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Healthy competition? Market structure and the quality of clinical care given to standardised patients in Tanzania

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ABSTRACT

The private health care sector in many low- and middle-income countries is rapidly expanding. Private sector advocates have long argued that market competition drives private providers to become more efficient and responsive to patients but empirical studies are limited to mostly high-income settings. We examine whether the number of competing health facilities in close proximity is associated with quality and prices, in a sample of 228 private for-profit and faith-based facilities in Tanzania. Primary data collection took place in the health facilities between February and June 2018. By exploiting data on the quality of clinical care given to unannounced standardised patients, we are able to compare quality across providers without confounding due to patient characteristics. We find that more local competition is associated with poorer clinical quality. The former is driven by an increase in unnecessary care rather than a reduction in appropriate care. Policymakers in such settings should be cautious in assuming that market competition will drive up quality of care.

1. Introduction

Poor quality health care accounts for between 5.7 and 8.4 million deaths each year in low- and middle-income countries (LMICs) (National Academies of Sciences, 2018). If countries are to make progress towards universal health coverage, health systems will need to address deficiencies in quality of care (WHO, OECD and World Bank, 2018). An important policy consideration is that many LMICs have pluralistic health systems, with sizeable and growing private health care sectors. Private providers are responsible for around 63–67 % of care for sick children and 30–39 % of maternal health care when averaged across 70 LMICs (Grepin, 2016). Ranging from small clinics to multi-speciality hospitals (Mackintosh et al., 2016), this market segment is likely to continue to increase rapidly, reflecting urbanisation, the growth of the middle class, and empanelment of private facilities within social health insurance systems.

Private sector advocates have long argued that market competition drives private providers to become more efficient and responsive to patients (Rosenthal and Newbrander, 1996). This position, however, has been the subject of much debate in LMICs (Hanson et al., 2008).[1] Indeed, theoretical support for competition as a driver of quality is ambiguous (Gaynor and Town, 2012, Gaynor et al., 2015). This is particularly the case when prices are unregulated, but can also be the case when prices are fixed.[2] If consumer demand is more sensitive to price than quality, providers will have an incentive to compete on price at the expense of quality. By contrast, if patients are less sensitive to price, quality becomes an important driver of choice and a key dimension on which providers will compete (Propper, 2018).[3] Whether this reflects optimal care depends on what aspects of quality patients value. If patients actually want antibiotics or steroids even when not clinically indicated,

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[1] The merits of health care competition in high-income countries are equally contentious. In the UK, for example, evidence on the effects of introducing choice within the public hospital system have been the subject of vigorous debate (Bloom et al., 2011; Pollock et al., 2011).

[2] Models that incorporate provider altruism and other realistic features of the hospital sector generate ambiguous predictions even when prices are fixed (Brekke et al., 2011; Brekke et al., 2014; Moscelli et al., 2021).

[3] Gaynor and Town (2012) show that simple insights can be gained from an amended version of the Dorfman-Steiner (1955) condition, $\frac{z}{p} = \frac{1}{d} \bullet \frac{\varepsilon_z}{\varepsilon_p}$, where z is quality, p is price, d is the marginal cost of quality, ε_z is elasticity of demand with respect to quality and ε_p is the price elasticity of demand. As is clear, the impact of competition on quality depends on how it affects the responsiveness of demand to quality relative to price.

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competition may do little to encourage care that is welfare improving. The effect of competition on quality is thus an empirical question.

Empirical studies on health care competition and quality of care are mostly, although not exclusively, limited to hospital markets in high-income countries. Studies tend to find that greater competition is associated with higher quality when prices are fixed by regulators while effects are mixed when prices are determined by the market (Gaynor and Town, 2012). Evidence from primary health care settings is particularly scarce, limited to a small number of high-income countries.[4] Generalising from this literature to LMIC settings is fraught with difficulty, given differences in health systems (Goddard, 2015).[5] Yet the policy questions of whether to allow or even encourage competition between health care providers, or whether and how to constrain it, remain just as relevant.

We study whether competition is associated with quality of clinical care, prices and patient experience of care in a sample of more than 220 for-profit and faith-based providers in Tanzania. Our focus is primary health care. We overcome two data challenges that have hampered previous efforts in similar settings. First, reliable facility-based data on the quality of clinical care are rarely available in routine administrative systems, and medical records to provide such information tend to be poorly maintained. We use standardised patients – healthy people who are trained to pose as real patients with symptoms of four conditions – to collect primary data on processes of care. These metrics provide a direct measure of provider behaviour, particularly appropriate for picking up the effort effects of competition. Through this method, we compile rich data on the history questions, examinations and diagnostic tests completed by the provider and the treatment given to the patient. Because we designed the standardised patient cases, and hence know the underlying condition presented, we can benchmark the care given against national treatment guidelines to develop condition-specific metrics of appropriate care and overprovision. Second, measuring health care competition is difficult when few LMICs maintain a complete database on the geographical location of public and private health facilities. Information on the private sector is particularly hard to come by because of challenges in the implementation of regulation around facility registration. We draw on a dataset containing the coordinates of the universe of health facilities in Tanzania to construct a geographical measure of health care competition.

Although our analysis is based on cross-sectional data, our use of standardised patients means we can compare quality across providers without confounding due to patient characteristics (including case-mix) since unobserved attributes of the patient are, by design, held constant (Das et al., 2016).[6] Such measures of quality are exogenous to the characteristics of both patients and the catchment population of the health facility. This guards against an important source of endogeneity that commonly threatens the identification of competition effects. Various scenarios are plausible: health facilities may locate to areas in which the population is less healthy or harder-to-treat patients may select higher quality facilities. When quality measures are based on real patient data, endogenous placement or selection of this nature can lead to under-estimates of the effect of competition. Our use of standardised patients helps in this regard, but does not address deeper concerns that the number of health facilities itself may be endogenous. To reduce such confounding, we control for a rich set of supply- and demand-side covariates.

We find that an increase in the number of competing health facilities in close proximity to a health facility is associated with a decrease in correct treatment. This is driven by an increase in unnecessary care rather than a reduction in required care (correct treatment is defined in part by the absence of unnecessary care). The positive association between competition and unnecessary care reflects a large increase in antibiotic overprescribing in facilities exposed to more competition. From a public health perspective, such a finding is of concern in light of the threat from antimicrobial resistance (Laxminarayan et al., 2013). Using data from patient exit interviews, results show that the number of competing health facilities is negatively associated with the price of health care, while there is no evidence of a relationship with patient experience of care.

Our findings contribute to several bodies of literature. First, we contribute to the small literature on competition from LMICs.[7] A study of outpatient care in public hospitals in China, where prices are partially regulated, found that competition was associated with lower mortality, shorter waiting times and lower outpatient costs (Pan et al., 2015). A mixed methods study of private health care facilities providing maternity care in Uttar Pradesh, India found that price competition, in the context of low insurance coverage, was intense but health providers also engaged in non-price competition on aspects of care observable to patients (Gautham et al., 2019). Second, we connect to the literature on quality competition in primary health care settings. With the notable exception of Gravelle et al. (2019) and Scott et al. (2022), studies lack data on clinical quality and instead use measures of patient satisfaction or indirect measures of clinical quality (Iversen and Ma, 2011, Gravelle et al., 2016; Dietrichson et al., 2020). Our novel use of standardised patients to study competition allows us to measure evidence-based processes of care that reflect the behaviour of providers in patient interactions. Moreover, we can separate out unnecessary care from recommended treatment at the individual patient level (King et al., 2021a) to provide a comprehensive assessment of whether patients get the right care (Saini et al., 2017). These measures speak to the notion of health care as a credence good, in which the patient does not know the quality of care they need, and may be susceptible to either undertreatment or overprovision of care (Dulleck and Kerschbamer, 2006). Third, our study relates to the literature on competition and prescribing behaviour (Kann et al., 2010; Schaumans, 2015). This is of interest because competition may encourage certain behaviours, such as antibiotic prescribing, that is valued by patients even if it generates no clinical benefit (Ashworth et al., 2016). Our contribution lies in being able to precisely identify whether the increase in antibiotic prescriptions represents wasteful or even harmful care.

