Does Division of Labor Increase Productivity? Evidence from Primary Care

Amanda Dahlstrand (Zurich), Shan Huang (SSE & Copenhagen),
Nestor Le Nestour (Stockholm), and Guy Michaels (LSE)

December 2025

Potential productivity gains from the division of labor

> *"The **greatest improvement** in the productive powers of labour seem to have been... the effects of the **division of labor**..."* — Smith (1776)

- Central economic idea with implications for countries, industries, social structures and occupations within organizations
- Smith described a pin factory, but more relevant today is the division of labor in services, especially in the knowledge economy
- To divide labor, organizations often use *Knowledge Hierarchies (KH)* (Garicano, 2000): Less specialized workers handle routine problems at the front end and direct more complex cases to specialized experts

Knowledge hierarchies (KH)

- Knowledge hierarchies are ubiquitous, for example:
  - Kitchen workers and chef de cuisine
  - Paralegals and attorneys
  - Technicians and professional engineers
  - Nurses and doctors

  But we have little evidence on the productivity effects of KH or when they are used

- To assess the productivity gains from a division of labor under KH, we need:
  1. "Common support" in tasks to be sent **both** to the KH and directly to experts
  2. To overcome **sorting** between the two routes
  3. To **trace quality and costs** through both routes

  → We study this for KH in primary healthcare

Knowledge hierarchies in primary care

- **Context**: primary healthcare in Sweden
  - Tax-funded, universal health insurance
  - Costs are rising rapidly and professional staff are in short supply
  - We focus on one (big) firm providing **online** primary care
- **Nurses & doctors**: distinct training and occupational profiles
- **Tasks**: patient cases – different symptoms, demographics, histories
- **Algorithm** assigns cases to one of **two routes**:
  1. Directly to doctors
  2. Initially to nurses, who may escalate some to doctors (*Knowledge Hierarchy*)
- Focus on "**overlap group**" of symptoms: algorithm usually directs these to doctors; but when doctors are busy, they are sometimes assigned initially to nurses
- **Limited information on downstream effects**: unclear whether allocation is efficient

Research questions

1. What are the tradeoffs for costs and patient health between the two routes?
2. What determines task allocation between routes, and what are the cost implications?
3. How could KH be used efficiently, and how much could be saved?

- **Outcomes**:
  - Patient health & labor market outcomes
  - Costs of provision (incl. downstream care) for the firm & Swedish health insurance

- **Methodology**: Use small fluctuations in doctor congestion (90% of waits $<$ 1 hour)
  1. OLS with calendar day x 3-hour block fixed effects & individual case controls
  2. (IV using congestion – wait time to see doctors among previous cases)

Short-term congestion induces variation in patient assignment:
This allows us to identify relative effects of the two routes

Preview of results

1. **Mean and distributional tradeoffs:**
   - In KH, nurses resolve 70% of cases, directing 30% to doctors
   - No significant effects on patient health (hospitalizations, income loss, mortality)
   - KH is 9% cheaper for taxpayers but leaves mean *total societal costs* unchanged
     But: KH saves $\approx$ 50% on about half of (easier) cases

2. **Economic factors determining when KH is used**:
   - KH is less profitable, so used only when firm is constrained (doctor congestion)
   - Relative to sending all cases to doctors, firm's selective use of KH saves 0.7% of total societal costs (2.4% of online primary care costs)

3. **Better use of knowledge hierarchy could further improve productivity:**
   - Reassigning cases within 15-minute windows could save **further** 2% of total societal costs (6.7% of online primary care costs)
   - Firm currently lacks information and incentives, but this can be achieved through rules

Contribution to broader economics literature

Division of labor within organizations, and especially knowledge hierarchies

Theoretical: Becker and Murphy (1992); Garicano (2000); Garicano & Rossi-Hansberg (2006)

Empirical: Caliendo, Monte & Rossi-Hansberg (2015); Caliendo, Mion, Opromolla & Rossi-Hansberg (2020)

→ We provide evidence on causal effects of division of labor and what it can achieve

Determinants of economic specialization

Ricardo (1817); Heckscher (1919); Ohlin (1924); Dornbusch et al. (1977); Katz and Murphy (1992); Acemoglu and Autor (2011)

→ We study study determinants and consequences of economic specialization within a firm with downstream consequences for quality and costs

Contribution to the literature in health economics

Specialization and occupational differentiation

- Licensing, scope of practice, and increased use of nurse practitioners (Shapiro, 1986; Kleiner, 2016; Traczynski and Udalova, 2018; Alexander and Schnell, 2019; McMichael, 2023; Dillender et al., 2024; Gottlieb et al., 2025)
- Nurse practitioners vs. doctors (Chan and Chen, 2022; Currie and Zhang, 2023)

→ We study a knowledge hierarchy on the task level; We study primary care

Productivity in healthcare

- Healthcare provision relies on specialized skills (Arrow, 1963; Chandra and Staiger, 2007; Doyle et al., 2010; Currie and MacLeod, 2017)
- Misallocation of inputs drives rising costs (Baicker and Chandra, 2004; Chandra et al., 2023)
- Coordination of skills in organizations (Chan, 2016; Silver, 2021; Kelly et al., 2023; Dahlstrand, 2024)

→ Evaluate productivity effects of organizational decisions at initial contact with healthcare

Waiting times in healthcare

- Long delays (11-12 days) in mental health emergencies for veterans can increase mortality (Costantini, 2025)

→ Not an emergency setting; $>$ 90% wait less than hour ($>$ 99.9% in same day)

Setting and data

The online primary care firm

- Firm employs **doctors** and **nurses** in Sweden
  - Large differences in training durations (7+ vs. 3 years), salaries (mean ≈104k vs. ≈46k USD/yr in 2020), competencies (treatments, referrals)
- For patients not registered with the firm (focus in this paper):
  - Firm is paid fee-for-service by national health insurance & patient copay
  - Highest-cost consultation per day can be charged at administratively set prices
- Patients request video consultations using an app
  - Gender, age, region automatically entered
  - Patients select their main symptom from a list
- **Algorithm** assigns patients to nurse or doctor consultation

Online care is common in OECD and Sweden is quite typical in 2023

Past years

Indicator	Countries
Telehealth share in 2023 (23 countries with data)	EE 35.6%; IL 29.2%; PT 26.4%; DK 25%; **SE** 25%; US 25-27%; ES 22.4%; AU 18.9%; NO 18.4%; SI 14.8%; LT 12.4%; HU 12.4%; BE 10.2%; PL 8.3%; CZ 8%*; FI 6.8%; FR 3.6%*; LU 1.9%; DE 1%*; CL 0%; GR 0%; KR 0%
Ratio of nurses to doctors in 2023 (26 countries with data)	FI 4.4; US 4.4; CA 3.7; KR 3.6; IE 3.6; IS 3.4; NZ 3.2; NO 3.1; AU 3.1; SL 3.0; NL 2.8; DE 2.6; **SE** 2.5; DK 2.3; CZ 2.1; GB 2.0; AT 1.9; EE 1.9; LT 1.6; IL 1.6; PL 1.5; HU 1.5; ES 1.3; IT 1.3: LV 1.2; MX 1.1
Prescriptions can be issued in teleconsultations (30 countries with data)	*YES*: AU; AT; BE; CA; CR; CZ; DE; EE; FR; GB-ENG; HU; IS; IE; IL; JP; KR; LV; LT; LU; MX; NL; NZ; NO; PL; PT; SI; **SE**; CH; TR; US
Primary care model may include fee-for-service (25 countries with data)	*YES*: AU; AT; BE; CA; CZ; DE; DK; EE; FI; FR; GB; GR; IT; LU; MX; NL; NZ; NO; PL; PT; SI; **SE**; US *NO*: LV; ES
Teleconsultations may be provided without prior contact (31 countries with data)	*YES*: AT; BE; CA; CH; CR; DE; DK; FI; FR; GB-ENG; HU; IS; IE; IL; IT; JP; LV; LT; NZ; NO; PL; PT; SI; **SE**; TR; US *NO*: AU; CZ; NL; MX; EE; LU

The table covers all OECD countries for which data are available in OECD (2025), OECD (2021), and official national sources. Fractions represent the share of OECD countries reported out of those with available data. The total number of OECD member countries is 38. Countries are identified using ISO 3166-1 alpha-2 codes. The information in the table refers to 2023, unless otherwise specified.*Teleconsultations include only those reimbursed through the national healthcare system.

Data

- **All consultations** with the primary care firm in 2019–2020
- Matched to data from **Statistics Sweden** and **National Board of Health and Welfare** for 2013–2023:
  - Demographics (incl. death) and socioeconomics (incl. income)
  - Secondary healthcare (emergency, hospital, specialist care) and prescriptions
  - Detailed costs of all other healthcare Costs
- **Analysis sample**: ≈500,000 unscheduled cases in overlap group
  - **Regions Scania + Stockholm** (≈53%): Primary care use outside firm in 2013–2020 (Scania) and 2013–2023 (Stockholm)

Sample restrictions Consultations over time Clinicians over time

Summary statistics of the analysis sample

	Mean	SD
Patient demographics		
Female	0.63	0.48
Toddler (2-4 years)	0.056	0.23
Child (5-12 years)	0.11	0.31
Teen (13-19 years)	0.12	0.32
Young adult (20-39 years)	0.46	0.50
Middle aged (40-59 years)	0.21	0.41
Senior (60+ years)	0.047	0.21
Annual income (median, 1000s SEK)	294.6	292.0
Immigrant 1st gen	0.16	0.36
Immigrant 2nd gen	0.096	0.29
Observations	495,555	

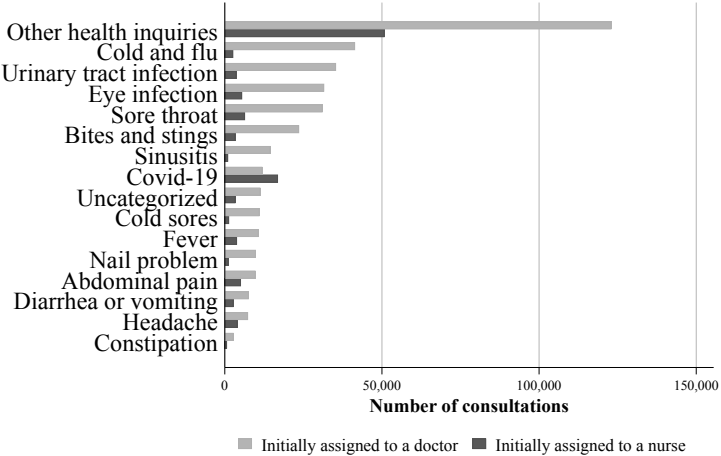
	Mean	SD
Health risks (prior 3 years)		
Any prior hospitalization	0.13	0.34
Any prior ED	0.34	0.47
Any prior urgent care	0.23	0.42
Any prior specialist care	0.64	0.48
Any comorbidity	0.25	0.43
Observations	495,555	

In-person primary care comparison

Annual income is defined for patients aged $\geq$20 with non-missing Nov 2018 values (N=316,418); the national median was 370,800 SEK. First-generation immigrant is defined as being born outside Sweden in 2019–2020; the national share of first-generation immigrants was 19.72% in 2020. Second-generation immigrant is defined as having two foreign-born parents; the national share of second-generation immigrants was 6.16% in 2020. Health risks indicate any event within 3 years to 2 days before initial assignment. Comorbidity indicates at least one of the 31 Elixhauser conditions diagnosed in specialist/hospital care within 3 years before initial assignment, adapted from 4-digit to 3-digit ICD codes; the most common in our data are Depression, Alcohol abuse, and Drug abuse.

Overlap group: Patients' self-reported symptoms

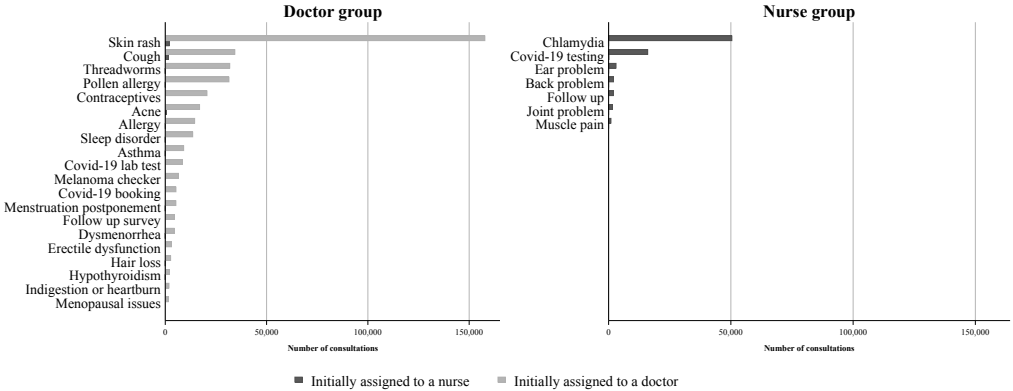
Diagnoses, incl. physical care | Congestion



Symptoms are reported from the analysis sample including all unscheduled cases from the overlap group

Nurse group and doctor group symptoms

Cases from these symptoms are allocated at least 95% of the time to just one clinician group



Doctor and nurse group symptoms have >95% of cases assigned to either doctors or nurses.

