Physician Treatment Preference Formation and Diffusion: The Case of Specialty Referrals

June 13, 2023

ASHEcon Annual Meeting

Maximilian J. Pany
Gabriel Weinreb
J. Michael McWilliams

Supported by grants from the National Institute on Aging of the National Institutes of Health (P01-AG032952 and T32-AG51108)

Do physicians who work together develop shared treatment preferences?

1. **Do physicians with more (vs less) opportunity to interact make more (vs less) similar treatment decisions?**
   - Physicians may consult or observe each other on treatment decisions
   - Less experienced physicians may emulate and learn from the treatment decisions of more experienced physicians
2. Leveraging **quasi-random assignment** of **patients to primary care physicians** (PCPs) and of **PCPs to each other**, we investigate whether PCPs' specialty referral preferences are more similar when they work together in
   - **vertical relationships**: residents and assigned teaching faculty
   - **horizontal relationships**: faculty who are spatially collocated
3. We find that **physicians' treatment preferences are influenced by interaction with other physicians**
   - PCPs who interacted more with each other have more similar specialty referral preferences
   - The effect is stronger for resident-teaching faculty interactions than for faculty-faculty interactions
   - The resident-teaching faculty effect is stronger for faculty with more clinical experience

Motivation

Variation in physician treatment decisions are a key determinant of health care spending and quality

1. **Though prices are widely recognized to drive commercial spending, differences in utilization are a key component as well**
   - Variation in utilization explains a large share of variation in both commercial and public spending (e.g., HCCI reports, Dartmouth Atlas)
2. **Variation in physicians' treatment preferences is likely more influential than variation in patients' preferences in driving utilization differences**
   - Physician supply-side factors explain a much larger share of regional variation in FFS Medicare expenditures than patient demand-side factors (Cutler et al. 2019)
3. **Regional quality variation is correlated with variation in physician practice patterns**
   - Life expectancy exhibits place-based effects, which correlate with higher quantity and quality of care (Finkelstein et al. 2021)
   - Variation in hospitals' comparative advantage in the treatment of heart attack patients help explain regional quality variation (Chandra & Staiger 2007, 2020)

But why do physicians' treatment decisions (for similar patients) vary?

1. **Physicians are supposed to be (perfect) agents for their patients**
   - Ideally, physicians make treatments decisions that a perfectly informed and rational patient would make for themselves (McGuire 2000)
   - Physicians also have profit motives
2. **But physicians' treatment preferences are not (entirely) rational**
   - Physicians may not be perfectly informed and may be subject to a variety of behavioral biases (Chandra et al. 2011), such as the availability heuristic (Ly 2021)
   - Physicians' *non*-evidence-based beliefs explain ~35% of end-of-life spending (Cutler et al. 2019)
   - Hospitals misperceive comparative advantage in treating heart attacks (Chandra & Staiger 2020)

And how do physicians' treatment preferences form and diffuse in the first place?

1. **Physician training may be a key source of treatment preferences**
   - Physicians from a higher vs lower ranked institution have lower diagnostic testing rates leading to similar health outcomes but 10-25% less expensive stays (Doyle et al. 2010)
   - Patients quasi-randomly assigned to specialists who co-trained with the patient's PCP rate their specialists more highly than those assigned to non-co-trained specialists (Pany & McWilliams 2023)
2. **Physician peer practice patterns may be another important source**
   - Variation in practice environment explains an estimated 60–80% of regional variation in cardiologist practice (Molitor 2018)

This study: A deep dive into how physician relationships influence preference formation, during training and beyond

1. **Existing evidence highlights the influence of physician preferences, yet evidence on how these preferences form and diffuse is lacking**
   - Ideally, want to observe preferences at an early stage of a physician’s career and either compare them to the preferences of more experienced physicians and/or trend their evolution over time
2. **Two key factors, physician training and peer practice environments, are likely mediated through physician-physician relationships**
   - Highlights the importance of understanding preference formation and diffusion in the context of these relationships
   - The influence of relationships likely varies across types of relationships
3. **In this study, we investigate whether physicians who work together develop shared treatment preferences**

Research question

Do physicians who work together develop shared treatment preferences?

Research question

Do physicians who work together develop shared treatment preferences?

1. **Vertical relationships:** resident-teaching faculty
2. **Horizontal relationships** faculty-faculty

Empirical approach

Study design

1. **Use specialty referrals as an expression of PCP preferences**
   - Following prior work (Pany & McWilliams, presented at ASHE 2022)
2. **Leverage quasi-random assignment of physicians to each other to examine preference similarity across physician relationships**
   - Exploit temporal and spatial variation in physicians working together
   - Because physician relationships are randomized, effects of patient selection to physicians averages out
3. **Study the effects of vertical and horizontal relationships**
   - Preferences are likely weaker (stronger) early (later) in a physician's career
   - Seniority and experience may modify preference diffusion
4. **If PCP preferences are more similar across provider dyads with more exposure, this would suggest preference diffusion**

Data

1. **Shift schedule data from a large primary care clinic with a prominent teaching mission** (2016–2019) +
   - Providers include residents (i.e., physicians in training), teaching faculty (aka “preceptors”), and non-teaching faculty
     - Residents are randomly assigned to faculty preceptors in a given academic year
     - Faculty are quasi-randomly assigned to each other on a given shift
     - By virtue of the above, patients are quasi-randomly assigned to providers
2. **Detailed electronic health record (EHR) data from a large Boston-area health care system** (2016–2019)
   - All patient encounters at the primary care clinic +
   - All referrals originating from clinic providers to 13 high-volume specialties (n=__k) +
   - Patient characteristics and comorbidities

Identifying physician interactions from shift schedule and patient encounter data

1. **Construct all provider dyads working a given shift**
   - 10 shifts per week, each has independent faculty and >1/2 have residents and preceptors
   - For a given shift-date (e.g., Monday PM 5/1/2017), create all combinations of providers seeing patients in clinic (either as primary providers or cosigners)
2. **Compare dyads with various levels of interaction to each other and to non-interacting dyads**
   - Creates counterfactuals of what similarity in outcome (treatment preferences) would have been with less (no) interaction
   - Given quasi-random assignment, this implicitly controls for observable and unobservable patient and physician level confounders