The structure of the article is as follows. The next section discusses the institutional setting. Section 3 describes the data and Section 4 outlines the empirical estimation. Section 5 reports the main results, examines their robustness, and presents extended findings. Section 6 discusses the findings in the context of the wider literature and the key limitations.

2. Study context

Tanzania has a mixed health care system, comprising public and private health facilities. The private sector includes faith-based health facilities that have long been important providers of primary and secondary care in the country, often closely integrated with the public health system. The private for-profit sector has steadily grown since a

[4] See Dietrichson et al. (2020) for a review of the evidence on quality competition in primary care settings.

[5] Two key differences, with potential implications for the impact of competition, are the availability of public information on the quality of health care providers and the extent of health care coverage (from health insurance or supply-side subsidies). In many high-income countries, consumers may be less sensitive to prices (because of relatively comprehensive insurance) and more sensitive to clinical quality (because of public reporting of provider quality).

[6] For studies that use quality metrics based on real patients, evidence suggests that simply adjusting for case-mix may be inadequate (Finkelstein et al., 2017).

[7] Evidence on whether patient choice is responsive to clinical quality – a precondition for competition to improve quality – is also limited in LMICs. A study in India found that patients who travel to health providers further away do in fact receive higher quality of care (Das and Mohpal, 2016).

ban was lifted by the government in 1991. These facilities are extremely heterogeneous, ranging from small clinics to international-standard hospitals. Based on 2019 data, 14 % of facilities are private for-profit and 15 % are faith-based health facilities (Darcy et al., 2019). In our sample, the private-for-profit facilities are mostly stand alone, although several are part of a small chain. The vast majority of faith-based facilities are Christian, managed as part of a small network by the local church. Most are staffed, in part, by government-salaried health workers. Across our entire sample, median outpatient visits is 380 per month and median monthly revenue is $2,700, with 60 % coming from patient user fees. Half of the health facilities have no doctor.[8]

Gate-keeping is limited, particularly in the private sector, such that patients can by-pass lower level facilities and go directly to the outpatient departments of hospitals. Primary care services are delivered not only by dispensaries and health centres, but also hospitals. There are no regulations on prices in the private sector, hence facilities can in principle compete on both price and quality. Insurance coverage is low: the main social health insurance programme covers less than 10 % of the population and private insurance is negligible, as of 2020. Government regulators do not give the public information on the quality of care of individual providers, although it is worth noting that health facilities have recently been subject to inspections ratings as part of the "star rating assessment" strategy (Yahya and Mohamed, 2018). We can assume therefore that consumers are most sensitive to aspects of quality that are observable (and valued).

Health care providers in Tanzania often receive support from NGOs and development partners. The health facilities in our analysis were part of a randomised controlled trial of SafeCare, a standards-based approach adapted to LMIC settings that involves assessments, mentoring, training, and access to loans. Results show, however, that the intervention had no effect on clinical quality or business performance outcomes (King et al., 2021b). Almost three-quarters of facilities also reported participating in other quality improvement programmes.

Available evidence suggests that the quality of clinical care in Tanzania is poor, albeit better in the private than the public sector (Leonard and Masatu, 2007, Das et al., 2008; Leslie et al., 2017). In outpatient settings, there is considerable overprovision of care. A study based on the same data used in this paper found that 81 % of standardised patients received unnecessary care, 67 % received care harmful to public health (prescription of unnecessary antibiotics or antimalarials), and 6 % received clinically harmful care (King et al., 2021a). More than one in 10 standardised patients were prescribed an antibiotic defined by WHO as 'Watch' (high priority for antimicrobial stewardship) though none of the cases presented merited antibiotic provision. Although overprovision was common in both for-profit and faith based sectors, clinically harmful care was more likely in for-profit facilities.

3. Data

3.1. Sample and data sources

We use cross-sectional data that were collected as part of an evaluation of the aforementioned SafeCare intervention (King et al., 2021b). Health facilities in our sample were recruited from the Northern, Eastern, Central, Southern and Southern Highlands zones of Tanzania. Eligible facilities were dispensaries and health centres which were members of APHFTA (the Association of Private Health Facilities in Tanzania that represents mainly for-profit facilities), and dispensaries, health centres and hospitals which were members of CSSC (the Christian Social Services Commission that represents most faith-based facilities). The initial sample included 237 health facilities, stratified equally into for-profit and faith-based groups, widely dispersed across both urban and rural areas, in 18 of mainland Tanzania's 22 regions. We use data from the endline sample of 228 health facilities (eight facilities permanently closed down and one closed for renovations).

Primary data were collected using three survey tools: a facility survey, patient exit interviews, and standardised patients. The first two survey tools were administered in the course of a day as part of a health facility visit. These took place in 228 facilities between February 7, 2018 and April 5, 2018. Standardised patients visited 227 of the health facilities (one facility owned by a private company served only their employees so standardised patients could not visit undercover) approximately two months later. A total of 909 standardised patient visits were done between May 3, 2018 and June 12, 2018. This is complemented by external data from the Tanzania Health Facility Registry, containing information on the geographical coordinates of the universe of health facilities in the country (Darcy et al., 2019). We also use high resolution population data from the WorldPop project (Stevens et al., 2015).

The health facility survey involved an interview with the in-charge of the facility. Informed consent was sought from the in-charge, both for the facility survey and for subsequent standardised patient visits. For the exit interviews, patients were eligible if they were at least 18 years of age or were accompanied by an adult caretaker, had received curative outpatient care (therefore excluding routine visits for growth checks, immunisations or antenatal care) and had completed their visit to the facility (including collecting prescribed treatments and making payments). Written consent was obtained from the patient or caretaker before the start of the interview.

We obtained ethics approval from the Ifakara Health Institute (04–2016) and the National Institute of Medical Research (IX/2415) in Tanzania, and the London School of Hygiene and Tropical Medicine (10493) in the UK.

3.2. Quality of care and prices

We focus on process of care measures of quality since they are informative about the care actually received by patients and are a direct measure of provider behaviour. We used standardised patients to address the challenge of measuring the quality of care received by patients when provider behaviour is typically unobserved and the underlying condition of the patient is unknown. Standardised patients are healthy people, who covertly pose as real patients and respond to the clinician's actions as a real patient would. They have a long history in medical education, as a means to test the knowledge and clinical skills of medical students (Wallace, 1997). Increasingly they are being used to evaluate the quality of clinical care, particularly in settings where routine data are not available through medical records (King et al. 2019; Kwan et al., 2019). Standardised patients are trained to portray a precise set of symptoms and consistently follow a script that guides them in how to respond to questions the clinician may have during history taking. We developed four standardised patient cases – asthma, non-malarial febrile illness, tuberculosis, and upper respiratory tract infection – adapting protocols and scripts used in previous studies (Das et al., 2012; Mohanan et al., 2015; Das et al., 2016). Table 1 summarises each case in terms of the initial presentation and further information shared by the patient. Each facility received the four standardised patient cases. Just before leaving the facility, standardised patients completed a structured questionnaire on a smartphone, which gathered information on the questions, examinations and diagnostic tests completed by the provider as well as the results of these tests, diagnoses offered, and treatment given.[9]

Standardised patient interactions provide information to measure a number of quality of clinical care outcomes. We define correct case management as the proportion of standardised patients who were

[8] Recent trial evidence from Nigeria suggests that assigning a doctor to health facilities reduces child mortality through better quality of care (Okeke, 2023).

[9] A follow-up telephone survey was conducted with facility managers indicating that detection of standardised patients was very low at 5.2 % of visits.

Table 1
Standardised patient cases and treatment definition.