Outline of a model

Costs and revenues for a case

- Taxpayer **pays firm using set prices**, where we assume a constant wedge θ
  - θ of the taxpayer's payment reflects the firm's net revenue
  - $(1-\theta)$ of the taxpayer's payment reflects the firm's production costs
- **Doctors**:
  - Firm revenue per consultation: c_d
  - Resolve all cases *within firm* with probability 1
- **Nurses**:
  - Firm revenue per consultation: c_n (where $c_n < c_d$, as in the data)
  - Probability of resolving type τ case: $p_\tau \in (0,1)$. Unresolved cases are directed to doctors
- Costs of a case's (out-of-firm) **downstream care**: $C_{d,\tau}$ (doctor), $C_{n,\tau}$ (nurse)
  - Random variables
  - We assume no markups in downstream care since much of it is publicly produced

Costs and revenues for a case (continued)

Given prices c_n, c_d, markdown θ, and costs of downstream care $C_{d,\tau}, C_{n,\tau}$:

- **Firm's net revenue** depends on initial assignment and, if assigned to a nurse, whether the nurse resolves the case
- **Total taxpayer costs**: payments to the firm (i.e., the firm's gross revenue) + downstream healthcare costs
- **Total societal costs** of producing care: total taxpayer costs – firm's net revenue

	Initially to nurse		Initially to doctor
	Resolved	*Unresolved*	*Resolved*
Firm's net revenue	θc_n	$\theta c_d - (1-\theta)c_n$	θc_d
Total taxpayer cost	$c_n + C_{n,\tau}$	$c_d + C_{n,\tau}$	$c_d + C_{d,\tau}$
Total societal cost	$(1-\theta)c_n + C_{n,\tau}$	$(1-\theta)(c_d+c_n)+C_{n,\tau}$	$(1-\theta)c_d + C_{d,\tau}$

The firm's case assignment problem

- Firm assigns cases initially to **nurses (KH)** or **doctors** based on case type (symptom) τ to **maximize net revenues**, subject to following constraints (most important first):
  1. Firm only has discretion in assigning clinicians to overlap-group cases; doctor-group cases are assigned to doctors and nurse-group cases are assigned to nurses
  2. Queue of doctor-group and overlap-group cases processed as first-come-first-served
  3. Clinician availability within short time windows

- Processed seprately from the queue:
  - Nurse-group cases (less urgent)
  - Cases directed from nurses to doctors are pre-scheduled visits outside the queue

Solving the firm's problem: processing the queue at each time t

- D_t doctors and N_t nurses available to take the (up to) $D_t + N_t$ first cases in queue:
  - **Doctor-group cases** assigned to doctors (excess cases remain in queue for next period)
  - **Overlap-group cases** handled by remaining clinicians ($\tilde{D}_t$ doctors and N_t nurses)

- Assignment of overlap cases depends on **doctor congestion:**
  - *Uncongested:* If no more than $\tilde{D}_t$ overlap cases, all are assigned to doctors
  - *Congested:* If more than $\tilde{D}_t$ overlap cases, assignment between doctors and nurses follows **relative net revenue advantage**

- Taxpayer's perspective: within-firm costs are always lower under the nurse route, but total costs depend on the distribution of downstream costs $C_{d,\tau}, C_{n,\tau}$

Evidence of the firm's case processing and assignment

The social planner's assignment rule follows absolute advantage

To minimize total societal costs, the social planner prefers assigning a case of type τ to a doctor if and only if:

$$\underbrace{(1-\theta)c_d + \mathbb{E}[C_{d,\tau}]}_{\text{Expected total societal cost of initial doctor assignment}} < \underbrace{p_\tau\big((1-\theta)c_n + \mathbb{E}[C_{n,\tau}]\big) + (1-p_\tau)\big((1-\theta)(c_d+c_n) + \mathbb{E}[C_{n,\tau}]\big)}_{\text{Expected total societal cost of initial nurse assignment}}$$

Takeaways for empirical work

1. **Identification**: Within short time windows, treatment (KH) assignment depends on case types (symptoms) and exogenous shifters (short-term small differences in congestion and queue composition)
2. **Estimate mean and distributional effects of KH**:
   - For overlap cases, KH should decrease firm net revenues and within-firm taxpayer costs
   - Within-firm cost distributions for KH and doctor route should not first-order stochastically dominate each other
   - KH effects on healthcare outcomes and downstream costs need to be estimated empirically
3. Examine case **assignment to nurses**:
   - Corr(type assigned to nurses, type's relative net revenue advantage of nurses)> 0
     - This correlation should be stronger during times of higher congestion
   - Corr(type assigned to nurses, type's relative within-firm taxpayer cost adv. of nurses)< 0
4. **Total societal costs** not minimized due to firm incentives and lack of downstream info
   - Examine how much societal costs are saved by implementing planner's solution

Empirics

1. Empirical Framework (Identification)

OLS estimation

$$Y_i = \delta_i Nurse_i + X_{1i}\beta_{1i} + X_{2i}\beta_{2i} + \epsilon_i$$

- Y_i: Outcome for patient case i
- $Nurse_i$: Initial assignment to nurse (vs. directly-to-doctor)
  - → We allow for heterogeneous effects in δ_i

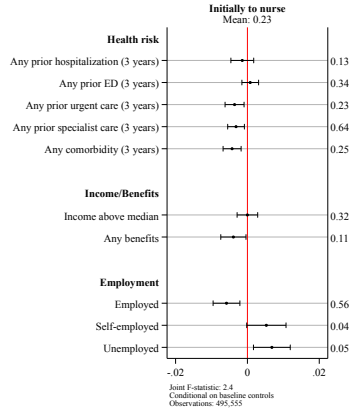
- X_{1i}: Baseline controls for predetermined factors likely **used by the algorithm** to assign cases between KH or directly-to-doctor routes
  - Calendar date-by-3-hour blocks, region, and symptoms × gender × age dummies × last consultation at the firm was with a doctor × has previous prescription from the firm
  - E.g.: 12 Nov 2019, 12-3pm; Stockholm; Woman aged 31 with "cold and flu" symptom who has seen a doctor within the firm before and has picked up a prescription.

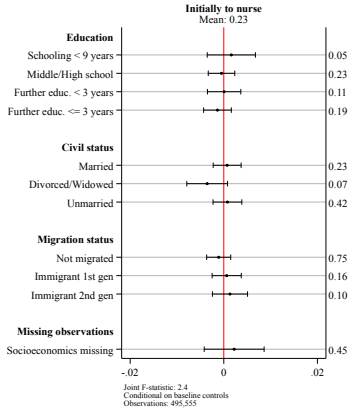
  Baseline controls Cell sizes
- X_{2i}: Other controls, e.g., comorbidity, past healthcare use, education, employment

  Additional controls

OLS identification

- OLS identification assumes that conditional on factors likely affecting the algorithm's assignment, *actual* assignment is effectively random Drop-out Balance congestion Identification threats



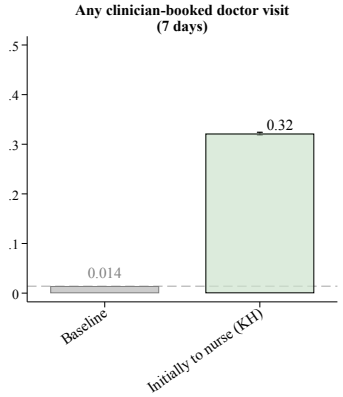


Bivariate regressions cond. on baseline controls (date-by-3h FEs, symptom × gender × age × previous firm visit, region). 95%-CIs from robust SEs.

Empirics

2. Effects of KH (relative to direct-to-doctor route)

≈30% of cases initially assigned to nurses are directed to a doctor

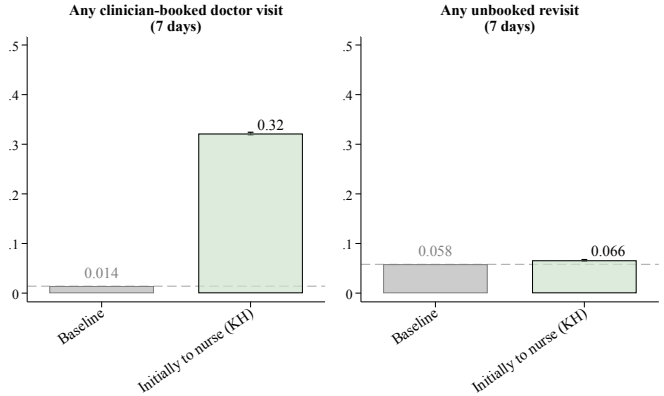


Observations: 495,555

Clinician-booked doctor visit: booked follow-up doctor consultation by a nurse or a doctor within 7 days of their intial consultation. *Unbooked revisit:* unscheduled return visit with the same symptom category within 7 days. Full set of controls. 95%-CIs from robust SEs.

≈30% of cases initially assigned to nurses are directed to a doctor, with little effect on (rare) unbooked revisits

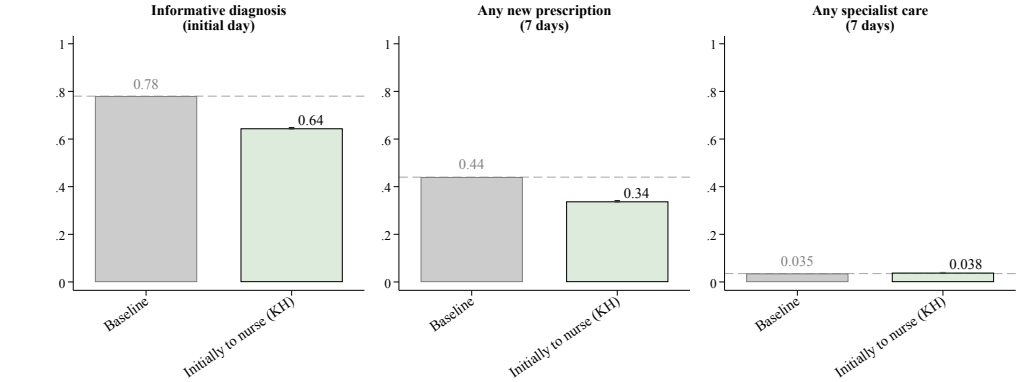
Resolved within +1 day | No pretrends



Observations: 495,555

Clinician-booked doctor visit: booked follow-up doctor consultation by a nurse or a doctor within 7 days of their intial consultation. *Unbooked revisit:* unscheduled return visit with the same symptom category within 7 days. Full set of controls. 95%-CIs from robust SEs.

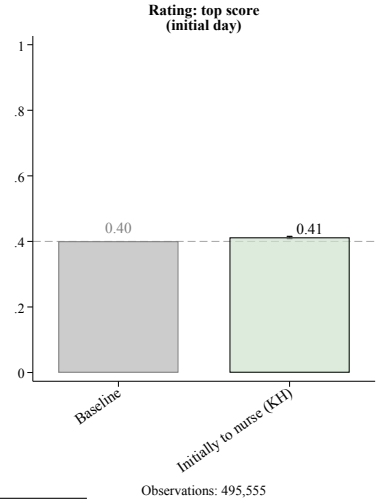
KH may reduce access to some doctor-specific expertise: Diagnosis and prescriptions



Observations: 495,555

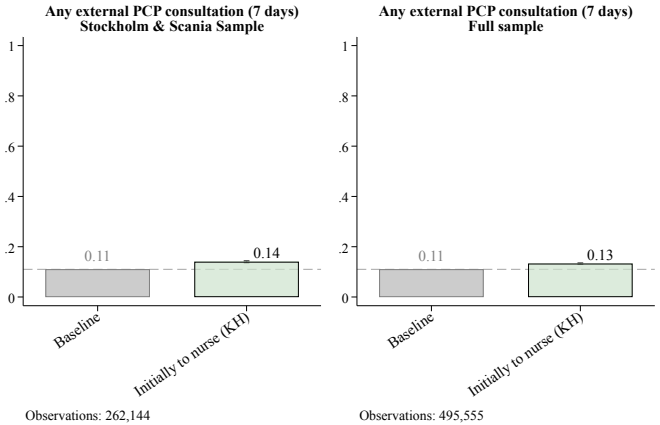
Informative diagnosis: a diagnosis belonging to ICD-10 chapters other than R (symptoms, e.g., cough, rash) and Z (factors influencing health status and health service contacts) within the initial day of the consultation. 7 days *Any new prescription*: a filled prescription within 7 days of the initial consultation. A prescription is defined as "new" if the same ATC code (at the 4 digit level) has not been filled in the previous 6 months. Full set of controls. 95%-CIs from robust SEs.