To make things more concrete

shift a

To make things more concrete

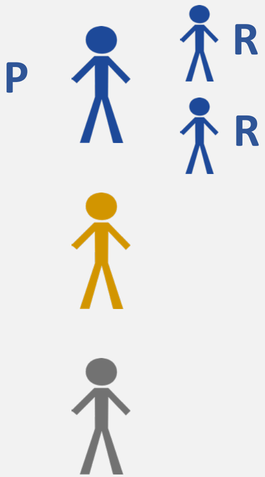
shift a

P

preceptors are teaching faculty

To make things more concrete

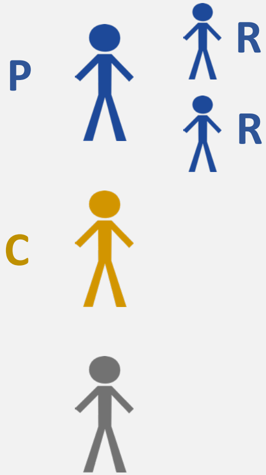
shift a



preceptors are teaching faculty, **who supervise assigned residents**

To make things more concrete

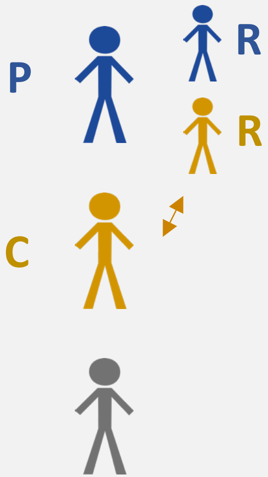
shift a



cosigners are non-teaching faculty

To make things more concrete

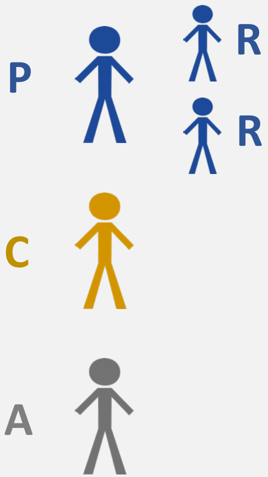
shift a



cosigners are non-teaching faculty, **who supervise unassigned residents when preceptors are busy**

