d \\ + HHI_d * \epsilon_t + \epsilon_t + \epsilon_d + \epsilon_f + \epsilon_{jdt}$$

- ▶ Y_{jdt} : binary, whether a trial j (led by innovator f) for disease d adopts DHT in year t .
- ▶ $PD_t = 1$ after 2003, when Part D was announced.
- ▶ $Exposure_d$, share of expenditure of trial j 's disease class d (a ICD10 category) by the above 65 uninsured to the total expenditure before 2003.
- ▶ HHI_d , Pre-2003 HHI of disease class d .

Event study: dynamic effects of Part D exposure

$$DHT_{jdt} = \beta_{\tau} (Exposure_d * 1\{t = \tau\}) + \epsilon_f + \epsilon_d + \lambda_t + u_{jdt}$$

- ▶ $(Exposure_d * 1\{t = \tau\})$: interactive term between Part-D exposure and year dummies.
- ▶ Coefficients are normalized relative to 2002, the year before Part D announcement.

Outline

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DHT adoption

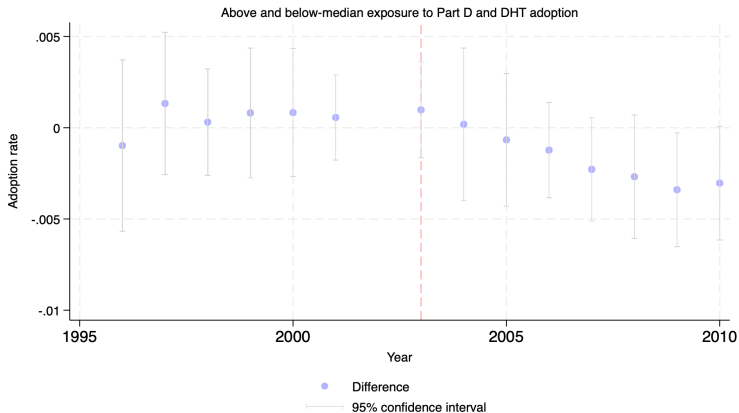
	DHT adoption				
	Baseline	$X = HHI$	$X = \text{Top-25 pharma}$	$X = \text{Pre-Part-D trial title}$	Other trials
$PD*Exposure$	-0.009*** (0.003)	-0.026*** (0.019)	-0.013*** (0.004)	-0.012*** (0.004)	0.005 (0.030)
$X*PD*Exposure$		0.044** (0.009)	0.026*** (0.008)	0.013*** (0.005)	
Disease area FEs	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes
$HHI*year$ FEs	no	yes	no	no	no
$Top-25\ pharma*year$ FEs	no	no	yes	no	no
$Pre-Part-D\ trial\ title*year$ FEs	no	no	no	yes	no
Obs	264,399	264,399	264,399	264,399	41,963

$p \leq 10\%*$, $p \leq 5\%**$, $p \leq 1\%***$

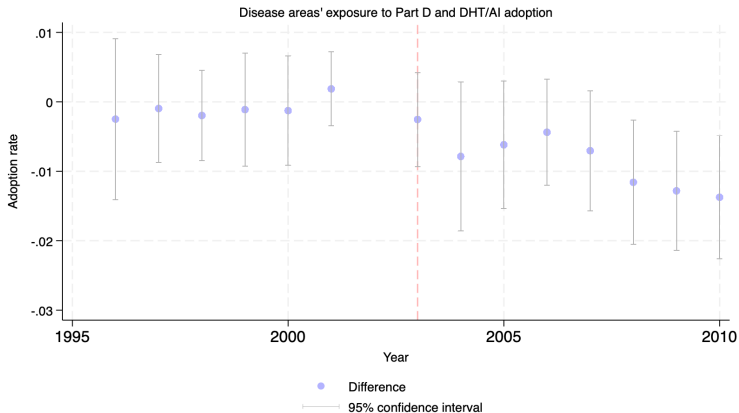
Disease-class clustered SE in parenthesis

Robustness checks

Part D exposure and DHT adoption: event study (median)



Part D exposure and DHT adoption: event study (continuous)