But patients are not significantly less satisfied in the KH



Rating: top score measure a top satisfaction rating (5 out of 5) for any consultation within the firm, within the initial day of the consultation. Full set of controls. 95%-CIs from robust SEs. Within 7 days

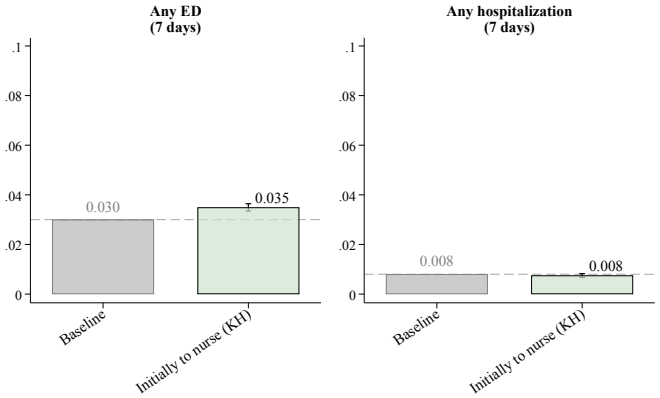
KH barely increases use of external primary care...



External PCP consultation: a visit to a primary care provider outside the firm within 7 days. Full sample: external primary care use is inferred from primary care prescriptions for patients outside Scania/Stockholm. For patients registered in Stockholm or Scania, visits are observed directly. Full set of controls. 95%-CIs from robust SEs.

KH has little impact on high-stakes ED visits or hospitalizations

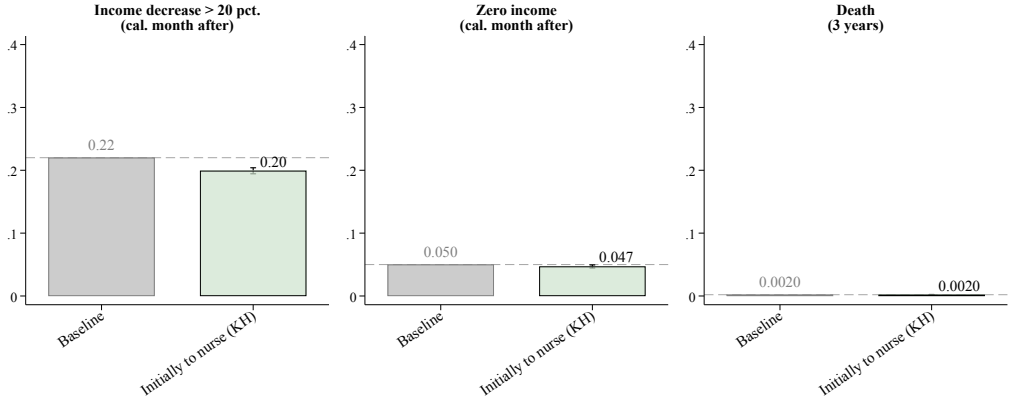
No pretrends



Observations: 495,555

ED: any emergency department visit within 7 days of the initial consultation. *Hospitalization*: any hospitalization within 7 days of the initial consultation. Full set of controls. 95%-CIs from robust SEs.

KH does not significantly increase chance of adverse events



Income decrease: whether the patient's gross income fell by at least 20% relative to their average income over the previous three months. *Zero income*: whether the patient had no earnings in the calendar month following the initial consultation. *Death*: whether the patient passed within 3 years of intial consultation. Income is defined for a subsample with stable earnings consisting of employed patients who earn more than 3,533 SEK (2010 values) in each of the three months prior, based on an annual threshold of 42,400 SEK (Saez et al., 2019). Full set of controls. 95%-CIs from robust SEs.

We found no important adverse effects of KH relative to doctor route

But what are the cost effects of KH?

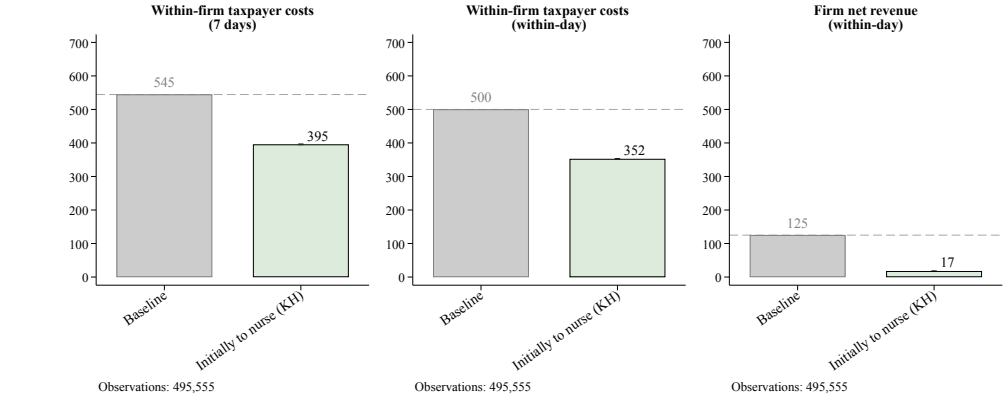
Calculation of within-firm taxpayer costs and firm net revenue

- **Within-firm taxpayer costs** from administratively set prices: 500 SEK for doctor consultation, 275 SEK for nurse consultation
- **But:** Firm is reimbursed for only *one consultation per day* (highest applicable)
  - Implementation of guidelines by Sveriges Kommuner och Landsting (SKL) (2019)

- To calculate the **firm net revenue**, we assume a margin of $\theta = 0.25$
  - Azar and Marinescu (2024) imply θ of 0.13 - 0.33
- Firm net revenue from a **doctor consultation**: $\theta \times 500$ SEK
- Firm net revenue from a **nurse consultation**:
  - Only nurse consultation: $\theta \times 275$ SEK
  - Any additional doctor consultation: $\theta \times 500 - (1 - \theta) \times 275$ SEK

- Aggregating all consultations (within-day; 7 days) does not meaningfully change estimates. Aggregate costs

KH reduces mean within-firm taxpayer costs by 28% (by reducing firm revenue)

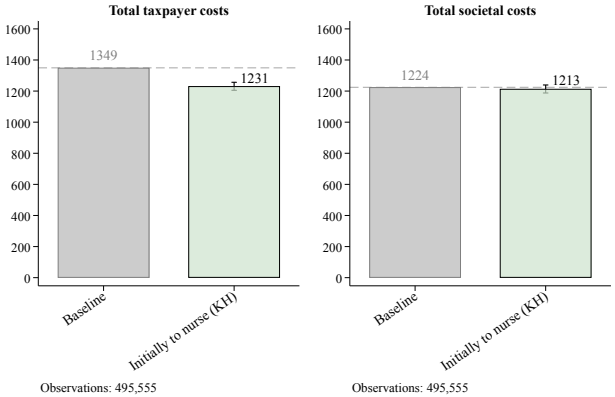


Within-firm taxpayer costs are for consultations at the firm. *7 days* includes the day of the initial consultation and up to one additional follow-up consultation within the next 7 days. *Firm net revenue* is calculated as revenue from consultations and costs measured as within-day taxpayer costs of the initial and potential follow-up consultations, multiplied by θ, where θ denotes the firm's markdown. Full set of controls. 95%-CIs from robust SEs.

Calculation of total taxpayer costs and total societal costs

- **Total taxpayer costs** reflect public spending on healthcare Cost of provision
  - Count up to one instance of each downstream event
- **Total societal costs** account for the transfer from taxpayer to firm
  - Calculate as *Total taxpayer costs - Firm's net revenue*
- Aggregating all consultations (using number of events instead of any within 7 days) does not meaningfully change estimates. Aggregate costs

Accounting also for downstream care, KH reduces mean total taxpayer costs by 9% – but does not affect mean total societal costs



Total taxpayer costs: total healthcare provision, including within-firm consultations, any prescription, specialist/urgent care/ED/hospital visit, external primary care (inferred from prescriptions for patients outside Scania/Stockholm). *Total societal costs*: total taxpayer costs minus the firm's net revenues. Full set of controls. 95%-CIs from robust SEs.

Robustness

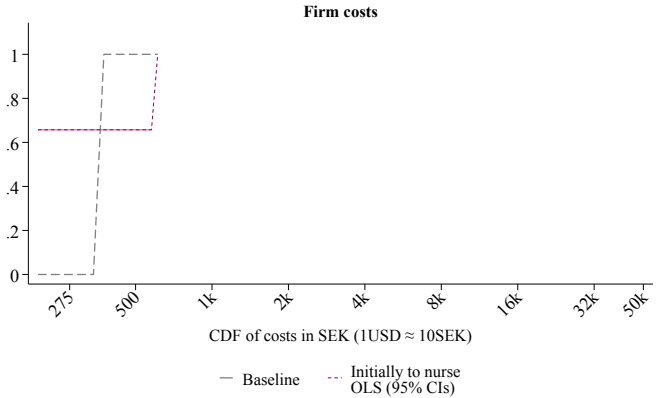
- IV instead of OLS identification IV identification and main results
- Aggregated total societal cost estimate instead of event indicator approach Aggregate cost estimate
- Aggregated total societal costs over 30 days instead of 7 days 30-day costs estimate
- Allowing different θ for nurse vs doctor consultations Robustness on θ
- Oster bounds instead of 95% confidence intervals Oster bounds on CDF

On average, KH yields similar health outcomes as doctor route, and shifts costs from taxpayer to firm without changing total societal costs.

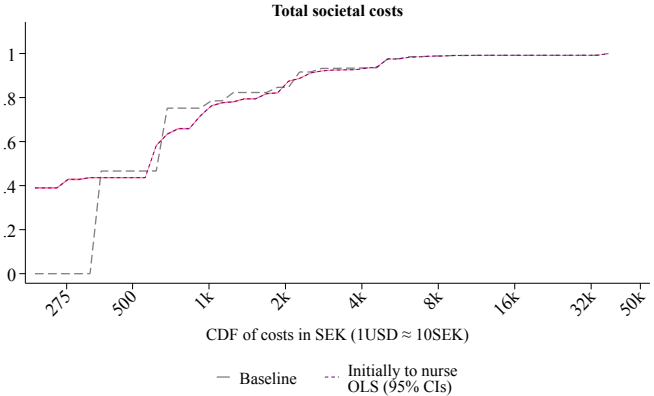
We now consider effects of KH on the distribution of costs

Firm costs are $(1-\theta) \times 500$ if sent to doctor and $(1-\theta) \times 275$ SEK if sent to nurse who resolves, and the sum of the two terms if the nurse does not resolve.

Firm costs under direct to doctor vs. KH assignment do not first-order stochastically dominate each other



The pattern is inherited by total societal costs (including all downstream costs): KH changes cost distribution, ≈halving costs for ≈half the patients



Where do KH savings come from? 30 days IV No controls

Using the main analysis sample. X-axis shows total societal costs in logarithmic scale. Full controls. 95% confidence intervals.To ensure CDF monotonicity with a non-saturated regression model, we have reordered the CDF and the confidence intervals following Chernozhukov, Fernandez-Val, and Galichon (2009)

Empirics

3. Allocation of tasks between the two routes

Heterogeneity by symptoms: When does KH decrease taxpayer costs, and does the firm assign accordingly?

- To measure **KH's relative cost advantage by symptom**, include symptom interactions in OLS regression:

$$Costs_{i,k(i)} = \delta_k Nurse_i \times Symptom_{k(i)} + X_{1i}\beta_{1i} + X_{2i}\beta_{2i} + \epsilon_i$$

  - Define (predicted nurse cost / predicted doctor cost) in symptom k: $\frac{\Sigma Cost_{i,k(i)}(nurse)}{\Sigma Cost_{i,k(i)}(doctor)}$
  - Define similarly KH's relative advantage in firm net revenues

- To measure the firm's **inital nurse assignment propensity by symptom**, estimate 1st-stage regression:

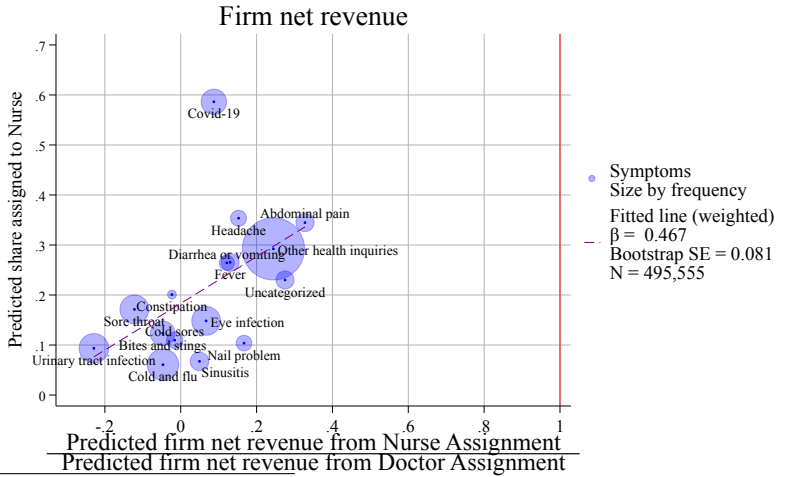
$$Nurse_i = \gamma_i DoctorCongestion_i + X_{1i}\lambda_{1i} + X_{2i}\lambda_{2i} + \nu_i$$

  - Predict assignment probabilities for each case; average by symptom k

- Plot **predicted nurse assignment probability** against **predicted cost (revenue) ratio**, by symptom