To make things more concrete

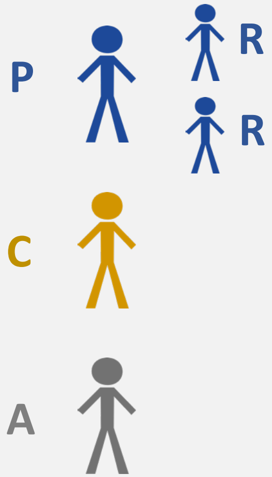
shift a



attendings are non-teaching faculty who independently see patients

To make things more concrete

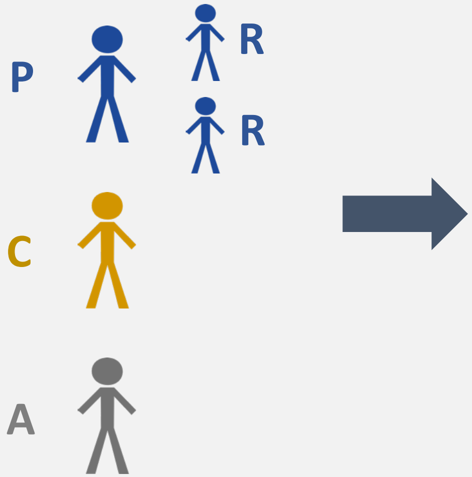
shift a



To make things more concrete

shift a

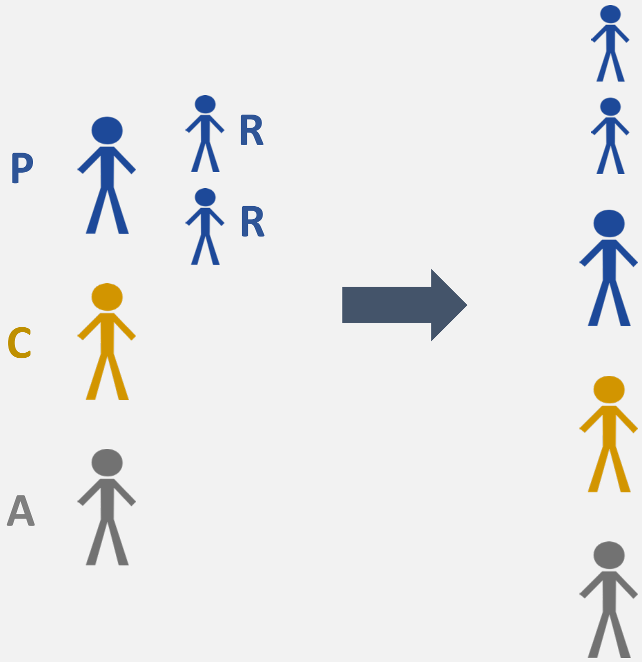
construct all dyads w/in shift a



To make things more concrete

shift a

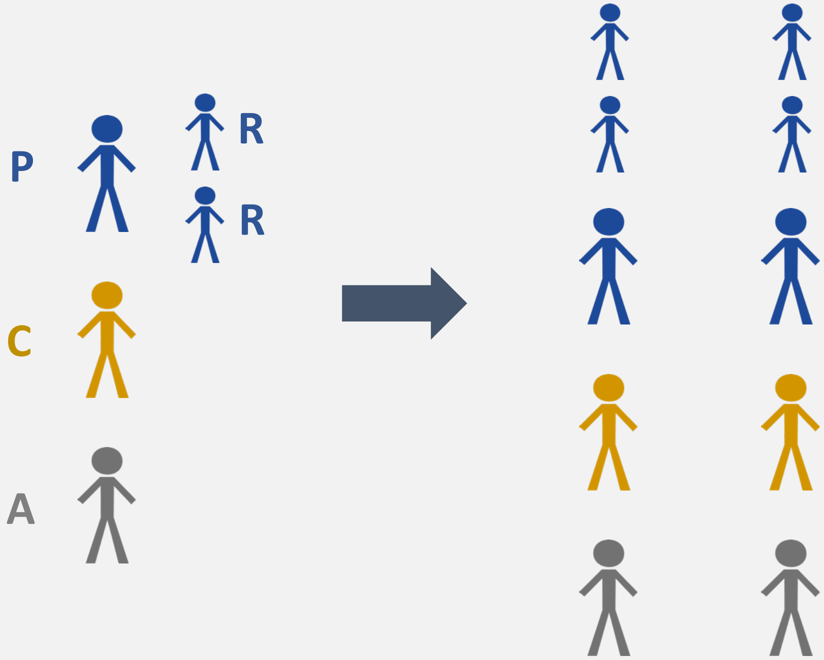
construct all dyads w/in shift a



To make things more concrete

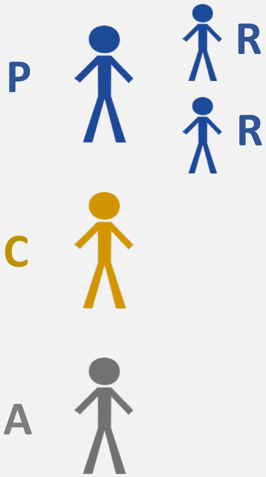
shift a

construct all dyads w/in shift a

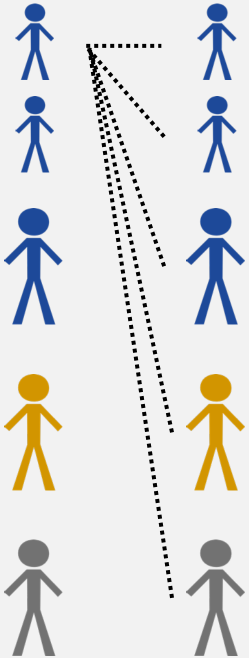


To make things more concrete

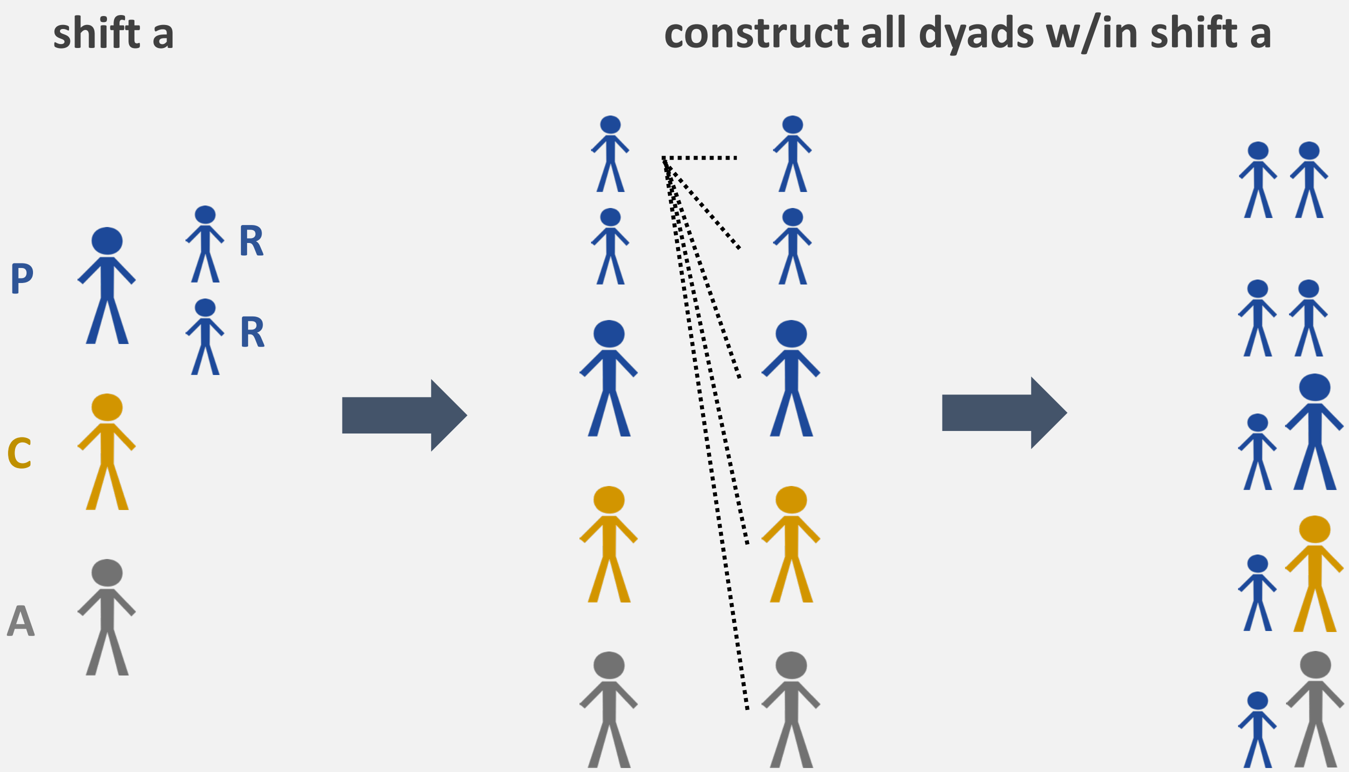
shift a



construct all dyads w/in shift a

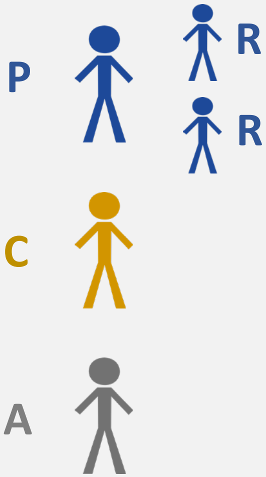


To make things more concrete

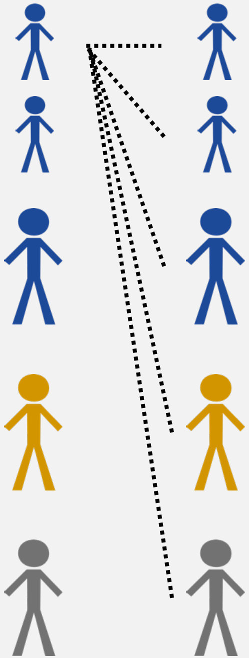


To make things more concrete

shift a

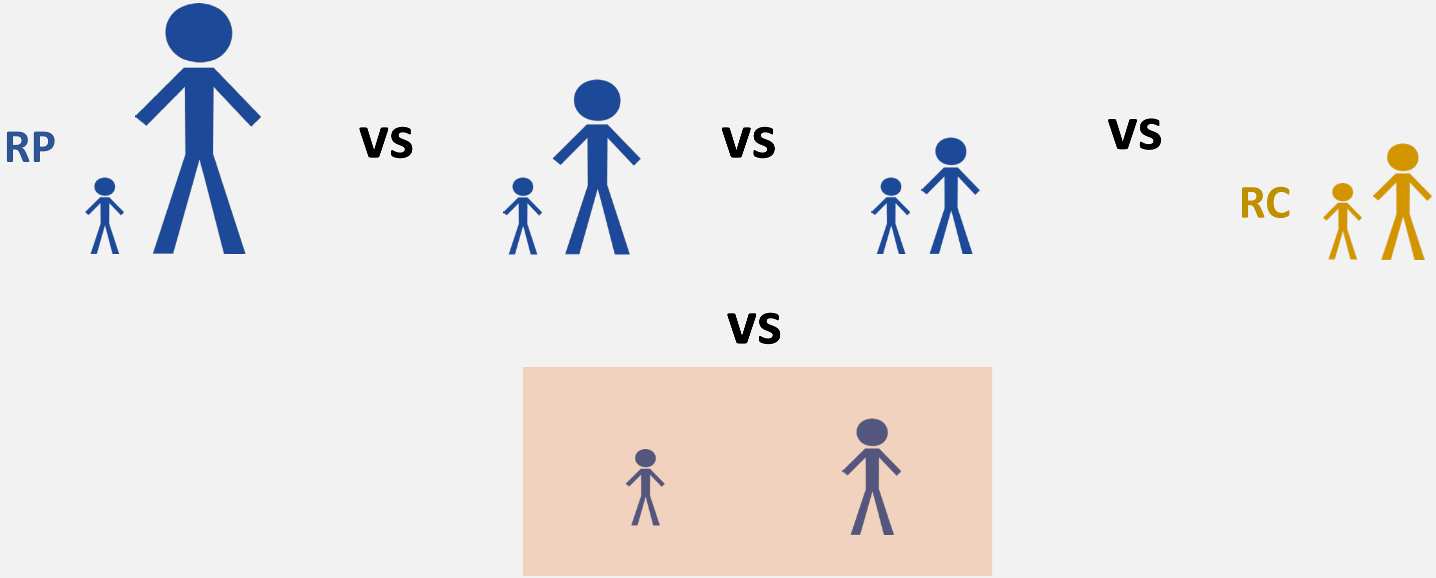


construct all dyads w/in shift a



