Turf Wars: How Growth and Competitive Shocks have Impacted the Care Delivery at Federally Qualified Health Centers

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Abstract

Federally Qualified Health Centers (FQHCs) are a critical and growing part of the health care safety net, doubling over the past 15 years to expand access to essential healthcare services in traditionally underserved communities. However, increasingly, FQHCs have opened care delivery locations in communities already served by another clinic, creating newly competitive markets. In this study, I explore the interaction between a growing safety net and competition, uniting and extending theoretical models of the Newhouse nonprofit hospital and Hotelling spatial competitive market to evaluate whether FQHCs respond to competitive pressures more like safety-net or for-profit organizations. Empirically, I examine whether and how competitive shocks affect the performance, allocation, and capacity of incumbent clinics. I find that FQHCs *respond like for-profit clinics* to competitive shocks, increasing their quality of care to attract more patients, cream skimming healthier patients with more generous insurance coverage, and becoming more operationally efficient. Strikingly, clinics also reallocate 5% of resources toward the new rival, recentering and concentrating their organization. Overall, this rapid expansion of the program has distorted incentives for individual clinics, inducing shifts away from their social mission. Policymakers must incentivize clinics to disperse into communities without established clinics and institute guardrails against underservice for uninsured patients and those with chronic conditions.

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1 Introduction

Federally Qualified Health Centers (FQHC) are a critical and growing part of the health care safety net in the United States. Estimates show that FQHCs directly provide care to 30 million patients annually, an increase of 10 million in just the past 10 years, including over 70% of whom are either covered by Medicaid or are uninsured.[1;2] While this growth in access has been heralded given the broad and compelling evidence documenting the value of FQHCs,[3;4;5;6;7] it has also resulted in clinics opening new care delivery locations in the service area of another, triggering an unprecedented spatial overlap between clinics.[8;9;10;11] Accordingly, this unfettered growth of access to FQHCs may have had unintended consequences, but these have not been well elucidated.

One concern FQHC leaders have articulated, in particular, is related to the potential for increased competition among FQHCs. Traditionally, FQHCs have operated under a mandate of collaboration, requiring centers to work together to collectively serve the needs of their communities.[12] In theory, the unmet need for services in the safety-net has been so great that which, or how many, clinics a patient used was unlikely to sufficiently threaten the number of patients any FQHC needed to operate effectively. However, an ultracompetitive environment could fundamentally change the calculus for many centers. For example, if enough centers joined a market, it has the potential reduce the volume at individual centers, forcing them to compete to attain or retain patients. Moreover, because reimbursement for all patients are not equivalent, market pressure could induce "cream skimming" that may erode budgetary surpluses at nearby clinics and potentially limit centers' capacity to cross-subsidize and engage in mission focused activities.[13;14;15;16]

However, most of the available evidence, largely from hospital and private primary care settings, suggests that competition is generally associated with increased efficiency and quality of care.[17;18;19;20] And there are reasons to hypothesize that FQHCs may respond to competitive pressures similarly, as each of the nearly 1,400 independent clinics are expected to tailor their delivery model to the needs of their communities.[16;21] Yet, FQHCs may present with constraints and considerations that are distinct from non-safety-net settings. First, as FQHCs are mandated to provide care to all patients regardless of their ability to pay,[22] clinics may not have the desire or capacity to strategically respond to competitive pressures.[13;14;15;16] Second, the payer mix of FQHCs includes a considerable fraction of patients who receive care for heavily subsidized rates or for free, and FQHCs may not respond to competitive markets in the same ways as those clinics where patient revenue covers a larger share of their incurred costs.[1] Third, there is likely a finite number of patients using safety net sites in some markets, potentially making the competition for patients even more fierce than other settings.[8;9;10;11] With scores of competitive shocks – instances of FQHCs opening a new site in the service area of another – occurring each year, any impacts may already be influencing how patients use FQHCs and how individual clinics perform.

Taken together, the impacts of competitive shocks on FQHCs remains a conspicuous gap in the academic literature, with fundamental implications for the design and functioning of safety-net clinics and their markets. In this study, I explore the interaction between an expanding safety net and competition, examining the impact of competitive shocks on the organization and delivery of healthcare at FQHCs. Using clinic-level data from 2010 through 2021 and a staggered difference-in-differences design, I compare changes in the performance, resource allocation, and capacity of healthcare among incumbent clinics after the first competitive shock from a new rival FQHC and compare it to changes among control FQHCs that never experienced a competitive shock.

This work unites the literatures on spatial competition, healthcare markets and performance, extending them into a new context: the health care safety net. I begin by detailing how FQHCs may respond to a competitive shock if they operated like for-profit firms as outlined in the classic Hotelling model.[23] I then specify a safety net utility function, beginning with the model of the Newhouse model of a nonprofit hospital and incorporating unique features of the Health Center Program.[24;25;26;27;28] Lastly, I conduct a comparative statics analysis *à la Hotelling* to generate hypotheses about how FQHC performance, resources allocation, and capacity may be impacted by their rival's proximity decisions and compare them with the predictions from the for-profit model.[23;18;29;30;31;32] From this analysis and given the competing demands on FQHCs, I hypothesize that FQHCs will respond to competitive shocks in a manner consistent with for-profit clinics, increasing their quality of care, reallocating and expanding resources toward the rival.

In the empirical analysis, I find that FQHCs do respond to the first entrance of a rival FQHC into their service area like for-profit entities: boosting quality, shifting resources toward the rival, and expanding services to more patients. Competitive shocks are associated with a significant increase in an incumbent FQHC's quality, but with a significant, short-run reduction in their financial stability as well. In part, this quality improvement is achieved via a net decrease in the prevalence of chronic conditions while increasing the intensity of the care provided to manage those conditions. This is accompanied by a significant shift in the incumbents' payer mix, caring for more patients on generous insurance plans. Concurrently, competitive shocks are associated with significant growth of the incumbent clinics, where they disproportionately move resources from outlying zip codes closer to the new rival and attract hundreds of new patients in that newly competitive zip code. Additionally, I find that competitive shocks are associated with significant, large increases in patient utilization of the incumbent clinics, especially among patients with generous insurance coverage. In part, this expanded capacity is driven by increased operational efficiency.

This study constitutes the first comprehensive evaluation of the impacts of competitive shocks on the Health Center Program, highlighting FQHCs as organizations that are sensitive and responsive to the service area entrance of a rival. By extending foundational economic theory on spatial competition and nonprofit healthcare firms to a new context,[23;24] this work outlines a novel framework to understand the behavior of safety net organizations, illustrating how they may respond like for-profit clinics to competitive shocks. This study challenges the existing paradigm that presents safety net providers as the victims of competition, strained by market pressures.[33;34] Instead, this work builds on research around the growth of FQHCs,[8;9;10;11] exploring whether FQHCs act as for-profit or safety net entities in their healthcare markets. Furthermore, this study presents the first evidence of FQHCs' dynamic response to competitive shocks, outlining a new line of scientific inquiry on market forces and the associated impacts on the performance, functioning, and stability of safety net health care organizations and the health of the patients they serve.

I begin by orienting this work within the policy context of the Health Center Program (Section 2). I then proceed into a comparative statics analysis which directly inform my hypotheses (Section 3). I detail the data (Section 4) and methodology (Section 5) used to empirically test my analysis, present the results (Section 6), and discuss them (Section 7).

2 Background

2.1 What is a Federally Qualified Health Center?

An FQHC is an independently-operated community health center that is designated by the Health Resources and Services Administration and receives subsidized grants from the federal government through Section 330 of the Public Health Service Act.[35] As of today, there are approximately 1,400 FQHCs operating about 15,000 care delivery locations in about 6,000 zip codes nationwide.[1] These grants reimburse FQHCs for the uncompensated care they provide, promoting the financial stability and financial viability of these clinics. These efforts are designed to support these safety net clinics in their multipronged mission: 1) to increase access to care for the poor, 2) to subsidize care for the uninsured, and 3) to serve as a modality to reduce disparities. Accordingly, FQHCs are subjected to more stringent regulatory oversights and are mandated to provide care to all individuals regardless of their ability to pay.[22] Notably, the dependability of these grants has been called into question,[36;37] such that FQHCs may not rely on federal support to maintain their organizations.

2.2 Where do FQHCs operate?

Currently, almost 20% of US zip codes contain at least one FQHC site (Exhibit 8.1.1). These areas are more likely to be low income with higher uninsured and Medicaid coverage rates.[10] Each clinic's service area is generally limited to only Medically Underserved Areas or within reach of a Medically Underserved Population (MUA/P).[38;39] As such, 75% of an FQHC's population is expected to be from an MUA/P, inhibiting the potential for a clinic to cost-shift within their clinic by operating a site in a higher-income area. Additionally, FQHCs are expected to maintain or increase their panel size, with the threat of a reduced HRSA grant should their practice contract significantly. Together, these incentives to both grow and primarily operate in underserved communities creates an environment where neighboring clinics will eventually spread and share their service area.

2.3 How are service area overlap and competition regulated?

When an FQHC seeks to open a care delivery site in the same zip code as an existing FQHC, HRSA's Service Area overlap policy takes effect.[40] The expanding (alternatively, the Rival) FQHC must make an application to HRSA, justifying this expansion into the service area of the existing clinic (alternatively, the Incumbent). The rival clinic must convince HRSA that they are stable and suitable for this expansion, and that there is sufficient unmet need in that community to justify the entrance of another FQHC. Critically, the stability, suitability, or resilience of the incumbent is not considered in this process. Given that the Health Center Program has doubled over the past 15 years,[1;2] the implications of this policy must be reevaluated. Furthermore, FQHCs are mandated by the Public Health Service Act to collaborate with all other health care actors within their service area.[12] This creates a contradictory policy environment, where these safety net clinics are incentivized to expand into the service areas of other FQHCs to continue capturing more of the market share but are also expected to cooperatively integrate themselves in the market.

2.4 How do FQHCs and private pricatice clinics compare?

Compared to private practices, FQHCs have a varied set of financial incentives that may differentially affect how they operate. For example, FQHCs are mission-driven organizations,[41;42] often internalizing their federal mandate as a core part of their value system. Such values compete with explicit profit incentives among private practices, often leading to worse health outcomes.[27;43] Accordingly, FQHCs have been shown to exchange some profit for quality,[6] with over 50% of FQHC CEOs identifying financial viability as a challenge.[16] It is this contradictory set of mandates that leads to complex decision making that is not well understood. Additionally, it is likely that competitive shocks will disrupt the delicate balance between those forces, given the existing literature on healthcare competition. As little research has explored the role of markets in the safety net, this study seeks to fill this gap to inform and guide policy makers as this program continues to grow.

3 Theory

Uniting and extending foundational work on non-profit hospitals and spatial competition,[23;24] I explore whether FQHCs respond to a competitive shock like a for-profit or safety net clinic, detailing a set of hypotheses. I begin by summarizing how an FQHC would respond if they operated like for-profit clinics, a natural corollary to Hotelling's competitive duopoly model. I then specify a safety net utility function, beginning with the Newhouse model of a nonprofit hospital and incorporating unique features of the Health Center Program. Lastly, I conduct a comparative statics analysis *à la Hotelling* to generate hypotheses about how FQHC performance, allocation, and capacity may be impacted by their rival's proximity decisions and compare them with the predictions from the for-profit model.