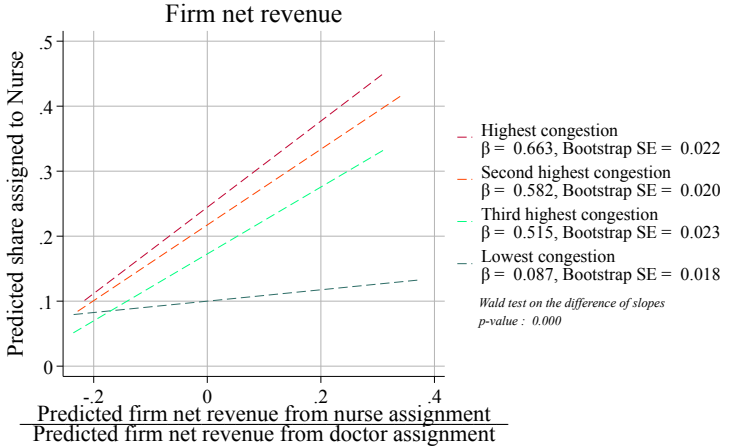
Symptoms that nurses are more likely to resolve are sent to them – assignment follows relative net revenue advantage

Pre- and low covid periods



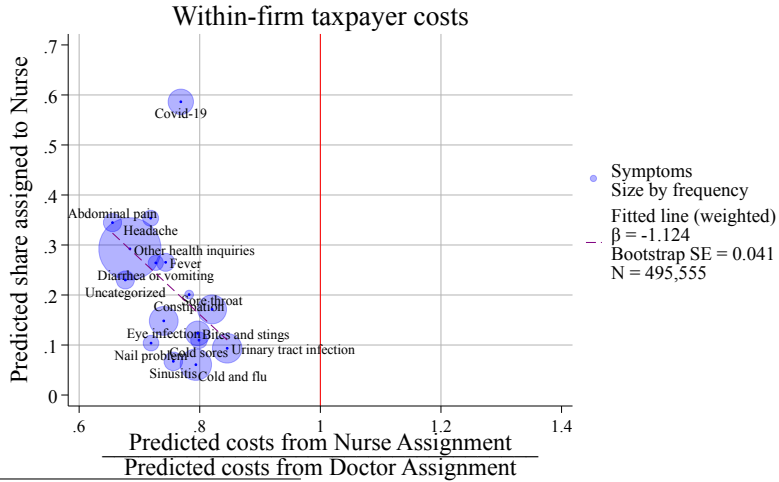
Using the main analysis sample

The firm assigns more by relative net revenue advantage when congestion is higher (constrained optimization)



Using the main analysis sample

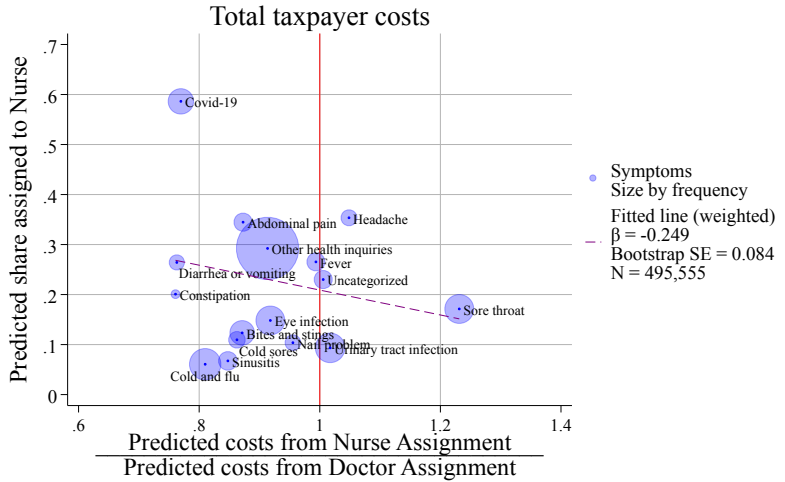
The firm's assignment lowers within-firm taxpayer costs...



Using the main analysis sample

...and also reduces total taxpayer costs

(since downstream costs do not increase)



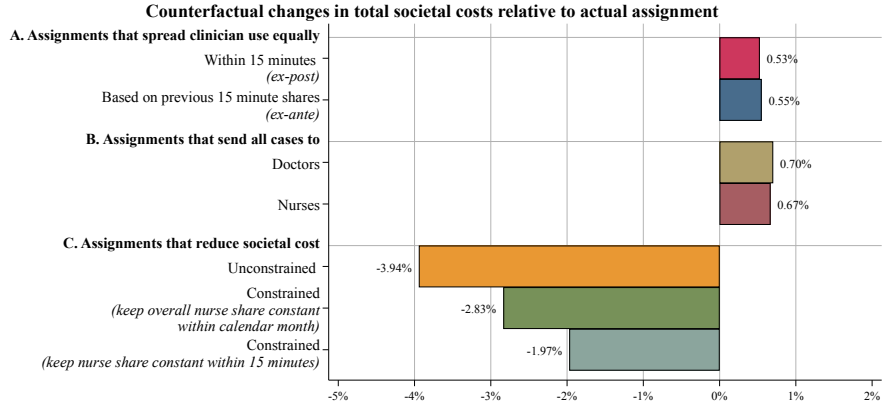
Empirics

4. Evaluating counterfactual assignments

Definition of counterfactual assignments

1. Assignments that spread clinician use equally across symptoms
   - **Ex-ante** assignments
     - Probabilistic allocation based on past consultations
     - Allocate the share of clinicians available within 15 minutes before patient login
     - Availability is defined as completion of consultation and follow-up (admin) tasks
   - **Ex-post** assignments
     - Share of clinicians assigned within the 15-minute window of patient login
2. Assignments that minimize total societal costs (social planner objective)
   - Unconstrained assignment by **absolute advantage**
   - Constrained assignment by **comparative advantage**:
     - Fix the share of nurse consultations within a time window (months; 15 minutes)
     - Within time window, assign symptom groups to nurses/doctors by lowest predicted cost
       Costs by symptoms
     - When all nurse consultations are filled, assign one symptom group probabilistically

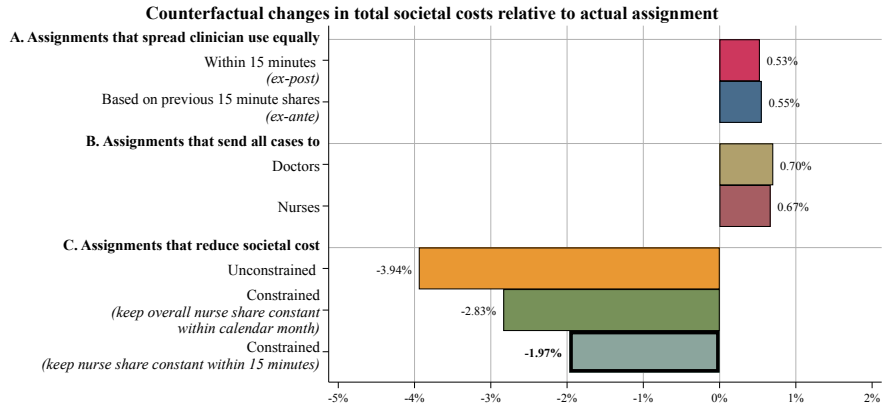
Actual assignment saves 0.7% of total societal costs (2.4% of online primary care costs) compared to doctor route



Costs by symptoms

111,625 actual nurse assignments. *Ex-ante* refers to the clinicians who became available (after finishing admin work and meetings) within 15 before a patient's login time. *Within 15 minutes* and *Calendar month* indicate allocation at the corresponding calendar unit (e.g., each individual 15 minutes or each month across the sample period).

Reassigning cases within 15-minute winddows could save further 2% of total societal costs (6.7% of online primary care costs)



Costs by symptoms | Aggregate costs

111,625 actual nurse assignments. *Ex-ante* refers to the clinicians who became available (after finishing admin work and meetings) within 15 before a patient's login time. *Within 15 minutes* and *Calendar month* indicate allocation at the corresponding calendar unit (e.g., each individual 15 minutes or each month across the sample period).

Conclusion: evidence on the productivity effects and use of common KH

1. We compare a knowledge hierarchy to direct-to-expert route in a large online healthcare firm with algorithmic allocation, studying **effects** on costs and patient outcomes
   - In KH, nurses handle 70% of cases themselves, sending 30% to doctors
   - KH does no major harm to patients (hospitalizations, income drops, or mortality)
   - KH cheaper for taxpayer but does not change mean overall costs
   - But KH generates large proportional savings on $\approx$ 50% easier tasks

2. ... we study the economic factors that determine **when KH is used**
   - Low doctor congestion: KH less profitable for firm, so not used
   - High doctor congestion: KH used when it has a relative advantage in net revenues, with assignment also following what saves total taxpayer costs

3. ...and how to make its use **more productive**
   - Current firm incentives (and information) align with assignment that minimizes within-firm taxpayer costs and saves total societal costs *during congested times*
   - Reassigning tasks based on *comparative advantage in total societal costs* saves 2% of costs

Thank you!

Please feel free to email comments:

Guy Michaels, g.michaels@lse.ac.uk

References I

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, volume 4, pages 1043–1171. Elsevier.

Alexander, D. and Schnell, M. (2019). Just what the nurse practitioner ordered: Independent prescriptive authority and population mental health. *Journal of Health Economics*, 66:145–162.

Arrow, K. J. (1963). Uncertainty and the Welfare Economics of Medical Care. *American economic review*, pages 1–34.

Azar, J. and Marinescu, I. (2024). Chapter 10 - Monopsony power in the labor market. In Dustmann, C. and Lemieux, T., editors, *Handbook of Labor Economics*, volume 5, pages 761–827. Elsevier.

Baicker, K. and Chandra, A. (2004). The Productivity of Physician Specialization: Evidence from the Medicare Program. *American Economic Review*, 94(2):357–361.

Becker, G. S. and Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics*, 107(4):1137–1160.

References II

Caliendo, Mion, Opromolla & Rossi-Hansberg (2020). Productivity and organisation in portuguese firms. *Journal of Political Economy*, 128(11):4211–4257.

Caliendo, Monte & Rossi-Hansberg (2015). The anatomy of french production hierarchies. *Journal of Political Economy*, 123(4):809–852.

Cattaneo, M. D., Crump, R. K., Farrell, M. H., and Feng, Y. (2024). On Binscatter. *American Economic Review*, 114(5):1488–1514.

Chan, D. and Chen, Y. (2022). The Productivity of Professions: Evidence from the Emergency Department. *NBER Working Paper*.

Chan, D. C. (2016). Teamwork and Moral Hazard: Evidence from the Emergency Department. *Journal of Political Economy*, 124(3):734–770.

Chandra, A., Colla, C., and Skinner, J. (2023). Productivity Variation and Input Misallocation: Evidence from Hospitals. *NBER Working Paper*, page w31569.

Chandra, A. and Staiger, D. (2007). Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks. *Journal of Political Economy*, 115(1):103–140. Publisher: The University of Chicago Press.

References III

Costantini, S. (2025). How Do Mental Health Treatment Delays Impact Long-Term Mortality? *American Economic Review*, 115(5):1672–1707.

Currie, J. and MacLeod, W. B. (2017). Diagnosing Expertise: Human Capital, Decision Making, and Performance among Physicians. *Journal of labor economics*, 35(1):1–43.

Currie, J. and Zhang, J. (2023). Doing More with Less: Predicting Primary Care Provider Effectiveness. *The Review of Economics and Statistics*, pages 1–45.

Dahlstrand, A. (2024). Defying Distance? The provision of services in the digital age. *Working Paper*.

Dillender, M., Lo Sasso, A. T., Phelan, B. J., and Richards, M. (2024). Occupational Licensing and the Healthcare Labor Market. *Journal of Human Resources*, pages 0722–12450R2.

Dornbusch, R., Fischer, S., and Samuelson, P. A. (1977). Comparative advantage, trade, and payments in a ricardian model with a continuum of goods. *The American Economic Review*, 67(5):823–839.

References IV

Doyle, J. J., Ewer, S. M., and Wagner, T. H. (2010). Returns to physician human capital: Evidence from patients randomized to physician teams. *Journal of Health Economics*, 29(6):866–882.

Garicano, L. (2000). Hierarchies and the Organization of Knowledge in Production. *Journal of Political Economy*, 108(5):874–904. Publisher: The University of Chicago Press.

Garicano & Rossi-Hansberg (2006). Organization and inequality in a knowledge economy. *The Quarterly Journal of Economics*, 121(4):1383–1435.

Gottlieb, J. D., Mahoney, N., Rinz, K., and Udalova, V. (2025). The rise of healthcare jobs. Working Paper 33583, National Bureau of Economic Research.

Heckscher, E. (1919). The effect of foreign trade on the distribution of income. *Ekonomisk Tidskrift*, 21:497–512.

Katz, L. F. and Murphy, K. M. (1992). Changes in Relative Wages, 1963–1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, 107(1):35–78.

Kelly, E., Propper, C., and Zaranko, B. (2023). Team Composition and the Returns to Human Capital: Evidence from Nursing Teams. *Centre for Economic Policy Research*.

References V

Kleiner, M. M. (2016). Battling over Jobs: Occupational Licensing in Health Care. *American Economic Review*, 106(5):165–170.