Part D exposure and demand concentration

	<i>Generic</i>	<i>Brand-name</i>
<i>ATC4 exposure, 2001–2002</i>	0.666*** (0.054)	0.850*** (0.086)
<i>Drug fixed effects</i>	yes	yes
<i>Year fixed effects</i>	yes	yes
<i>Observations</i>	37,060	20,858

$p \leq 10\%*$, $p \leq 5\%**$, $p \leq 1\%***$

Drug-level clustered SE in parentheses

- ▶ Higher pre-Part D exposure predicts a larger post-2006 spending share paid by Part D enrollees.
- ▶ A one-standard-deviation increase in exposure is associated with an 8.5% increase in Part D coverage for brand-name drugs and 6.7% for generics.
- ▶ This supports the interpretation that exposure captures the shift of elderly drug demand into concentrated Part D purchasing.

Revenue suppression

$$\log(Y_{dt}) = \beta_1 PD_t * Exposure_d + \epsilon_t + \epsilon_d + \epsilon_{dt}$$

$$\log(Y_{dt}) = \beta_{11} HHI_d * PD_t * Exposure_d + \beta_{12} PD_t * Exposure_d + HHI_d * \epsilon_t + \epsilon_t + \epsilon_d + \epsilon_{dt}$$

Average firm revenue per disease		
	Baseline	$X = HHI$
$PD * Exposure$	-0.342** (0.148)	-1.16*** (0.396)
$X * PD * Exposure$		1.23*** (0.495)
<i>Disease area FEs</i>	yes	yes
<i>Year FEs</i>	yes	yes
<i>HHI*year FEs</i>	no	yes
<i>Obs</i>	10,791	10,791

$p \leq 10\%*$, $p \leq 5\%**$, $p \leq 1\%***$

Disease-class clustered SE in parentheses

Outcome variable: log average firm revenue per disease (based on the MEPS)

Trial duration and welfare implication

	Log trial duration	
	Baseline	$X = HHI$
$PD*Exposure$	0.202*** (0.054)	0.411*** (0.160)
$X*PD*Exposure$		-0.428** (0.200)
<i>Disease area FEs</i>	yes	yes
<i>Sponsor FEs</i>	yes	yes
<i>Year FEs</i>	yes	yes
<i>Obs</i>	263,877	263,877

$p \leq 10\%*$, $p \leq 5\%**$, $p \leq 1\%***$
Disease-class clustered SE in parentheses

- ▶ DHT adoption is associated with a 27% shorter trial duration, while a one-standard-deviation higher Part-D exposure is associated with 2% higher trial duration.
- ▶ Back-of-envelope: at the pre-period mean of 2,722 days, the estimate implies 3.3 extra days and around \$46–\$68 lower per-patient per year benefit under a non-orphan QALY

Conclusion

- ▶ Medicare Part D expands drug insurance coverage, but also increases buyer-side concentration and reduces revenue in prescription drug markets.
- ▶ Disease areas more exposed to Part D experienced slower DHT adoption in pharmaceutical clinical trials.
- ▶ The reduction is concentrated in competitive disease markets and among smaller sponsors, consistent with revenue compression and financial constraint.
- ▶ Lower DHT adoption is associated with slower evidence generation, with exposed trials lasting about 3.3 days longer (1 s.d. exposure).
- ▶ Policy implication: insurance expansions and affordability reforms should account for dynamic effects on technology adoption and innovation productivity.

Thank you!

A stylized model of price negotiation

Nash bargaining implies:

$$P_{jt} = \frac{mmc_{jt} - \frac{\partial \log(W_{f-65t} * S_{j-65t} + W_{f+65t} * S_{j+65t})}{\partial P_{jt}}}{1 + \frac{\rho_{jft}}{1 - \rho_{jft}} * \frac{\partial \log(\tilde{\pi}_{ft} - \tilde{\pi}_{ft}^{-j})}{\partial P_{jt}}}$$

- ▶ mmc_{jt} delivery cost of drug j .
- ▶ $\frac{\partial \log(W_{f-65t} * S_{j-65t} + W_{f+65t} * S_{j+65t})}{\partial P_{jt}}$ (net) price elasticity of demand for drug j .
- ▶ $\tilde{\pi}_{ft} - \tilde{\pi}_{ft}^{-j}$ profit loss to insurer f under negotiation failure of j .
- ▶ ρ_{jft} negotiation power of insurer f relative to the manufacture.
- ▶ $\frac{\partial P_{jt}}{\partial W_{f+65t}} < 0$ $\frac{\partial P_{jt}}{\partial \rho_{jft}} < 0$.

