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

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## Incentive Design in Principal-Agent Problems

- Many incentive design problems involve multi-tasking, i.e., tasks are complements / substitutes
  - $\blacktriangleright$  doctor scans for illness A  $\rightarrow$  easier to also scan for B
  - lacktriangle teacher spends more time on subject A ightarrow harder to increase student scores in B
- ▶ Well developed theory since Holmstrom and Milgrom [1991]
- ► Empirics have lagged behind:
  - ightharpoonup counterfactuals require interaction between pairs of outcomes ightharpoonup of parameters grows rapidly with number of tasks
  - We prove identification but it requires
    - aggregate variation in incentives
    - cross-sectional variation across agents in exposure to tasks
  - ightharpoonup most applied work focuses on testing

## This Paper

- ► Empirically tractable model of multitasking
- ▶ Proof of sufficient conditions for identification
- ► Application to Quality of Outcomes Framework (QOF) in England
  - world's largest pay-for-performance scheme in primary care
- Strong evidence of
  - physicians responding to financial incentives
  - ► interactions between indicators (multitasking)
- Counterfactuals:
  - ► removal of QOF: payer's utility ↓ by 5%
  - ▶ optimal re-design: payer's utility ↑ by 3%

## Roadmap

- Setting & Data
- 2 Model
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# GP clinics (GPCs)

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

# Quality of Outcomes Framework (QOF)

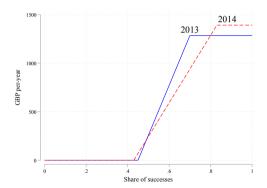
- Started 2004; several changes over time
- ▶ Gives GPCs yearly financial incentives to perform tasks ("indicators"), e.g.:
  - ightharpoonup DM11: % of diabetes patients in whom the last glycohaemoglobin IFCC-HbA1c  $\leq$  64 mmol/mol
  - ▶ PAD4: % of patients with peripheral arterial disease taking aspirin or an alternative anti-platelet
- ▶ Voluntary participation (95.1% in 2019)
- ightharpoonup Total payments pprox £1B / year
- ightharpoonup 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<sub>ijt</sub>
- ▶ GPC covariates  $x_{it}$  (number of doctors in the clinic, average age, share of fully qualified physicians)
- $\triangleright$  Nr of relevant patients  $n_{ijt}$  (diabetics, asthmatics, etc)
- Incentives for each indicator over time

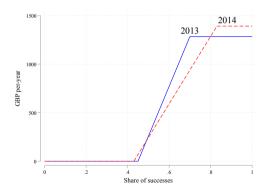
#### Piecewise linear incentives

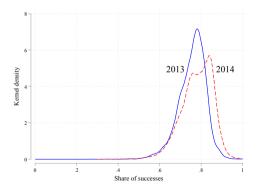
- ▶ Success rate  $y_{ijt} \in [0,1]$
- lacktriangle Revenue per patient has slope  $lpha_{jt}$  for  $y_{ijt} \in \left[ \underline{y_{jt}}, \overline{y_{jt}} \right]$
- ▶ DM11, Practice with 300 patients:



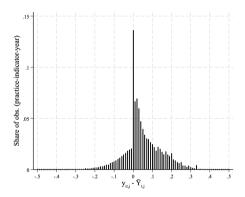
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# Bunching suggests strong response to financial incentives



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

- Achievement above  $\overline{y_{jt}}$  suggests non-financial motivation and/or complementarities between tasks
  - ▶ there is significant heterogeneity in bunching across indicators

# Summary of Reduced Form Evidence (details in the paper)

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

◆ Details

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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
  - abstract from sequential nature of tasks
- ► GPC utility:

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

► Financial Return (observed)

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- Direct Costs

## Simplified model: 2 tasks

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

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

- ► Financial Return, Non-financial return, Direct Costs
- Complementarities
  - $ightharpoonup \lambda_{12} > 0$ : tasks are "substitutes"
  - $\lambda_{12} < 0$ : 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

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

- Implies constant returns to scale
- Assume GPCs
  - have the same cost matrix Λ
  - $\triangleright$  Differ in non-financial returns  $\theta$

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#### Variation

- ightharpoonup Exogenous variation in aggregate incentives (changes in  $y, \overline{y}, \alpha$  over time)
- Variation patient composition:
  - ► 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 composition might be endogenous
  - ▶ Patients might choose GPCs particularly motivated to treat their illness
- ▶ We will estimate unobserved GPC quality in each illness using a demand model
  - ▶ disease prevalence in the region is an IV for patient composition at each GPC
- ▶ Let  $z_{i\ell}$  be distance from location  $\ell$  to GPC i
- ▶ In a location  $\ell$ , a patient of illness j has utility for GPC i in year t of:

$$u_{i\ell jt} = -\eta_j \log(z_{i\ell}) + \mu_j x_{it} + \xi_{ijt} + \varepsilon_{ij\ell t}$$

- ▶ Logit market shares are  $P_{ij\ell t}$
- ▶ If  $N_{t\ell j}$  is prevalence of illness j in location  $\ell$ , observed number of patients is