3.1 Conceptual Motivation

The economic literature on nonprofit hospitals has illustrated that, in unconcentrated markets, such facilities may operate more like for-profit entities.[24;25;26;27;28] That is, they will improve their performance and efficiency while lowering costs to attract more and often higher margin patients. However, unlike hospitals, FQHCs are less able to adjust the cost of care for patients - given the predominance of Medicaid and uninsured individuals who experience few to no out-of-pocket costs to use these clinics - and instead are more geographically mobile, better able to open new care delivery locations away from their centralized hub. Therefore, the inclusion of a spatial Hotelling framework complements this foundation,[23;18;29;31;32] building a model that relates the spatial distribution of these clinics to their performance.

Given the explicit policy incentives to grow their boarders and serve more patients within their communities (Section 2) and a recent significant increase in FQHC proximity,[8;9;11;10] it is likely that competitive shocks (i.e., rival entering an incumbent's service area) may lead to competition for patients between clinics. Accordingly, FQHCs may respond by increasing their quality or changing where they operate care delivery sites, bounded by their operational capacity. Uniting the Newhouse and Hotelling frameworks, I generate predictions about the impacts of competitive shocks on the performance, allocation and capacity of incumbent FQHCs operating under for-profit and safety net models, which is formalized in this section.

3.2 For-Profit Model

In the Hotelling model of a competitive duopoly, 1) two firms set prices and their location 2) in a single market with individuals uniformly distributed on a line 3) to maximize their profit.[23] Approaching a competitive equilibrium, these firms will move closer together, lowering their prices until both firms are offering the same good at the same price from the center of the line.[23] Since I posit that FQHCs cannot compete on price, clinics must improve their quality to attract the marginal patient, as demonstrated by other types of healthcare actors in the literature.[23;18;32] That is, responding to a competitive shock under a profit-maximizing utility function, I predict that the incumbent FQHC will increase their quality of care, move closer to the new rival, and seek to expand their capacity to see more patients.

3.3 Safety Net Model

3.3.1 Safety Net Utility Function

From the literature on non-profit hospitals, I begin with the premise that FQHCs likely maximize both quality of care and profits. I assume that each clinic j provides an average quality of care to each patient as a function of their visit capacity $V_{max,j}$, the number of patients treated n_j, and the probability of the clinic meeting the average patient's quality of care needs in any visit p_j, taking the following form:

$$Q_j(n_j, p_j, V_{max,j}) = 1 - (1 - p_j)^{V_{max,j}/n_j} \tag{1}$$

The variables $V_{max,j}, n_j, p_j$ are set *a priori* in each period (herein, each year) by the FQHC. Q_j represents the cumulative odds of the average patient meeting their quality measures, aligning this model with the quality tracking performed by HRSA.[44] Quality is measured, reported, and scored across FQHCs in an annualized fashion, with each patient either being compliant or noncompliant at the end of every calendar year, as captured in this form.

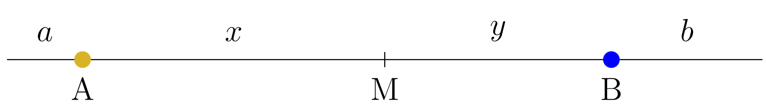
Additionally, clinics are assumed to be compensated exclusively via a fee-for-service model and, given the explicit mandate by HRSA to continually reach new patients, to steadily expand n_j over time. Assuming that these features are additively separable, each FQHC generates a cumulative annual utility U_j, such that:

$$U_j = n_j\big[z_j + q_jQ_j + \bar{v}_j[R_j(\bar{\alpha}) - C_jq_jp_j] - F_j\big] \tag{2}$$

where z_j, q_j are the FQHC's value of reaching more patients and the value of the average quality provided. Q_j is the average quality provided by the FQHC and the clinic receives $R(\bar{\alpha})$ dollars to provide the average visit for their average payor generosity $\bar{\alpha}$, with patients' averaging $\bar{v}_j$ visits per year. The costs to provide each visit has a variable $C_jq_jp_j$ and fixed F_j component. The variable component is adjusted by the value of the per-visit level of quality, such that clinics will incur a cost as they increase the average quality provided.

3.3.2 Modified Hotelling Model

Begin with a population uniformly distributed on a line. On this line, there are two clinics, A and B, separated by a distance of $x + y$ and completely partitioning the market:



A patient living at point M would have to travel a distance of x to receive care at clinic A of quality Q_A or a distance of y to receive care at clinic B at quality Q_B. While FQHCs are multi-location practices, this simplified model is reasonable as the average distance between care delivery locations within the same health center is smaller than the average distance between clinics, with the model above representing the geographic center of each FQHC.

Furthermore, assume that the price of care at both clinics is the same for each patient, as is the case for Medicaid enrollees and uninsured patients who constitute the majority of FQHC patients.[22] Therefore, a patient at point M is indifferent to selecting clinic A or B when the difference between the quality and cost to travel to each clinic are the same:

$$Q_A - ky = Q_B - kx \tag{3}$$

where k is the unit cost of travel for the patient. Extending this, clinic A attracts all the patients living in $a + x$ while clinic B attracts the patients living in $y + b$. As an identity, I define the market of length and size ℓ to be the sum of the component segments:

$$\ell = a + x + y + b \tag{4}$$

Combining these equations, I can derive expressions for the lengths x, y as functions of the relative difference in quality between clinics A and B:

$$x = \frac{1}{2}\left[\ell - a - b + \frac{Q_A - Q_B}{k}\right] \qquad y = \frac{1}{2}\left[\ell - a - b + \frac{Q_B - Q_A}{k}\right] \tag{5}$$

I see that differences in quality and market share for each clinic are positively associated, indicating that a clinic could expand their market share by increasing their quality. As price is not a factor for patient choice, such avenues to drive growth may be used by clinics.

3.3.3 Analytical Constraints

I assume that FQHC optimization decisions are primary bounded by their visit capacity V_{max}. As these clinics operate in medically underserved areas, I assume that epidemiological bounds (i.e., demand for health care) is not limiting in this setting. Therefore, when optimizing their utility, I posit that an FQHC will provide each patient with some average number of visits $\bar{v}$ such that they do not provide more care than their capacity allows, s.t. $n\bar{v} \leq V_{max}$.

3.3.4 Comparative Statics

To unify the prior sections, I link the definition of the total population served as follows:

$$n_A = a + x \qquad n_B = y + b \tag{6}$$

and write the following Lagrangian to optimize:

$$\mathcal{L}_A = n_A\big[z_A + q_A Q_A + \bar{v_A}[R_A(\bar{\alpha}) - C_A q_A p_A] - F_A\big] - \lambda(V_{max,A} - \bar{v_A} n_A) \tag{7}$$

From this, I can derive the first order conditions for clinic A, first for the location effects:

$$\begin{aligned}
\text{FOC for } b: \frac{\partial \mathcal{L}_A}{\partial b} &= \frac{\partial}{\partial b} n_A\big[z_A + q_A Q_A + \bar{v_A}[R_A(\bar{\alpha}) - C_A q_A p_A] - F_A\big] - \lambda(V_{max,A} - \bar{v_A} n_A) \\
&= \frac{\partial}{\partial b}(\ell - b - y)\big[z_A + q_A Q_A + \bar{v_A}[R_A(\bar{\alpha}) - C_A q_A p_A] - F_A\big] - \lambda\big(V_{max,A} - \bar{v_A}(\ell - b - y)\big) \\
&= (\ell - b - y)\big(q_A \frac{\partial Q_A}{\partial b}\big) - \big[z_A + q_A Q_A + \bar{v_A}[R_A(\bar{\alpha}) - C_A q_A p_A] - F_A\big] - \lambda \bar{v_A} = 0
\end{aligned} \tag{8}$$

$$\text{FOC for } a: \frac{\partial \mathcal{L}_A}{\partial a} = (a+x) q_A \frac{\partial Q_A}{\partial a} + \big[z_A + q_A Q_A + \bar{v_A}[R_A(\bar{\alpha}) - C_A q_A p_A] - F_A\big] + \lambda \bar{v_A} = 0 \tag{9}$$

and then I derive FOCs for the performance and operational effects:

$$\text{FOC for } p_A: \frac{\partial \mathcal{L}_A}{\partial p_A} = n_A q_A \frac{\partial Q_A}{\partial p_A} - V_{max,A} C_A = 0 \tag{10}$$

$$\text{FOC for } \bar{v_A}: \frac{\partial \mathcal{L}_A}{\partial \bar{v_A}} = n_A q_A \frac{\partial Q_A}{\partial \bar{v_A}} + n_A(R(\bar{\alpha}) - C_A q_A p_A) + \lambda n_A = 0 \tag{11}$$

$$\text{FOC for } V_{max,A}: \frac{\partial \mathcal{L}_A}{\partial V_{max,A}} = n_A q_A \frac{\partial Q_A}{\partial V_{max,A}} + (R_A(\bar{\alpha}) - C_A q_A p_A) - \lambda V_{max,A} = 0 \tag{12}$$

In equations 8 through 12, given the concavity of equation 1 across its domain, the first order conditions are all positive and the second order conditions are all negative, indicating that the conditions for an optimum are satisfied.

Combining these equations and assuming a positive profit from the average visit, I can identify how a competitive shock by the rival (a sharp increase in b) affects the functioning of an incumbent FQHC, specifying the comparative static analytical results:

$$\frac{\partial a}{\partial b} < 0 \qquad \frac{\partial \bar{v_A}}{\partial b} < 0 \qquad \frac{\partial p_A}{\partial b} > 0 \qquad \frac{\partial V_{max,A}}{\partial b} < 0$$

predicting that a competitive shock may result in the incumbent moving away from the rival, decreasing their per-patient visit rate, increasing their per-visit quality, and reducing their total visit capacity. That is, a safety net clinic will not engage competitively with the rival, electing to contract their operation and reorganize to decrease the travel costs for their remaining patients. Notably, the opposing signs on the per-patient visit rate $\bar{v_A}$ and per-visit quality p_A terms indicate that the net impact on quality is ambiguous.

3.4 Hypotheses

Compiling the for-profit and safety net predictions, I find that the expected FQHC response to a competitive shock differs across these models. If an FQHC responds like a for-profit clinic, then it will increase their quality of care, move toward the new rival, and expand services. If an FQHC responds like a safety net clinic, it will instead move away from the rival and lower their visit capacity, with ambiguous changes in their quality of care. Given their increasingly strained resources and tenuous policy environment,[36;16] I hypothesize that FQHCs will respond like for-profit clinics instead of as safety net organizations. Such a response would be consistent with the existing literature on nonprofit hospitals.[27;28]

Change in FQHC Choice Variables, by Profit Orientation		
Choice Variables	Safety Net	For-Profit
Quality, Q_A	Ambiguous	Positive
Location, a	Negative	Positive
Capacity, $V_{max,A}$	Negative	Positive

4 Data

This study evaluates the impacts of competitive shocks on the organization and care delivery of FQHCs between 2010 and 2021, conducted from August, 2022 through October, 2023.