- ▶ The effect of Part D on price and innovation:
 - ▶ *Duggan and Morton, AER, 2010 2011; Kohout and Sood, JPubE, 2013; Lakdawalla and Yin, REStats, 2014; Kohout and Sood, JPubE, 2013; Chorniy, Miller and Tang, IJIO, 2019; Sanzenbacher and Wettstein, JHE, 2020. Yue, working paper, 2025.* [back](#)
- ▶ Impact of customer concentration:
 - ▶ *Banerjee et al.(2008); Cen et al., 2016 (2017); Chen et al. (2022); Chu et al. (2019); Hui et al. (2012); Dong et al. (2021); Dhaliwa et al. (2016); Campello and Gao (2017); Irvine et al. (2016); Ni et al. (2023); Patatoukas (2012); Li et al. (2023).* [back](#)
- ▶ Factors of tech diffusion:
 - ▶ *Hargadon and Douglas (2001); Conley and Udry (2010); Adhvaryu (2014); Arrow, Bilir, and Sorensen (2020); Young (2009); Teece (1977); Glitz and Meyersson (2020); (Arrow, 1969); Schumpeter (1934); Kyle (2007); Duflo, Kremer, and Robinson (2008); Gross (2018); Basker and Simcoe (2021); Slattery, (2020).* [back](#)

NDC: example

Store at controlled room temperature
20-25°C (68-77°F) [see USP].

Dispense in tight containers (USP).

DOSAGE AND USE
See package insert for full prescribing
information.

*Each tablet contains atorvastatin calcium
equivalent to 40 mg atorvastatin.

Distributed by
Parke-Davis
Division of Pfizer Inc
NY, NY 10017

MADE IN IRELAND



NDC 0071-0157-23

Lipitor®
(atorvastatin calcium)

40 mg*

tablets

90 Tablets

Rx only



NS 0071-0157-23 1

FPO: UPC @ 80%

GTIN: 00300710157231

LOT/EXP:

PAA056783



Figure 1: NDC 0071-0157-23

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How we do this

- ▶ Mechanisms:
 - ▶ Heterogeneous response of DHT adoption according to:
 - ▶ Market competition, measured by pre-Part-D disease-area HHI.
 - ▶ Firm size, measured by whether the sponsor is a top-25 pharmaceutical firm.
 - ▶ Response of Part D coverage share and average firm revenue per disease according to disease-area exposure to Part D.
 - ▶ Heterogeneous response of revenue according to market competition.
- ▶ Trial productivity:
 - ▶ Effect of Part D exposure on trial duration as an operational consequence of lower DHT adoption.
- ▶ Placebo tests using DHT keyword lists with varying degrees of classification confidence, as well as trial settings less directly linked to U.S. pharmaceutical revenue.

Examples of DHT use in drug trials by functional category

Trial ID	Study Title	DHT Function Category	Brief Summary (Excerpt)
NCT00093860	Safety and Efficacy of In-fliximab in Psoriasis	Digital trial operations, data capture, and participant follow-up platforms	This study will examine the effectiveness of the drug in-fliximab in treating psoriasis, with adherence tracked through mobile ePRO monitoring tools.
NCT00995826	Safety, Tolerability and Pharmacokinetic Study of Multiple Doses of CS-8958	Computerized instruments and digital measurement tools	Also continuous cardiac telemetry will be performed as well as physical examinations and spirometry assessments.
NCT01198925	Assessment of the Optimal Dosing of Piperacillin-tazobactam in Intensive Care Unit Patients: Extended Versus Continuous Infusion	Algorithmic or AI-enabled analytics	A population pharmacokinetic analysis with Monte Carlo simulations will be used to determine 95% probability of target attainment (PTA95) versus MIC.

