Designing Incentives for Multitasking Agents: Evidence from Payments to English Physicians

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Incentive Design in Principal-Agent Problems

- Central to healthcare, education, org econ, etc
- ▶ Often, actions and outcomes are high-dimensional
 - ▶ doctor chooses tests, prescriptions → clinical outcomes
 - lacktriangleright teacher chooses topics and methods ightarrow test scores, human capital, etc
- ▶ Often, there is multitasking: higher effort in one task influences the cost of other tasks [Holmstrom and Milgrom, 1991]

Empirical models of multitasking

- ► Counterfactuals require estimates of
 - distribution of types
 - ▶ interaction between outcomes
- ► Each task potentially interacts with all other tasks
 - number of parameters grows quadratically
- Most applied work focuses on testing for multi-tasking

This Paper

- Empirically tractable model of multitasking
- Sufficient conditions for identification
- ▶ Application to Quality of Outcomes Framework (QOF) in England 2009-2019
 - world's largest P4P scheme in primary care
- Strong evidence of
 - physicians responding to financial incentives
 - interactions between indicators
- Variation:
 - in QOF incentives over time
 - practice location exogenously shifts patient composition
- Estimate model & counterfactual design of incentives
 - ▶ QOF increases average achievement by $\approx 40\%$
 - optimal re-design increases payer's utility by 3%

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
 - ► We can consider counterfactual design
- ▶ 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

Roadmap

- Setting and Data
- 2 Model
- Open Demand
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GP practices (GPPs)

- ▶ GPPs provide primary care: prescriptions, minor interventions, referral to secondary care
- Approximately 8000 GPPs in England
- ► Each GPP has about 5 doctors (but we study GPPs)
- ► Zero prices to patients
- Revenue:
 - $ho \approx 75\%$ capitation (# of individuals registered, mild risk adjustment)
 - ightharpoonup pprox 25% financial incentives, mainly from QOF

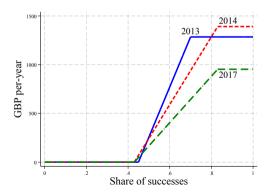
QOF

- Gives GPPs yearly financial incentives to perform certain tasks ("indicators"):
 - ► "The percentage of patients aged 75 or over with a fragility fracture on or after 1 April 2012, who are currently treated with an appropriate bone-sparing agent"
 - ► "The percentage of patients on the chronic kidney disease (CKD) register in whom the last blood pressure reading, measured in the previous 15 months, is 140/85 or less."
- Started 2004, changes over time in
 - intensity of incentives
 - which tasks are incentivized
- ▶ Voluntary participation (95.1% in 2019)
- ightharpoonup Total payments pprox £1B
- ightharpoonup Electronic record-keeping ightarrow minimal errors / cheating
- ▶ We focus on 40 indicators that are "truly clinical"

QOF payments

- ▶ Indicator j has n_i relevant patients
- ▶ If task is successful for k_j patients, achievement is $k_j/n_j = y_j \in [0,1]$
- Revenue per patient for indicator j is $\rho_{jt}(y_{ijt})$: piece-wise linear with slope α_{jt} and thresholds $y_{jt}, \overline{y_{jt}}$:

DM11: % diabetes patients in whom the last glycohaemoglobin IFCC-HbA1c is 64 mmol/mol or less



Data

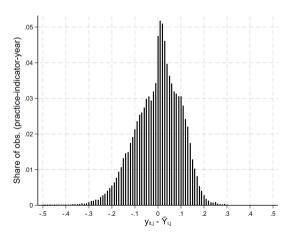
- ► GPP *i*, indicator *j*, year *t*
- ► Achievement *y_{ijt}*
- ▶ GPP covariates x_{it} (number of physicians, average age, etc)
- ► Nr of relevant patients n_{ijt}
- ▶ Thresholds $\overline{y_{jt}}, y_{jt}$
- ▶ Incentives α_{jt}
- ► Everything in 2020 £

