Designing Incentives for Multitasking Agents: Evidence from Payments to Physicians in England

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Incentive Design with Multi-tasking

- Many incentive design problems involve multi-tasking, i.e., tasks are complements / substitutes
 - $lue{}$ doctor tests blood for illness A ightarrow easy to also test for illness B
 - lacktriangle teacher spends more time on subject A ightarrow hard to also increase exam scores in subject B
- ▶ Well developed theory since Holmstrom and Milgrom [1991]
- Empirics have lagged behind:
 - ightharpoonup counterfactuals require estimating interaction between pairs of tasks ightharpoonup 4 of parameters grows rapidly with # of tasks
 - most applied work focuses on testing

This Paper

- Empirically tractable model of multitasking
- Proof of sufficient conditions for identification combining
 - aggregate variation in incentives
 - cross-sectional variation across agents in exposure to tasks
- Application to Quality and Outcomes Framework (QOF) in England
 - world's largest pay-for-performance scheme in primary care
- Strong evidence of interactions between tasks (multitasking)
- Counterfactuals (preliminary):
 - removal of QOF: payer's utility ↓ by 5%
 - \blacktriangleright optimal re-design: payer's utility \uparrow by 3%

Roadmap

- Setting & Data
- 2 Model
- Identification & Estimation
- 4 Estimates & GOF
- **(5)** Counterfactuals (preliminary)
- Conclusion

GP clinics (GPCs)

- ► ≈ 8000 GPCs in England
- ▶ Provide prescriptions, minor interventions, referral to secondary care
- Zero prices to patients
- Revenue:
 - ho pprox 75% capitation (# of individuals registered, very mild risk adjustment)
 - $\blacktriangleright~\approx~25\%$ financial incentives, mainly from QOF

Quality and Outcomes Framework (QOF)

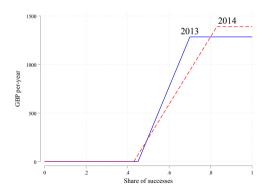
- ▶ Started 2004; several changes over time
- ► Gives GPCs yearly financial incentives to perform tasks ("indicators"), e.g.:
 - \blacktriangleright DM11: % of diabetes patients in whom the last glycohaemoglobin IFCC-HbA1c \le 64 mmol/mol
 - PAD4: % of patients with peripheral arterial disease taking aspirin or an alternative anti-platelet
- ► Success rate between 0% and 100%
- ightharpoonup Total payments pprox £1B / year
- lacktriangleright Electronic record-keeping ightarrow minimal errors / cheating
- ▶ We focus on 40 "truly clinical" indicators

Data

- ▶ NHS public data covering 2009-2019
- ► GPC *i*, indicator *j*, year *t*
- ► Achievement *y_{ijt}*
- ▶ GPC covariates x_{it} (# of doctors in the clinic, average age, share of fully qualified physicians)
- ▶ # of relevant patients n_{ijt} (diabetics, asthmatics, etc)
- ► Incentives for each indicator over time

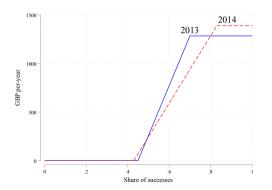
Piecewise linear incentives

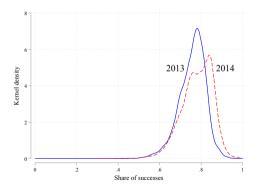
- ▶ Success rate $y_{ijt} \in [0,1]$
- lacktriangle Revenue per patient has slope $lpha_{jt}$ for $y_{ijt} \in \left[\underline{y_{jt}}, \overline{y_{jt}} \right]$
- ► For instance, DM11 in a GPC with 300 patients:



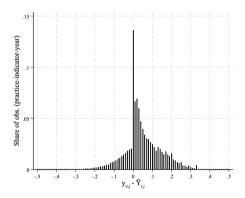
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Bunching suggests strong response to financial incentives



For all indicators, distribution of $y_{ijt} - \overline{y_{jt}}$

- Achievement above $\overline{y_{jt}}$ suggests non-financial motivation and/or complementarities between tasks

Summary of Reduced Form Evidence (details in the paper)

- Practices respond to
 - incentives
 - ▶ incentives × exposure (n. of relevant patients)
- Cross-indicator interactions:
 - ▶ $\uparrow \uparrow$ incentives for $j \Rightarrow \Delta$ outcomes of k, ceteris paribus