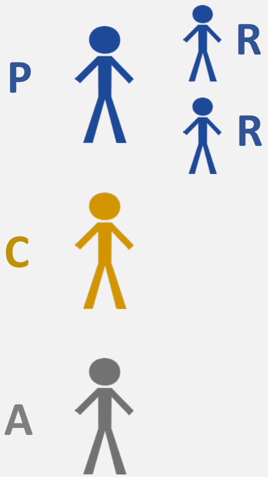
Analysis 1: Are preferences of residents like those of the faculty they interact with most?

(Leverages variation in supervision intensity across resident-faculty dyads)



To make things more concrete

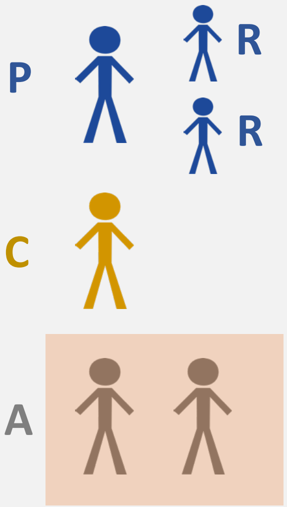
shift a



attendings are non-teaching faculty who independently see patients

To make things more concrete

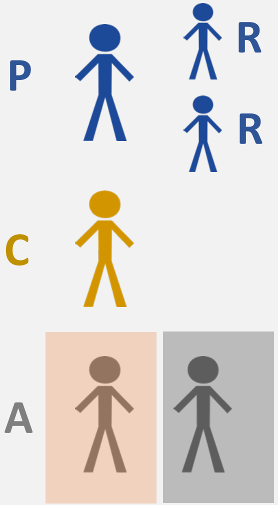
shift a



attendings are either collocated in the same physical suite

To make things more concrete

shift a



attendings are either collocated in the same physical suite,
or located in different suites (not collocated)

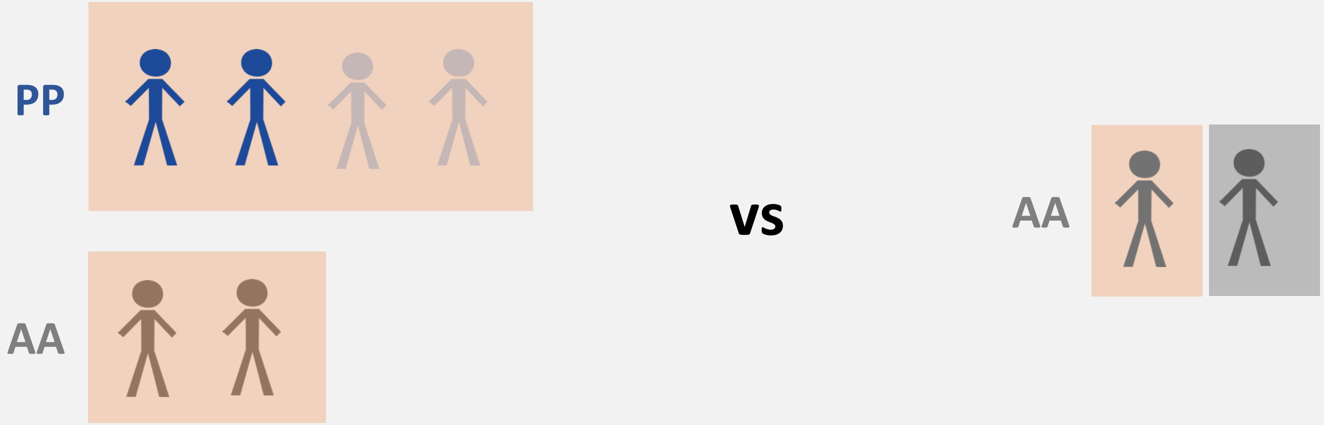
To make things more concrete

shift a

preceptors are collocated with other preceptors & residents in a back room when not with patients

Analysis 2: Are preferences of collocated faculty more similar to than those of non-collocated faculty?