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

- $\blacktriangleright$  We recover unobserved quality  $\xi_{iit}$ 
  - $\blacktriangleright$  which is indeed correlated with  $y_{ijt}$  (i.e., composition is endogenous)  $\blacksquare$

## Endogenous patient composition

- ► Then, we allow  $\theta_{ijt}$  to depend on
  - observed GPC characteristics x<sub>ii</sub>
  - ightharpoonup unobserved quality  $\xi_{ijt}$

$$\theta_{ijt} \sim F\left(\theta \mid x_{it}, \xi_{ijt}\right)$$

- $\blacktriangleright$  We also allow for correlation between elements of the vector  $\theta_{it}$
- ▶ We prove that Λ and  $F(\theta \mid x_{it}, \xi_{ijt})$  are separately identified

#### Estimation

- ightharpoonup First, we obtain  $\xi_{ijt}$
- Assume observed  $y_{ijt}$  is the optimal achievement (up to integers)
- ► Use the linear-quadratic FOCs
  - $ightharpoonup rac{\partial U_{it}}{\partial y_{ijt}}$  is linear in  $\theta_{ijt}$
- $\triangleright$  Can derive the (discrete-continuous) distribution of  $\theta_{ijt}$  analytically  $\bullet$  Details
- ► We parameterize

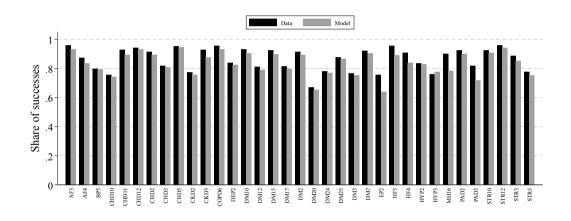
$$\theta_{it} \sim \mathcal{N}\left(\beta_{\mathsf{x}} \mathsf{x}_{it} + \beta_{\xi} \xi_{it}, \Sigma\right)$$

- We estimate:
  - $\triangleright$  elements  $\lambda_{ii}$  (in  $\Lambda$ ) fully flexibly
  - vectors  $\beta_x, \beta_\xi$ .
  - ightharpoonup diagonal elements of  $\Sigma$  flexibly and otherwise allow for simple correlations via a factor structure.
- ▶ Estimate by MLE ( $\approx$ 1060 parameters)

# Roadmap

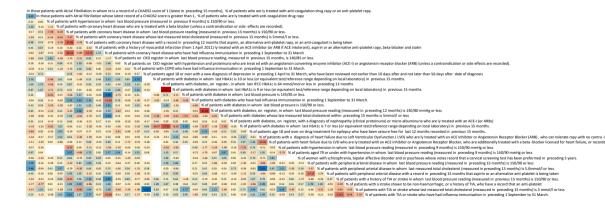
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## Goodness of Fit



#### Cost matrix A

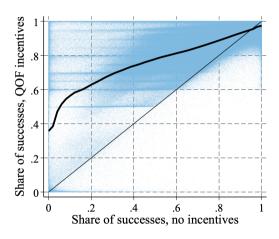
► Most indicators are complements (yellow / blue)



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## Shutting Down QOF: achievement



## Optimal incentive design

- $\triangleright$   $b_j$  are health benefits net of medical costs for indicator j (observed, in £, from NICE guidelines)
  - ▶ known only for 20 indicators (out of 40)
- Fix  $y_j$  and set  $\overline{y_j} = 1$
- lacktriangle Choose slopes  $lpha=(lpha_1,lpha_2,\dots)$  to maximize the payer's objective

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

where  $y_{iit}$  is optimally chosen by GPCs in response to  $\alpha$ 

- ightharpoonup Computational feasibility: we k-means cluster GPCs into 20 groups by  $x_i, \xi_i, n_{ijt}$ 
  - ► Maximize approximate W.
  - ► At the solution, compute outcomes for all GPCs

## Optimal incentives

	No QOF $\Delta$ from QOF	QOF	Optimized 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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## Next Steps

▶ Integrate into the estimation indicators removing during sample period

#### 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

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### 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

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

▶ 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

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

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

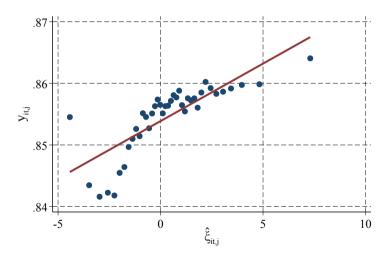


# Summary Reduced Form

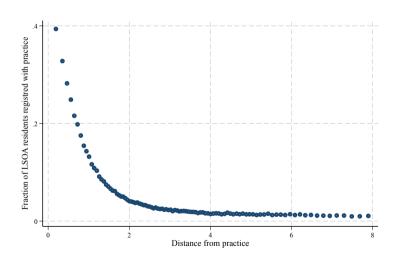
	Extra achievement indicator $j$ (mean = 0.43, std = 0.11)					
	OLS	OLS	OLS	OLS	IV	
Payment per patient	0.117	0.278	0.302	0.289	0.24	
(std = 0.09)	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)	
Share of patients		-0.541	-0.443	-0.425	0.084	
(std = 0.04)		(0.009)	(0.008)	(0.009)	(0.011)	
Share of patients × 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

