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DECENTRALIZATION, ETHNIC FRACTIONALIZATION, AND PUBLIC SERVICES: EVIDENCE FROM KENYAN HEALTHCARE

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JEL Classification: D72, H51, H77, I18, J15

Keywords: Kenya

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Decentralization, Ethnic Fractionalization, and Public Services: Evidence from Kenyan Healthcare

Camille Hémet [*] ⓡ Liam Wren-Lewis [†] ⓡ Jessica Mahoney [‡] ⓡ

March 23, 2023

Abstract

This paper examines how use of public services changed following a major constitutional reform in Kenya. Following an important period of inter-ethnic conflict, responsibility for local health services was decentralized to 47 newly created county governments. Using an event-study design, we find that use of public clinics for births increased significantly after the reform, but only in counties that were relatively ethnically homogeneous. We also find a significant increase in the correlation between county ethnic fractionalization and a range of other measures of public health service use. Results suggest that services in these counties are less likely to require payments after devolution. Additionally, using within-county variation, we find an increase in public service use among individuals that are of the same ethnicity as the members of the county government executive.

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The ⓡ symbol signals that all authors' names have been randomized using a uniform distribution. This has been done using the AEA randomization tool, registered in the random authors archive under the following reference: ytWvTxfl0aLf. This working paper shall therefore be cited as Hémet ⓡ al. (2023).

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1 Introduction

There is a well-documented negative correlation between ethnic diversity and public good provision observed in both developed and developing countries. This can be explained by ethnic diversity being associated with greater heterogeneity in preferences for different types of public goods, leading ethnically diverse communities to shift their demand away from public goods (Alesina et al., 1999). Alternatively, a lack of cooperation across ethnic groups may undermine collective action (Miguel and Gugerty, 2005; Algan et al., 2016). In ethnically diverse contexts, decentralization can therefore be viewed as an opportunity to form more homogeneous local jurisdictions and alleviate concerns related to inter-ethnic cleavages. Over the past 50 years, many countries have implemented reforms to introduce new forms of decentralized government, with the aim of improving governance by getting closer to the citizens and their preferences (Oates, 1972) while enabling them to hold local government accountable (Bank, 2012). Yet, little is known on the interplay between decentralization and ethnic heterogeneity in explaining local public goods provision.

In this paper, we research the extent to which decentralization can alleviate concerns related to ethnic fractionalization by investigating how the effect of decentralization on public health services depends on local ethnic heterogeneity. To this aim, we rely on a national devolution policy in Kenya that was implemented in 2013 following a constitutional reform in 2010.[1] The policy resulted in the creation of 47 new county governments led by a directly-elected governor and county assembly. In so doing, the eight provinces – the jurisdictions which had previously been the highest level of sub-national government – were disbanded. The new county governments then took over the roles of the provincial authorities in addition to new responsibilities. One of the most critical sectors affected was healthcare: county governments were put in charge of running all public health clinics, including overseeing staffing. This reform implied that, almost overnight, citizens went from living in a province in which health services were administered through a federally managed bureaucracy, to living in a county in which health clinics were directly managed by a democratically elected governor.

We take advantage of this devolution reform to compute difference-in-differences estimators of the differential effect of county-level ethnic fractionalization on various health-related outcomes, ranging from birth in public clinics and other birth related outcomes to the use of public clinics more generally. In a first set of results, based on the Demographic and Health Survey, we observe that births occur significantly more frequently in public clinics (instead of at home) in less fractionalized counties after devolution. Consistent with these results, we find that, after devolution, pregnant women living in less diverse counties are more likely to undertake antenatal visits in a public facility and also more likely to benefit from the presence of a nurse or

[1] Devolution is the process by which the central government transfers authority to make political, financial, and budgetary decisions to semi-autonomous local governments. It is the strongest form of administrative decentralization. Other forms, such as deconcentration or delegation, do not allow sub-national governments autonomy in their decision-making processes.

midwife during childbirth. Relying on alternative data sources (the Kenyan Household Health Expenditure and Use Survey - KHHEUS - and the Afrobarometer), we further observe an increase in the likelihood of using a public health centre more generally in less fractionalized counties after devolution. Overall, these findings suggest that the use of public health services significantly increased after devolution in more homogeneous counties.

Interestingly, the various data sets at hand also enable us to look at supply-side characteristics of public health provision. In particular, the KHHEUS and Afrobarometer ask respondents whether they had to make a payment when they visited a public clinic. Here again, our results point in the same direction: in less ethnically diverse counties, individuals were less likely to have made some form of payment in a public clinic after devolution. This second set of results also suggests that devolution was more efficient in more homogeneous counties, in terms of local jurisdiction capacity to offer free health care services.

Going further, we discuss and investigate the potential mechanisms underlying our findings. In particular, we discuss mechanisms that relate to the change in the distance between individuals' ethnicity and the ethnic representation of local government, or the ethnic composition of workers at public clinics. Such mechanisms could stem from both the supply-side and the demand-side. For instance, the use of public hospitals could increase if one's ethnicity is more represented in the hospital's workforce, which is more likely to occur in less diverse counties. On the other hand, if county governors are of the same ethnicity as the majority group in their jurisdiction, they may feel more accountable and hence ensure that public health is actually free of charge. Although our data do not allow us to directly test these mechanisms, we provide suggestive evidence that they may be at play. This includes looking at variation within counties, exploiting individual ethnicity data.