(Leverages variation in spatial interaction across faculty-faculty dyads)



Econometric model

1. **Leverage quasi-random assignment of patients to physicians and physicians to each other**
   - Differences in patient and physician characteristics across dyads average out

2. **For each dyad *ij* working a shift *k*, estimate equations of the form:**

$$\boldsymbol{E}\left[dissimilarity_{ij}\right] = \boldsymbol{\beta_1} relationship_{ij} + \beta_2 specialty + \beta_3 academic\ year + \boldsymbol{\epsilon}_{ijk}$$

   - $\boldsymbol{\beta_1}$ estimates the avg. referral dissimilarity between specified physician-physician relationship types

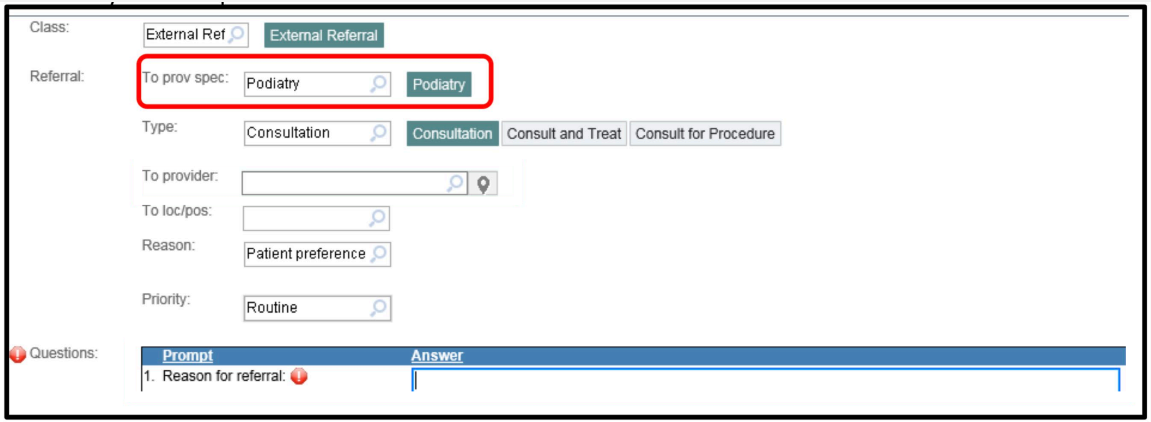
Measuring similarity in physician treatment preferences using specialty referrals

1. **Measure PCP preferences**
   - Each PCPs preference for a given specialist = share of directed over all referrals to the specialist within their specialty

Measuring PCP preferences: **Directed referrals** go to a specific specialist

Source: https://hit.healthsystem.virginia.edu/departments/epic/resources/epic-learning-library/

Measuring PCP preferences:
Undirected referrals go to a specialty department



Source: https://hit.healthsystem.virginia.edu/departments/epic/resources/epic-learning-library/

Measuring similarity in physician treatment preferences using specialty referrals

1. Measure PCP preferences

- Each PCPs preference for a given specialist = share of directed over all referrals to the specialist within their specialty

2. Measure dissimilarity in PCP preference for each dyad

- For each PCP, construct vector of preferences for each specialist (with as many elements as specialists the PCP refers to)
- For each dyad, take specialist-wise difference of PCP preference, square differences, sum the results, then take square root of the resulting scalar => measure of referral dissimilarity at the dyad level
- Referral dissimilarity is higher if dyad members have more differing referral patterns

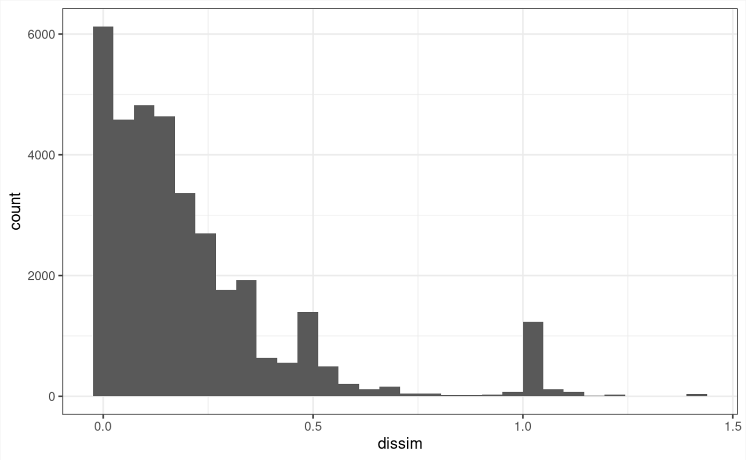
RP 

$$\begin{bmatrix} s_1' \\ s_2' \\ \cdots \\ s_n' \end{bmatrix} - \begin{bmatrix} s_1 \\ s_2 \end{bmatrix} = \begin{pmatrix} s_1' - s_1 \\ s_2' - s_2 \\ \cdots \\ s_n' - 0 \end{pmatrix} \longrightarrow \sqrt{(s_1' - s_1)^2 + \cdots + (s_n' - 0)^2}$$