SP case	Initial presentation	Further details given if asked	Required care	Palliative drugs	Appropriate tests
Asthma	"I have had a problem with breathing, and last night it became terrible"	Attacks of shortness of breath and wheezing, triggered by exertion, normally at night, lasting 15 min to 2 h and becoming more frequent over last year	Prescription of inhaled bronchodilator or steroid	Other β-2 antagonists and steroids, antihistamines, xanthines	Allergy tests, electrocardiogram, HIV, X-ray
Non-malarial febrile illness	"I have a fever and I think I have malaria"	Fever and headache lasting three days, joint and muscle pain. Has taken paracetamol for two days.	Malaria test with a negative result, and no antimalarial prescribed or dispensed	Cold and flu combinations, cough syrups, NSAIDs, paracetamol	Complete blood count, HIV
Tuberculosis	"I have had a cough and it is not getting better"	Three week cough with yellow sputum, no blood, low grade fever, chest pain, night sweats, loss of appetite and weight. Completed seven day course of amoxicillin with no improvement.	Referral for sputum test, or to a higher level facility	Cold and flu combinations, cough syrups, NSAIDs, paracetamol	Complete blood count, HIV, malaria, X-ray, Widal
Upper respiratory tract infection	"I have a cough and my head and throat hurt"	Symptoms for three days, blocked nose and sneezing, no fever.	No antibiotic prescribed or dispensed	Cold and flu combinations, cough syrups, NSAIDs, paracetamol	HIV, malaria

Notes: The table summarises the four standardised patient cases which were selected for this study as a measure of quality of care. It shows the statement with which SPs initially presented to providers, and further case-specific information which was provided when probed. It also shows our definition of correct treatment for each case based on national standard treatment guidelines. The four cases were chosen after a systematic review of the literature (King, Das et al. 2019), assessing the clinical significance and disease prevalence in Tanzania, the risk to the SP fieldworkers, feasibility, and ethical concerns (e.g. not taking up too much provider time or resources). SP presentations were developed in partnership with an expert working group to make sure that the presentation could lead to correct diagnosis and treatment, and the exact wording and presentation style was refined during piloting and training. NSAIDs are non-steroidal anti-inflammatory drugs.

managed in accordance with the national standard treatment guidelines.[10] This corresponds to "required care" in Table 1. The definition of the indicator allows for the provision of "palliative drugs" and "appropriate tests", but equals zero if any other drugs or tests not mentioned in the standard treatment guidelines were recommended by the provider. We define unnecessary care as any care given to the patient not classified as required care, a palliative drug or an appropriate test (King et al., 2021a).[11] As is clear, correct treatment and unnecessary care are closely related given that the former is partly defined in terms of the absence of the latter. We also report results for a looser definition of correct treatment which allows for unnecessary care as long as the required care is provided. Following Das et al. (2016), we capture additional measures of process quality: whether any antibiotic was prescribed, and adherence to an essential checklist of questions and examinations. Based on national treatment guidelines, none of the four cases warranted antibiotics, hence this indicator reflects unnecessary prescription of antibiotics. Checklist adherence is measured both as a percentage of condition-specific checklist items completed[12] and as an index generated using Item Response Theory (IRT) to give more weight to items that discriminate better among providers.

We also examine the price of health care and patient experience of care. These outcomes are relevant because providers may respond to the pressures of competition by improving quality along observable, albeit subjective, dimensions of care or by reducing prices. We measure price as the total amount of money spent during the health care visit, as reported by patients in the exit interviews.[13] We convert values into US dollars. We measure experience of care as an index, based on the responses of patients to 21 items covering various dimensions, such as the waiting time, degree of privacy, and ability of the clinician to communicate well. We conducted face-to-face exit interviews with patients as they were about to leave the health facility. Fieldworkers read out statements and patients were asked to say whether they agreed, disagreed or neither agreed or disagreed. In accordance with best practice, we alternated between positively and negatively framed questions to address the upward bias that comes with using all positive questions (Evans and Welander Tarneberg, 2018). Fieldworkers aimed to interview a maximum of eight patients per facility. To generate a composite score, we assign a value to each response (disagree 0, neutral 0.5, agree 1), reverse score the negatively framed statements, and take the average across the 21 items. Because waiting time has been the focus of various studies in the competition literature (Propper et al., 2008; Moscelli et al., 2021), we pull this indicator out as a separate outcome. A total of 1404 patient exit interviews were completed.

3.3. Measure of competition

Health care competition has a strong geographic component to it because travel for patients is costly in terms of both time and money. We use a geographical measure of competition that draws on the Tanzania Health Facility Registry which contains the geographical coordinates of the universe of health facilities in the country (Darcy et al., 2019).[14] We calculate the density (count) of competing health facilities within 5 km of each of our study health facilities. This measure implies a facility has a catchment area of 2.5 km since any facility less than 5 km away will have a catchment area that overlaps with the index facility. We define competitors as health facilities of the same level – either hospital, health centre, or dispensary – as the study facility in question.[15] Because the continuous measure of competition is highly skewed, as shown in Figure A1, we categorise each study health facility as having zero competitors, one to five competitors or more than five competitors, which corresponds roughly to terciles.

There is no commonly used definition of a catchment area in Tanzania, and this is particularly true of the private sector which is not

[10] These guidelines are condition-specific and based on evidence of clinical effectiveness (Ministry of Health, 2017).

[11] The full list of unnecessary drugs and tests actually given to the standardised patients is in the appendix.

[12] The condition-specific items are shown in the appendix.

[13] We also have data on how much SPs spent on health care. However, this measure does not reflect how much real patients would have spent because SPs were trained to refuse potentially harmful treatments (that would have incurred expenditure). For this reason, our preferred measure is the amount reported by real patients in exit interviews.

[14] The Health Facility Registry is a single authoritative source of health facility information in Tanzania that was developed between 2009 and 2015, harmonising multiple health facility lists managed by donors, government ministries, agencies and implementing partners. For more information, see also https://hfrs.moh.go.tz/web/index.php.

[15] To streamline terminology, we simply refer to the number of competitors.

subject to government norms and central planning. It is worth noting our focus is outpatient care for which patients are not anticipated to travel far. Moreover, data from our patient exit survey suggest that most patients used health facilities nearby.[16] Nevertheless, the 5 km market definition is somewhat arbitrary and we therefore examine the sensitivity of our findings to different thresholds.[17] A commonly used alternative in the health care competition literature is the Herfindahl-Hirschman Index (HHI). Although we do not have the data to construct such a measure, we note that it is based on patient flows to generate market shares which are likely to be endogenous since patients may be attracted to better quality health facilities (Kessler and McClellan, 2000).

3.4. Covariates

We identify potential confounders on the basis of the existing empirical and theoretical literature on health care competition. Conceptually, this literature (Gaynor et al., 2015) distinguishes between cost shifters (characteristics of health facilities that affect the cost of providing services) and demand shifters (characteristics of the local population that affect demand for health services). On the cost side, we use data from our health facility survey to control for number of doctors, number of nurses and midwives, number of consultation rooms, number of beds, facility level (dispensary, health centre, or hospital), profit-status (for-profit or faith-based), person in-charge (clinician, administrator, or both clinician and administrator) and location (Dar es Salaam[18] or not). On the demand side, we control for the population living within 5 km of the health facility and the proportion of the population within 5 km under five years of age, based on high resolution population data (Stevens et al., 2015). For outcomes from the patient exit survey, we also adjust for patient case-mix, with gender, seven age categories, six education categories, and 11 disease groups. Because our analysis uses data from a trial, we also control for treatment assignment.

3.5. Summary statistics

Table 2 presents the descriptive statistics. There is substantial room for improvement in the quality of care received by patients. Only 8.6 % of standardised patient visits are correctly managed, while in 81 % of visits unnecessary care is given. Using a looser definition, less than one-third of visits are correctly treated. The overprovision of antibiotics is widespread and the mean proportion of checklist items (history taking and exams) completed is 0.32, suggesting that provider knowledge and/or effort is low. The mean price is $5.04 per health care visit. Patient satisfaction with the experience of care is high at 0.91 and there is minimal variation between patients. Almost three-quarters of patients agree with the statement that they had to wait a long time to be seen. The health facility sample is equally divided into for-profit and faith-based health facilities. More than half of the sample is dispensaries (55 %), and the rest health centres (29 %) and hospitals (16 %). The average number of doctors and nurses working in these facilities is low, although there is considerable variation by level of facility. The mean population within 5 km of a facility is 199,000. Of the study facilities, 36 % have no competitors within 5 km, 36 % have one to five competitors, and 29 % have more than five competitors. The mean number of competitors is 11 and the standard deviation is 25, indicating the large variation in the measure. Table A1 in the Appendix shows the summary statistics by level of competition. Here, we note that facilities with more competitors are more likely to be for-profit, dispensaries, and located in the city with a high population density.

Table 2
Study sample descriptive statistics.