Summary Stats

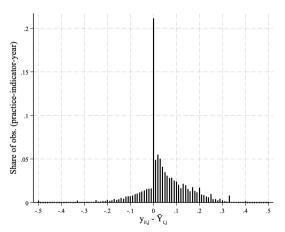
		Mean	Std. Dev.	P-10	Median	P-90	Obs.
	Panel B:			Indicator-practice-year			
Share of successes	y it,j	0.878	0.121	0.722	0.906	1	2389540
Number of patients	$n_{it,j}$	177	264	4	87	445	2389540
Revenues per patient	$ ho_j(\mathbf{y}_{it,j})$	11.16	12.64	2.32	7.23	27.99	2389540

Practices respond to incentives

DM11: % diabetes patients in whom the last glycohaemoglobin IFCC-HbA1c is 64 mmol/mol or less



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



- Bunching suggests strong response to financial incentives
- ▶ $y_{ijt} > \overline{y_{jt}}$ suggests GPPs also have non-financial incentives and/or some tasks are complements.

Achievement responds to incentives

▶ Column (4) uses variation in incentives within GPP-indicator over time

Panel B: Share of successes – $y_{\ell,j} = \delta^{\dagger} \overline{Y}_{t,j} + \delta^2 \alpha_{t,j} + \zeta^1 x_l + \zeta^2 \widehat{\xi_l} + \epsilon_{\ell t,j}$							
$\overline{\mathbf{Y}}_{t,j}$	0.281	0.276	0.241	0.279	0.289		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
$\overline{Y}_{t,j} \times \text{Large practic}$	ce			0.076	0.004		
				(0.002)	(0.000)		
$\alpha_{t,j}$	0.087	0.082	0.031	0.094	0.170		
	(0.005)	(0.005)	(0.007)	(0.005)	(0.006)		
$\alpha_{t,j} imes ext{Large practic}$	е			0.115	-0.135		
				(0.009)	(0.004)		
Practice-level avera	age residual $\hat{\xi_i}$	from practice-ch	oice model		0.129		
					(0.005)		
FE	Ind.	Ind., Practice	Ind.× Practice	Ind.× Practice	Ind.		
Controls	N	N	N	N	Υ		
R-squared	0.412	0.476	0.656	0.656	0.431		
Observations	2353922	2353922	2332413	2332413	2060431		

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2 tasks

- ▶ Single GPP, 2 tasks (j = 1, 2)
- \triangleright Number of patients n_j
- ▶ A clinic chooses outcomes $y_i \in [0,1]$
 - lacktriangle large number of patients ightarrow negligible outcome noise
- ▶ Payer chooses revenue functions $\rho_j(\cdot)$
- ► GPP utility:

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

- Revenue, Altruism, Costs, Complementarities
 - ► (Altruism is short-hand for all non-financial incentives)
- ▶ If $\lambda_{12} > 0$, tasks are "substitutes"
- ▶ If λ_{12} < 0, tasks are "complements"

Many tasks

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

$$\Lambda = \begin{bmatrix} n_{1}\lambda_{1} & n_{2}\lambda_{12} & \cdots & n_{J}\lambda_{1J} \\ n_{1}\lambda_{12} & n_{2}\lambda_{2} & & & \\ \vdots & & \ddots & & \\ n_{1}\lambda_{1J} & n_{2}\lambda_{2J} & & n_{J}\lambda_{J} \end{bmatrix}$$

- ▶ For each j, the n_i patients are identical
- ▶ If all n_j scale up, solution is unchanged
- ▶ If n_j increases, other things equal, incentives for task j increase

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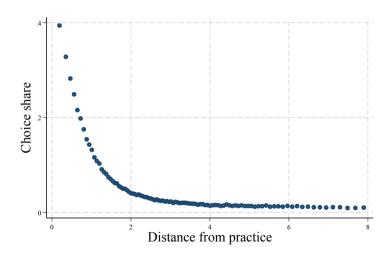
Demand

- ▶ Patients might select into "high-quality" practices
 - must consider demand
- \blacktriangleright We use exogenous variation in patient-practice location z_{it} to identify choice-relevant unobservable quality
- ▶ Simple logit: share of patients from location ℓ choosing practice i in year t is