4.1 Data Sources

The primary data source for this study was the Uniform Data System (UDS) linked with IRS form 990 tax documents from 2010 through 2021. The UDS is an annual report submitted by each FQHC to the Health Resources and Services Administration (HRSA) as required for their continued participation in the Health Center Program. These data contain a rich summary of each FQHC's patient demographics, service area(s) (i.e., set of zip codes where an FQHC operates a care delivery site),[40] care delivery system attributes, quality of care metrics, and annual financial profile.[44] While self-reported, submitted data is reviewed by independent parties to ensure quality.[44;45;46] I also abstracted annual IRS form 990 tax documents to access a more detailed financial profile of each clinic, including summaries of expenses and revenue, liquidity, debts, and assets.[47] These files were joined by linking Employer Identification Numbers (EIN) from the IRS data with HRSA grantee records.

4.2 Study Sample

From the set of all FQHCs, I reduced my sample to include only those that continually operated from 2010 through 2021 as well as FQHCs that had no entrant FQHCs operating in their service area between 2010 and 2012. This led to an analytic sample of 406 FQHCs from 2010 through 2021 (4,872 FQHC-years), comprised of 325 control and 81 treated FQHCs. Herein, this is referred to as the **core dataset**.

From this core sample, I construct an additional dataset with each service area zip code for all FQHCs in this sample. The UDS contains detailed information on care delivery locations as well as the number of patients in each FQHC's panel by their insurance status at the zip code level. I leverage this granularity to evaluate second-order effects of an entrant FQHC on the incumbent's resources, patient panel and payor mix. Combining the above FQHC-year dataset with the zip code-level data and removing those zip codes without a complete panel of data in the study period, yielding a final sample of 21,040 FQHC-zip-year observations was constructed. Herein, this sample is referred to as the **allocation dataset**.

Service area boundaries are used throughout this study for a series of reasons. First, they are salient for both regulators and FQHCs, as the service area is defined by each clinic's geographical footprint to which federal funding is directly tied.[40] Second, they are a discreet measure of a clinic's target community, with a discontinuity at the bounds of a clinic's impact. Lastly, I posit that FQHCs make decisions as a unified clinic, even if they operate multiple service delivery sites. Therefore, competition in one zip code could spillover into neighboring zip codes via patient movement across boarders or through organizational responses from the incumbent FQHC, meriting a holistic service area evaluation.

4.3 Study Variables

4.3.1 Outcomes

For these datasets, I respectively evaluate the effects of competitive shocks on a different domain of outcome measure, evaluating FQHC performance, access, and utilization.

Contained in the core dataset, the primary outcome variables are the total number of patients by insurance coverage, a composite of 6 quality performance measures reported annually by each FQHC, and Altman's Z score, a measure of financial risk. The total numbers of patients are disaggregated into one of four insurance groups: Medicaid, Medicare, Uninsured, and Private. The quality composite includes 4 measures of process quality (i.e., cervical and colorectal cancer screening, and BMI assessment for adult and children) and 2 intermediate health outcome measures (i.e., blood pressure control for hypertension and HbA1c control for diabetes mellitus). These selected measures were compiled by each FQHC across the study period. I construct a modified Altman's Z score via data from the IRS form 990 tax documents, following a model in the literature that has been used to assess the bankruptcy risk and financial distress of nonprofit health care firms.[48] Additionally, I measure a composite risk profile, averaging the prevalence for several chronic conditions (i.e., hypertension, heart disease, diabetes, HIV, and depression), and the intensity of care (i.e., visits per year per presenting condition) provided to manage those conditions, labeled as the Complexity of their panel and the Intensity of their care. Lastly, to evaluate changes in capacity, I also measure the number of care delivery sites operated by each FQHC as well as the number of staff employed. From this, I construct a measure of operational efficiency, taking the log of the ratio of patients served to staff.

In the allocation dataset, I measure a set of secondary outcomes including the total number of patients, the payer mix, and the amount of clinic resources and access in that zip code. From the UDS, counts of the number of patients served and their primary insurance coverage (i.e., Medicaid, Medicare, Private, Uninsured) are reported by zip code. Additionally, each FQHC reports the details on each of their care delivery locations, including the address and hours of operation, which I can estimate the hours of clinic access per week, zip code, and clinic, representing the amount of access to care they provide.

4.3.2 Treatment

The primary independent variable is a binary indicator variable for whether an FQHC experienced an entrant FQHC operating a care delivery site in their service area in that year or any year prior (i.e., a competitive shock). The clinics sampled did not have an FQHC operating in their service area from 2010 through 2012. Treated FQHCs (i.e., incumbents) were classified accordingly if an entrant FQHC opened a site in one of their service area zip codes from 2013 through 2021, with the rest classified as control FQHCs ($N_{treated}$ = 81, $N_{control}$ = 325). This allows for a sufficiently long period leading up to the initial treatment cohort, facilitating pre-period robustness testing. For FQHCs that gained additional entrants or lost their first entrant, I only evaluated the first entrant effect and considered these clinics as treated throughout the rest of the study period. To identify episodes of service area overlap, I used UDS-reported zip codes for each site. Care delivery locations with missing zip codes were geocoded using R package tidygeocoder based on street address, city, and state.[49] 2,351 of 188,381 total observations were unable to be geolocated and were excluded.

However, there is strong potential for anticipation on the part of the potential incumbent. Part detailed by HRSA, potential rivals are expected to communicate with incumbent clinics before opening a competitive care delivery location.[40] The potential rival is expected, but not mandated, to send a letter to the incumbent's Board of Directors ahead of expansion and receive their written approval. Accordingly, this early information could trigger a competitive response among the incumbent clinics before experiencing a competitive shock and I accordingly adjust certain analyses by including 1 year of anticipation.

4.3.3 Covariates and Modifiers

A set of time-varying covariates are used in this analysis to adjust for differences in treated and control FQHCs, aggregated in the UDS by clinic-year, including: race/ethnicity (non-Hispanic Black, non-Hispanic Asian, and percent Hispanic-Latino), percent with incomes below 100% of the federal poverty limit, percent homeless, and percent migrant farm workers.

As distance is a critical driver of health care utilization and is proposed in this study to be influenced by the market structure, it is likely that the effects of a competitive shock across the entire service area of the incumbent clinic will be significantly associated with distance to the competitive zip code. To evaluate this heterogeneity, I interact treatment effect estimates in the secondary analysis by this distance to the competitive zip code from the outlying zip codes (population centroid-to-centroid), evaluating how incumbent's shift their resources and how patient utilization of the incumbent changes as a function of distance to the rival. Additionally, I include a stratified analysis, evaluating changes in the newly competitive zip code and the farthest 13% of zip codes, as about 13% of the zip codes in the allocation dataset receive the new care delivery site from the rival.

5 Empirical Approach

5.1 Model Specification

This study used a difference-in-differences (DID) analysis, which compared the change in my outcomes of interest in treated FQHCs relative to changes in those outcomes in control FQHCs. Because the treatment (i.e., first entrant opening a site in service area) occurred at different times, I rely on methods developed specifically to estimate DID with variation in treatment timing.[50;51;52;53;54] These approaches relax the assumption of constant treatment effects over time, separately estimating treatment effects for each year of designation and a weighted average treatment effect across periods. The advantage of a difference-in-differences method as compared with a pre-post design is the use of a contemporaneous control group that can account for secular trends unrelated to the policy of interest.

I used a two-stage regression model outlined by Gardner (2022),[53] specifying my core model as follows:

$$\textbf{First Stage: } Y_{gpit} = \lambda_g + \gamma_p + X_{gpit}\delta_{pt} + \epsilon_{gpit}$$

$$\textbf{Second Stage: } Y_{gpit} - \widehat{\lambda}_g - \widehat{\gamma}_p - X_{gpit}\widehat{\delta_{pt}} = \beta_0 + \beta_1 D_{gp} + \eta_{gpit}$$

In the first stage, outcome variable Y_{gpit} is regressed on unit of observation group fixed effects λ_g, year period fixed effects γ_p, and time-varying covariates X_{gpit}. In the second stage, I regress the residual of the first stage on the binary treatment status D_{gp}. Conditional on the parallel trends assumption, this regression provides consistent estimates for the treatment effect, $ATT = \mathbb{E}\big[\beta_1 | D_{gp} = 1\big]$. This model is used in all analyses unless otherwise specified.

This approach allows for significant model flexibility which I leverage in my secondary analysis of resource allocation by zip code to estimate heterogeneous treatment effects. By changing the second stage to incorporate an interaction term, I can rewrite it as follows:

$$\textbf{Interacted Second Stage: } Y_{gpit} - \widehat{\lambda}_g - \widehat{\gamma}_p - X_{gpit}\widehat{\delta_{pt}} = \beta_0 + \beta_1 D_{gp} + \beta_2 H_i + \beta_3 D_{gp} H_i + \eta_{gpit}$$

By interacting a time-invariant variable H_i with the treatment indicator, and conditional on the parallel trends assumption, this regression provides consistent estimates of the heterogeneity in the ATT across levels or unit shifts in that variable, $\mathbb{E}\big[\beta_3|D_{gp}=1\big]$. I use this variation in the secondary analysis of resource allocation, stratifying the treatment effect estimates by the distance between the centroids of the competitive zip code and the index zip code. That is, I interact the treatment status D_{gp} with the distance to the competitive zip code, H_i, scaled to 10-kilometer (km) increments for ease of of interpretation. Conditional on the parallel trends assumption, this model provides consistent estimates for the ATT in the competitive zip code and the change in the ATT for every 10km between the competitive zip code and the index zip code. That is:

$$\textbf{ATT(in competitive zip)} = \mathbb{E}\big[\beta_1|D_{gp}=1\big]$$

$$\textbf{ATT(in zip code H km away)} = \mathbb{E}\big[\beta_1|D_{gp}=1\big] + \frac{H}{10}\cdot\mathbb{E}\big[\beta_3|D_{gp}=1\big]$$

5.2 Statistical Analysis

I begin by visualizing trends in FQHC colocation and compiling descriptive statistics on the sample population (Section 6.1). In the primary analysis, I use the core dataset (FQHC-year units) to conduct a two-stage DID analysis on the effects of competitive shocks on the total population served, payer mix, quality of care, and financial stability of incumbent FQHCs (Section 6.2). Standard errors are clustered at the state level, accounting for serial correlation in outcomes over time. To evaluate the potential effects of competitive shocks on patient selection and stinting, I repeat this analysis on composite measures of population complexity and intensity of care. Additionally, I stratified the population by insurance payer, estimating the effects of a competitive shock on the payer mix. I also include event study plots, allowing for the visual evaluation of pre-period trends between treated and control FQHCs as well as changes in the effect estimates over time.

In the secondary analysis, I use the allocation dataset (FQHC-zip-year units) to conduct a two-stage DID analysis using the zip code model on the effects of competitive shocks on volume of patients served (total and by insurance payer) as well as measures of FQHC access, including analyses stratified by or interacted with the distance from the competitive shock (Section 6.3). Conservative clinic-level treatment status is used, such that if at least one zip code in an FQHC's service area experiences a competitor, then all zip codes in that service area are classified as treated. Standard errors are clustered at the zip level. In the tertiary analysis, I use the core dataset (FQHC-year units) to conduct a two-stage DID analysis on the effects of competitive shocks on the patient utilization and FQHC capacity (Section 6.4), clustering standard errors at the state level.

5.3 Sensitivity Analysis

Lastly, I conducted a series of sensitivity analyses to evaluate the robustness of these results (Section 6.5). I evaluate alternative staggered difference-in-differences estimation methods. I also evaluate variations in the primary, performance effect estimates across three subsets of time periods in the sample. Across all performance, access, and utilization outcome measures, I conduct a Benjamini-Hochberg analysis to correct for multiple hypothesis testing.