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Simplified model: 1 task

- ▶ 1 GPC
- ▶ 1 Task
- n identical patients
- ▶ GPC chooses achievement $y \in [0,1]$
 - ightharpoonup assume n large ightharpoonup negligible noise in y
- ► GPC utility:

$$U(y) = n\rho(y) + n\theta y - n\lambda y^2$$

- ► Financial Return (observed)
- ► Cost function $\theta y \lambda y^2$. Our interpretation:
 - ▶ Non-financial return (expect to estimate θ > 0 to explain $y > \overline{y}$)
 - Direct Costs

Simplified model: 2 tasks

- Achievement $y = (y_1, y_2)$
- ▶ Number of patients n_1, n_2
- ► GPC utility:

$$U(y) = n_1 \rho_1(y_1) + n_2 \rho_2(y_2) + n_1 \theta_1 y_1 + n_2 \theta_2 y_2 - n_1 \lambda_1 y_1^2 - n_2 \lambda_2 y_2^2 - 2(n_1 + n_2) \lambda_{12} y_1 y_2$$

- ► We now add Complementarities
 - $\lambda_{12} > 0$: tasks are "substitutes"
 - ▶ λ_{12} < 0: tasks are "complements"

Many tasks (J > 2)

- Achievement $y = (y_1, \dots, y_j, \dots, y_J)$
- ► GPC utility

$$U(y) = \sum_{j} n_{j} \left(\rho_{j}(y_{j}) + \theta_{j} y_{j} \right) - y \Lambda y^{T}$$

where

$$\Lambda = \begin{bmatrix} n_1 \lambda_1 & n_2 \lambda_{12} & \cdots & n_J \lambda_{1J} \\ n_1 \lambda_{12} & n_2 \lambda_2 & & & \\ \vdots & & \ddots & & \\ n_1 \lambda_{1J} & n_2 \lambda_{2J} & & n_J \lambda_J \end{bmatrix}$$

- ► Model implies constant returns to scale
- We assume that GPCs
 - are homogeneous in λ_j and $\lambda_{j,j'}$
 - ightharpoonup data rationalized by heterogeneity in $heta_j$

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Variation

- ▶ Exogenous variation in aggregate incentives (changes in y, \overline{y}, α over time)
- ▶ Variation patient composition (\approx shift-share instrument):
 - ► Clinic A: 90 diabetics, 10 asthmatics
 - Clinic B: 10 diabetics, 90 asthmatics
 - ▶ Suppose payments rewarding diabetics health ↑↑
 - this incentive is most important for A
 - Compare asthmatic patients in A vs. B
 - ▶ If asthmatics health improves more in A, diabetes and asthma care are complements

Endogenous patient composition

- ▶ Patient might select into "high quality" (high θ) practices [Brown et al., 2023]
- lacktriangle Solution: BLP to recover unobserved GPC quality $\xi
 ightarrow$ let heta depend on ξ
- ▶ Utility of patient p, with illness j, in location ℓ , for GPC i in year t:

$$u_{
ho i \ell j t} = -\eta_j \log (z_{i \ell}) + \mu'_j x_{i t} + \xi_{i j t} + \varepsilon_{
ho j j \ell t}$$

- ▶ Logit market shares P_{ijℓt}
- ▶ IV: exogenous distance $z_{i\ell}$ from location ℓ to GPC i Details
- ▶ If $\psi_{t\ell j}$ is (imputed) prevalence of illness j in location ℓ , observed number of patients is

$$n_{ijt} = \sum_{\ell} \psi_{t\ell j} P_{ij\ell t}$$

- We find ξ_{ijt} is indeed correlated with y_{ijt} (i.e., choice affected by quality) Details
- ▶ In sum, the identifying assumption is: $n_{ijt} \perp \theta_{ijt}$ but only conditional on x_{it}, ξ_{ijt}

Distribution of unobservables

- ▶ We prove that Λ and $F(\theta \mid x_{it}, \xi_{ijt})$ are separately identified
- ► We parameterize

$$heta_{itj} = \gamma_j^1 x_{it} + \gamma_j^2 \xi_{ijt} + \omega_i \zeta_{it} + \sigma_j v_{ijt}, \qquad \zeta_{it} \sim \mathcal{N}\left(0,1\right), v_{ijt} \sim \mathcal{N}\left(0,1\right)$$