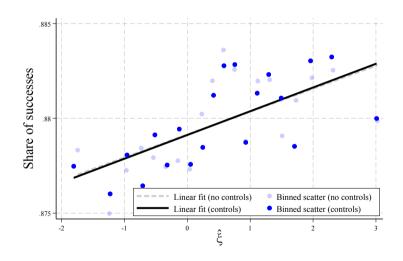
$$s_{it}^{\ell} = \frac{\exp\left\{\gamma z_i^{\ell} + \eta x_i + \xi_{it}^{\ell}\right\}}{1 + \sum\limits_{d: z_i^{\ell} < 5} \exp\left\{\gamma z_d^{\ell} + \eta x_d + \xi_{dt}^{\ell}\right\}} \qquad , z_i^{\ell} \leq 5 \text{ kilometers.}$$

- lacksquare Aggregate $\widehat{\xi_i} = \mathbb{E}_{\ell,t}[\xi_{it}^\ell]$
- **Assumption:** n_{ijt} iid conditional on $x_i, \hat{\xi}_i$
- ightharpoonup Currently working on adding health conditions by location (i.e., estimate ξ_{ij})
 - we will approximate market size for GPP *i* condition *j*: total number of patients with that condition in all GPPs within 10Km of *i*
 - ▶ allows patients with condition j to choose GPP i because it is high-quality for condition j (but possibly low-quality for $k \neq j$)

Distance shifts demand



Demand residual is correlated with achievement



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Identification

- ▶ Goal: identify technology Λ separately from type distribution $f(\theta)$
- ▶ Data: demand n_{it} , achievement y_{it} , characteristics x_{it} , z_{it} , incentives $\rho_{jt}(\cdot)$
- ▶ We prove that the model is identified if:
- **Assumption (LQU):** Utility U(y) is Linear-Quadratic
- ▶ Assumption (exogeneity): Instrument z_{it} such that demand is $n_{it} = \sigma(x_{it}, z_{it}, \xi_{it})$
 - n_{it} and θ_{it} independent conditional on (x_{it}, ξ_{it})
- ▶ Assumption (independence): $f(\theta_{it}|x_{it},\xi_{it}) = \prod_j f_j(\theta_{it,j}|x_{it},\xi_{it})$
 - currently working on relaxing.
- ▶ Assumption (variation): Rich variation in incentives (α_{jt}) and task assignments (z_{it}) to distinguish any function of y_{it}
 - ▶ Intuition: Change incentives for blood sugar control. Compare GPP A with many diabetics to GPP B with few. If A's cholesterol outcomes improve more than B's \rightarrow cholesterol & blood sugar are complements

Estimation

- ightharpoonup Assume y_{ijt} is the optimal effort choice made by the GPPs (up to integers)
- lacktriangle Let $ilde{x_i} = \left(x_i, \hat{\xi_i}
 ight)$ be GPP covariates, including demand residuals
- ► Assume that, for each *ijt*,

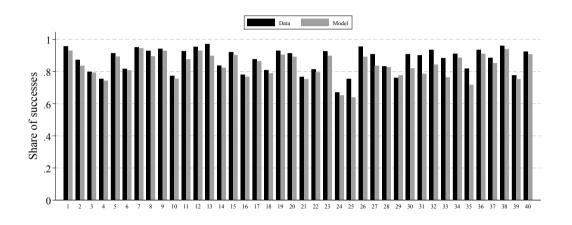
$$heta_{ijt} \sim \mathcal{N}\left(\mu_{j}\tilde{x_{i}}, \sigma_{j}\right), \qquad \qquad \left(n_{it} \mid \tilde{x_{i}}\right) \perp \left(\theta_{it} \mid \tilde{x_{i}}\right)$$

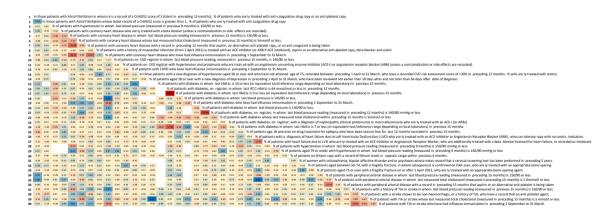
- ► Given LQU, $\frac{\partial U_{it}}{\partial y_{iit}}$ is linear in θ_{ijt}
 - ightharpoonup Can derive (discrete-continuous) distribution of θ_{iit} analytically: ightharpoonup
- ► Estimate Λ and $\{\sigma_j, \mu_j\}_i$ by MLE (1060 parameters)

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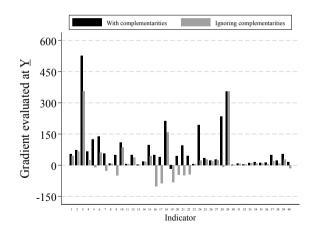
Goodness of Fit





How important is Multitasking?

