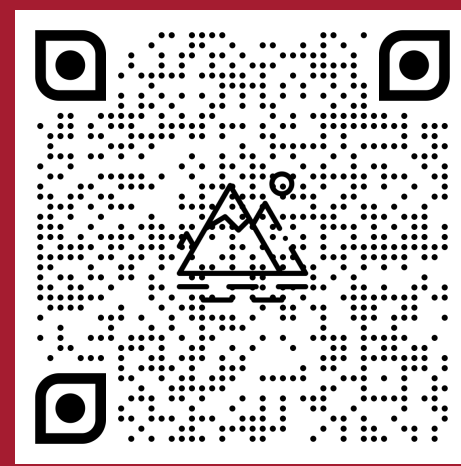


The Value of (Sub) Specialization: Evidence from Oncology

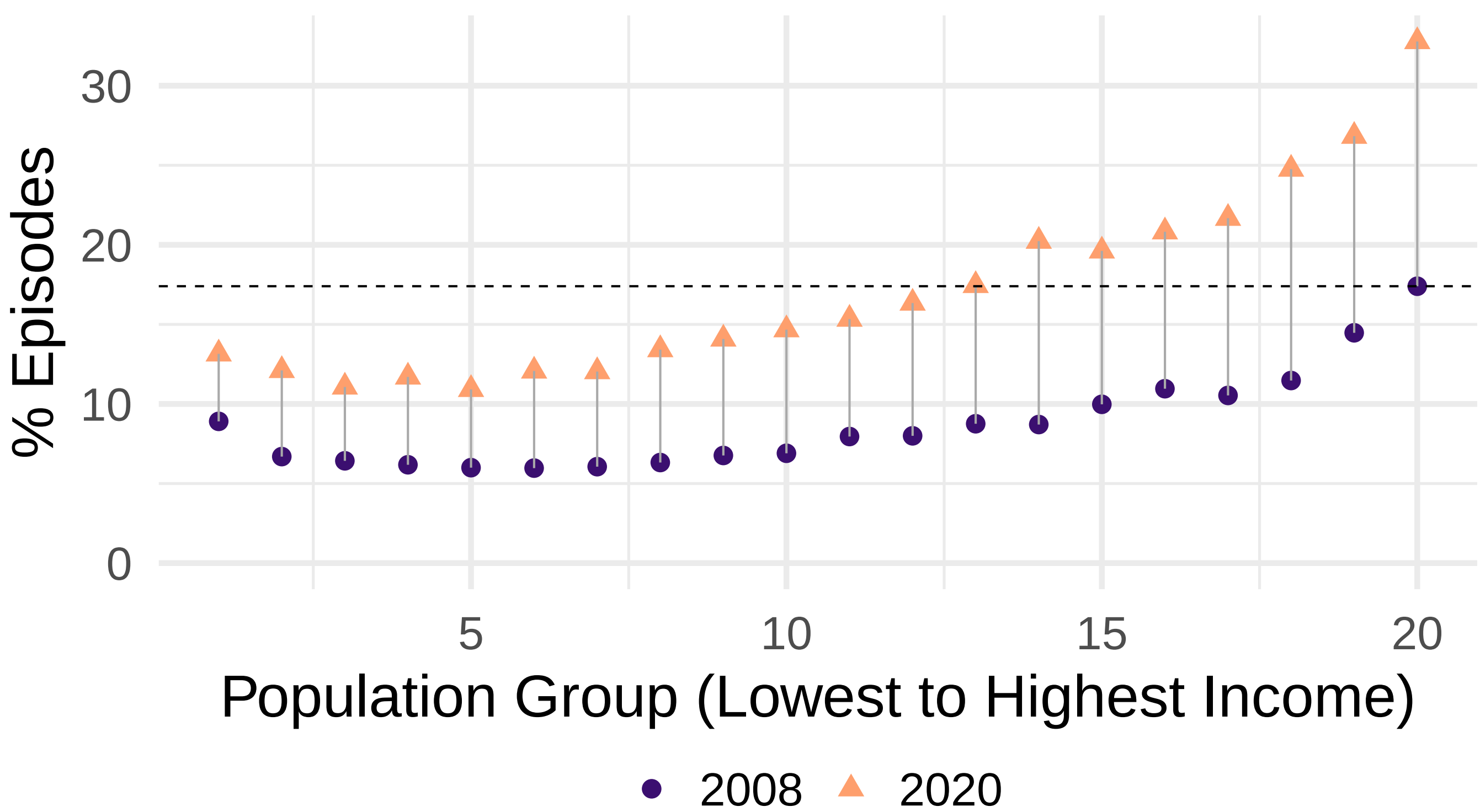
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Background and Motivation

Figure 1. Proportion of Chemotherapy Episodes Across Income Groups, 2008 and 2020



- Subspecialists $\geq 80\%$ of chemotherapy in one cancer group [Karadakic et al., 2025]
- Oncologic care is increasingly complex $\Rightarrow$ incentivizing specialization [Lozinski, 2024]
- Subspecialization has expanded rapidly (9% in 2008 to 17.5% of episodes in 2020)
- Higher-income areas gained access faster than lower-income areas

Research Question and Result Summary

What are the effects of access to highly specialized medical oncologists?