Variable and category	n (%) or mean (SD)	Facilities	Observations
Standardised patient outcomes			
Correct treatment only (%)	78 (8.6 %)	227	909
Unnecessary care (%)	740 (81 %)	227	909
Correct treatment with other care (%)	256 (28 %)	227	909
Antibiotic prescribed (%)	570 (63 %)	227	909
Checklist items completed (index, 0 to 1)	0.318 (0.135)	227	908
Patient exit outcomes			
Price of health care visit (US$)	5.04 (8.12)	222	1404
Patient satisfaction with experience of care (index, 0 to 1)	0.907 (0.09)	222	1404
Patient agreed waiting time was long (%)	979 (70 %)	222	1404
Competing health care facilities			
Number of competitors	11.2 (24.6)	228	228
Categories of competitors			
0 competitors (%)	81 (36 %)	228	228
1–5 competitors (%)	82 (36 %)	228	228
6 or more competitors (%)	65 (29 %)	228	228
Facility characteristics			
Type of organisation			
For-profit (%)	111 (49 %)	228	228
Non-profit, faith-based (%)	117 (51 %)	228	228
Facility type			
Dispensary (%)	126 (55 %)	228	228
Health Centre (%)	66 (29 %)	228	228
Hospital (%)	36 (16 %)	228	228
Facility location			
Dar Es Salaam (%)	42 (18 %)	228	228
Outside Dar Es Salaam (%)	186 (82 %)	228	228
Manager in-charge			
Clinician (%)	160 (70 %)	228	228
Administrator (%)	18 (8 %)	228	228
Shared by clinician and administrator (%)	50 (22 %)	228	228
Number of medical doctors	1.3 (2.0)	228	228
Number of nurses and midwives	6.6 (11.9)	228	228
Number of outpatient consulting rooms	2.3 (2.2)	228	228
Number of beds	28.4 (52.6)	228	228
Population characteristics			
Population in 5 km radius of facility ('00,000)	1.99 (4.35)	228	228
Population share under five in 5 km radius of facility	0.14 (0.025)	228	228

4. Empirical estimation

We are primarily interested in estimating differences in the quality of care received by (standardised) patients from providers with varying levels of competition, as measured by the number of rivals in close proximity. Our main model is:

$$q_{(i(scf)} = \beta_0 + \beta_1' COMP_f + \beta_2' X_f + \alpha_c + \mu_{(i(scf)} \tag{1}$$

which regresses quality q (correct case management and other measures of quality from the standardised patients) in visit i with standardised patient s presenting case c in health facility f on categories of the number of competitors. We include a vector of controls (X_f) which measure characteristics of the health facility and the local population, as well as case fixed effects (α_c) to account for systematic differences across the disease cases. Given the hierarchical nature of the data, we use multi-

[16] The median travel time was 25 min (mean was 35 min), and 90 percent of patients travelled less than 90 min to reach the facility from their home. In terms of mode of transport, 35 percent travelled by foot, 23 percent by motorcycle taxi, and 21 percent by public transport.

[17] For comparison, the study of competition amongst GP practices in England uses a radius of 2 km to define the number of competitors (Gravelle et al., 2016).

[18] Dar es Salaam is the commercial capital of the country and by far the largest city.

level mixed effects models with facility random effects to account for the clustering of observations within health facilities. For binary outcomes, we use multilevel mixed effects logistic regression and report the results as average marginal effects. We generate two sets of estimates for each measure of quality. We first includes only facility controls and then we add local population characteristics and case controls.

The coefficients of interest are β_1' in equation (1). These show the association between varying levels of competition and quality of care. We argue that these estimates are informative, not least because the use of standardised patients to measure quality allows us to compare quality across providers without confounding due to patient case-mix since unobserved attributes of the patient, including their underlying health, are held constant. In other words, our measures of quality are exogenous to the characteristics of the facility's patients and its catchment population. In doing so, they address an important source of potential bias that threatens studies of competition that rely on measures of quality from real patients. Bias in the measure of quality may arise for various reasons to do with where health facilities locate and the sorting of patients to facilities. Health facilities may locate in areas where patients are less healthy, or harder-to-treat patients may select higher quality facilities, making it more difficult to achieve quality indicators, thereby under-estimating the effects of competition. The standardised patient approach addresses this source of bias but does little to deal with the more fundamental problem that the number of hospitals itself may have been endogenous. For that, we must rely on the covariates.

There are two further issues that threaten identification of competition effects (Propper, 2018). The first concerns situations in which a health facility's choice of location is based on supply-side considerations. It is possible that more skilled health workers are attracted to areas with better amenities which happen to be where there are more health facilities. In this case, higher quality is driven by the availability of more skilled health workers rather than the effort effect of competition. It is also possible that new health facilities avoid locating near higher quality facilities, biasing estimates of the effect of competition downwards. In an effort to address these concerns, we include controls for different types of clinical staff and the manager, infrastructure, and a dummy for Dar es Salaam.[19] The second issue relates to our measure of competition, in which a market is defined as a fixed radius around a health facility. If the population density is greater in the catchment area of health facilities with more rivals, competition for patients may not in fact be higher. The same is true in areas with healthier populations where demand for health care is likely to be lower. To address these endogeneity concerns, we control for the population in 5 km radius and the proportion of the population under five years of age.

We are also interested in using the patient exit data to estimate differences in prices and experience of care for patients from providers with varying levels of competition. Our model is:

$$p_{jf} = \beta_0 + \beta_1' COMP_f + \beta_2' X_f + \beta_3' z_j + \mu_{jf} \tag{2}$$

where p (price and measures of experience of care) for patient j presenting in health facility f on categories of the number of competitors. We include the same vector of facility and local population controls (X_f) as before, as well as a patient case-mix controls (z_j). We again use multilevel mixed effects models with facility random effects to account for the clustering of patient observations within health facilities. We note that the advantages of using standardised patients – in dealing with confounding linked to the local population or patient – no longer applies to regressions involving these outcomes. Therefore, despite the patient case-mix controls, one must be more careful in interpreting these competition estimates.

We extend the main findings in two ways. First, we examine whether the type of nearby health facility matters. Here, we include categories of the number of facilities of a different level in the regressions. Second, we perform a sub-group analysis with respect to facility type to examine whether the associations differ between faith-based and for-profit health facilities.

5. Results

5.1. Main results

Table 3 presents results from estimating equation (1) in the full sample of health facilities. We report results for different process measures of quality obtained from the standardised patients. Panel A presents results based on regressions that include facility controls. Panel B adds local area population controls and fixed effects for the standardised patient case and fieldworker. The association between the number of competitors and correct treatment is negative and statistically significant. Our preferred estimate suggests that patients in facilities with more than five competitors are 6.6 percentage points less likely to receive correct treatment compared with the reference category of zero competitors (column 1, panel B). To aide interpretation, we note that the average number of facilities is 2.0 in the 1–5 category and 36.6 in the 6 or more category. There is a significant association between competition and unnecessary care. Patients in facilities with more than five competitors are 12.1 percentage points more likely to receive unnecessary care (column 2, panel B). These two sets of results are consistent given that correct treatment is partly defined by whether the patient receives unnecessary care. For the looser definition of correct treatment, there is no significant association between competition and quality (column 3), suggesting that facilities with more competitors do not skimp on required care. This confirms that the result in column 1 is driven by greater provision of unnecessary care rather than a reduction in required care. Having more than five competitors is associated with an increase of 12.7 percentage points in the overprovision of antibiotics (column 4, panel B). Although estimates are consistently negative, there is no evidence of an association between the number of competitors and adherence to an essential checklist of questions and examinations (column 5).[20]

Table 4 presents results for outcomes measured in the patient exit interviews. There is a negative association between high levels of competition and the price of health care. In the fully specified model, compared to the zero competitors, prices are US$1.49 lower in facilities with one to five competitors, and US$2.85 lower in facilities with more than five competitors (column 1, panel B). The magnitude of these associations is large when we consider that the mean price is US$5.04 across the entire sample. There is no evidence of a relationship between the number of competitors and patient satisfaction with the experience of care (column 2). Finally, patients at facilities with more competitors are less likely to perceive waiting times are long (column 3).