McMichael, B. J. (2023). Supply-side health policy: The impact of scope-of-practice laws on mortality. *Journal of Public Economics*, 222:104901.

OECD (2021). The covid-19 pandemic and the future of telemedicine. Accessed on October 9, 2025.

OECD (2025). Oecd health statistics data explorer. Accessed on October 9, 2025.

Ohlin, B. (1924). *Handelns teori (The Theory of Trade)*. PhD thesis, Stockholm University, Stockholm, Sweden.

Ricardo, D. (1817). The theory of comparative advantage. In Sraffa, P. w. C. o. M. D., editor, *Principles of Political Economy and Taxation*, volume 1. Cambridge University Press, Cambridge, London.

Saez, E., Schoefer, B., and Seim, D. (2019). Payroll Taxes, Firm Behavior, and Rent Sharing: Evidence from a Young Workers' Tax Cut in Sweden. *American Economic Review*, 109(5):1717–1763.

References VI

Shapiro, C. (1986). Investment, Moral Hazard, and Occupational Licensing. *The Review of Economic Studies*, 53(5):843–862. Publisher: [Oxford University Press, Review of Economic Studies, Ltd.].

Silver, D. (2021). Haste or Waste? Peer Pressure and Productivity in the Emergency Department. *The Review of Economic Studies*, 88(3):1385–1417.

Smith, A. (1776). *An Inquiry Into the Nature and Causes of the Wealth of Nations*.

Sveriges Kommuner och Landsting (SKL) (2019). Meddelande från styrelsen - Utvecklingen av digitala vårdtjänster.

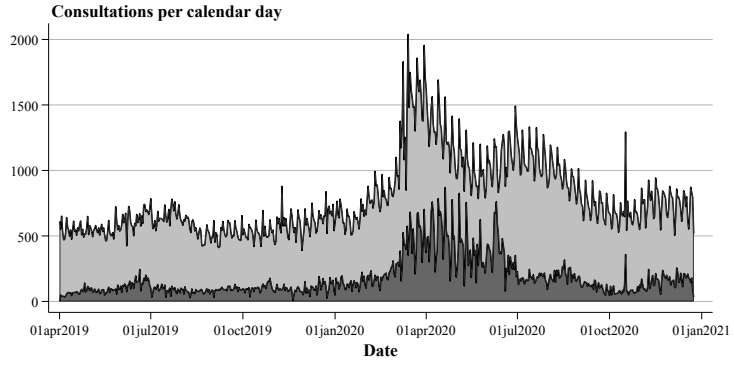
Traczynski, J. and Udalova, V. (2018). Nurse practitioner independence, health care utilization, and health outcomes. *Journal of Health Economics*, 58:90–109.

Restrictions for analysis sample

	Nurse	Total
All observed consultations		1,814,706
1. Keep only consultations that involve either doctors or nurses	14.5%	1,668,303
2. Exclude scheduled or in-person consultations	19.5%	1,239,527
3. Exclude observations outside the analysis time window	21.1%	1,126,662
4. Exclude patients registered with the provider	20.6%	1,054,985
5. Exclude infants (ages 0-1)	21.2%	995,177
6. Exclude follow-ups within two hours by the same patient	21.2%	970,277
7. Exclude consultations with missing characteristics → *Broad drop-in sample*	21.2%	969,483
a) *Doctor group*		
· Restrict broad drop-in sample to doctor group	1.2%	381,791
· Exclude singleton observations in the full control scheme	1.2%	380,901
b) *Nurse group*		
· Restrict broad drop-in sample to nurse group	98.9%	85,729
· Exclude singleton observations in the full control scheme	99.0%	84,610
c) *Rare symptom group*		
· Restrict broad drop-in sample to rare symptoms	53.1%	5,961
· Exclude singleton observations in the full control scheme	58.4%	3,592
d) *Main analysis sample*		
· Restrict broad drop-in sample to overlap group	22.7%	496,002
· Exclude singleton observations in the full control scheme	22.7%	495,555

Back

Consultations over time

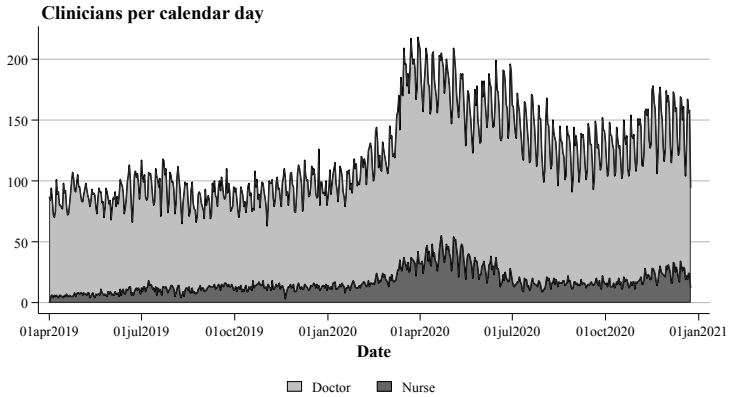


Back

Total consultations (mean/day):	781.63
Doctor consultations (mean/day):	603.97
Nurse consultations (mean/day):	177.67

Using the main analysis sample

Active clinicians over time



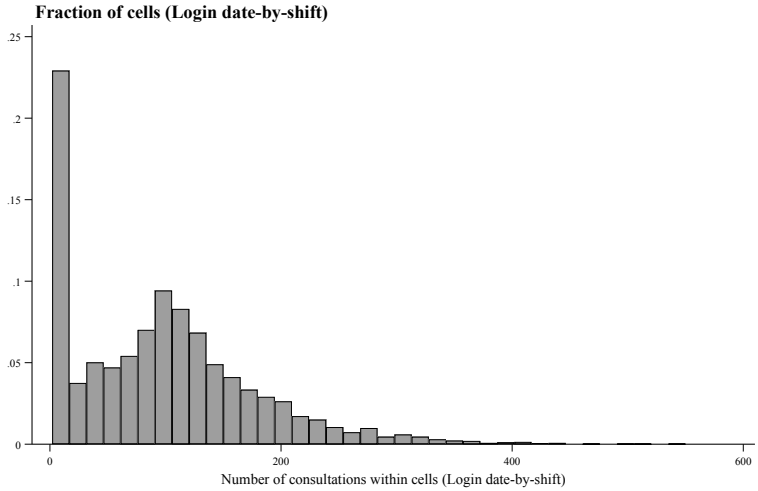
Back

Total clinicians (mean/day):	120
Doctors (mean/day):	103
Nurses (mean/day):	17

Using the main analysis sample

Observations within time windows

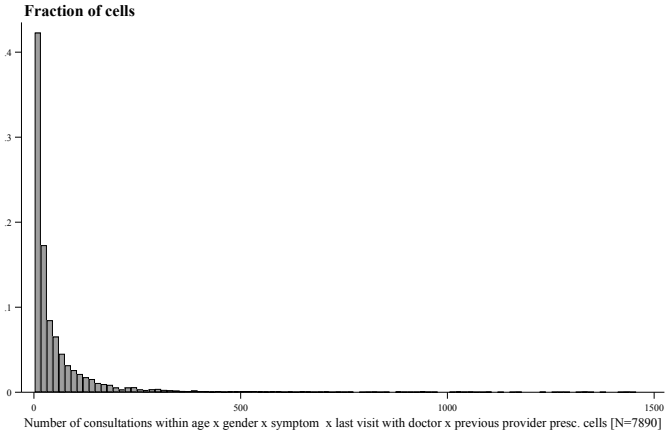
Back



Cell size of the time fixed effects in the analysis sample. Time fixed effects are defined as calendar date-by-3 hour windows

Observations within cells of age × gender × symptoms × last visit was with a doctor × previously collected provider prescription

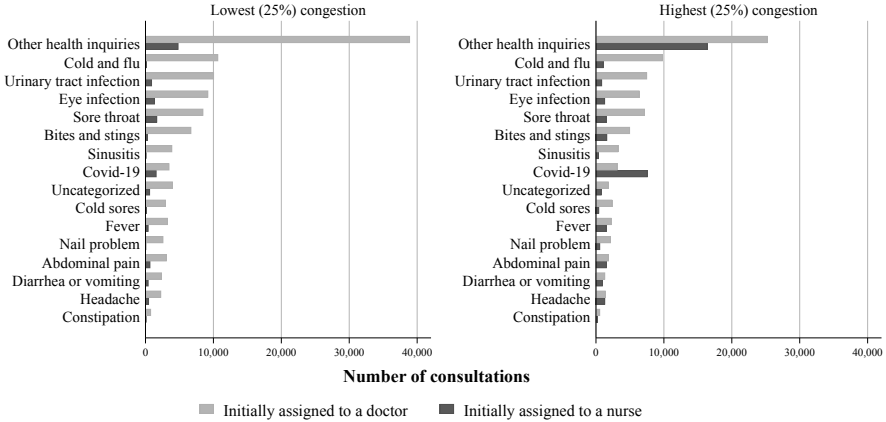
Back



Cell sizes of the interaction term in the controls. Interaction term include: Average number of visits in age × gender × symptom last visit was with a doctor × previously collected provider prescription cells is 62.

Firm prefers to assign all overlap group symptoms to doctors (see times of low congestion)

Back



Patients' self-reported symptoms in the main analysis sample. Congestion quartiles defined in Drop-in sample.

Most frequent diagnoses

Analysis sample

- **J06**: Acute upper respiratory infections
- **N30**: Cystitis
- **J03**: Acute tonsillitis
- **T14**: Injury of unspecified body region
- **Z71**: Other counseling/medical advice
- **H10**: Conjunctivitis
- **R52**: Pain, unspecified
- **N39**: Other disorders of urinary system
- **J01**: Acute sinusitis
- **Z53**: Other specific treatment, not carried out

Symptom "health inquiries"

- **Z71**: Other counseling/medical advice (7.17%)
- **R52**: Pain, unspecified (5.89%)
- **M79**: Soft tissue disorders, unspecified (5.24%)

Back

Consultations in Scania

- **F41**: Other anxiety disorders
- **J06**: Acute upper respiratory infections
- **Z00**: General medical examination
- **R52**: Pain, unspecified
- **R10**: Abdominal and pelvic pain
- **F43**: Reaction to severe stress
- **R05**: Cough
- **H66**: Otitis media
- **Z71**: Other counseling/medical advice
- **N30**: Cystitis

Baseline controls

Back

Predetermined baseline factors likely **used by the algorithm** to assign cases between KH or directly-to-doctor routes

- **Fixed effects for calendar date × 3-hour windows**
  e.g. 12 November 2019, 12-3pm; 12 November 2019 3-6pm
- **Age FE × gender × symptoms × last visit was with a doctor × previously collected provider prescription**
  Age in 1-year bins from 2 to 70+
  Female indicator
  Symptoms as 16 indicators, e.g. "Cold and flu", "Urinary tract infection"
  Indicators for past provider interactions: previous consultation was with a doctor and picked up prescription from provider
- **Patient's region in Sweden**
  Six aggregated administrative areas, e.g. Norrland (Middle + Upper Norrland)

Time windows

Additional controls

Back

Other predetermined factors that **may matter for patient outcomes**

- **Any comorbidity**
  Indicator for diagnosis from 3 years to 1 calendar day prior to the consultation date
- **Past emergency department, hospital, specialist, urgent care use**
  Indicators for any visit from 3 years to 1 calendar day prior to the consultation date

- **Income/benefits**
  Indicators for income $>$ median and any benefit receipt
- **Civil status**
  Indicators for married, divorced/widowed, unmarried
- **Education level**
  Indicators for $<$ 9 years, middle/high school, further/higher education $<$ 3 years, further/higher education $\geq$ 3 years
- **Employment status**
  Indicators for employee, self-employed, unemployed
- **Missing socioeconomic variables**
  Indicator for any missing information on income/benefits, civil statues, education, or employment

Costs of public healthcare provision

Back - Data Back - Results

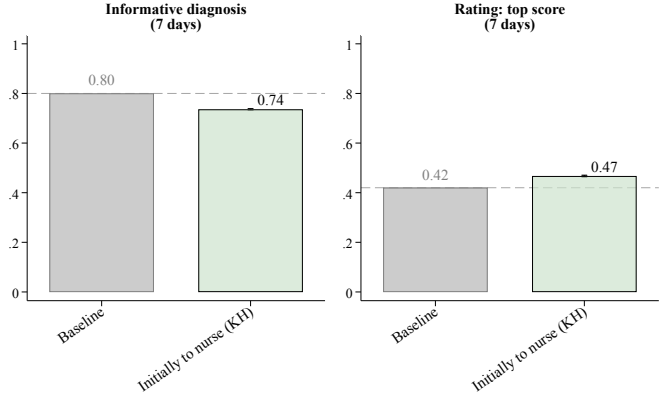
Cost category	Cost in SEK
Provider doctor (online) consultation	500
Provider nurse (online) consultation	275
Drug prescription	260
External primary care consultation*	1,452
Specialist visit	3,931
Emergency department visit	3,992
Urgent care center visit	2,002
Hospitalization	28,488

*For patients from Scania and Stockholm, we observe visits at primary care clinics within the regions directly. For other patients, primary care visits are inferred from new drug prescriptions (within 6 months) issued in primary care (accuracy for Scania/Stockholm: 87.12%).