Given concerns about the potential endogeneity of a rival FQHCs decision to enter the service area of an incumbent, I conduct a series of analyses to address these concerns. I compare the demographics and performance metrics between rival and incumbent FQHCs. I also compare how far rivals traveled to open their new care delivery location and create a newly competitive zip code, visualizing the distribution of distances and geographic locations.

5.4 Technical Aspects

I estimated all DID models with the did2s package.[55] Analyses were conducted using R version 4.1.3 and all statistical tests are reported with p-values derived from two-tailed tests of statistical significance (at $p < 0.05$).

6 Results

6.1 Study Population

Descriptive analyses reveal that FQHCs have expanded steadily over the past 25 years (Figure 1). Clinics increasingly are opening new care delivery sites in zip codes with existing sites. This growth has resulted in multiple FQHCs operating in the same zip codes, with most clinics today having at least one competitor FQHC in their service area. Over the past decade, the rate of new FQHC creation has been outpaced by the incidence of competitive shocks converting monopolistic FQHC markets into competitive oligopolies.

From the set of FQHCs that had no rival clinics in their service area between 2010 and 2012, I identify a final analytical sample of 406 FQHCs (81 treated, 325 control) from across the US (Table 1). Compared to control FQHCs, treated clinics were more likely to serve more patients overall, caring for more Black, low-income, homeless, and Medicaid patients as well as fewer Medicare and privately-insured patients (all p-values <0.05).

6.2 Difference-in-differences Estimates of Performance

In my analysis of primary performance metrics, I find that competitive shocks were associated with significant improvements in FQHC composite quality of care and significant decreases in their financial resilience (Table 2). For example, treated FQHCs improved their composite quality of care from 55.94% before the competitive shock to 60.43% afterward. Concurrently, FQHCs that did not experience a competitive shock improved their composite quality of care from 54.93% to 57.15%. This corresponds to an unadjusted between-group difference of 2.27 percentage points (pp). After adjustment for clinic level characteristics, the staggered difference-in-differences (DID) estimate was statistically significant improvement of 2.24 percentage points (95% CI: 0.04 pp to 4.44 pp) and corresponds to a 4.0% improvement in their composite quality of care. A significant reduction in their Altman's Z score were also estimated (-0.21, 95% CI: -0.39 to -0.03), which is driven by a relative decrease in assets (not shown). Event study plots confirm these primary findings, showing sustained improvements in quality of care while significant reductions in financial resilience were concentrated in the first and second years after a competitive shock (Figure 2).

Evaluating patient selection on disease burden, I find that competitive shocks were associated with significant reductions in the prevalence of chronic conditions and with significant increases in the intensity to care for such conditions (Table 3). For example, the average burden of 5 chronic conditions at treated FQHCs increased from 6.95% before the competitive shock to 7.87% afterward. Concurrently, the average prevalence of these chronic conditions at FQHCs that did not experience a competitive shock increased from 6.57% to 7.81%, an unadjusted between-group difference of -0.32 pp. After adjustment for clinic level characteristics, the staggered DID estimate was a statistically significant decrease of 0.32 percentage points (95% CI: -0.62 pp to -0.02 pp) which corresponds to a 4.6% reduction in the prevalence of these conditions. Despite the relative decrease, the chronic condition burden at treated FQHCs increased at a slower rate than at control clinics. Furthermore, treated FQHCs increased the average number of visits per year provided to care for those chronic conditions (0.11 visits, 95% CI: 0.04 to 0.18). Event study plots confirm these findings (Figure 3).

Evaluating patient volume and 3rd party insurance payer mix, I find that competitive shocks were associated with significant increases in the number of Medicaid and commercially insured patients (Table 4). For example, the number of patients served by treated FQHCs who were enrolled in Medicaid increased from 9,001 before the competitive shock to 11,973 afterward. Concurrently, the number of Medicaid patients at control FQHCs increased from 4,809 to 5,925. This corresponds to an unadjusted between-group difference of 1855 patients. After adjustment for clinic level characteristics, the staggered DID estimate was a statistically significant increase of 1844 patients (95% CI: 402 to 3,286 patients) and corresponds to a 20.5% increase. Additionally, significant increases in the commercially insured population were also observed (1,266 patients, 95% CI: 104 to 2,428 patients). Event study plots confirm these findings as well, showing sustained changes in the payer mix (Figure 4).

6.3 Difference-in-differences Estimates of Resource Allocation

Analyzing changes in resource allocation to care, I find that competitive shocks were associated with significant shifts in the incumbent clinic's resources and patient population toward the new rival (Table 5). For example, in the competitive zip code, incumbent FQHCs experience a significant increase in the number of patients served (294.53 patients, 95% CI: 188.27 to 400.79). In outlying indirectly competitive zip codes in the incumbent's service area, the magnitude of this effect decreases. That is, for every 10 kilometers from this competitive zip code, the incumbent's growth in indirectly competitive zip codes decreases by 21.92 patients (95% CI: -30.83 to -13.01). In the farthest 20% of zip codes, this effect becomes negative, as see in the event study (Figure 6). Similarly, I find a significant increase of hours of clinic access per week in the competitive zip code (14.36 hours per week of clinic time, 95% CI: 10.45 to 18.27), decreasing significantly as a function of distance in outlying zip codes (-0.39 hours per week of clinic time, 95% CI: -0.75 to -0.03).

I present event study plots for access metrics on subsamples of the full dataset, evaluating changes in the competitive zip codes and the outlying 13% of zip codes (Figure 6). These results corroborate the initial findings, illustrating significant decreases in access in the farthest zip codes and significant increases in the competitive zip code. This corresponds to a 5% shift in clinic resources away from outlying zip codes and toward the rival.

6.4 Difference-in-differences Estimates of Capacity

Analyzing changes in FQHC capacity, I find competitive shocks to be associated with significant increases in FQHC patient volume at incumbent (Table 4), in part, driven by increased operational efficiency (Table 7). Incumbent FQHCs increase their number of care delivery locations by 0.8 sites (95% CI: 0.1 to 1.6). In terms of staffing, I find a non-significant increase. Given the increase in patients with no change in the staffing rates, I find significant increases in the patient-to-staff ratio, indicating that the incumbent increases their operational efficiency. XX These trends are confirmed by the event study plots (Figure 7).

6.5 Sensitivity and Supporting Analyses

I find that these results are robust to alternative model specifications (Figure A1) and variation in treatment effects over time (Figure A2). Correcting for multiple hypotheses, all significant performance, resource allocation, and capacity results remained significant at the 10% false-positive rate (Figure A3). Pre-period parallel trends were evaluated and found to be not significant in all primary and secondary analyses (Not shown). I also find that rival and incumbent FQHCs are descriptively similar at baseline (Table A1), with rival clinics serving slightly fewer low-income and Asian patients while serving more privately insured patients (all p-values <0.05). Additionally, 75% of rival clinics traveled fewer than 25km to open their new, competing care delivery location (Figure A4). If a rival travelled further than 25km, then they were doing so in predominately rural areas (Figure A5).

7 Discussion

XX I want a nicer summary paragraph

In what is the first theoretical and empirical study on the effects of competition on FQHCs, I find that competitive shocks significantly impacted the organization and care delivery of FQHCs. Incumbent clinics provided significantly higher quality health care, driven in part by a short-run reduction in financial resilience and a long-run shift toward a patient population with fewer chronic conditions and more generous insurance coverage. In terms of resources, I find that incumbents expand access and serve more patients overall while reducing access in outlying communities. This growth is disproportionately concentrated in these newly competitive zip codes and those most proximal thereto. These trends are associated with FQHCs reallocating resources away from outlying zip codes toward the new rival and is further supported by an expansion of clinic capacity via increased operational efficiency.

This study highlights FQHCs as dynamic organizations that are both sensitive and responsive to their markets. Not only do they experience shocks to their performance, but they respond to the emergence of a rival by reallocating resources and growing toward them. These results support the novel application of foundational theoretical spatial competitive equilibrium and nonprofit hospital models to the health care safety net.[23;24] This work indicates that after experiencing a competitive shock, FQHCs may respond like for-profit rather than safety net clinics, following patterns observed among nonprofit hospitals and general practitioners in single-payer systems.[18;28] As FQHCs are a critical and growing part of the US safety net, understanding the potential benefits and harms of competition is vital.

In fact, this study corroborates the concerns of FQHC leaders, with robust evidence of negative financial impacts and cream-skimming associated with competitive shocks. However, I propose that these downsides are outweighed by the net benefit of competition on quality and access. Given that this patient selection is not accompanied with absolute reductions in the proportion of patients with chronic conditions or without insurance, I do not find evidence of crowding out. That is, it is possible that FQHCs maintain their mission to serve as a safety net by subsidizing their competitive edge via cream skimming, ameliorating the short run reductions in financial welfare to achieve long-term improvements in quality and sustain expanded access to more patients.

However, these findings indicate a marked divergence from how we traditionally understood FQHC decision making and behavior,[33;34] outlining a series of long-term implications for the health care safety net. Since FQHCs respond like for-profit clinics to competition, profitability may be prioritized ahead of allocating resources to improve quality or recruit more patients. While accentuated under competitive pressures, this value system may have been foundational to clinics for decades, contrary to the standard narrative of FQHCs as primarily mission-driven organizations.[41;42] Additionally, the competitive inclination for FQHCs to move closer together has resulted in clusters of access separated by persistently underserved areas.[8;9;11;10;56] Unless modified, FQHCs in competitive markets have little incentive to meet these unmet needs and may even exacerbate this problem by reallocating resources away from outlying, uncompetitive communities toward the rival clinics.

These insights have implications for policy makers engaged in efforts to improve the performance, shape, and efficiency of this safety net. Federal policy makers could establish incentives against stinting uninsured individuals or those with chronic conditions via additional payments to subsidize the provision of wrap-around care for these patients. This would increase the desirability of such patients to the myriad clinics in each market, likely reducing the selection effects observed in this study. Additionally, these findings support the introduction of dispersive incentives, expanding FQHCs' funding to open new sites in areas without another clinic. These competitive pressures have amplified a well-documented tendency for FQHCs to cluster,[8;9;11;10;56] meriting the inclusion of bonus payments for clinics willing to help resolve the "last mile" deficiencies. Lastly, federal legislators may make grants more transparent and dependable for clinics. Federal funding for the Health Center Program goes through a triennial redetermination process, such that clinics face a potential budgetary crisis every three years.[36;37] This recurrent threat is likely a contributing driver to the strength of these findings, as FQHCs may make existential decisions after a competitive shock without the long-term security of predetermined federal support. By securing the financing behind the Health Center Program,[12] policymakers can attenuate the need for clinics to sacrifice their safety net mandate to secure their financial foundation.