5.2. Robustness

We run a number of robustness checks to test the sensitivity of our results to alternate definitions of the local health care market and additional controls. Our baseline results were based on a definition of the local health care market that uses a 5 km radius to calculate the number of nearby health facilities. While this definition is consistent with our own survey data on travel time, it remains somewhat arbitrary. We show the sensitivity of our results to incremental changes of 1 km either side of the 5 km radius that was used in our baseline model. Table 5 presents results from four additional sets of regressions. In

[19] We do not control for smaller geographical areas, e.g. district, because this absorbs much of the variation in our measure of competition.

[20] The finding is qualitatively the same when we use an adherence checklist index generated using IRT: the coefficient (standard error) is −0.011 (0.093) on 1–5 competitors and −0.054 (0.14) on 6 or more competitors.

Table 3
Health care competition and process quality of care from standardised patients.

	Correct treatment only (1)	Unnecessary care (2)	Correct treatment with other care (3)	Antibiotic prescribed (4)	Checklist items completed (5)
Panel A. Facility controls					
Number of competitors: 1–5	−0.008	0.024	0.026	0.035	−0.016
	(0.028)	(0.037)	(0.038)	(0.045)	(0.015)
Number of competitors: 6 +	−0.072**	0.103**	0.008	0.125**	−0.033
	(0.030)	(0.045)	(0.054)	(0.059)	(0.021)
Mean	0.11	0.78	0.32	0.58	0.33
Facilities	227	227	227	227	227
Observations	909	909	909	909	908
Panel B. Facility controls, local population characteristics, SP case fixed effects					
Number of competitors: 1–5	−0.007	0.040	0.035	0.050	−0.006
	(0.026)	(0.039)	(0.033)	(0.047)	(0.016)
Number of competitors: 6 +	−0.066**	0.121**	0.032	0.127*	−0.023
	(0.032)	(0.048)	(0.050)	(0.067)	(0.024)
Mean	0.11	0.78	0.32	0.58	0.33
Facilities	227	227	227	227	227
Observations	909	909	909	909	908

Notes: Quality of care measures are from the standardised patients. Estimates are from multilevel mixed effects regression models with facility random effects. A logistic model is used for binary outcomes, with average marginal effects reported. A linear model is used for continuous outcomes. Standard errors are reported in parentheses. In Panel A, regressions include facility controls (number of doctors, number of nurses and midwives, number of consultation rooms, number of beds, facility level, for profit or faith-based, person in-charge, and location). In Panel B, regressions additionally include controls for local population (population living within 5 km of the health facility and the proportion of the population within 5 km under five years of age), SP case fixed effects. The mean is reported for each outcome in facilities with no competitors *** significant at 1 %, ** at 5 %, * at 10 %.

Table 4
Health care competition and patient exit outcomes.

	Price of health care visit (1)	Patient experience of care (2)	Patient agreed waiting time was long (3)
Panel A. Facility controls			
Number of competitors: 1–5	−1.680*	−0.009	−0.093**
	(0.916)	(0.009)	(0.036)
Number of competitors: 6 +	−2.821**	−0.001	−0.136**
	(1.251)	(0.012)	(0.053)
Mean	4.60	0.90	0.63
Facilities	222	222	222
Observations	1404	1404	1404
Panel B. Facility, local population characteristics, patient controls			
Number of competitors: 1–5	−1.492	−0.009	−0.091**
	(0.915)	(0.009)	(0.036)
Number of competitors: 6 +	−2.854**	−0.001	−0.140**
	(1.358)	(0.013)	(0.057)
Mean	4.60	0.90	0.63
Facilities	222	222	222
Observations	1404	1404	1403

Notes: Patient experience of care and price of health care are measured using patient exit interviews. Estimates are from multilevel mixed effects regression models with facility random effects. A logistic model is used for binary outcomes, with average marginal effects reported. A linear model is used for continuous outcomes. Standard errors are reported in parentheses. In Panel A, regressions include facility controls (number of doctors, number of nurses and midwives, number of consultation rooms, number of beds, facility level, for profit or faith-based, person in-charge, and location). In Panel B, regressions additional include controls for local population (population living within 5 km of the health facility and the proportion of the population within 5 km under five years of age) and patient case-mix (age, sex, education, illness). The mean is reported for each outcome in facilities with no competitors *** significant at 1 %, ** at 5 %, * at 10 %.

general, the marginal effects on the categories of competition remain qualitatively similar across the different radii. The exception is the price of health care, which appears to be sensitive to the spatial definition of competition. At 3 km, 4 km and 7 km, there is no evidence of an association between more than five competitors and price, with estimates considerably smaller in magnitude.

Table A2 and Table A3 show results in which we include further controls to our preferred specification. Panel A of Table A2 shows the baseline results for the standardised patient measures of quality of care. In Panel B we add standardised patient fieldworker fixed effects. In Panel C, we add the monthly number of outpatients visits and monthly revenue to control more precisely for size of facility, while noting that size could be endogenous to quality. Panel A of Table A3 shows the baseline results for the exit interview outcomes. In Panel B we add patient wealth.[21] In Panel C, we again add the monthly number of outpatients visits and monthly revenue. For the most part, the coefficients of interest remain similar in magnitude. It is worth noting that, due to missing data, the number of observations in some of the regressions falls with the inclusion of covariates, increasing the standard errors.

5.3. Competitors and other nearby facilities

Our baseline results were based on the notion that competitors are rival health facilities of the same type. Here, we ask whether other nearby health facilities matter (Table 6). We add to our preferred baseline model categories of the number of health facilities of a different level (to the index health facility) within 5 km. While the marginal effect estimates on the number of competitors remains similar to the baseline results, there is no evidence of an association between the number of health facilities of a different level and our key outcomes (columns 1–4). This suggests that spatial competition from facilities of the same type is what appears to matter, rather than the nearby presence of facilities of any type. It is worth noting that “other nearby facilities” group together different levels of facility, potentially masking heterogeneity.

5.4. Heterogeneity

Our sample includes faith-based and for-profit private health facilities, providing the basis for an interesting comparison between profit-orientated and mission-orientated production (Besley and Ghatak, 2005). In a subgroup analysis, we estimate the relationship between competition and outcomes for health facilities in each sector. Specifically, we include in the regressions an interaction between sector and the competition categories. Table 7 reports the marginal effects for each

[21] Patient wealth is measured using an asset index constructed using principal components analysis.

Table 5
Robustness to alternative competition radii.

	Correct treatment only (1)	Unnecessary care (2)	Correct treatment with other care (3)	Antibiotic prescribed (4)	Checklist items completed (5)	Price of health care visit (6)	Patient experience of care (7)	Patient agreed waiting time was long (8)
Panel A: Number of competing facilities within 3 km								
Number of competitors: 1–5	0.007 (0.025)	0.016 (0.034)	0.054* (0.030)	0.044 (0.043)	−0.016 (0.015)	−1.013 (0.891)	−0.0001 (0.009)	−0.073** (0.037)
Number of competitors: 6 +	−0.068** (0.029)	0.080* (0.047)	0.020 (0.049)	0.097 (0.066)	−0.026 (0.023)	−0.781 (1.358)	−0.004 (0.013)	−0.127** (0.060)
Panel B: Number of competing facilities within 4 km								
Number of competitors: 1–5	0.005 (0.025)	0.012 (0.035)	0.047 (0.030)	0.044 (0.044)	−0.007 (0.015)	−1.192 (0.895)	−0.001 (0.009)	−0.057 (0.036)
Number of competitors: 6 +	−0.062** (0.030)	0.106** (0.045)	0.029 (0.047)	0.117* (0.064)	−0.024 (0.023)	−2.130 (1.326)	0.002 (0.013)	−0.123** (0.058)
Panel C: Number of competing facilities within 5 km								
Number of competitors: 1–5	−0.007 (0.026)	0.040 (0.039)	0.035 (0.033)	0.050 (0.047)	−0.006 (0.016)	−1.492 (0.915)	−0.009 (0.009)	−0.091** (0.036)
Number of competitors: 6 +	−0.066** (0.032)	0.121** (0.048)	0.032 (0.050)	0.127* (0.067)	−0.023 (0.024)	−2.854** (1.358)	−0.001 (0.013)	−0.140** (0.057)
Panel D: Number of competing facilities within 6 km								
Number of competitors: 1–5	−0.018 (0.028)	0.035 (0.038)	0.019 (0.032)	0.009 (0.046)	−0.017 (0.016)	−1.332 (0.938)	−0.009 (0.009)	−0.084** (0.037)
Number of competitors: 6 +	−0.068** (0.034)	0.135*** (0.046)	−0.013 (0.047)	0.135** (0.063)	−0.031 (0.023)	−2.495* (1.340)	−0.003 (0.013)	−0.117** (0.056)
Panel E: Number of competing facilities within 7 km								
Number of competitors: 1–5	−0.008 (0.030)	0.012 (0.040)	0.024 (0.033)	0.008 (0.048)	−0.023 (0.017)	0.234 (0.961)	−0.010 (0.009)	−0.057 (0.038)
Number of competitors: 6 +	−0.080** (0.035)	0.137*** (0.046)	−0.005 (0.047)	0.119* (0.064)	−0.010 (0.023)	−1.783 (1.338)	−0.008 (0.013)	−0.104* (0.056)