= ref. dissimilarity

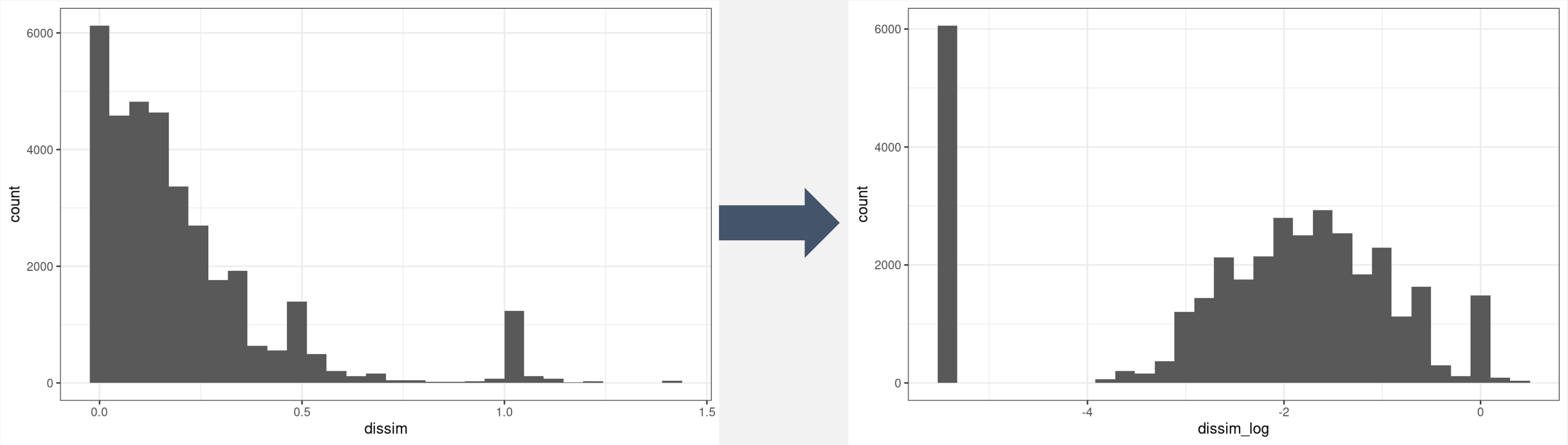
Results

Distribution of logged preference dissimilarity score



Dyad relationship	Dyad-shifts-AY, no.	Shared patients	Referral dissimilarity				
			mean	sd	q1	median	q3
Resident (R) - primary/assigned preceptor cosigner	2499	29	0.19	0.23	0.052	0.12	0.24
R - secondary preceptor cosigner	2245	8.8	0.18	0.23	0.038	0.12	0.24
R - other preceptor cosigner	11297	3	0.2	0.24	0.047	0.13	0.25
R - non-preceptor cosigner	16473	2.9	0.22	0.24	0.071	0.16	0.29
R - preceptor who never cosigned (ref. group)	2696	0	0.21	0.22	0.071	0.15	0.28

Distribution of logged preference dissimilarity score



Dyad relationship	Dyad-shifts-AY, no.	Shared patients	Referral dissimilarity				
			mean	sd	q1	median	q3
Resident (R) - primary/assigned preceptor cosigner	2499	29	0.19	0.23	0.052	0.12	0.24
R - secondary preceptor cosigner	2245	8.8	0.18	0.23	0.038	0.12	0.24
R - other preceptor cosigner	11297	3	0.2	0.24	0.047	0.13	0.25
R - non-preceptor cosigner	16473	2.9	0.22	0.24	0.071	0.16	0.29
R - preceptor who never cosigned (ref. group)	2696	0	0.21	0.22	0.071	0.15	0.28

Residents' referral preferences are more similar to those of teaching faculty they interact with more

	log(referral dissimilarity)		
	effect, %	SE, %	p-value
Dyad relationship			
Resident (R) - primary/assigned preceptor cosigner	-21.9	4.28	<0.001
R - secondary preceptor cosigner	-32.6	4.4	<0.001
R - other preceptor cosigner	-29.6	3.28	<0.001
R - non-preceptor cosigner	-0.941	3.19	0.76
R - preceptor who never cosigned (ref. group)	ref.		ref.
Outcome, mean		0.213	
Observations, n		35,210	
Specialty FEs		✓	
Academic year FEs		✓	

Note: Effect is calculated as (exp(coef)-1)*100. Mean outcome is among members of the reference group and on the linear scale.

Does faculty referral experience moderate concordance in resident-teaching faculty referral similarity?

1. **If yes, supports that physicians preferentially learn from those with more vs less experience**
   - This would be consistent with an ability to discriminate good vs not-so-good advice and practice styles
   - It would also indicate that physicians believe that other physicians have information (e.g., tacit knowledge acquired over the course of practice) about quality
2. **If no, preference concordance may be more about vertical nature of trainee-faculty relationship than resident discrimination of experienced vs less experienced teachers**
   - Mechanism may still be learning, but a more indiscriminate form that depends on the vertical vs horizontal nature of the relationship
   - Alternatively, mechanism may not be learning but power dynamic
   - Test would be if resident referral patterns persist beyond their trainee status, but unfortunately can’t examine this here

Faculty referral experience moderates concordance in resident-teaching faculty referral similarity

	log(referral dissimilarity)	
	effect, %	p-value
Dyad relationship		
Resident (R) - primary/assigned preceptor cosigner (RP')	-28.9	<0.001
R - secondary preceptor cosigner (RP'')	-50.1	<0.001
R - other preceptor cosigner (RP˚)	-42.4	<0.001
R - non-preceptor cosigner (RC)	-1	0.87
R - preceptor who never cosigned (RP; ref. group)	ref.	ref.
Dyad relationship X referral experience		
RP'	-1.1	0.012
RP''	-0.7	0.14
RP˚	-0.9	0.005
RC	-1.6	<0.001
RP	-1.4	0.001
Outcome, mean		
Observations, n	35,210	
Specialty FEs	✓	
Academic year FEs	✓	

Note: Effect is calculated as (exp(coef)-1)*100. Mean outcome is among members of the reference group and on the linear scale.

Analysis 2: Are preferences for collocated faculty more similar than those for non-collocated faculty?

	Model 1		Model 2	
	Coef	p-value	Coef	p-value
Dyad relationship				
Collocated non-teaching faculty	0.0073	0.15		
Collocated teaching faculty			-0.014	0.11
F-F (ref. group)	ref.	ref.	ref.	ref.
Specialty FEs	✓		✓	
Academic year FEs	✓		✓	

Sensitivity analyses

1. **Results robust to restricting to scheduled shifts only**
   - Residents are scheduled to work in clinic 1 day per week, but have a ‘flex day’ that they can easily swap into and which accounts for a non-trivial amount of their volume
   - Restricting to residents’ primary and flex day leaves results qualitatively unchanged
   - Restricting to residents’ primary day only is qualitatively consistent but attenuates results (as expected)

Discussion

(Select) Limitations

1. **Identification**
   - Residual selection of faculty physicians to each other?
     - Residents are truly randomly assigned to teaching faculty
     - While faculty are quasi-randomly assigned to each other, cannot rule out that more senior faculty have ability to preference shifts, reasons for which may include working alongside established colleagues
   - Identification of referral dissimilarity is across dyads within academic year
     - Given quasi-random assignment, no reason to think that dissimilarity should significantly vary absent a real effect of the dyadic relationship
     - However, given sample constraints, cannot trace dynamic evolution of within-dyad preferences over time
2. **Generalizability**
   - Other practice settings (the study setting is a large academic primary care practice with a strong teaching mission)?
   - Other treatment decisions (e.g., decision to order lab tests and other studies or prescribe medication)?
   - Physicians with specialist training?