- For **health outcomes** of patients receiving chemotherapy
 - Reduces 3-year mortality by 10% relative to the mean
 - No short term mortality effects
- For **health care spending** per chemotherapy episode
 - Lower Part B chemotherapy drug related spending
 - No difference in total episode spending
- For **health care utilization** of patients
 - Cancer specific trial enrollment increases by 111%
 - Newer chemotherapy agents (based on FDA approval year)
 - No evidence of larger care teams and care fragmentation

Data and Sample

- 100% Medicare Part B and D claims
- Oncology Care Model: 6-month non-overlapping chemotherapy episodes [Keating et al., 2021]
- Includes physician-administered IV and oral systemic therapy
- Episodes assigned primary cancer type and principal oncologist (by plurality of office visits)
- Focus on first episodes and 5 most common cancer groups: breast, GI, hematologic, prostate/GU, thoracic
- Patients: aged ≥ 67 , enrolled in Parts A and B
- Exclude patients with large distance to nearest oncologist

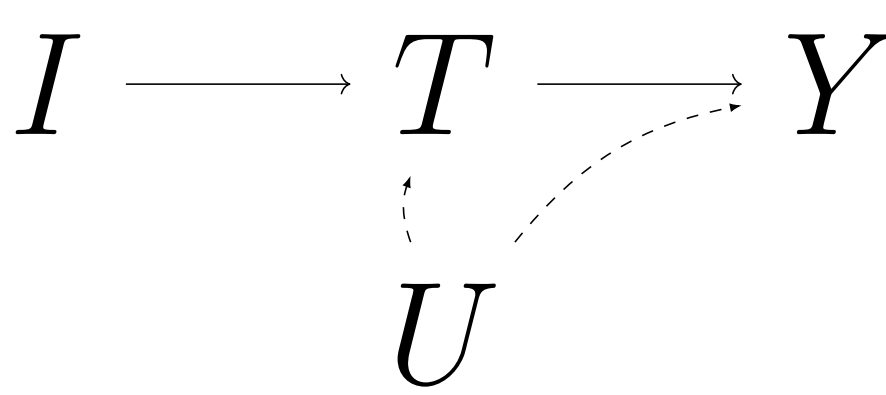
Final sample: 2.2M episodes, $\approx 17,300$ oncologists (2008-2020)

Empirical Strategy - Two Stage Least Squares

- Treatment:** Binary indicator for office visit with subspecialist of relevant cancer type (e.g. breast cancer subspecialist for breast cancer patient)
- Instrument:** Differential distance of patient to nearest relevant subspecialist and general oncologist (transformed for statistical modeling)

$$DD_{cit} = \ln(x + \sqrt{x^2 + 1}) \text{ where } x = \text{Dist. Subspecialist}_{ct} - \text{Dist. Generalist}_t$$

Figure 2. Directed Acyclic Graph (DAG) illustrating Instrumental Variable Design



First Stage Estimation (Subspecialist Access and Differential Distance):