 \triangleright Allows for correlation in θ_{iti} within GPC (via a simple factor structure, ζ_{it})

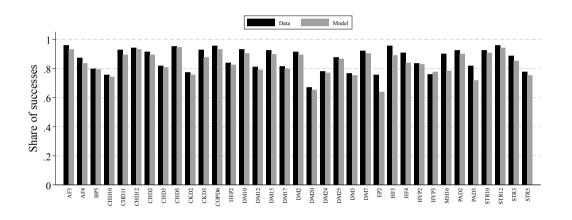
Estimation

- ightharpoonup Assume observed y_{ijt} is optimal (up to integers)
- $ightharpoonup \frac{\partial U_{it}}{\partial y_{ijt}}$ is linear in θ_{ijt}
- ▶ Intuition: analytical likelihood for θ_{iit} is similar to a Tobit
 - First-order conditions holds for "interior" y
 - ▶ Inequalities hold if bunching at $y = \overline{y}$ or y = 1 Details
- ▶ Integrate numerically over ζ_{it}

Roadmap

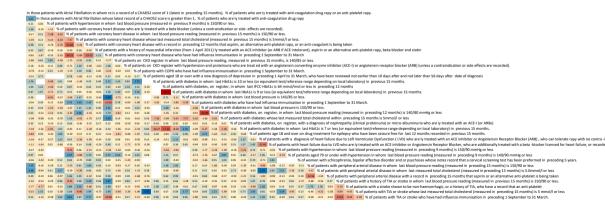
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Goodness of Fit: average achievement



Cost Matrix A

► Most indicators are complements (yellow / blue)



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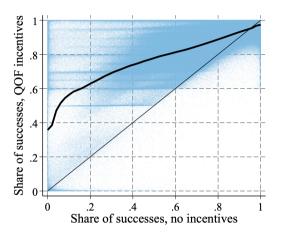
Payer's objective

- \triangleright b_i are health benefits net of medical costs for indicator j
 - ▶ observed, in £, from NICE guidelines
 - known only for 20 indicators (out of 40)
- ► Payer's objective is

$$W = \sum_{i,j,t} n_{ijt} \int \left(y_{ijt}^{\star} b_j - \rho_{jt} \left(y_{ijt} \right) \right) f \left(\theta_{ijt} \right) d\theta_{ijt}$$

where y_{iit}^{\star} is optimally chosen by GPCs and depends on incentives $\rho_{jt}(\cdot)$ chosen by the payer.

Shutting Down QOF: achievement



► Payer's objective drops by 5%

Optimal incentive design

- ▶ Fix y_j and set $\overline{y_j} = 1$
- ▶ Choose slopes $\alpha = (\alpha_1, \alpha_2, ...)$ to maximize the payer's objective W
- ightharpoonup Computational feasibility: we k-means cluster GPCs into 20 groups by x_i, ξ_i, n_{ijt}
 - ► Maximize approximate *W*.
 - ▶ At the solution, compute outcomes for all GPCs

Optimal incentives

	N. OOF	005	0.11.11.1005
	No QOF	QOF	Optimized QOF
	Δ from QOF		Δ from QOF
Practice payoffs	-348	3,240	164
	-11%		5%
QOF payments	-353	353	199
	-100%		56%
Medical costs	-1,431	43,189	683
	-3%		2%
Health benefits	-5,553	131,565	3,857
	-4%		3%
Welfare	-4,117	91,264	3,139
	-5%		3%

- ► Shutting down QOF: payer's objective ↓↓ by 5%
- ▶ Optimizing the QOF: payer's objective ↑↑ by 3%

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Conclusion

- ► Empirically tractable principal-agent model with multitasking
- ▶ Sufficient conditions for identification relying on variation in exposure to different tasks
- Apply model to QOF program in England
- Ample evidence of response to incentives and multitasking
- Model allows counterfactuals:
 - Program generates large welfare gains
 - ► Scope for optimization of incentives accounting for multitasking

Thank you!