Costs to the Swedish regions from reports or our data.

Diagnoses and patient satisfaction in initial consultations

Back: diagnosis Back: satisfaction

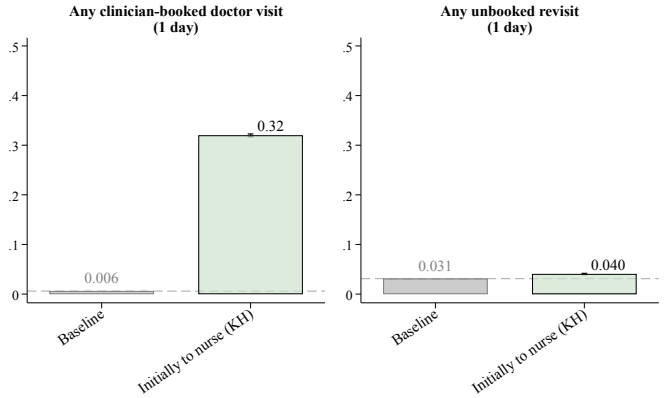


Observations: 495,555

Informative diagnosis includes diagnosis belonging to ICD-10 chapters other than R (symptoms, e.g., cough, rash) and Z (factors influencing health status and health service contacts) within 7 days of the consultation. *Rating: top score* measure a top satisfaction rating (5 out of 5) for any consultation within the firm, within 7 days of the initial consultation. Full set of controls. 95%-CIs from robust SEs.

Cases directed within KH are largely resolved within +1 day

Back

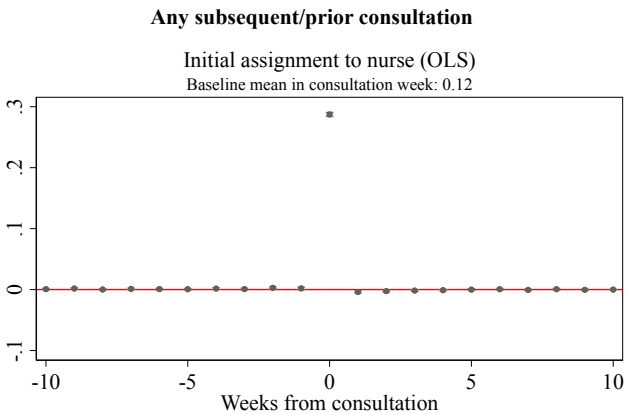


Observations: 495,555

Clinician-booked doctor visit: booked follow-up doctor consultation by a nurse or a doctor within the initial day of their consultation. *Unbooked revisit:* unscheduled return visit with the same symptom category within the intial day. Full set of controls. 95%-CIs from robust SEs.

No pre-differences in levels or trends in consultations

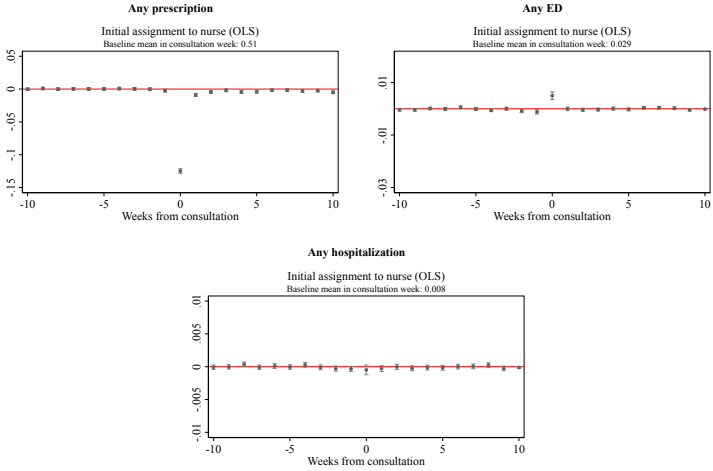
Back



Coefficient estimates are shown from separate regressions of the outcome in time period relative to the initial consultation. Full set of controls. 95%-CIs from robust SEs.

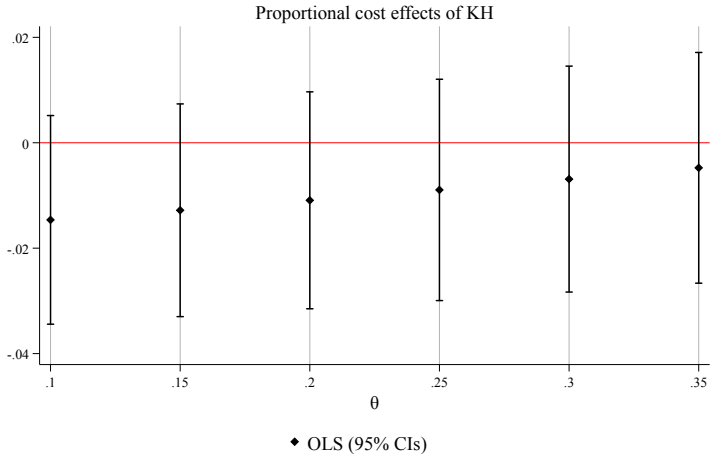
No pre-differences in levels or trends in healthcare use

Back



Coefficient estimates are shown from separate regressions of the outcome in time period relative to the initial consultation. Full set of controls. 95%-CIs from robust SEs.

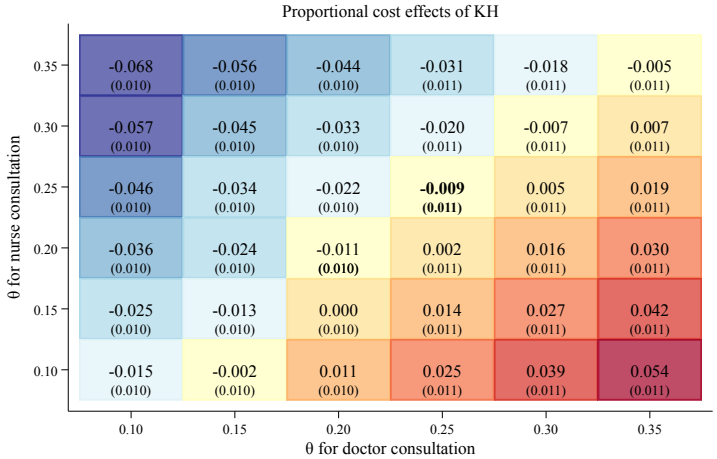
Alternative θ assumptions on total societal costs Back



Regressions use the full set of controls. 95%-CIs from robust SEs.

Alternative θ assumptions on total societal costs

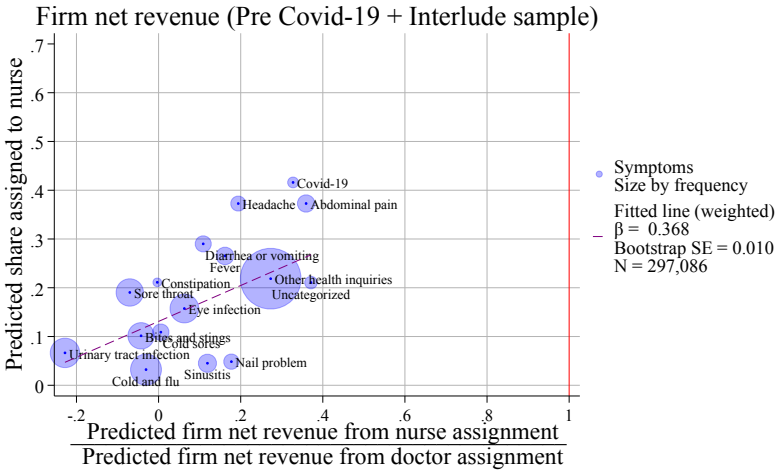
Back



Regressions use the full set of controls. Robust SEs are in parentheses.

Pre Covid-19 and lull period

Back



The pre-Covid-19 period is defined as the time preceding the last month in which a Covid-19 consultation appears in our sample (prior to 1 March 2020). The interlude period is defined as the interval between 6 July and 24 October 2020.

Why allocate some patients to nurses? Because firm approx. follows first-come first served and wants to minimize maximal waiting times

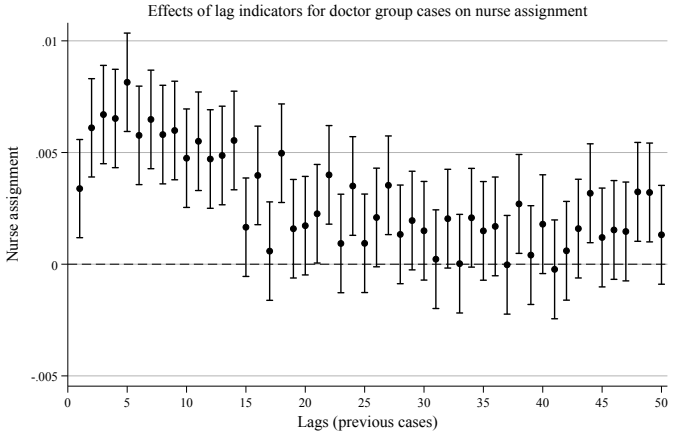
Back

	Exit rank in overlap group (1)	Exit rank in doctor group (2)	Exit rank in overlap and doctor group (3)	Exit rank in broader drop-in sample (4)
A: Date-by-1 hour fixed effects				
Login rank	0.96	0.97	0.97	1.00
	(0.0018)	(0.0029)	(0.0020)	(0.0034)
Doctor group			8.77	4.23
			(0.089)	(1.80)
Nurse group				89.4
				(6.27)
Observations	494,819	379,823	876,110	966,308
R-squared	1.00	1.00	1.00	1.00
B: Date-by-3 hour fixed effects				
Login rank	0.98	0.99	0.99	0.99
	(0.00064)	(0.0010)	(0.00071)	(0.0011)
Doctor group			8.79	3.61
			(0.090)	(1.32)
Nurse group				89.2
				(6.41)
Observations	495,555	380,901	876,456	966,622
R-squared	1.00	1.00	1.00	1.00

All regressions use the full set of controls. Exit rank is defined as the rank when sorted by the meeting start time and login rank is the rank when sorted by patient's login time. Robust standard errors are in parenthesis.

Patient composition also matters: If doctor group patients arrive right before me, then I'm more likely to see a nurse – but fades out

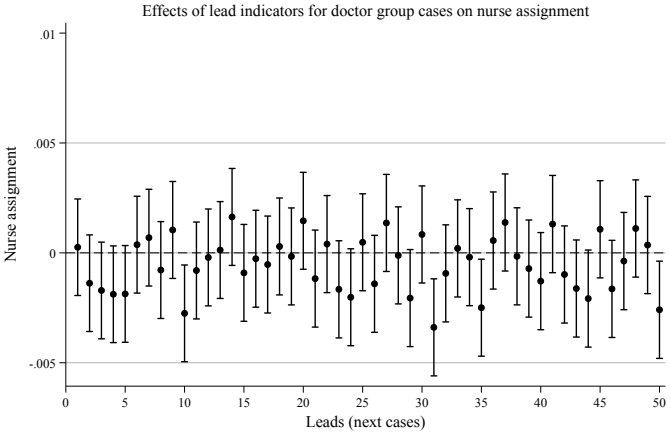
Back



Each point shows an OLS estimate from regressing nurse assignment on an indicator for whether the case at lag n-1 belongs to doctor group. Lags refer to the next case at different points in time, sorted by the patient's login time. The vertical lines indicate 95% confidence intervals.

If patients who arrive after me belong to doctor group, this does not affect my probability of seeing a nurse

Back

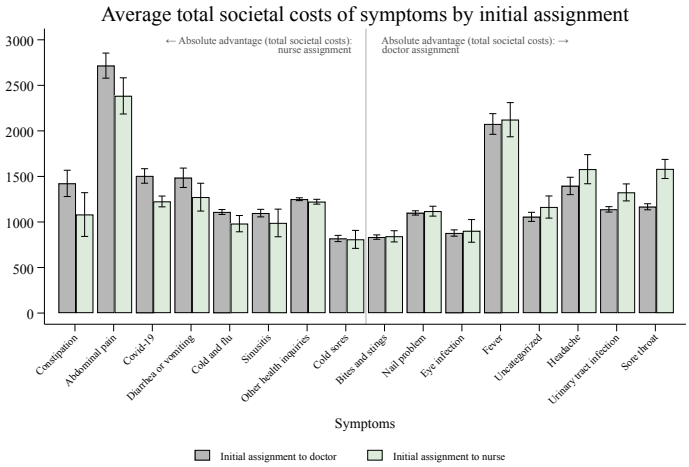


Each point shows an OLS estimate from regressing nurse assignment on an indicator for whether the case at lead n+1 belongs to doctor group. Leads refer to the next case at different points in time, sorted by the patient's login time. The vertical lines indicate 95% confidence intervals.