Notes: Quality of care measures in columns 1 to 5 are from the standardised patients. Patient experience of care and price of health care in columns 6 to 8 are measured using patient exit interviews. Estimates are from multilevel mixed effects regression models with facility random effects. A logistic model is used for binary outcomes, with average marginal effects reported. A linear model is used for continuous outcomes. Standard errors are reported in parentheses. *** significant at 1 %, ** at 5 %, * at 10 %.

subgroup and the p value of a test of whether they are equal between sectors, for each categorical increase in the number of competitors.[22] There is limited evidence of heterogeneity between sectors for the three clinical quality outcomes. The marginal effects of competition on correct treatment are significantly different between the two sectors at the lower level of competition (Panel A). However, this could be a chance finding since there is no consistent pattern across the different levels of exposure to competition, making the finding difficult to explain. The results in Panel D show that there is a strong negative association between competition and prices in the for-profit sector (column 1), while the marginal effects on competition are close to zero in faith-based health facilities (column 2). Differences in the marginal effects between sectors are significant, as indicated by the p value for the test of differences in column 3. Table A4 reports subgroup effects by type of facility, showing that the results on clinical quality are largely driven by dispensaries. It is also important to note that hospitals do not contribute to the coefficients on six or more competitors since no hospital in the sample has this number of competitors.

[22] For the binary outcomes, our calculation of the magnitude of the interaction effect accounts for the fact that we are using nonlinear models (Ai and Norton, 2003).

6. Discussion

Using data from standardised patients and patient exit interviews, we examined whether health care competition is associated with quality and prices among private providers of health care in Tanzania. Our results show that an increase in the number of competing health facilities in close proximity is associated with lower prices and poorer clinical quality. The latter is driven by an increase in unnecessary care – largely antibiotic overprescribing – rather than a reduction in appropriate care. The broader context around these findings is that on average less than 10 percent of patients received the right care, that is, the correct treatment without any unnecessary care, highlighting considerable room for improvement.

The finding that providers who are subject to more competition respond by increasing prescriptions of antibiotics is consistent with the idea that providers believe patients value antibiotics, even when they are prescribed unnecessarily. This mismatch between what patients value, or are perceived to value, and optimal clinical care, means competition can in principle drive health providers towards the former and, in doing so, undermine the latter. Such a situation is plausible, where there is good evidence that patient demand for antibiotics is high and misperceptions of when antibiotics are needed are common (Radyowijati and Haak, 2003). Studies from high-income countries are mixed. A study in Taiwan found that markets with lower concentration

Table 6
Competitors and other nearby health facilities.

	Correct treatment only (1)	Unnecessary care (2)	Correct treatment with other care (3)	Price of health care visit (4)
Number of competitors: 1–5	−0.011 (0.027)	0.046 (0.039)	0.040 (0.032)	−1.45 (0.937)
Number of competitors: 6 +	−0.062* (0.035)	0.116** (0.051)	0.051 (0.052)	−3.16** (1.45)
Other nearby facilities: 1–5	−0.026 (0.021)	0.043 (0.031)	−0.039 (0.031)	1.11 (0.857)
Other nearby facilities: 6+	0.034 (0.046)	−0.039 (0.059)	−0.059 (0.052)	−0.279 (1.41)
Facilities	227	227	227	222
Observations	909	909	909	1404

Notes: The regressions are similar to those reported in Panel B of Tables 3 and 4, except that we also include categories of the number of health facilities of a different level. The categorical variables for the number of competitors refer to the number of health facilities of the same level (as the index facility) within 5 km. The categorical variables for the number of other nearby facilities refer to the number of health facilities of a different level (from the index facility) within 5 km. Estimates are from multilevel mixed effects regression models with facility random effects. A logistic model is used for binary outcomes, with average marginal effects reported. A linear model is used for continuous outcomes. Standard errors are reported in parentheses. *** significant at 1 %, ** at 5 %, * at 10 %.

Table 7
Subgroup effects in for-profit and faith-based health facilities.

	For-profit health facilities (1)	Faith-based health facilities (2)	P value of test (for-profit = faith-based) (3)
Panel A. Correct treatment only (standardised patients)			
Number of competitors: 1–5	0.073* (0.041)	−0.038 (0.029)	0.023
Number of competitors: 6 +	−0.013 (0.038)	−0.045 (0.057)	0.612
Panel B. Unnecessary treatment (standardised patients)			
Number of competitors: 1–5	−0.021 (0.071)	0.070 (0.043)	0.255
Number of competitors: 6 +	0.093 (0.072)	0.057 (0.081)	0.721
Panel C. Correct treatment with other care (standardised patients)			
Number of competitors: 1–5	0.078 (0.062)	0.014 (0.038)	0.365
Number of competitors: 6 +	0.039 (0.067)	0.116 (0.083)	0.428
Panel D. Price of health care visit (patient exit interviews)			
Number of competitors: 1–5	−5.18*** (1.81)	−0.46 (1.05)	0.022
Number of competitors: 6 +	−6.28*** (1.94)	−0.78 (2.14)	0.041

Notes: Subgroup effects are based on multilevel mixed effects regression models with facility random effects, which include an interaction between facility sector and the competition dummy variables. A logistic model is used for binary outcomes, with the magnitude of the interaction effect computed following Ai and Norton (2003). A linear model is used for continuous outcomes. Standard errors are reported in parentheses. The regressions include facility controls (number of doctors, number of nurses and midwives, number of consultation rooms, number of beds, facility level, for profit or faith-based, person in-charge, and location), controls for local population (population living within 5 km of the health facility and the proportion of the population within 5 km under five years of age) and SP or patient case-mix controls which vary by outcome. *** significant at 1 %, ** at 5 %, * at 10 %.

were associated with greater antibiotic use (Bennett et al., 2015) while a study of GPs in Australia found no effect on antibiotic prescribing practices (Scott et al., 2022).

Our results indicate that competition is associated with a reduction in perceived waiting times, an element of the experience of care that is observable to the patient. This is in line with evidence on the introduction of quasi-market reforms to the English health care system, where hospitals facing more competition reduced elective procedure waiting times, though at the expense of unobserved quality (Propper et al., 2008). If we take the findings on the price of health care at face value, they are consistent with competition putting downward pressure on prices by increasing the price elasticity of demand. Since there was a positive association between competition and unnecessary care, we speculate that the downward pressure must have acted on the consultation fee and outweighed any increase in patient costs from the unnecessary drugs. These findings on the price of care fit with the context in Tanzania where the coverage of health insurance is low. In settings where patients have health insurance and are thus insulated against price changes, such a mechanism is less likely to be at play. A number of empirical studies from high-income countries provide evidence of a negative relationship between competition and prices (Propper et al., 2004; Propper et al., 2008; Gaynor and Town, 2012).

Our findings highlight that competition has both costs and benefits to patients, and to society more widely. The lower prices associated with competition represent a benefit to patients and would be straightforward to quantify. More uncertain is how to value the cost of the increase in unnecessary care associated with competition. Much of it can be considered an economic waste of resources, which falls mostly on the patient. It should be noted, however, that these are not purely private costs: many facilities in this sample receive state subsidy through the posting of government-salaried health workers, and faith-based organisations subsidise care with charitable funds. While social health insurance coverage remains low, it is expanding, and pays for care including at private-for-profit facilities. There is also the potential health costs linked to harmful care given to the patient and the negative externality from antimicrobial resistance (King et al., 2021a), both of which are difficult to quantify, though inappropriate use of antibiotics is widely understood to be a major driver of resistance (Llor and Bjerrum, 2014).