This study has several limitations. First, this analysis is conducted on data that is reported by each FQHC, containing repeated cross-sections of their patient panel and business annually. While I do find some evidence of aggregate-level shifts in patient panel complexity and demographics, there is likely some amount of unobservable patient turnover. Additionally, while the metrics are self-reported, there is a robust validation process conducted by HRSA to support the accuracy of the data.[44;45;46] Second, the exact reasons behind the selection criteria used by the rivals could be potentially endogenous to the changes in the incumbent's performance. However, supporting analyses show that the rivals shock the incumbent, they are largely growing into neighboring areas. And, when a rival does cross a significant distance, they are largely crossing areas of very low population density, where placing a clinic may be financially risky. Third, I do not use patient-level spending data to fully account for changes in cost savings in non-FQHC settings. It is possible that improved health outcomes and financial constraints could significantly alter patterns of care utilization of hospitals, urgent care centers, and pharmacies, which will be addressed in future work.

8 Conclusion

This study finds that FQHCs respond to competitive shocks like for-profit clinics, experiencing a significant boost in performance and efficiency, expanding and reallocating their resources toward the new rival, and jeopardizing their social mission to maintain a competitive edge. Policy guardrails may be instituted to incentivize clinics to grow into persistently underserved communities and provide care to patients without health insurance and those with chronic conditions in addition to solidifying federal grant funding. XX

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Table 1: Sample Demographics

Characteristic	Control (N = 325)	Treated (N = 81)	p-value
Demographics			
Total Patients	12,468 (10,939)	20,988 (17,430)	<0.001
Non-Hispanic Asian, %	1.29 (4.13)	1.31 (2.58)	0.009
Non-Hispanic Black, %	13.42 (19.70)	24.17 (27.29)	<0.001
Hispanic-Latino, %	17.12 (21.58)	19.70 (25.52)	0.508
Poverty (<100% FPL), %	62.62 (16.66)	71.17 (16.19)	<0.001
Special Populations			
Migrant Farm Worker, %	2.03 (5.79)	4.01 (13.7)	0.636
Homeless, %	2.59 (8.64)	3.53 (6.92)	0.030
Insurance Payer Mix			
Medicaid, %	28.97 (13.24)	36.09 (14.78)	<0.001
Private, %	22.39 (14.24)	15.11 (11.29)	<0.001
Medicare, %	10.67 (5.98)	8.51 (4.71)	0.004
Uninsured, %	36.66 (16.48)	38.87 (16.63)	0.282

Notes: Data from year 2010, representing mean (sd). Data extracted from the Uniform Data System for each FQHC.

Table 2: Effects of Competitive Shocks on Performance

	Control		Treated			Adjusted DID	
Outcome	Pre	Post	Pre	Post	Unadj. DID	Estimate	95% CI
Total Patients	13,460	15,159	21,794	25,926	2,434	2,705	(-677, 6,087)
Quality, %	54.93	57.15	55.94	60.43	2.27	2.24**	(0.04, 4.44)
Altman's Z	2.51	2.67	2.62	2.42	-0.36	-0.21**	(-0.39, -0.03)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Notes: Data presented here are difference-in-differences (DID) estimated impacts of competitive shocks on FQHC performance across these primary outcomes. Quality represents a composite of 4 process measures and 2 intermediate health outcomes (see Section 4 for details). Higher values for Altman's Z scores indicate more financial resilience.

Table 3: Effects of Competitive Shocks on Chronic Disease Prevalence and Care Intensity

	Control		Treated			Adjusted DID	
Outcome	Pre	Post	Pre	Post	Unadj. DID	Estimate	95% CI
Complexity	6.57	7.81	6.95	7.87	-0.32	-0.32**	(-0.62, -0.02)
Intensity	2.29	2.37	2.30	2.38	0.00	0.11***	(0.04, 0.18)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Notes: Data presented here are difference-in-differences (DID) estimated impacts of competitive shocks on these outcome measures. *Complexity* is a simple average of the prevalence of 5 chronic conditions and *Intensity* represents the average number of visits provided to manage those chronic conditions (See Section 4 for more details).

Table 4: Effects of Competitive Shocks on Payer Mix

	Control		Treated			Adjusted DID	
Outcome	Pre	Post	Pre	Post	Unadj. DID	Estimate	95% CI
Medicaid	4,809	5,926	9,000	11,973	1,855	1,844**	(402, 3,286)
Private	2,799	3,734	3,647	5,289	706	1,266**	(104, 2,428)
Medicare	1,474	1,999	2,148	2,560	-113	280*	(-42, 602)
Uninsured	4,229	3,393	6,734	5,968	69	-623	(-1,862, 617)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Notes: Data presented here are difference-in-differences (DID) estimated impacts of competitive shocks on FQHC 3rd party insurance payer mix. Notably, payers are ranked from most generous (Medicaid) to least (Uninsured).

Table 5: Effects of Competitive Shocks on Access to Care and Payer Mix, by Distance to Competitive Shock

	Effect Estimate in Competitive Zip		Change in Effect Estimate (per 10km from Competitive Zip)	
Outcome	Estimate	95% CI	Estimate	95% CI
Total Patients	218.1***	(135.5, 300.7)	-18.3***	(-26.2, -10.5)
By Payer				
Medicaid	115.6***	(61.5, 169.7)	-8.9***	(-14.3, -3.5)
Private	48.0***	(17.1, 78.9)	-2.8**	(-5.1, -0.5)
Medicare	16.8***	(4.3, 29.2)	-2.3***	(-3.2, -1.4)
Uninsured	15.0	(-21.3, 51.3)	-3.1	(-8.9, 2.8)
Access to Care				
Hours per Week	3.3*	(-0.5, 7.1)	-0.6***	(-0.9, -0.2)
Locations	0.0	(-0.1, 0.1)	0.0	(0.0, 0.0)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Note: Estimates follow the form outlined in Section 5, providing direct DID effect estimates in competitive zip code, a, and the change in those effect estimates as a function of distance to the competitive zip code, b. I find significant increases in patients in competitive and rival-proximate zip codes with a loss of patients in outlying zip codes. For example, the estimated ATT of a competitive shock on an incumbent FQHC's total patient population in a zip code 20 km from the competitive shock would be: $218.1 + \frac{20km}{10km} * (-18.3) = 181.5$ patients.

Table 6: Effects of Competitive Shocks on Access to Care and Payer Mix, Stratified by Zip Code

	Effect Estimate in Farthest 13% of Zips		Effect Estimate in Competitive Zips	
Outcome	Estimate	95% CI	Estimate	95% CI
Total Patients	-147***	(-254, -41)	196**	(19, 372)
By Payer				
Medicaid	-76**	(-146, -7)	141**	(16, 266)
Private	-37***	(-58, -16)	51	(-37, 139)
Medicare	-21***	(-58, -16)	12	(-14, 37)
Uninsured	26	(-10, 63)	-65	(-155, 25)
Access to Care				
Hours per Week	-5.4**	(-10.5, -0.2)	9.1**	(1.1, 17.0)
Locations	-0.1	(-0.2, 0.1)	0.1	(-0.1, 0.3)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Notes: Data presented here are difference-in-differences (DID) estimated impacts of competitive shocks on FQHC patients by payer mix in newly competitive and outlying zip codes. Notably, payers are ranked from most generous (Medicaid) to least (Uninsured). Estimates are adjusted for 1 year of anticipation. Since competitive zip codes comprise 13% of the treated zip codes in the allocation dataset, I collected the farthest 13% for the outlying sample.

Table 7: Effects of Competitive Shocks on Capacity

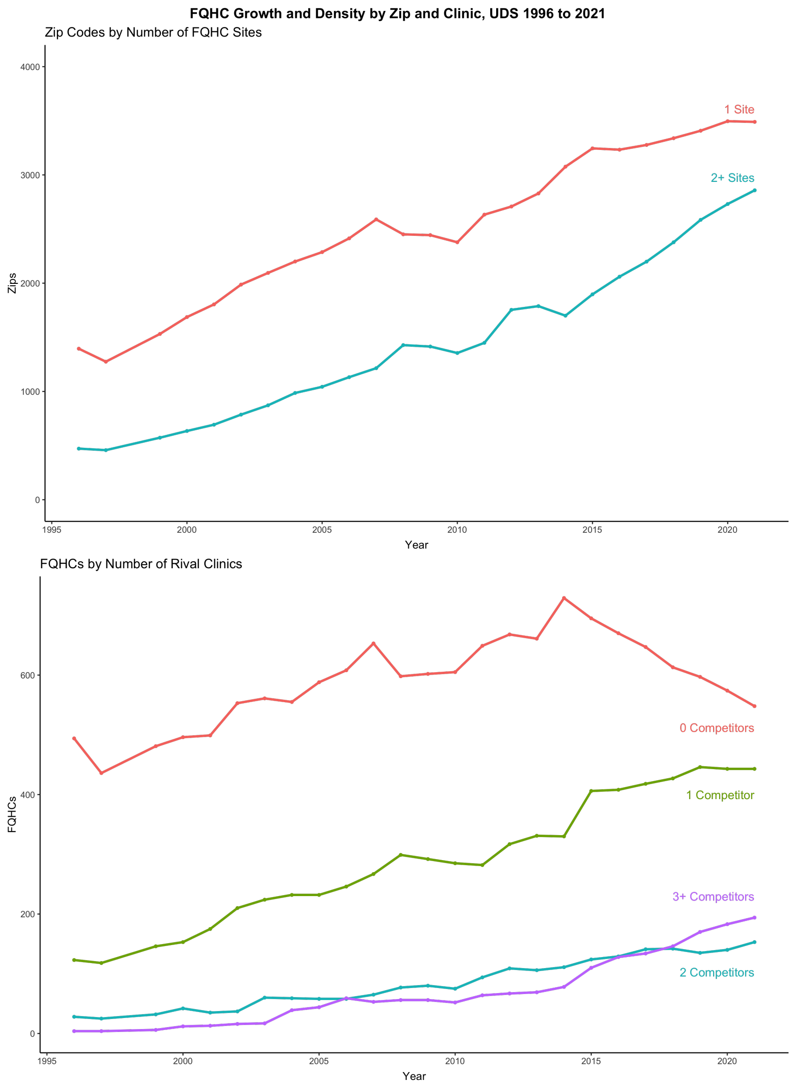
	Control		Treated			Adjusted DID	
Outcome	Pre	Post	Pre	Post	Unadj. DID	Estimate	95% CI
Staff	141	171	230	263	3	19	(-5, 42)
Sites	4.5	6.6	7.5	9.7	0.2	0.9**	(0.2, 1.7)
Staffing Ratio	4.61	4.49	4.72	4.61	0.01	0.05**	(0, 0.1)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Notes: Data presented here are difference-in-differences (DID) estimated impacts of competitive shocks on incumbent FQHC capacity measures, including staffing FTEs, number of care delivery locations, and staffing ratio (log of Patients per Staff). Estimates are adjusted for 1 year of anticipation.