Average total societal costs of each by initial assignment

Back - Definition

Back - Counterfactual



Comparison of analysis sample patients to those in a wider sample of PCP consultations

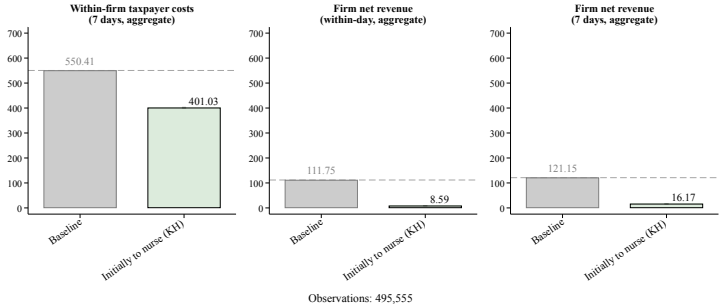
Back

	(1) Analysis sample	(2) Scania sample
Female	0.63	0.59
Toddler (2-4 years)	0.056	0.023
Child (5-12 years)	0.11	0.035
Teen (13-19 years)	0.12	0.033
Young adult (20-39 years)	0.46	0.18
Middle aged (40-59 years)	0.21	0.25
Senior (60+ years)	0.047	0.48
Nurse consultation	0.23	0.52
Observations	495,555	5,427,400

In our analysis, we use overlap group symptoms, which account for 27% of all visits within the provider. The ratio of overlap group symptoms to the full sample (matched on ICDs) in the Scania sample is 27.57%.

Aggregate within-firm taxpayer costs and firm net revenues

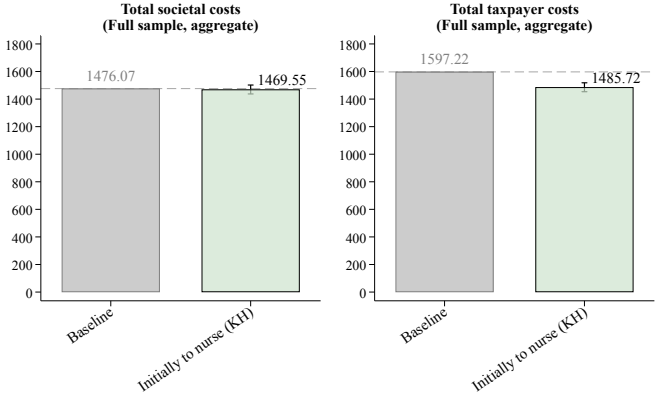
Back - Costs Back - Robustness



Aggregate costs refers to using counts rather than indicators for incurred costs. *Aggregate within-firm taxpayer costs* includes up to one consultation within-day (per reimbursement rules) and all aggregated follow-up consultations within 7 days of the initial assignment. *Firm net revenue* includes revenues up to one consultation (per reimbursement rules). Consultations that are not reimbursed are treated as costs to the firm.

Aggregate total societal and taxpayer costs

Back - Costs Back - Robustness

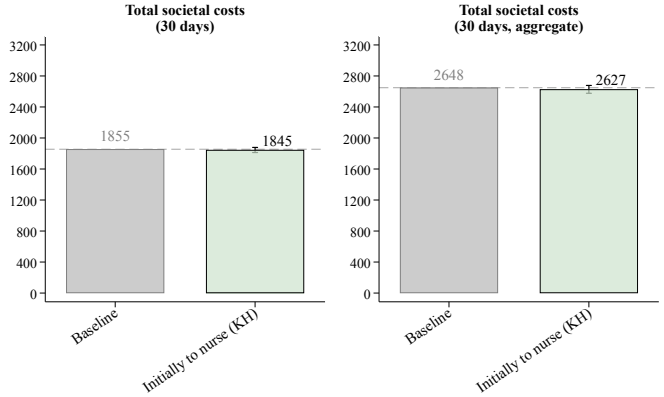


Observations: 495,555

Aggregate total taxpayer costs of total healthcare provision includes each occurrence of downstream events (counting all within-firm visits, emergency department visit, specialist or urgent care visit, hospitalization, or prescription within 7 days). *Aggregate total societal costs* are aggregate total taxpayer costs - firm net revenue.

Aggregate total societal and taxpayer costs in 30 days

Back - Costs Back - Robustness

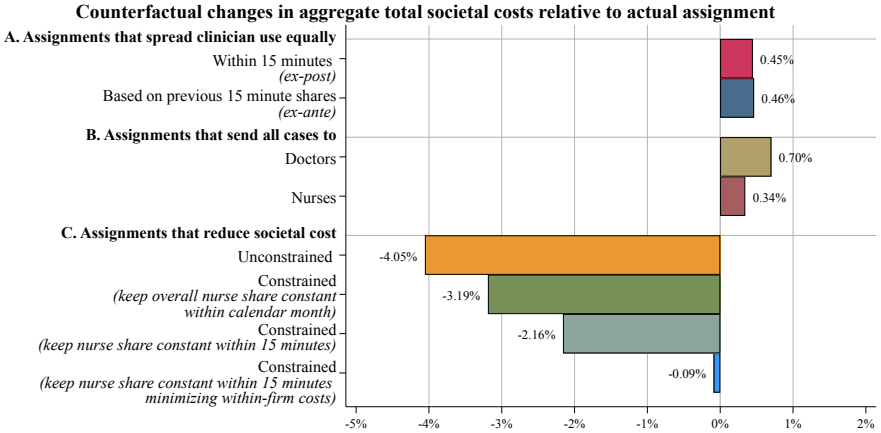


Observations: 495,555

Aggregate total taxpayer costs of total healthcare provision includes each occurrence of downstream events (counting all within-firm visits, emergency department visit, specialist or urgent care visit, hospitalization, or prescription within 7 days). *Aggregate total societal costs* are aggregate total taxpayer costs - firm net revenue.

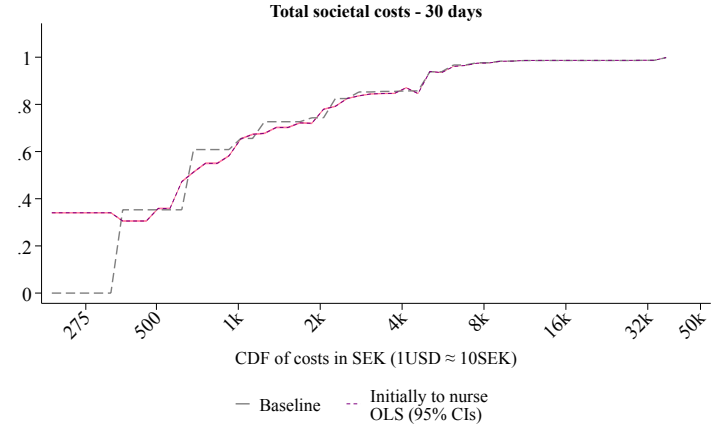
Counterfactuals using aggregate total societal costs

Back



CDF of total societal costs using 30 day time window

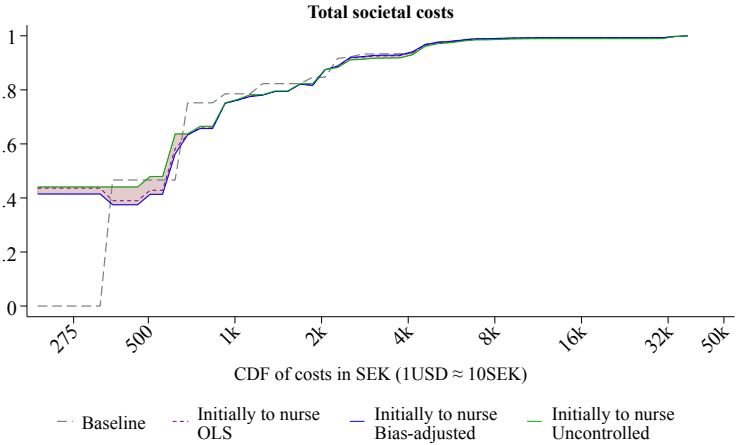
Back



30 day time window counts costs after intial consultation for 30 days rather than 7 days.

Oster bounds on CDF

Back



International healthcare comparison

Back

Indicator	Countries
Telehealth share in 2019 (15 countries with data)	DK 29.9%; EE 20.6%; PT 18%; IL 15.6%; FI 8.3%; ES 4.1%; HU 3.7%;CZ 3.7%*; NO 2.2%; SI 1.5%; LT 1%; FR 0%*; AU 0%; GR 0%
Telehealth share in 2020 (19 countries with data)	PT 37.5%; US 36-48%; EE 35.9%; ES 30.6%; DK 29.9%; IL 29.5%; **SE** 27.6%; LT 26.5%; NO 17.8%; BE 13.9%; AU 9.5%; FI 9.1%; CZ 8.6%*; FR 5.7%*; CL 4.5%; HU 4.2%; SI 3.7%; DE 1.1%*; GR 0%
Ratio of nurses to doctors in 2019 (38 countries with data)	JP 4.7; FI 4.4; US 4.3; CH 4.1; LU 3.9; IE 3.9; IS 3.9; NO 3.6; CA 3.6; BE 3.5; FR 3.3; DE 3.2; SI 3.2; KR 3.2; AU 3.2; NZ 3; NL 2.9; GB 2.8; **SE** 2.5; DK 2.4; CZ 2.1; PL 2.1; AT 2; HU; 1.9; EE 1.8; LT 1.7; GR 1.6; SK 1.6; IT 1.5; IL 1.5; ES 1.3; PT 1.3; LV 1.3; TR 1.2; MX 1.2; CR 1.1; CL 1.1; CO 0.6

The table covers all OECD countries for which data are available in OECD (2025), OECD (2021), and official national sources. Fractions represent the share of OECD countries reported out of those with available data. The total number of OECD member countries is 38. Countries are identified using ISO 3166-1 alpha-2 codes. The information in the table refers to 2023, unless otherwise specified.*Teleconsultations only include those reimbursed through the national healthcare system.

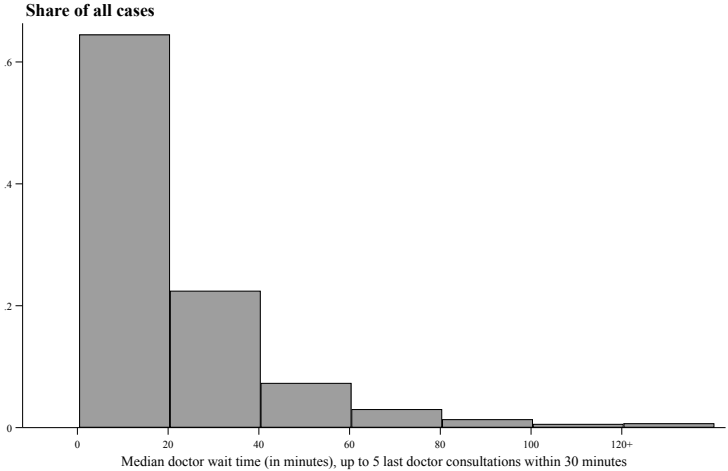
Identification threats

Back - OLS

- We include interacted controls that the algorithm likely uses and other detailed controls, but the algorithm might still use more data or have a complex functional form
- Algorithm may also have changed over time

→ To mitigate endogeneity concerns, we also develop an **instrument for congestion**

Doctor wait time in past consultations, in minutes



Using the analysis sample.

Back

Measure: Doctor Congestion

Back - Robustness Back - OLS

$$\text{Doctor Congestion}_i = \log \mathcal{D}_{t(i)}$$

- $\mathcal{D}_{t(i)}$ = **median patient wait time for doctor consultations within 30 minutes prior to i's login** Instrument
  - → Restrict to up to 5 most recent doctor consultations
  - → Winsorize (99th pct.), set missings to the lowest median wait time

- Instrument captures when doctors are busy
- First-stage regression is:

$$Nurse_i = \gamma_i \text{Doctor Congestion}_i + X_{1i}\lambda_{1i} + X_{2i}\lambda_{2i} + \nu_i$$

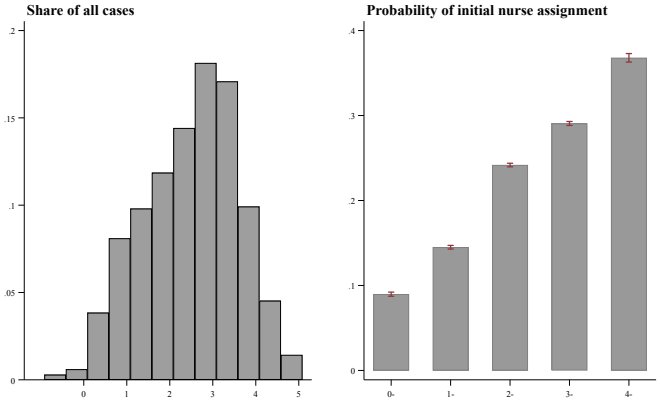
IV identification

Back - Robustness Back - OLS

- **Relevance**: Doctor congestion in previous cases (Doctor Congestion$_i$) increases probability that case i is assigned to a nurse ($Nurse_i$)
- **Independence**: Conditional on baseline controls X_{1i}, Doctor Congestion$_i$ is independent of case characteristics X_{2i}
- **Monotonicity**: Doctor Congestion$_i$ congestion always (weakly) shifts cases to nurses
  → Conditional Expectation Functions of nurse assignment (given instrument) do not reject monotonicity (Cattaneo et al., 2024) Monotonicity
- **Exclusion**: Conditional on initial case assignment, congestion does not meaningfully affect potential outcomes
  → Congestion barely affects clinician time and patient wait time in the analysis sample, or patient outcomes in doctor group and nurse group Consultation characteristics Doctor group and nurse group cases