Our empirical approach relies on cross-sectional data such that the estimates are vulnerable to residual confounding. While this is a feature of much of the empirical literature on competition, some studies have used natural experiments induced by policy changes to help identify the causal effects of competition. Our use of standardised patients goes some way to addressing an important source of endogeneity arising from unobserved differences in patients but we are nonetheless careful to interpret the results as robust associations. In particular, we did not have available a rich set of demand-side controls, which raises the possibility that our measure of competition picks up variation in demand that feeds through into differences in consultation time available for each patient and quality of care. Nonetheless, we note that our evidence is novel for low-income settings and it is unlikely that rich administrative longitudinal data on quality of care – that are typically needed to take advantage of natural experiments – will be available in the near future.

We study quality of care in an outpatient setting, albeit across various types of health facility. We are therefore unable to say anything about performance in other departments. Nevertheless, a key strength of the study is that we focus on processes of care that are both informative about the care actually received by patients and the most direct measure of provider behaviour. Studies in high-income countries tend to, though not exclusively (Gravelle et al., 2016), focus on outcomes such as 30-day mortality. While health outcomes are an important measure of quality, they are a function of many other factors, such as the population demographics and underlying health status. Process quality of care is the measure on which the provider herself can have a direct influence.

We use the density of health facilities nearby as our measure of competition. In low-income countries it is unusual to have even these data. Most studies in high-income country have used the Herfindahl-Hirschman Index (HHI), which is based on relative market shares of patient visits across health facilities. The advantage of using density of facilities is that, unlike measures based on market share, it is independent of patient decisions which may themselves be based on quality.

There are a number of policy implications arising from the study. First, decision makers should be careful in thinking that market competition will drive up quality. It may in fact have a detrimental impact on quality of care, as our findings suggest. Various features of the market in which we conducted this study work against regulation by competition. Prices were unregulated, information on quality was not available to the public, and health education amongst patients was likely low making it difficult for them to evaluate the quality of clinical care. Yet these features are typical of the private sector in many LMICs.

Second, whether health care competition improves quality has important implications for programmes seeking to engage with the private sector (Montagu and Goodman, 2016). Such programmes have risen to prominence in the past two decades, with funding from bilateral and multilateral donors. The most popular programmes include social franchising, accreditation, and patient vouchers. A common thread across these programmes is that they seek to harness market forces to incentivise private providers towards better quality of care. Voucher programmes use subsidies to encourage greater patient choice. In principle, providers are meant to respond by improving quality to attract more patients. Social franchising and accreditation programmes envisage a virtuous circle in which providers are motivated to raise quality because it attracts more patients, increases revenue, and allows for further investment in quality. Programmes that seek to leverage demand-side competition to incentivise quality or sustain quality improvement over the long-term are unlikely to succeed if this mechanism is not operating, as suggested by our findings.

Finally, our study highlights that quality of care is in great need of improvement and policy attention. Stronger routine information systems that are used by health care workers and managers at a local level and include measures of the quality of care received by patients are surely needed. Data generated from standardised patients by researchers are informative but it is routine data systems that will hasten quality improvement on a day-to-day basis.

CRediT authorship contribution statement

Timothy Powell-Jackson: Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Conceptualization. **Jessica J.C. King:** Writing – review & editing, Formal analysis, Data curation. **Christina Makungu:** Writing – review & editing, Data curation, Conceptualization. **Catherine Goodman:** Writing – review & editing, Funding acquisition, Data curation, Conceptualization.

Ethics

Ethics approval was obtained from the IRB of the Ifakara Health Institute (04–2016) and the National Institute of Medical Research (IX/2415) in Tanzania, and the London School of Hygiene and Tropical Medicine (10493) in the UK.

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Declaration of competing interest

The authors declare that they have no conflict of interest.

Appendix

Table A1
Facility characteristics by number of competitors

	Number of competitors: 0 (1)	Number of competitors: 1–5 (2)	Number of competitors: 6+ (3)
Facility characteristics			
Type of organisation			
For-profit (%)	12 (14.8 %)	42 (51.2 %)	57 (87.7 %)
Non-profit, faith-based (%)	69 (85.2 %)	40 (48.8 %)	8 (12.3 %)
Facility type			
Dispensary (%)	17 (21.0 %)	51 (62.2 %)	58 (89.2 %)
Health Centre (%)	38 (46.9 %)	21 (25.6 %)	7 (10.8 %)
Hospital (%)	26 (32.1 %)	10 (12.2 %)	0 (0.0 %)
Facility location			
Dar Es Salaam (%)	2 (2.5 %)	5 (6.1 %)	35 (53.8 %)
Outside Dar Es Salaam (%)	79 (97.5 %)	77 (93.9 %)	30 (46.2 %)
Manager in-charge			
Clinician (%)	51 (63.0 %)	61 (74.4 %)	48 (73.8 %)
Administrator (%)	7 (8.6 %)	5 (6.1 %)	6 (9.2 %)
Shared by clinician and administrator (%)	23 (28.4 %)	16 (19.5 %)	11 (16.9 %)
Number of medical doctors	1.6 (2.4)	1.2 (2.0)	1.0 (1.4)
Number of nurses and midwives	10.7 (16.3)	5.2 (10.0)	3.1 (3.0)
Number of outpatient consulting rooms	2.7 (2.0)	2.3 (2.9)	2.0 (1.3)
Number of beds	54.3 (65.2)	22.9 (47.4)	2.9 (9.8)
Population characteristics			
Population in 5 km radius of facility ('00,000)	0.1 (0.3)	0.5 (0.9)	6.2 (6.4)
Population share under five in 5 km radius of facility	0.15 (0.02)	0.15 (0.02)	0.12 (0.02)

Notes: Table shows the n (%) or mean (SD) in each cell.

Table A2
Robustness of SP outcomes to additional controls

	Correct treatment only (1)	Unnecessary care (2)	Correct treatment with other care (3)	Antibiotic prescribed (4)	Checklist items completed (5)
Panel A: Baseline (facility controls, local population characteristics, SP case fixed effects)					
Number of competitors: 1–5	−0.007	0.040	0.035	0.050	−0.006
	(0.026)	(0.039)	(0.033)	(0.047)	(0.016)
Number of competitors: 6 +	−0.066**	0.121**	0.032	0.127*	−0.023
	(0.032)	(0.048)	(0.050)	(0.067)	(0.024)
Observations	909	909	909	909	908
Panel B: SP fieldworker fixed effects					
Number of competitors: 1–5	0.001	0.040	0.035	0.050	−0.006
	(0.030)	(0.039)	(0.033)	(0.047)	(0.016)
Number of competitors: 6 +	−0.063*	0.121**	0.032	0.127*	−0.023
	(0.035)	(0.048)	(0.050)	(0.067)	(0.024)
Observations	849	909	909	909	908
Panel C: Facility utilisation and revenue					
Number of competitors: 1–5	−0.015	0.025	0.004	0.043	−0.018
	(0.026)	(0.036)	(0.032)	(0.046)	(0.016)
Number of competitors: 6 +	−0.059*	0.092*	−0.022	0.113*	−0.023
	(0.033)	(0.048)	(0.050)	(0.068)	(0.024)
Observations	868	868	868	868	867

Table A3
Robustness of exit interview outcomes to additional controls

	Price of health care visit (1)	Patient experience of care (2)	Patient agreed waiting time was long (3)
Panel A: Baseline (facility, local population characteristics, patient controls)			
Number of competitors: 1–5	−1.492	−0.009	−0.091**
	(0.915)	(0.009)	(0.036)
Number of competitors: 6 +	−2.854**	−0.001	−0.140**
	(1.358)	(0.013)	(0.057)
Observations	1404	1404	1403
Panel B: Patient wealth			
Number of competitors: 1–5	−1.455	−0.010	−0.094***
	(0.919)	(0.009)	(0.035)
Number of competitors: 6 +	−2.793**	−0.003	−0.146***
	(1.364)	(0.013)	(0.056)
Observations	1404	1404	1403
Panel C: Facility utilisation and revenue			
Number of competitors: 1–5	−1.235	−0.009	−0.100***
	(0.940)	(0.009)	(0.037)
Number of competitors: 6 +	−2.149	0.005	−0.136**
	(1.425)	(0.013)	(0.059)
Observations	1335	1335	1334