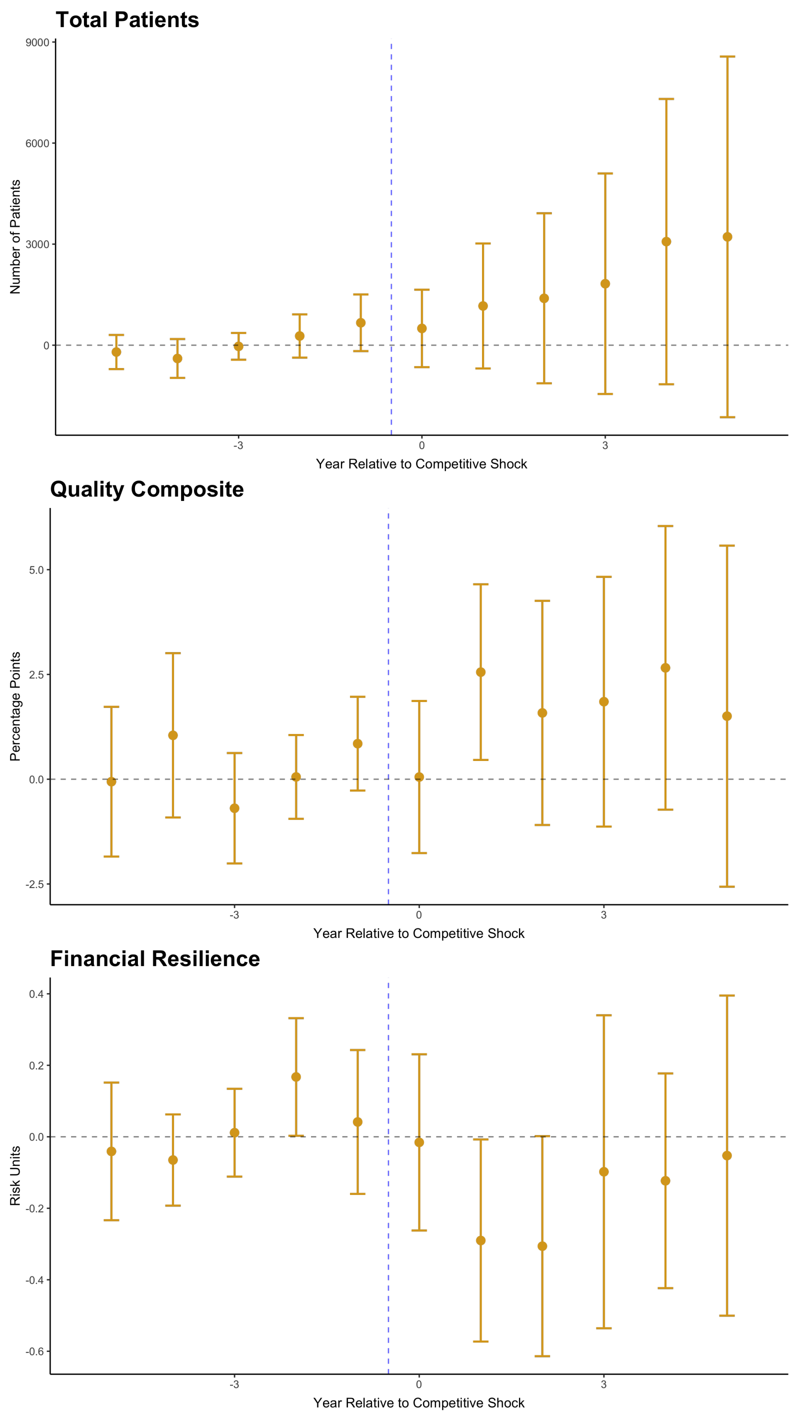
Figures

Figure 1: Trends in FQHC growth over the past 25 years



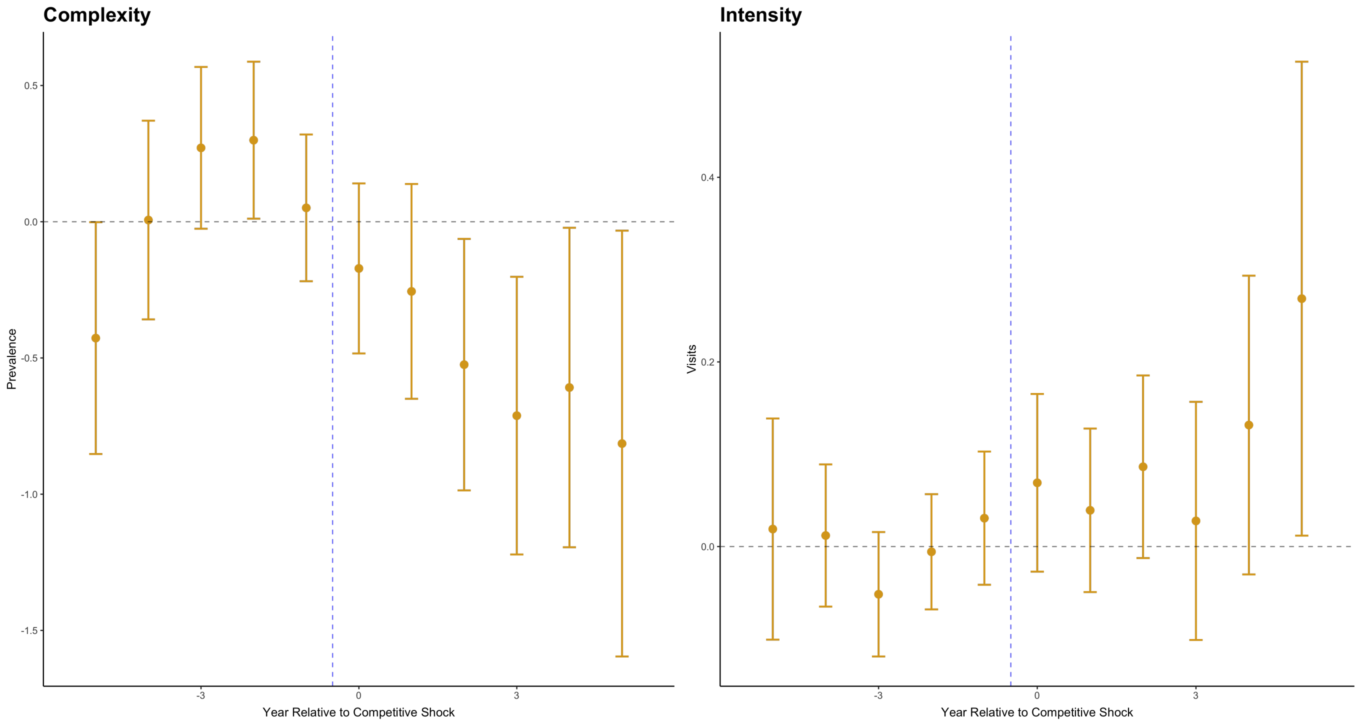
Notes: Trends in FQHC allocation and density over the past 25 years. In the top panel, I present the number of zip codes in the US that have 1 or 2+ FQHC care delivery sites. In the bottom panel, I present the number of FQHCs that have 0, 1, 2, or 3+ rival FQHCs operating a care delivery site in their service area.

Figure 2: Event Study of Competitive Shocks on FQHC Performance



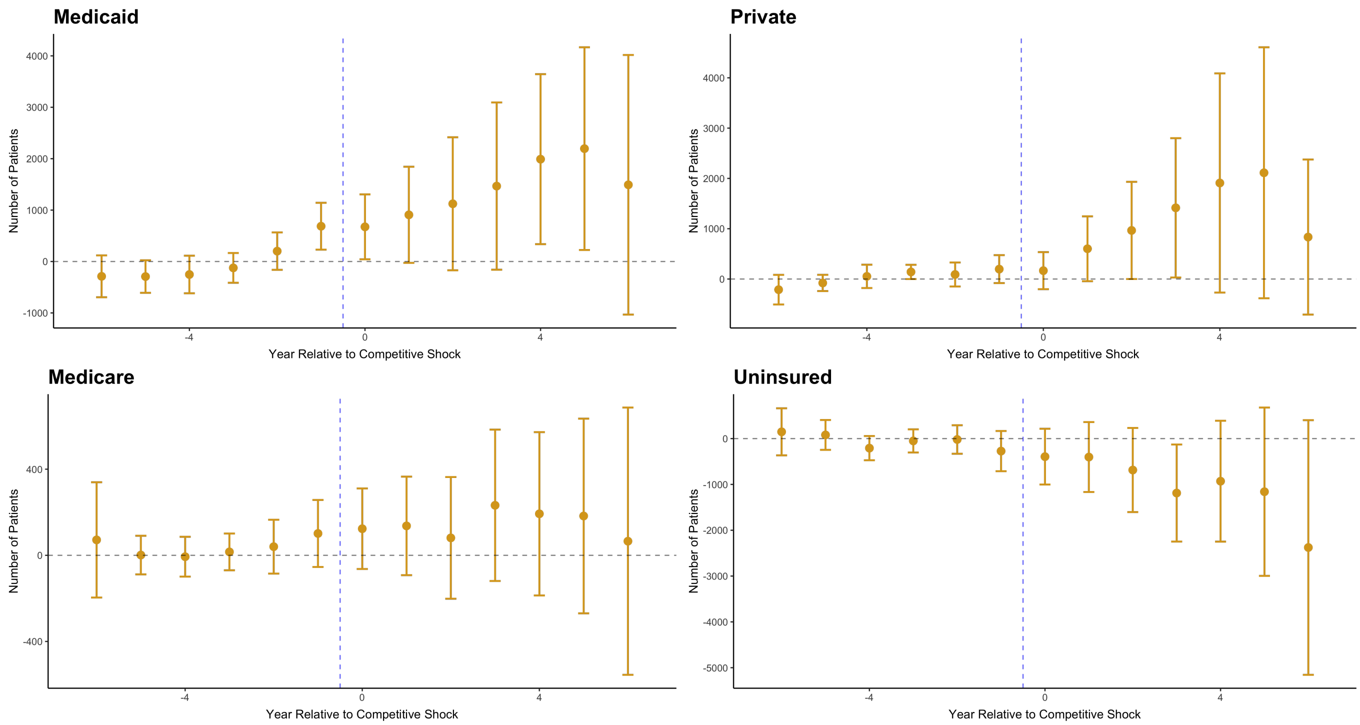
Notes: Data presented here are event studies for the DID estimates of competitive shocks on the primary performance outcome measures in Table 2.