Relevance in raw data

Back - Robustness Back - OLS

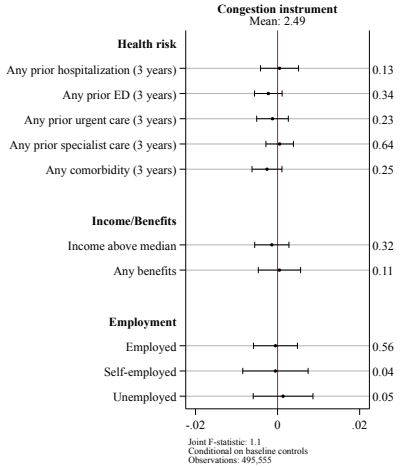


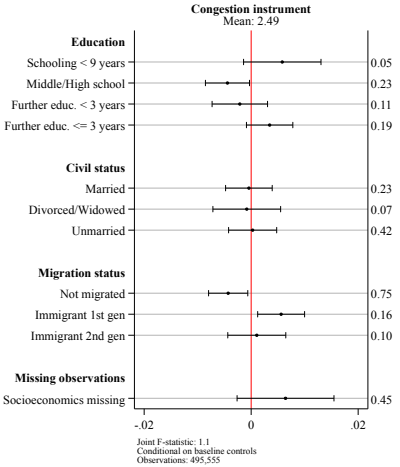
→ **First stage with controls: coef = 0.056 (KP F-stat = 3,725)**

Bars represent 95%-CIs for group means. First stage with all controls and robust SEs. Sample of cases where symptoms are strictly deterministically assigned to either a nurse or a doctor, with fewer than 1% of cases assigned to either clinician type.

IV identification: Independence

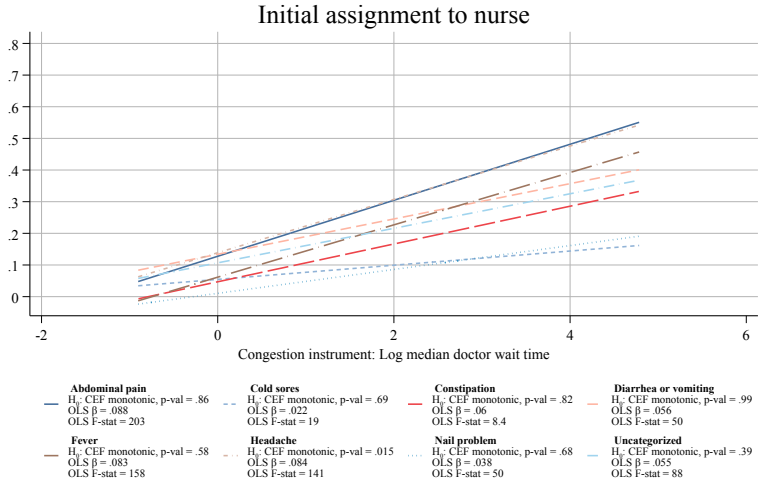
Back





Bivariate regressions cond. on baseline controls (date-by-3h FEs, symptom × gender × age × previous firm visit, region). 95%-CIs from robust SEs.

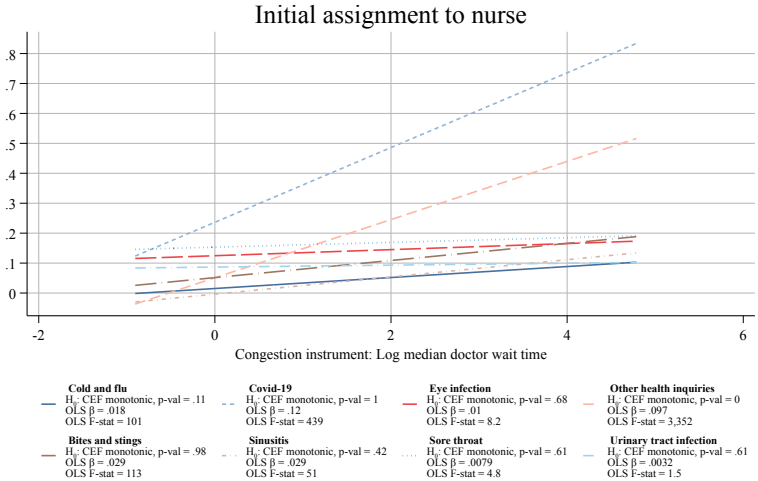
Monotonicity by symptom categories



Back

Controls: time fixed effects, symptom, demographic controls and interactions. Symptom subsamples are defined in the analysis sample.

Monotonicity by symptom categories



Back

Controls: time fixed effects, symptom, demographic controls and interactions. Symptom subsamples are defined in the analysis sample.

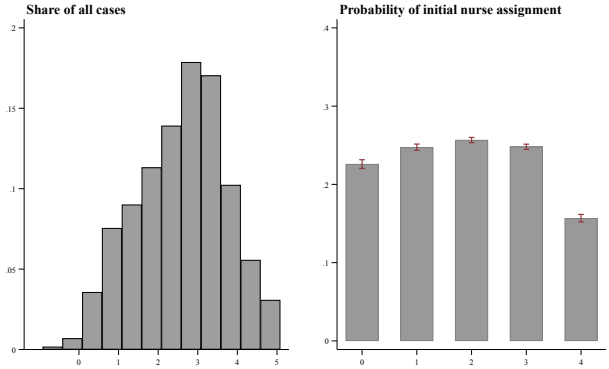
Differences in consultation characteristics under low/high congestion

Back - OLS Back - IV

	High congestion	Low congestion	T-test		Observations	
	Mean	Mean	Difference	p-val.	High congestion	Low congestion
No show	0.00090	0.0013	-0.00039	0.00	123,871	124,071
	(0.030)	(0.036)				
Patient waiting time in min.	44.3	5.62	38.6	0.00	123,871	124,071
	(36.1)	(13.9)				
Technical error	0.0046	0.0075	-0.0029	0.00	123,871	124,071
	(0.068)	(0.086)				
Nurse total time	10.8	11.3	-0.50	0.00	39,506	13,483
	(6.68)	(8.32)				
Doctor total time	11.7	11.8	-0.069	0.02	84,365	110,588
	(6.45)	(6.62)				
Consultation time below one minute	0.047	0.051	-0.0038	0.00	123,871	124,071
	(0.21)	(0.22)				
Consultation time below 30 seconds	0.015	0.016	-0.00052	0.30	123,871	124,071
	(0.12)	(0.13)				
Rating: top score	0.38	0.40	-0.022	0.00	123,871	124,071
	(0.49)	(0.49)				

For reference: In in-person primary care, nationwide over 25% have to wait $>$ 24 hours for their first doctors appointment. (Source: https://skr.se/vantetiderivarden/vantetidsstatistik/medicinskbedomning.54389.html)

Contrast for exclusion restriction: Instrument has no bite in strict doctor group and strict nurse group

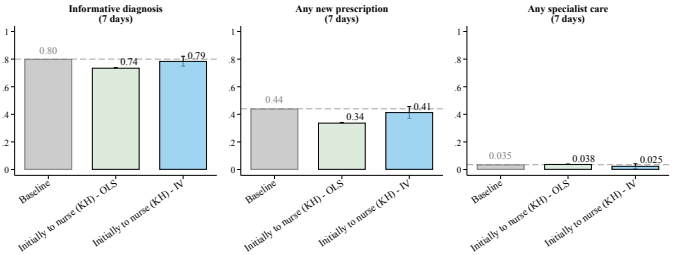


Back

Strictly doctor group or nurse group symptom categories have >99% of cases assigned to either doctors or nurses.

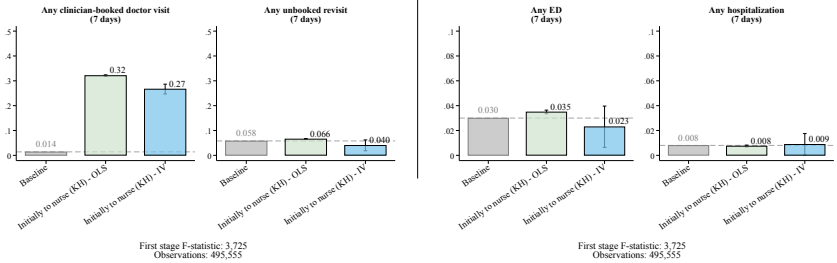
Main outcomes with IV (1)

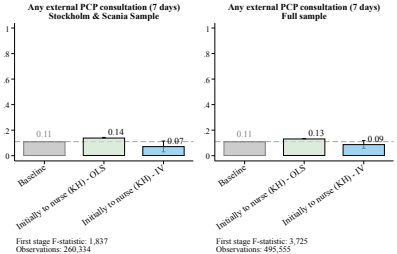
Back - Robustness Back - OLS



Main outcomes with IV (2)

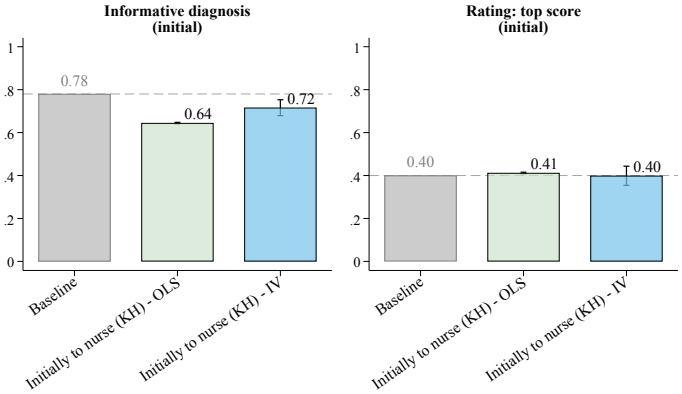
Back - Robustness Back - OLS





Main outcomes with IV (3)

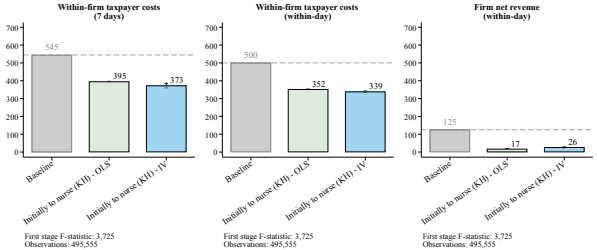
Back - Robustness Back - OLS

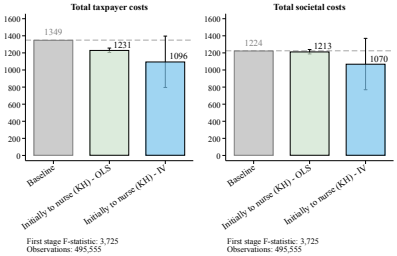


First stage F-statistic: 3,725
Observations: 495,555

Main outcomes with IV - costs

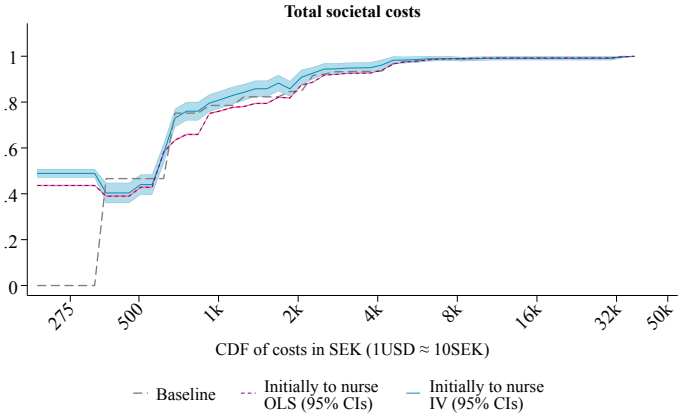
Back - Robustness Back - OLS





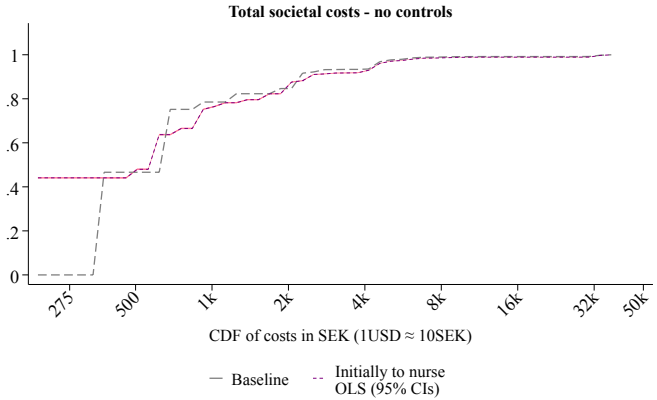
CDF of total societal costs with IV

Back



CDF of total societal costs with no controls

Back



Using the main analysis sample. X-axis shows total societal costs in logarithmic scale. Full controls. 95% confidence intervals.