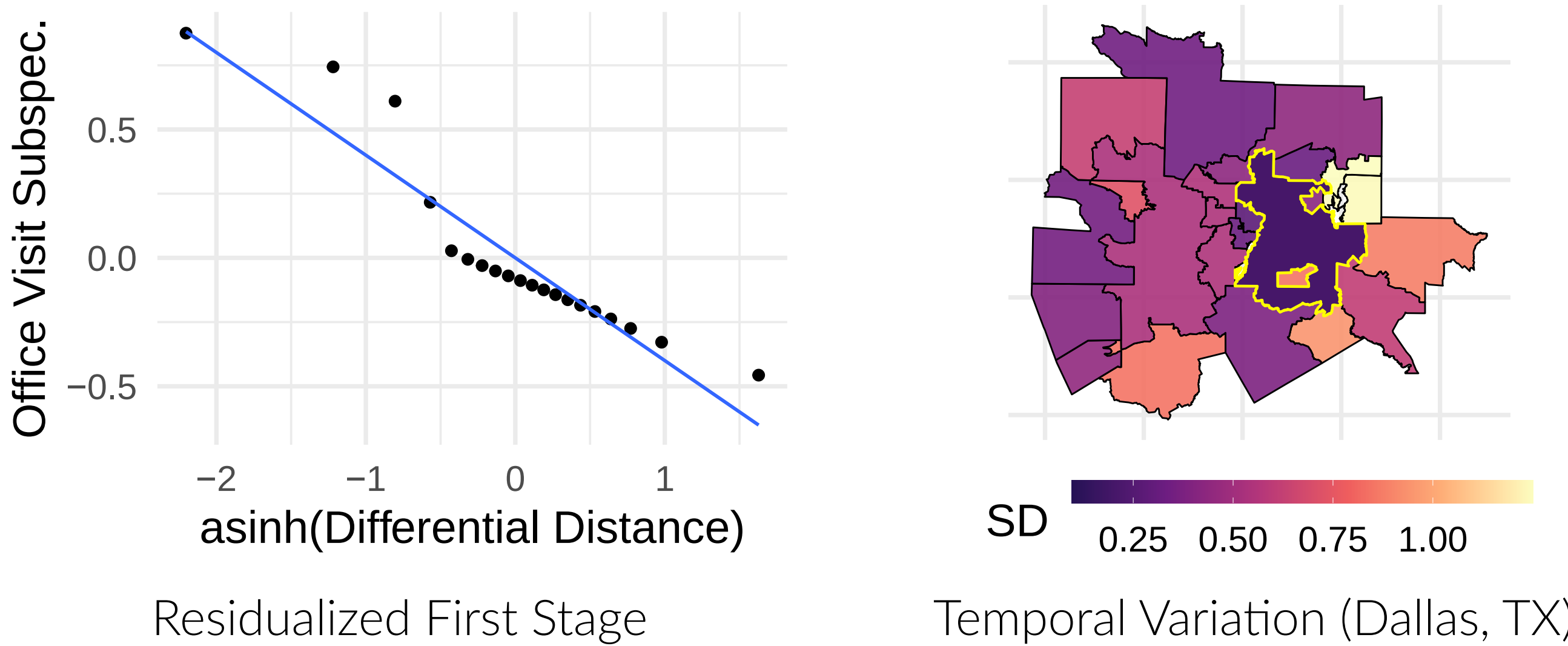
$$\text{Access}_i = \alpha + \beta DD_{t(i)z(i)} + \delta X_i + \tau_{t(i)} + \gamma_{z(i)} + \psi Z_{t(i)z(i)} + \varepsilon_i \quad (1)$$

Second Stage Estimation (Outcome and Access instrumented via Differential Distance):

$$Y_i = \alpha + \beta \widehat{\text{Access}}_i + \delta X_i + \tau_{t(i)} + \gamma_{z(i)} + \psi Z_{t(i)z(i)} + \varepsilon_i \quad (2)$$

- Fixed effects: $\tau_{t(i)}$ = cancer types $\times$ year, $\gamma_{z(i)}$ = ZCTA
- Controls: $Z_{t(i)z(i)}$ = time-varying ZCTA characteristics, X_i = demographics and comorbidities