Table A4
Subgroup effects by type of health facility

	Dispensary (1)	Health facility (2)	Hospital (3)
Panel A. Correct treatment only (standardised patients)			
Number of competitors: 1–5	−0.035	−0.013	0.043
	(0.045)	(0.041)	(0.074)
Number of competitors: 6 +	−0.086*	−0.026	No estimate
	(0.046)	(0.075)	
Panel B. Unnecessary treatment (standardised patients)			
Number of competitors: 1–5	0.043	0.043	−0.036
	(0.062)	(0.053)	(0.078)
Number of competitors: 6 +	0.13*	0.096	No estimate
	(0.066)	(0.076)	
Panel C. Correct treatment with other care (standardised patients)			
Number of competitors: 1–5	0.0065	0.040	0.011
	(0.051)	(0.050)	(0.071)
Number of competitors: 6 +	−0.013	0.079	No estimate
	(0.058)	(0.091)	

Notes: Subgroup effects are based on multilevel mixed effects regression models with facility random effects, which include an interaction between facility sector and the competition dummy variables. A logistic model is used for binary outcomes, with the magnitude of the interaction effect computed following Ai and Norton (2003). The regressions include facility controls (number of doctors, number of nurses and midwives, number of consultation rooms, number of beds, facility level, for profit or faith-based, person in-charge, and location), controls for local population (population living within 5 km of the health facility and the proportion of the population within 5 km under five years of age) and SP or patient case-mix controls which vary by outcome. No hospital has 6 or more competitors; hence there is no estimate. None of the differences between types of facility are statistically significant.

Table A5
SP checklist items (history taking and exams) by case

Asthma (34 items)	Non-malarial febrile illness (18 items)	TB (29 items)	Upper respiratory tract infection (20 items)
• Probes time of day of symptoms • Asks if has any allergies • Probes other health-seeking or medication taken • Probes wheezing • Probes chest pain • Asks age • Asks about family history of asthma • Probes type of breathing difficulty (current episode) • Probes circumstances of episode • Probes length of attack • Asks if shortness of breath is constant or episodic • Probes if had eaten anything unusual • Probes previous breathing difficulties • Probes when difficulties started or how long they've happened for • Probes frequency of attacks (how often) • Probes what brings on attacks/if any trigger • Probes if anything improves symptoms/if you do anything to cope with it • Does the breathing trouble/wake you at night? • How far can you walk during an attack? • Are you breathless even at rest during an attack? • Have your lips become blue during at attack? • Asks if asthmatic • Asks about childhood history of breathing difficulties • Asks occupation/job • Asks if smokes • Probes weight loss • Probes night sweats • Probes fever • Asks if cough produces mucus/sputum • Throat/tonsil exam • Pulse measured • Temperature taken (thermometer, any type) • Blood pressure measured • Listened with stethoscope	• Probes time of day of symptoms • Probes duration of symptoms • Probes other health-seeking or medication taken • Probes duration taking medication • Probes cough • Probes fainting or convulsions • Asks if taken a malaria test • Probes loss of appetite • Probes breathing difficulty • Probes vomiting and/or diarrhoea • Asks age • Asks occupation/job • Asks if smokes • Throat/tonsil exam • Pulse measured • Temperature taken (thermometer, any type) • Blood pressure measured • Listened with stethoscope	• Asks occupation/job • Probes duration of symptoms • Have you had contact with anyone with TB? • Asks if cough produces mucus/ sputum • Asks if blood in sputum • Probes weight loss • Probes night sweats • Probes chest pain • Probes fever • Probes time of day of symptoms • Probes loss of appetite • Probes personal history of TB • Asks about family history of TB • Probes wheezing • Asks about family history of persistent cough • Probes breathing difficulty • Asks if smokes • Asks if drinks alcohol • Probes other health-seeking or medication taken • Asks age • Probes personal history of diabetes • Probes HIV testing/status • Probes name or type of medication • Probes duration taking medication • Throat/tonsil exam • Pulse measured • Temperature taken (thermometer, any type) • Blood pressure measured • Listened with stethoscope	• Probes time of day of symptoms • Probes duration of symptoms • Probes fever • Asks if blood in sputum • Probes wheezing • Probes breathing difficulty • Probes other health-seeking or medication taken • Asks if has any allergies • Asks age • Asks occupation/job • Asks if smokes • Asks if cough produces mucus/ sputum • Probes chest pain • Probes loss of appetite • Probes personal history of TB • Throat/tonsil exam • Pulse measured • Temperature taken (thermometer, any type) • Blood pressure measured • Listened with stethoscope

Notes: The checklist items are listed in no particular order and there was no requirement that providers should complete items in any particular sequence.

Table A6
Patient experience of care items

	Patient experience statement
1	I had to wait a long time to be served
2	The waiting area was satisfactory
3	The clinician was thorough in investigating my symptoms
4	The clinician did not listen carefully to me
5	The clinician gave me sufficient information about my illness/condition and care
6	The clinician explained things to me in a way that was easy to understand
7	The clinician spent enough time with me
8	It was difficult to find my way to the different rooms I needed to visit in the facility
9	I was attended to in private without being seen or overheard by others
10	I am worried that a patient could pick up an infection from visiting this facility
11	The clinicians who served me seemed highly knowledgeable about my condition
12	Some of the drugs or supplies I was prescribed/ordered were not available at the facility
13	All the services I needed were available at this facility
14	The facility appears well managed and organised
15	I was given clear information on how to take the medicines I've received
16	I understood the fees I was charged
17	I trust the staff here to act in my best interests
18	The facility is run down or in a poor state of repair
19	The facility is clean
20	The staff at the facility, including at reception and the pharmacy, were polite to me
21	The services were reasonably priced

Notes: The response options to each item are: agree; neutral; disagree. In scoring the response options we assigned a value of 1 for "agree", a value of 0.5 for "neutral" and a value of 0 for "disagree". Questions 1, 4, 8, 10, 12, and 18 were reverse scored since they are negatively framed.

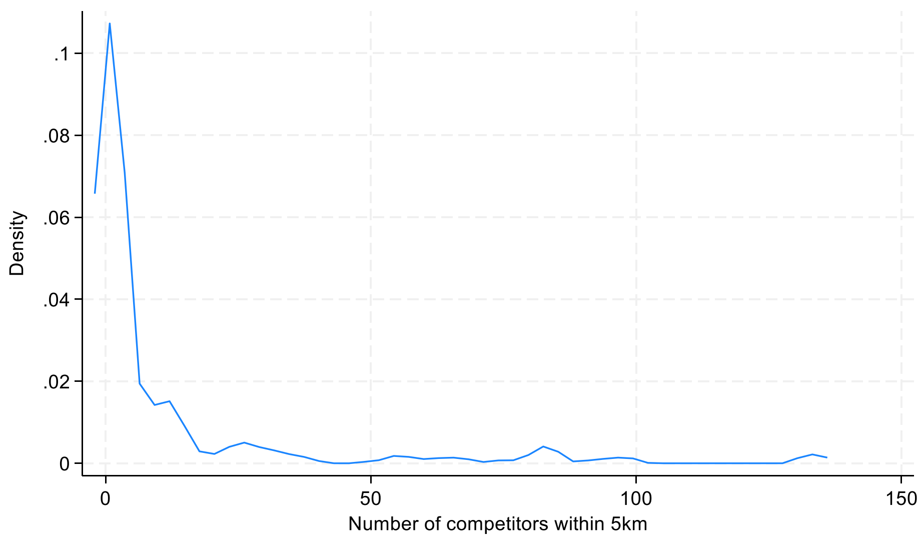

Fig. A1. Distribution in the measure of competition
Notes: The figure is a kernel density graph of the number of competitors within 5 km. Each observation is a health facility.

Data availability

Data will be made available on request.

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