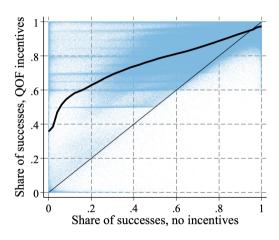
- ▶ Given estimates, for each j, calculate $\mathbb{E}_{it}[\partial U_{it}/\partial y_{it,j}]$, evaluated at $\underline{y_{tj}}$ (beginning of incentives)
 - then repeat this using $\lambda[j,k] = 0$ if $j \neq k$



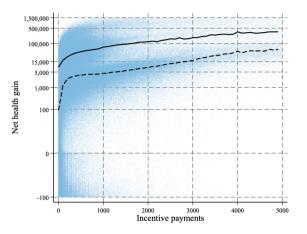
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Shutting Down QOF: achievement



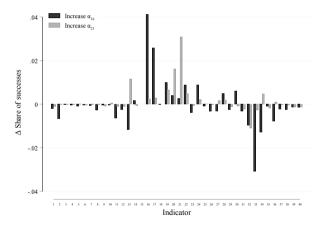
Shutting Down QOF: health gains (in £)



ightharpoonup Ratio of QOF payments to median health gains (in £) is pprox 1:5

Increasing incentives for one indicator

- ▶ Increase incentives for indicators16 & 21 (by £40)
- ► Significant impact on other indicators



Empirical incentive design

- \triangleright b_j are health benefits net of medical costs for indicator j (in £, from NICE guidelines)
 - ▶ so far only 20/40 indicators
- ▶ Set y_j fixed and $\overline{y_j} = 1$ for each years
- ightharpoonup Choose α_j to maximize the payer's objective

$$W = \sum_{i,j,t} n_{ijt} \int (y_{ijt}b_j - \rho_{jt}(y_{ijt} \mid \alpha_{jt})) f(\theta_{ijt} \mid \tilde{x_i}) d\theta_{ijt}$$

where y_{iit} is chosen by GPPs to maximize utility

- ightharpoonup Requires, for each α , solving the problem for all GPPs ightarrow unfeasible
- ▶ We use k-means to cluster GPPs in terms of x_i, ξ_i, n_{ijt}
 - For every group $g=1,\ldots,20$ obtain weight π_g and average values x_g,ξ_g,n_{gjt}
 - \blacktriangleright Maximize this approximate W. At the solution, compute outcomes for all GPPs

Optimal incentives increase payer utility by 3%

	$\begin{array}{c} \text{No QOF} \\ \Delta \text{ from QOF} \end{array}$	QOF	$\begin{array}{c} \text{Optimized QOF} \\ \Delta \text{ from QOF} \end{array}$
Practice payoffs	-348 -11%	3,240	164 5%
QOF payments	$^{-361}_{-100\%}$	361	$221\\61\%$
Medical costs	$-1,449 \\ -3\%$	43,465	$731 \\ 2\%$
Health benefits	-5,574 -4%	131,900	$\frac{3,915}{3\%}$
Welfare	$^{-4,113}_{-5\%}$	91,314	$3{,}128$ 3%

 $Notes: \ All\ monetary\ values\ are\ in\ GBP\ millions.\ Welfare\ is\ computed\ as$ the Practice payoffs + Health benefits - QOF payments - Medical costs

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Next Steps

- ► Include co-morbidities in demand
- ► Integrate "missing indicators" into the estimation

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:

U'(y) Linear in ε

- ▶ Given LQU, $\frac{\partial U_{it}}{\partial y_{iit}}$ is linear in θ_{ijt}
- ► 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 $y_1 = 1$, 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

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



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