First Stage Relationship and Variation



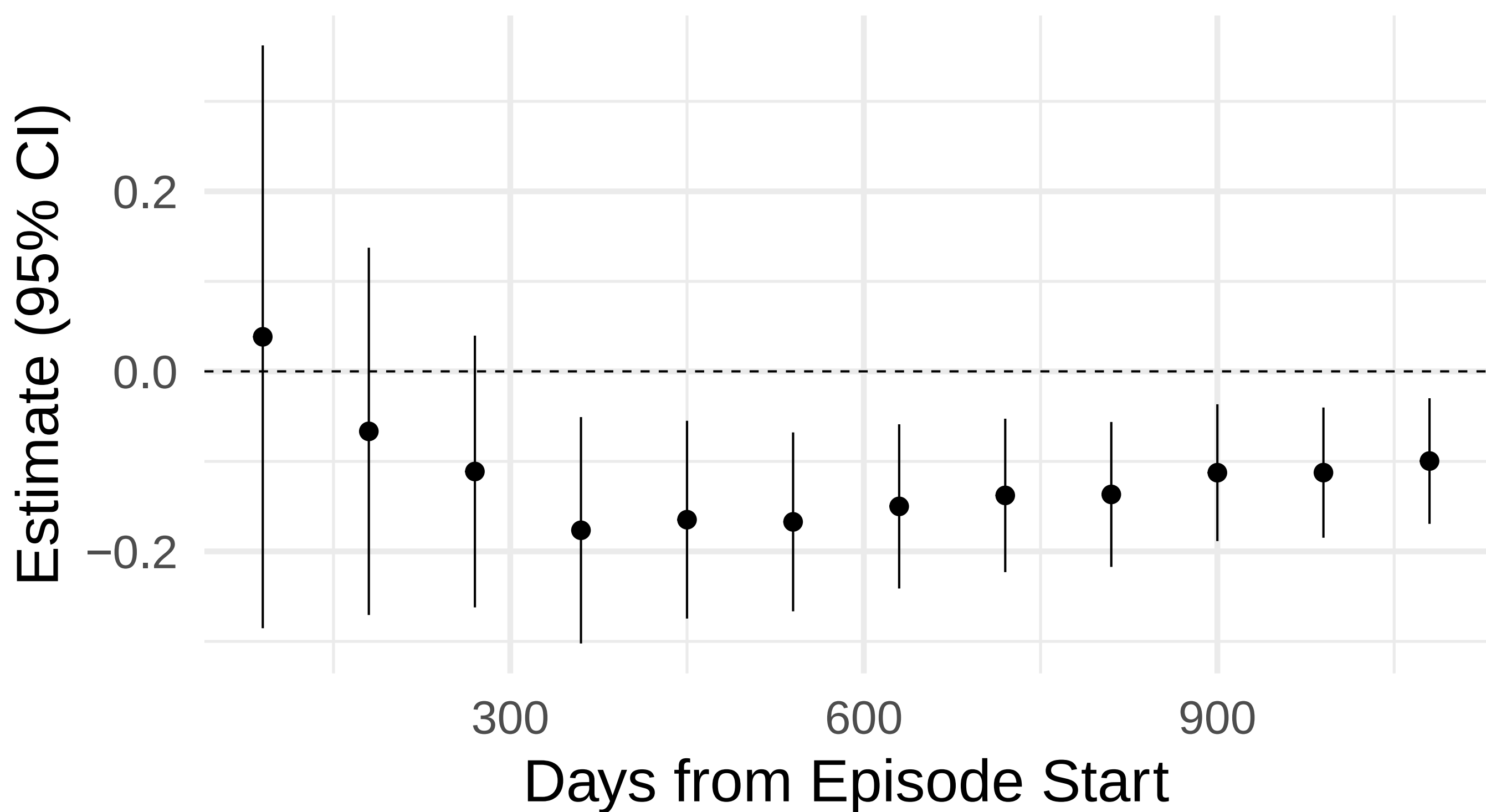
- First stage strong negative relationship** between access to subspecialists and differential distance (F-Statistic for Equation 1 equals 1,823)
- Variation in access to subspecialists results from changes in differential distance within the same ZCTA (see e.g. Dallas TX)
- Conditional on controls and fixed effect **differential distance is uncorrelated with observable patient characteristics**

Key Takeaway

$\Rightarrow$ **Identifying variation** within ZCTA changes in access resulting from changes in differential distance over time (e.g. provider exit, entry or subspecialization)

Main Result: Mortality Effect of Subspecialist Access

Figure 3. 2SLS Estimates of Subspecialist Access on Mortality (Effect Scaled to Mean Mortality)



$\Rightarrow$ Subspecialist access leads to **10% mortality reduction** in 1,080 day mortality

Result: Clinical Trial Enrollment and Subspecialist Access

Link Medicare claims to ClinicalTrials.gov and classify trials into cancer categories using GPT-4

	Cancer Trials				
	Any	Concordant	Discordant	Unspecified	Non-Cancer
Office Visit Subs.	0.023*** (0.007)	0.020** (0.006)	0.003 (0.002)	-0.001 (0.002)	0.001 (0.001)
Adj R ²	0.025	0.022	0.006	0.001	0.000
Observations	1,122,816	1,122,816	1,122,816	1,122,816	1,122,816
Mean Dep. Var.	0.021	0.018	0.003	0.001	0.001

Notes: Sample includes all first chemotherapy episodes between 2014 and 2020. All models include demographic, ZCTA level and chronic conditions controls as well fixed effects for the beneficiaries' ZCTA and cancer type by year. Standard errors are clustered at the ZCTA level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

$\Rightarrow$ Subspecialist access leads to **110% increase in cancer trial enrollment**, driven entirely by trials concordant to patients cancer type

Takeaway and Policy Implications

- Subspecialists **improve survival** and **trial access** without raising episode spending
- How can benefits of specialized oncologic care be made available despite geographic concentration?

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