Figure 3: Event Study of Competitive Shocks on Chronic Condition Prevalence and Care Intensity



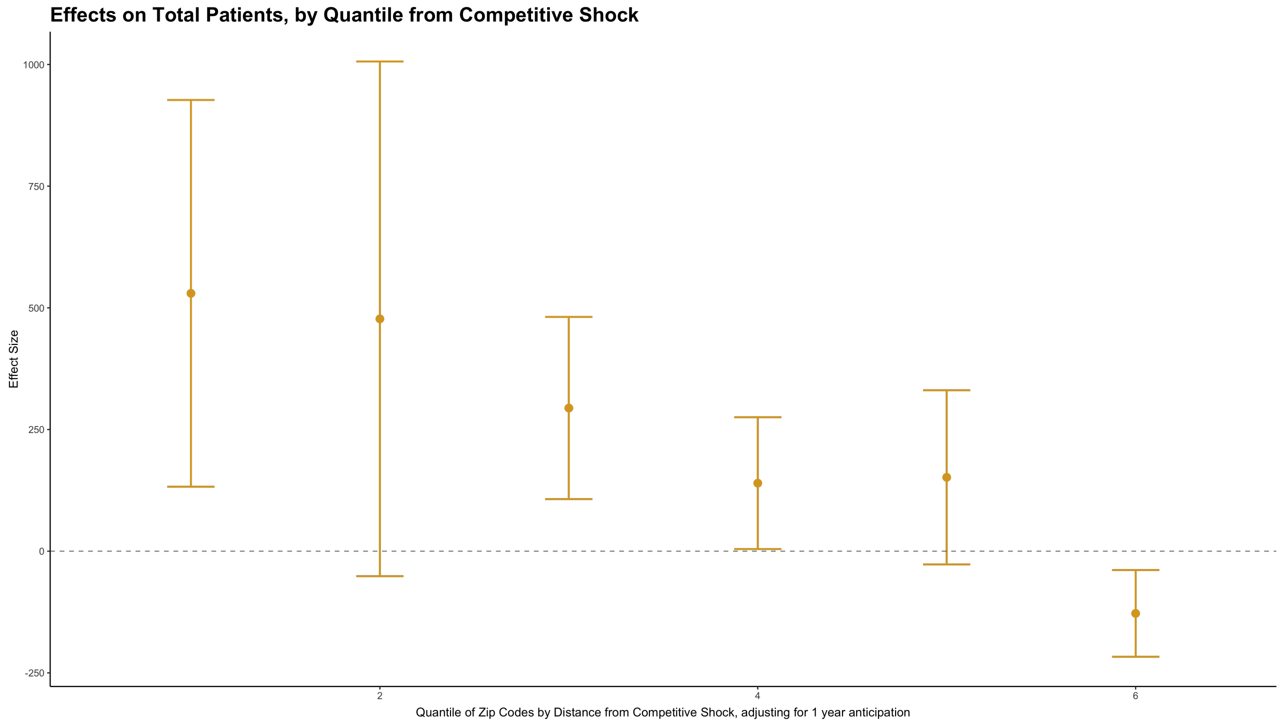
Notes: Data presented here are event studies for the DID estimates of competitive shocks on the disease prevalence and intensity of care outcome measures in Table 3.

Figure 4: Event Study of Competitive Shocks on Payer Mix



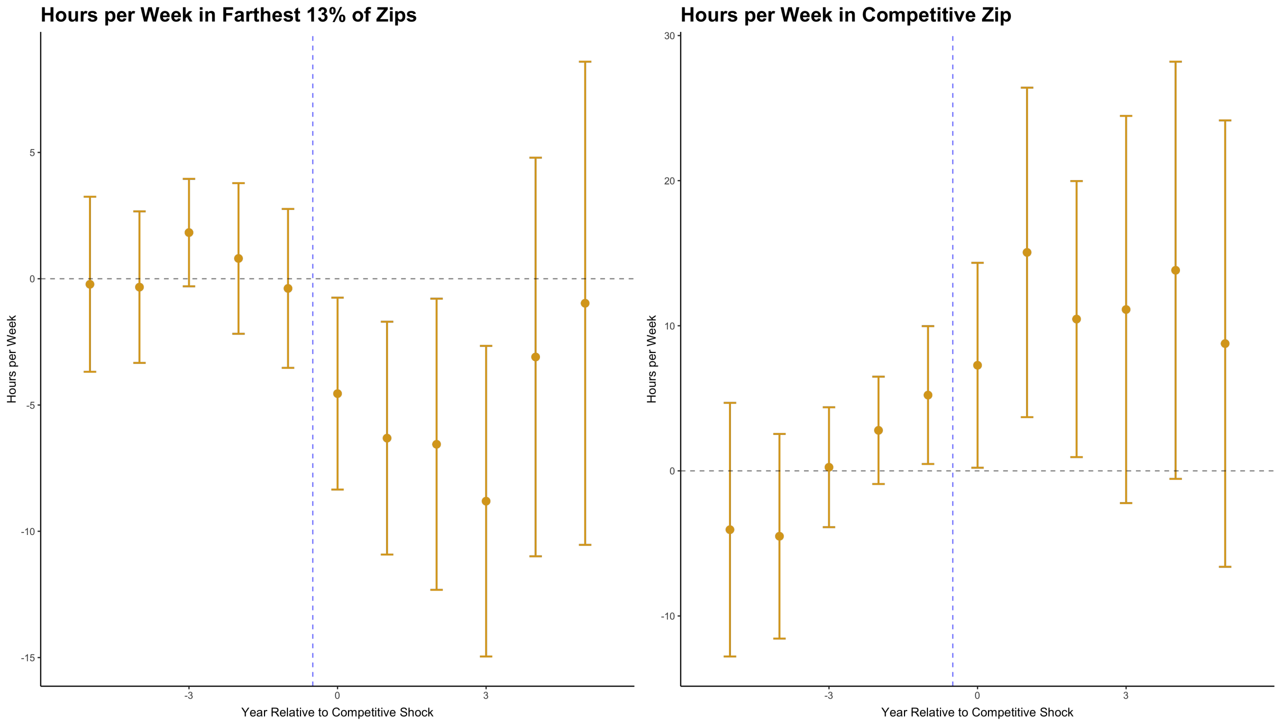
Notes: Data presented here are event studies for the DID estimates of competitive shocks on the payer mix outcome measures in Table 4. Some amount of anticipation is expected, see details in Section 4

Figure 5: Effects of Competitive Shocks on Patients by Distance to Competitive Shock



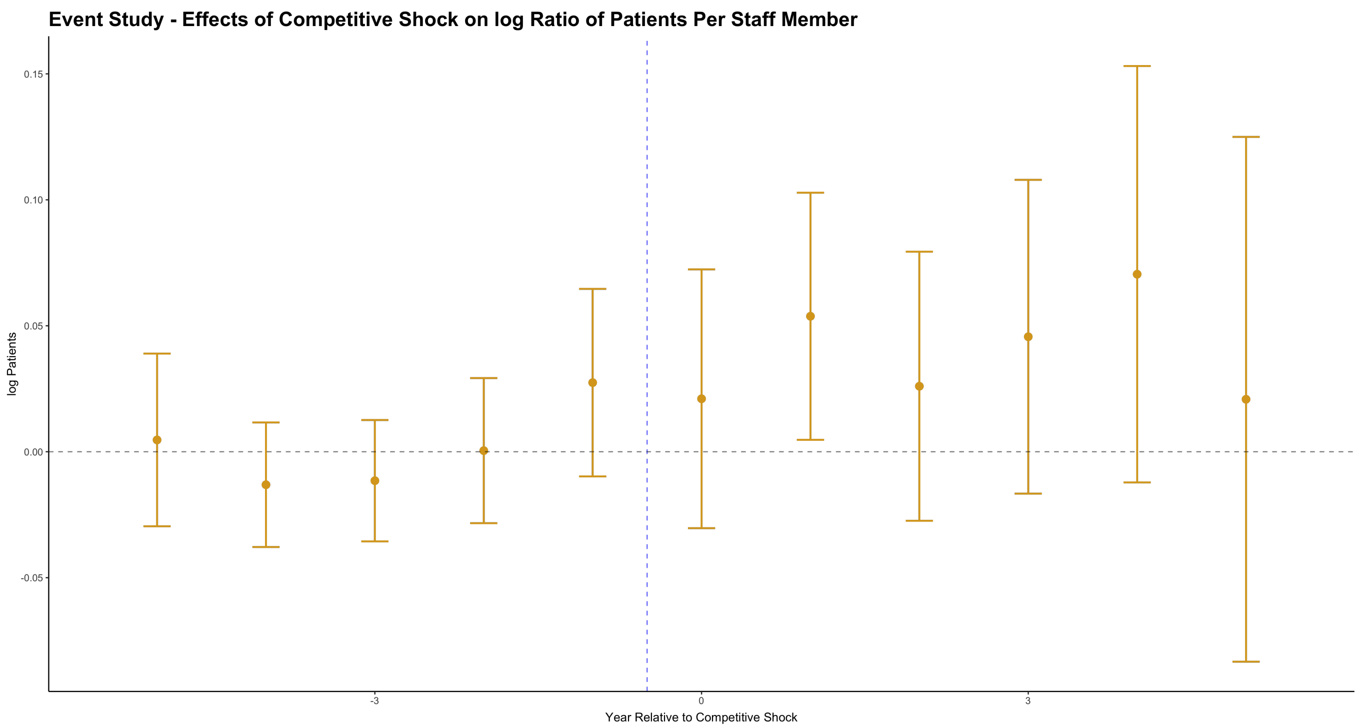
Notes: Data presented here are DID estimates of competitive shocks on patients served, aggregated into 6 quantiles representing the distance in that zip code from the competitive shock. That is, effect in 1st quantile (far left) encompasses the 1/6th of zip codes in the incumbents' service areas that are closest to and including the newly competitive zip code, while the 6th quantile (far right) includes the farthest 1/6th of zip codes in the incumbents' service areas. This is an alternative presentation of the results in Table 5. Estimates adjusted for 1 year of anticipation.

Figure 6: Event Study of Competitive Shocks on Proximal and Distal Changes in Access



Notes: Data presented here are event studies for the DID estimates of competitive shocks on access to incumbent FQHCs (hours per week available) in competitive zip code (right panel) and in the farthest 13% of zip codes (left panel). This is an alternative presentation of the results in Table 6. Since competitive zip codes comprise 13% of the treated zip codes in the allocation dataset, I collected the farthest 13% for the outlying sample.

Figure 7: Event Study of Competitive Shocks on Incumbent Efficiency



Notes: Data presented here are event studies for the DID estimates of competitive shocks on the operational efficiency of the incumbent FQHCs in Table 7.

References

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Appendix

Table A1: Demographics of Incumbent and Rival Clinics

Characteristic	Incumbent (N = 81)	Rival (N = 81)	p-value
Primary Outcomes			
Total Patients	25,069 (17,769)	31,540 (32,472)	>0.9
Quality, %	57 (11)	58 (11)	0.7
Altman's Z	2.46 (1.50)	2.37 (1.38)	>0.9
Demographics			
Non-Hispanic Asian, %	1.52 (3.20)	0.93 (1.86)	0.010
Non-Hispanic Black, %	22 (26)	19 (24)	0.3
Hispanic-Latino, %	25 (28)	22 (28)	0.2
Poverty (<100% FPL), %	68 (18)	63 (18)	0.069
Special Populations			
Migrant Farm Worker, %	4 (10)	8 (20)	0.5
Homeless, %	4 (6)	9 (21)	0.5
Insurance Payer Mix			
Medicaid, %	43 (17)	38 (16)	0.12
Private, %	19 (12)	23 (14)	0.043
Medicare, %	11 (6)	11 (7)	>0.9
Uninsured, %	27 (16)	26 (21)	0.3

Notes: Data from year of competitive shock, representing mean (sd).