Contributions

- ▶ The effect of Part D on price, revenue, innovation and drug access. [literature 1](#)
 - ▶ We document that Part-D-led **DHT adoption reduction**, driven by revenue reduction due to **competition**.
- ▶ The effect of consumer concentration. [literature 2](#)
 - ▶ We provide the first **causal evidence** on the impact of consumer concentration on technology adoption by leveraging a **large-scale public policy reform**.
- ▶ Drivers of technology diffusion. [literature 3](#)
 - ▶ **Market structure** and technology adoption.

Model setting and proposition

- ▶ A sponsor chooses whether to adopt DHT, $I \in 0, 1$, and trial effort e :

$$V(I; R, F, b) = \max_{e \geq 0} Rp(e, I, b) - c(e, I, b) - FI$$

- ▶ R is expected net revenue, F is the fixed cost of DHT adoption, and b is the productivity benefit of DHT.
- ▶ DHT is adopted iff:

$$V(1; R, F, b) - V(0; R, F, b) \geq 0$$

- ▶ **Proposition:** If Part D compresses expected revenue from R_0 to $R_1 < R_0$, DHT adoption weakly decreases.
- ▶ The reduction is more likely when F is high, b is modest.

Proof sketch

- ▶ Define the net gain from adoption:

$$\Delta(R, F, b) = V(1; R, F, b) - V(0; R, F, b)$$

- ▶ By the envelope theorem:

$$\frac{\partial \Delta(R, F, b)}{\partial R} = p(e_1, 1, b) - p(e_0, 0, b)$$

- ▶ If DHT improves trial productivity, then:

$$p(e_1, 1, b) > p(e_0, 0, b)$$

- ▶ Therefore, $\Delta(R, F, b)$ is increasing in R .
- ▶ Revenue compression from R_0 to $R_1 < R_0$ lowers the net gain from adoption:

$$\Delta(R_1, F, b) < \Delta(R_0, F, b)$$

- ▶ If $\Delta(R_0, F, b) \geq 0 > \Delta(R_1, F, b)$, the firm adopts DHT before revenue compression but not after.

Robustness: trials not conducted in the US

	(1) Baseline	(2) <i>HHI</i>
PD $\times$ Exposure	0.004 (0.004)	0.012 (0.013)
PD $\times$ Exposure $\times$ <i>HHI</i>		-0.020 (0.025)
R-squared	0.606	0.606
Disease FE	Yes	Yes
Sponsor FE	Yes	Yes
Year FE	Yes	Yes
<i>HHI</i> $\times$ Year FE	No	Yes
Observations	112,223	112,223

- No significant impact on Non-US trials.

Robustness: mean adoption under alternative keyword lists

Measure	Mean	Std. dev.	Observations
Baseline	0.007	0.084	264,409
Safe-list	0.002	0.041	264,409
Expanded list	0.006	0.077	264,409

- ▶ The safe-list is more restrictive and captures fewer detected DHT events.
- ▶ Scaling the estimates by these baseline rates gives economically meaningful contractions in adoption.

Robustness: alternative DHT keyword lists

	Safe-list		Expanded list	
	Baseline	$X = HHI$	Baseline	$X = HHI$
<i>PD Exposure</i>	-0.007** (0.003)	-0.021** (0.010)	-0.008** (0.004)	-0.025** (0.013)
<i>X*PD Exposure</i>		0.041** (0.022)		0.047* (0.027)
<i>Disease area FEs</i>	yes	yes	yes	yes
<i>Sponsor FEs</i>	yes	yes	yes	yes
<i>Year FEs</i>	yes	yes	yes	yes
<i>HHIyear FEs</i>	no	yes	no	yes
<i>Obs</i>	263,881	263,881	263,881	263,881

$p \leq 10\%*$, $p \leq 5\%**$, $p \leq 1\%***$

Disease-class clustered SE in parentheses

- ▶ Results remain negative under both a high-specificity safe-list and an expanded keyword list.