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Additional slides:

Literature

- ▶ Empirical models of multitasking: Slade [1996], Buser and Peter [2012], Hong, Hossain, List, and Tanaka [2018], Goes, Ilk, Lin, and Zhao [2018], Manthei and Sliwka [2019], Rodríguez-Lesmes and Vera-Hernández [2021], Kim, Sudhir, and Uetake [2022], Dinerstein and Opper [2022]
 - We go beyond testing.
 - lacktriangle We quantify complementarities ightarrow can consider counterfactual designs
- ▶ Pay-for-performance in healthcare: Gaynor et al. [2004], Dumont et al. [2008], Mullen et al. [2010], Choné and Ma [2011], Clemens and Gottlieb [2014], Li et al. [2014], Einav et al. [2018], Gupta [2021], Rodríguez-Lesmes and Vera-Hernández [2021], Einav et al. [2022], Gaynor et al. [2023], Dunn et al. [2024], Shi [2024, and many more]
 - ▶ We incorporate multitasking
 - ▶ We focus on primary care in non-US context

Analytic MLE

► For instance, in the 2D case:

$$\frac{\partial U}{\partial y_1} = n_1 \rho_1'(y_1) + n_1 \theta_1 - 2n_1 \lambda_1 y_1 - (n_1 + n_2) \lambda_{12} y_2$$

▶ If data is $y_1 = 1$, and knowing $\rho'_1(1) = 0$, then

$$\frac{\partial U}{\partial y_1} \mid_{y_1=1} \geq 0 \Leftrightarrow \theta_1 \geq 2\lambda_1 + \frac{n_1 + n_2}{n_1} \lambda_{12} y_2$$

▶ If $y_1 \in (\overline{y_1}, 1)$, the FOC holds, so

$$\frac{\partial U}{\partial y_1} = 0 \Leftrightarrow \theta_1 = 2\lambda_1 y_1 + \frac{n_1 + n_2}{n_1} \lambda_{12} y_2 - \rho_1'(y_1)$$

▶ Bunching: $y_1 = \overline{Y_1}$. This implies

$$n_1\rho_1'\left(\overline{Y_1}\right) + n_1\theta_1 - 2n_1\lambda_1\overline{Y_1} - (n_1+n_2)\lambda_{12}y_2 \ge 0$$

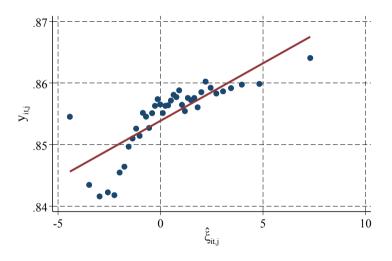
$$n_1\theta_1 - 2n_1\lambda_1\overline{Y_1} - (n_1 + n_2)\lambda_{12}y_2 \leq 0$$

Summary Reduced Form

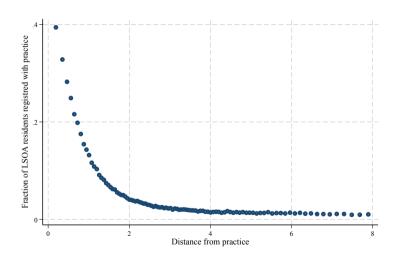
	Extra achievement indicator j (mean = 0.43, std = 0.11)						
	OLS	OLS	OLS	OLS	IV		
Payment per patient	0.117	0.278	0.302	0.289	0.24		
(std = 0.09)	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)		
Share of patients		-0.541	-0.443	-0.425	0.084		
(std = 0.04)		(0.009)	(800.0)	(0.009)	(0.011)		
Share of patients × payment per patient		3.008	1.62	1.684	3.152		
(std = 0.004)		(0.091)	(0.089)	(0.091)	(0.109)		
Controls			Yes	Yes	Yes		
FE		Ind.	Ind., Practice	Ind., Practice	Ind., Practice		
R-squared	0.012	0.285	0.362	0.363	-		
Observations	2145595	2145595	2145595	2014257	2005257		



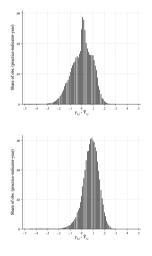
Demand residual is correlated with achievement

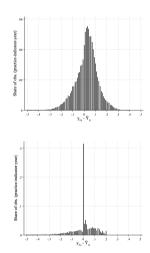


Distance shifts demand



Practices respond to incentives: heterogeneity







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