What we learned

1. **Physicians' treatment preferences are influenced by interaction with other physicians**
   - PCPs who interacted more with each other have more similar specialty referral preferences
   - The effect is stronger for resident-teaching faculty interactions than for faculty-faculty interactions
2. **Experience influences the extent to which preferences between residents and faculty concord**
   - May reflect discernment of exemplars to learn from among trainees

Study findings in context

1. **Implications for physician treatment preference formation and diffusion**

2. **The impact of physician relationships**
   - Physician peer motivation (Pany & McWilliams 2023)
   - Chief residents as exemplars for the profession (Chen & McWilliams 2023)

3. **Information asymmetry revisited**
   - Can physician interactions be leveraged to solve physician-physician information asymmetry about treatment options?

Conclusions

1. **Physician relationships matter for treatment preference formation!**
2. **Treatment preferences may be especially malleable early in a physician's career**
3. **Raises important, policy-relevant question: can we encourage and support physician interaction to improve care?**

Next steps

1. Refine analyses of collocated faculty
2. Explore the impact of preference strength on the dissimilarity measure
3. Dynamic preference evolution of resident-teaching faculty over time
   - Though sample size may limit

Thank you!

References 1/2

Chandra A, Cutler D, Song Z. Chapter Six - Who Ordered That? The Economics of Treatment Choices in Medical Care. In: Pauly MV, Mcguire TG, Barros PP, eds. *Handbook of Health Economics*. Vol 2. Handbook of Health Economics. Elsevier; 2011:397-432. doi:10.1016/B978-0-444-53592-4.00006-2

Chandra A, Staiger DO. Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks. Journal of Political Economy. 2007;115(1):103-140. doi:10.1086/512249

Chandra A, Staiger DO. Identifying Sources of Inefficiency in Healthcare*. The Quarterly Journal of Economics. 2020;135(2):785-843. doi:10.1093/qje/qjz040

Chen L, McWilliams JM. Performance on Patient Experience Measures of Former Chief Medical Residents as Physician Exemplars Chosen by the Profession. *JAMA Internal Medicine*. 2023;183(4):350-359. doi:10.1001/jamainternmed.2023.0025

Cutler D, Skinner JS, Stern AD, Wennberg D. Physician Beliefs and Patient Preferences: A New Look at Regional Variation in Health Care Spending. *American Economic Journal: Economic Policy*. 2019;11(1):192-221. doi:10.1257/pol.20150421

Doyle JJ, Ewer SM, Wagner TH. Returns to physician human capital: Evidence from patients randomized to physician teams. *Journal of Health Economics*. 2010;29(6):866-882. doi:10.1016/j.jhealeco.2010.08.004

References 2/2

Finkelstein A, Gentzkow M, Williams H. Place-Based Drivers of Mortality: Evidence from Migration. *American Economic Review*. 2021;111(8):2697-2735. doi:10.1257/aer.20190825

Ly DP. The Influence of the Availability Heuristic on Physicians in the Emergency Department. *Ann Emerg Med*. 2021;78(5):650-657. doi:10.1016/j.annemergmed.2021.06.012

Mcguire TG. Chapter 9 - Physician Agency. In: Culyer AJ, Newhouse JP, eds. *Handbook of Health Economics*. Vol 1. Handbook of Health Economics. Elsevier; 2000:461-536. doi:10.1016/S1574-0064(00)80168-7

Molitor D. The Evolution of Physician Practice Styles: Evidence from Cardiologist Migration. *American Economic Journal: Economic Policy*. 2018;10(1):326-356.

Pany MJ, McWilliams JM. Physician-Peer Relationships and Patient Experiences With Specialist Care. Published online 2023.

Appendix

Shift schedules

1. **Shifts**
   - 10 shifts per week: Mon–Fr, AM and PM
   - Each shift has non-teaching faculty who independently see patients
   - All PM shifts (and some AM shifts) have teaching faculty (preceptors) and residents
2. **Each preceptor has 2–4 residents assigned for a given shift**
   - Preceptors see patients with their assigned residents and cosign their orders, but do not see their own patients during precepting shifts
3. **Residents require a faculty member to see their patients and cosign their orders**
   - If assigned preceptors are unavailable to see patients with a given resident, the resident may ask any available preceptor or even non-teaching faculty to see a patient with them

Patient encounters

1. **Allow empirical validation of shift schedules**
2. **Show actual patient encounters, which can differ from shift schedules (e.g., if providers swap shifts)**
3. **Provider relationships & interactions**
   - Effective exposure is interacting with others => actual shifts worked
   - At the same time, residents may reach out to their assigned preceptors for advice asynchronously and weight their opinions more highly than that of non-preceptor faculty, potentially leading to stronger preference diffusion
   - Our study design captures both!

Included specialties for purposes of specialty referrals used to construct PCP preferences

1. Cardiology, pulmonology, neurology, endocrinology, dermatology, rheumatology, allergy & immunology
2. Urology, obstetrics-gynecology, reproductive endocrinology & infertility
3. General surgery, orthopedic surgery, neurosurgery

Econometric model

1. **Analysis 1:** Resident-teaching faculty

   $\boldsymbol{E}\left[dissimilarity_{ij}\right] = R_iP_j' + R_iP_j'' + R_iP_j^o + R_iC_j + \ specialty + academic\ year + \boldsymbol{\epsilon}_{ijk}$

   R_iP_j' … resident with primary (assigned) preceptor who cosigns orders

   R_iP_j'' … resident with secondary preceptor (next most interactions) who cosigns

   $R_iP_j^o$ … resident with any other preceptor who cosigns

   R_iC_j … resident with cosigner who is not a preceptor

   (R_iP_j … resident with another resident's preceptor who never cosigns for them = ref. group)