Figure A1: Event Study of Primary Effects by Different Estimation Strategies

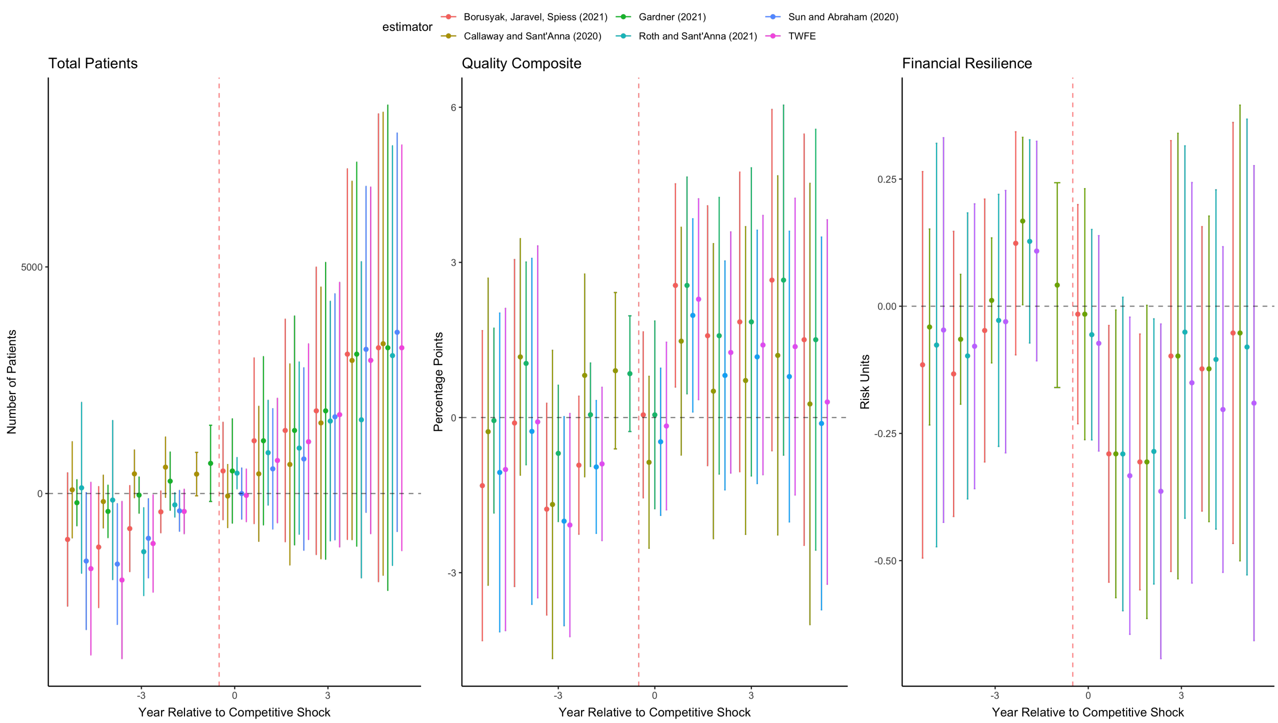


Figure A2: Core Effects by Year of Competitive Shock

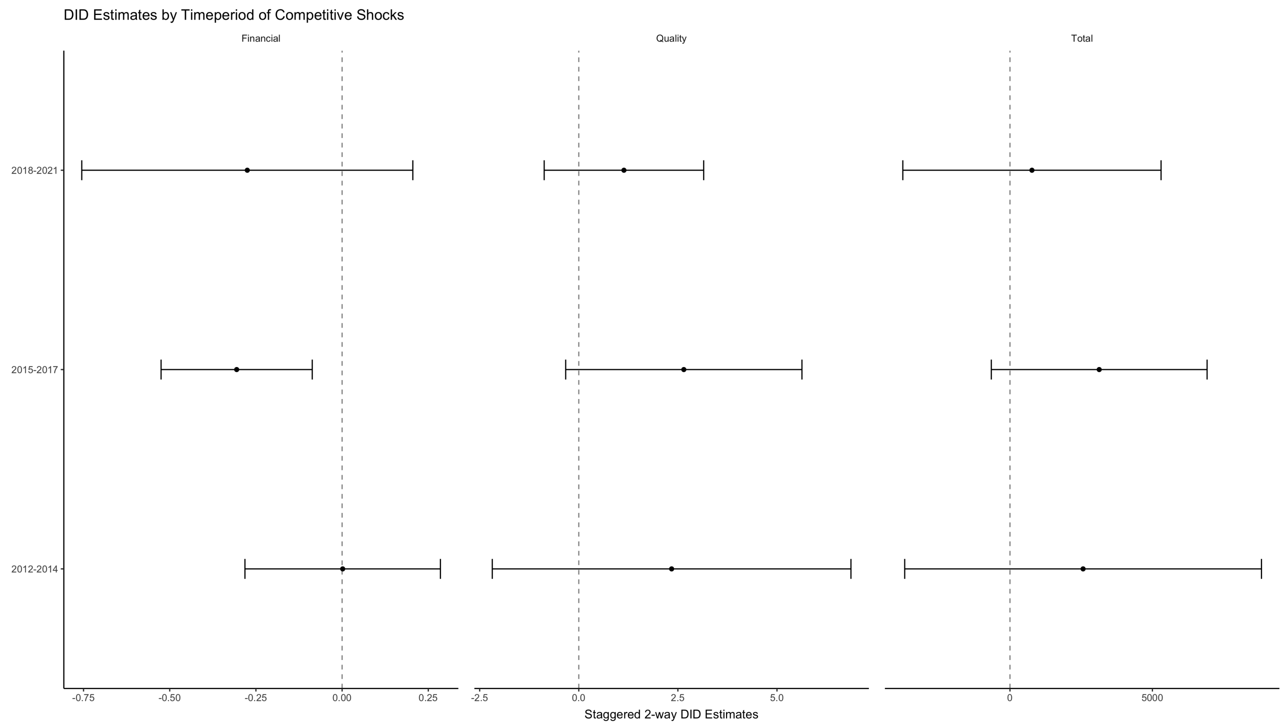
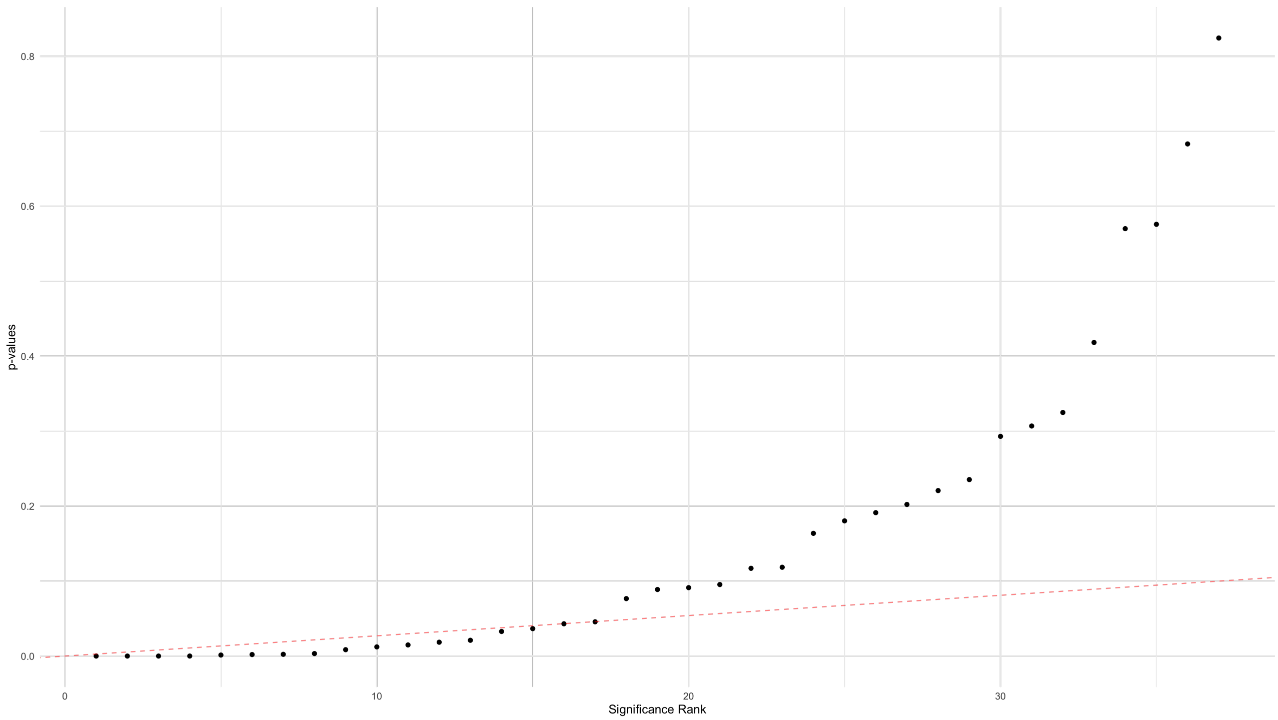


Figure A3: Benjamini-Hochberg Procedure of Mutliple Hypothesis Testing



Note: All effect esimtates with p-value < 0.05 remain significant after the multiple hypothesis correction presented here. A false-positive rate of 10% was used.

Figure A4: Distribution of Distance Traveled by Rival

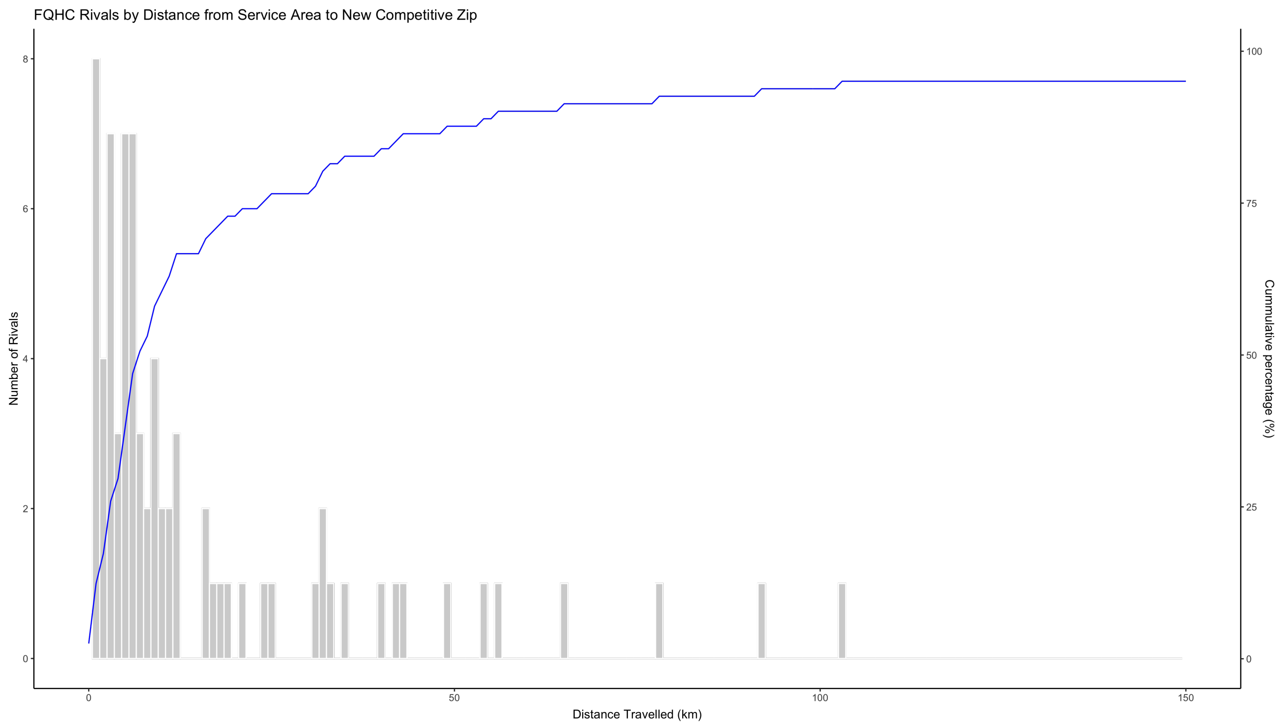


Figure A5: Map of Competitive FQHCs by Distance Rival Traveled