Robustness: excluding pre-2000 observations

	DHT adoption	
	Baseline	$X = HHI$
<i>PD Exposure</i>	-0.009** (0.004)	-0.028*** (0.010)
<i>X*PD Exposure</i>		0.051** (0.022)
<i>Disease area FEs</i>	yes	yes
<i>Sponsor FEs</i>	yes	yes
<i>Year FEs</i>	yes	yes
<i>HHIyear FEs</i>	no	yes
<i>Obs</i>	252,456	252,456

$p \leq 10\%*$, $p \leq 5\%**$, $p \leq 1\%***$

Disease-class clustered SE in parentheses

- The result is not driven by early ClinicalTrials.gov reporting before 2000.

Robustness: newly initiated trials only

	DHT adoption	
	Baseline	$X = HHI$
<i>PD Exposure</i>	-0.014*** (0.005)	-0.053*** (0.014)
<i>X*PD Exposure</i>		0.103*** (0.035)
<i>Disease area FEs</i>	yes	yes
<i>Sponsor FEs</i>	yes	yes
<i>Year FEs</i>	yes	yes
<i>HHI year FEs</i>	no	yes
<i>Obs</i>	76,698	76,698

$p \leq 10\%^*$, $p \leq 5\%^{**}$, $p \leq 1\%^{***}$

Disease-class clustered SE in parentheses

- The effect is stronger when focusing on trial-design decisions at trial initiation.

Robustness: disease-year adoption intensity

	Outcome: $\log(\text{tech_num}+1)$		Outcome: tech_num (PPML)	
	(1) Baseline	(2) HHI	(3) Baseline	(4) HHI
PD $\times$ Exposure	-0.032** (0.015)	-0.108*** (0.026)	-3.118* (1.740)	-9.702*** (2.800)
PD $\times$ Exposure $\times$ HHI		0.146*** (0.046)		16.094** (7.266)
Disease FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
$HHI \times Year$ FE	No	Yes	No	Yes
Observations	9,129	9,129	3,731	3,731

- The disease-year results show the same negative exposure gradient after accounting for zero-trial disease-years.

Placebo: academic-only versus other trials

	Academic-only trials		Other trials	
	(1) Baseline	(2) HHI	(3) Baseline	(4) HHI
PD $\times$ Exposure	-0.009* (0.005)	-0.027** (0.012)	-0.013** (0.005)	0.055*** (0.017)
PD $\times$ Exposure $\times$ HHI		0.041 (0.028)		0.116*** (0.039)
R-squared	0.773	0.773	0.292	0.292
Disease FE	Yes	Yes	Yes	Yes
Sponsor FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HHI $\times$ Year FE	No	Yes	No	Yes
Observations	41,050	41,050	222,803	222,803

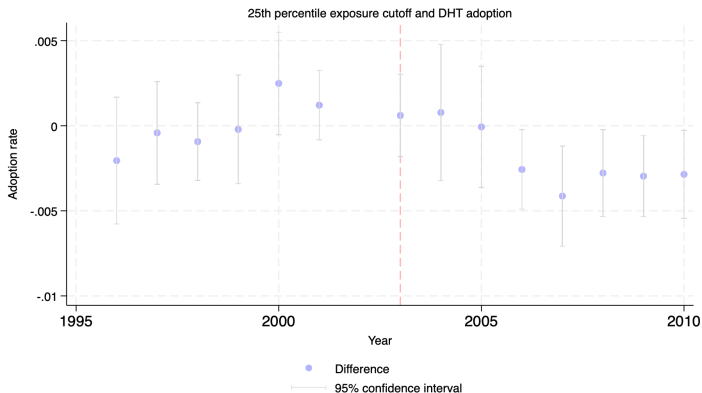
- The exposure gradient is weaker in academic-only trials and clearer in commercially linked trials.

Robustness: regulatory versus discretionary DHT

	Regulatory	Discretionary
Part D exposure	-0.002 (0.002)	-0.009** (0.003)
R-squared	0.225	0.204
Disease fixed effects	Yes	Yes
Sponsor fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	263,881	263,881

- ▶ The effect is concentrated in discretionary patient-facing or endpoint-oriented DHTs, rather than regulatory-facing digital infrastructure.

Alternative exposure cutoff: 25th percentile



Alternative exposure cutoff: 75th percentile