2. **Analysis 2:** Collocated vs non-collocated faculty

   $\boldsymbol{E}[\cdot] = A_iA_j \times collocated + P_iP_j + specialty + academic\ year + \boldsymbol{\epsilon}_{ijk}$

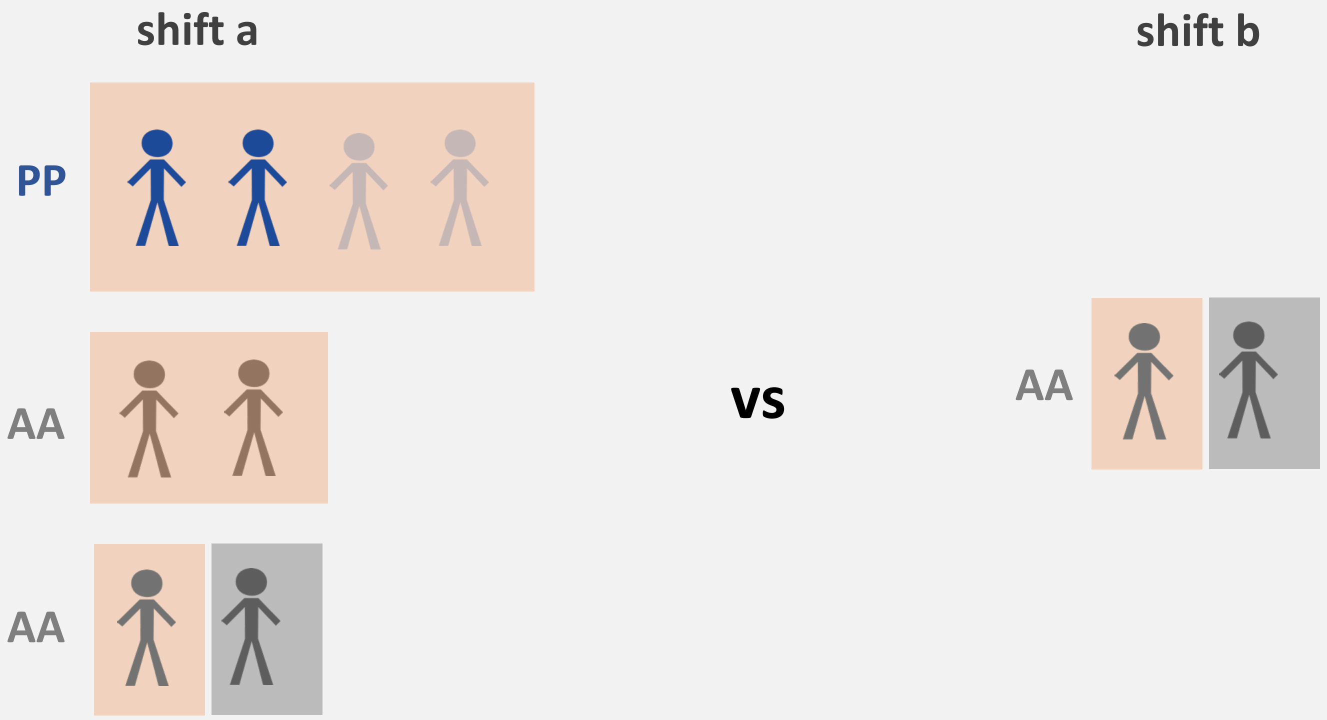
   A_iA_j … attending with another attending (never share patients)

   P_iP_j … preceptor with another preceptor, who do not share patients but are physically collocated

   (Ref. group is A_iA_j who are not collocated)

Future refinement to analysis 2: Are preferences of faculty like those of other faculty they interact with most?

(Leverages spatial & temporal variation in physician assignments across shifts)



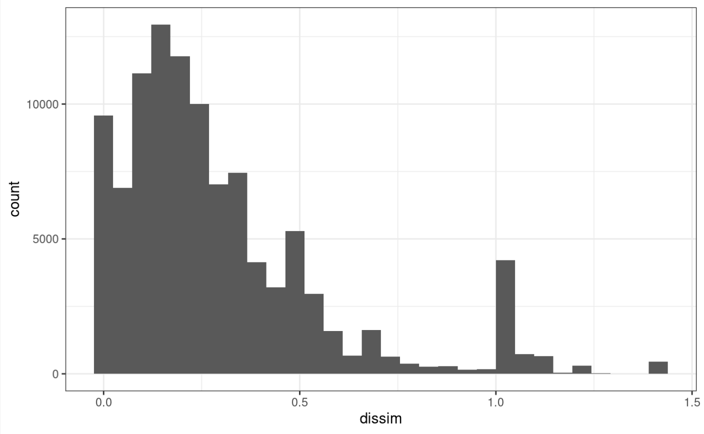
Measuring similarity in physician treatment preferences using specialty referrals

1. **Measure PCP preferences**
   - Each PCPs preference for a given specialist = share of directed over all referrals to the specialist within their specialty
2. **Measure dissimilarity in PCP preference for each dyad**
   - For each PCP, construct vector of preferences for each specialist (with as many elements as specialists the PCP refers to)
   - For each dyad, take specialist-wise difference of PCP preference, square differences, sum the results, then take square root of the resulting scalar
   - This gives a measure of referral dissimilarity at the dyad level
   - Referral dissimilarity is higher if dyad members have more differing referral patterns

For each dyad of PCP *i and PCP j and specialty* l, calculate: $dissimilarity_{ij} = \sqrt{\sum_{k \in l} (share_{ik} - share_{jk})^2}$,

where $share_{ik} = \frac{referrals\ directed\ to\ specialist\ k}{all\ referrals\ of\ PCP\ i\ to\ specialty\ l}$ and analogously for $share_{jk}$.

Distribution of preference dissimilarity score



Dyad relationship	Dyad-shifts-AY, no.	Referral dissimilarity				
		mean	sd	q1	median	q3
Non-teaching faculty (F) - F (ref. group)	70,295	0.33	0.27	0.14	0.25	0.43
Resident - non-preceptor cosigner (R-C)	14,934	0.24	0.25	0.077	0.16	0.3
Resident - non-assigned preceptor cosigner (R-CP)	17,904	0.22	0.25	0.058	0.14	0.28
Resident - assigned preceptor cosigner (R-CP assigned)	1,416	0.19	0.23	0.054	0.12	0.24