Our work is at the crossroads of two strands of literature that approach the question of the supply of local public goods: that on ethnic diversity, and that on decentralization. We add to the literature on the economic and social effects of ethnic diversity, which follows the seminal paper of Easterly and Levine (1997).[2] More specifically, our paper contributes to the literature investigating the impact of ethnic diversity on public goods, by focusing on how diversity influences the extent to which individuals use public goods and services. By focusing on public service use in the immediate aftermath of a change in governance, we therefore complement a literature which has typically focused on longer-run cross-sectional differences in public service provision (Miguel and Gugerty, 2005; Okten and Osili, 2004; Khwaja, 2009; Munshi and Rosenzweig, 2018; Alesina et al., 2019, 1999; Algan et al., 2016).

Our paper also relates to the literature on decentralization, which discusses what is the efficient level of government intervention. The early work by Oates (1972) on fiscal federalism sets the

[2]This literature generally shows a negative relationship, though not always robust, between ethnic diversity and welfare spending (Luttmer, 2001), trust (Alesina and La Ferrara, 2002) or participation in social activities (Alesina and La Ferrara, 2000).

theoretical framework on which the subsequent empirical literature is based. The argument is that decentralized provision of local public goods can be welfare enhancing, as public good provision will be better tailored to the preferences of the local electorate. Empirically, decentralization is indeed found to provide greater utility to citizens (Flèche, 2020; Frey and Stutzer, 2000). Additionally, voters are more easily able to exert pressure on local officials than they are to federal authorities (Seabright, 1996), which can in turn improve public good provision. On the other hand, decentralization may incur welfare costs related to dis-economy of scale (Oates, 1972; Saito, 2008), or increased risk of corruption and elite capture (Waller et al., 2002; Platteau and Abraham, 2002; Mookherjee and Bardhan, 2006; Saito, 2008). Compared to this literature, our study focuses on the short run heterogeneous effects of decentralization, by capturing how citizens respond to devolution in their use of public health services.

Importantly, our paper bridges these two strands of literature by investigating the interplay between diversity and decentralization. Proponents of political decentralization argue that it can be used as a way to create more ethnically homogeneous local jurisdictions, which may ease tensions and favor government intervention in countries where ethnicity is politically salient and a source of conflict. Indeed, the theory of Oates (1972) implies that decentralization would be particularly desirable in a context characterized by a pronounced diversity in individual preferences (e.g. for a local public good or service) coupled with geographic proximity to those with similar preferences. To the best of our knowledge, few studies directly test this theoretical intuition, and our paper contributes to filling this gap. Our work therefore complements a recent working paper by Seidel (2020), who finds that regional ethnic heterogeneity is negatively correlated with public good provision, but only in decentralized countries. Our results are consistent with this cross-sectional result, and add further weight to the causal interpretation by analyzing the dynamic processes around decentralization. Our paper is also related to Alesina et al. (2019), who investigate the question of ethnic diversity and illegal deforestation in the context of devolution in Indonesia. They provide evidence that the reduction in diversity due to devolution leads to a reduction in deforestation, a public bad controlled by local authorities, which are more politically accountable in more homogenous jurisdictions. By contrast, we study the provision of public health services, which enable us to look at the supply and demand side and therefore to shed light on alternative mechanisms than political accountability. Our work is finally closely linked to a recent working paper by Bluhm et al. (2021) that also relies on the 2010 Kenyan constitutional reform to investigate how the associated redistricting of local administration impacted ethnic voting. Using a standard measure of regional ethnic fractionalization combined with a new measure of ethnic-group fragmentation across regions, they find that ethnofederalism (when local jurisdictions tend to be defined along ethnic groups borders, rather than across them) reduces the salience of ethnicity and the extent of ethnic voting in national politics. They do not look at impacts on public good provision, but their results are consistent with ours since a reduction in ethnic tensions could be part of a possible mechanism behind our results.

The rest of the paper is structured as follows. Section 2 describes the main contextual elements of this paper: section 2.1 discusses the importance of ethnic affiliation in Kenya, while sections 2.2, 2.3 and 2.4 provide details on the 2013 devolution process, the role of newly formed county governments, and the post-devolution provision of healthcare, respectively. Section 3 describes the data sources used, and section 4 exposes the empirical strategy. The results are presented in section 5: results on the perinatal use of public health care are reported in section 5.1 and results on the general use of public clinics are in section 5.2. We then propose a discussion of the possible mechanisms underlying our results in section 6. Section 7 concludes.

2 Context

2.1 Ethnicity in Kenya

Ethnic affiliation is an important political, economic, and social factor in Kenyan society. Kenya is a multi-ethnic state, with no one ethnic group claiming a clear national-level majority. The largest group are the Kikuyu, who in 2014 comprised only 16.3% of the population. The next few largest groups, the Luo, Luhya, and Kalenjin, also make up only 11-14% of the country (DHS, 2015). In general, the main ethnic groups – Kikuyu, Kalenjin, Luo, Luhyya, and various Coastal groups – vie for national political power, however the makeup of political alliances and coalitions are ever-changing (Posner, 2007). Given the fact that no one group can completely dominate political life, Kenyan politics have been categorized by shifting political alliances since the days of colonial rule.

Throughout the 1990s and early 2000s, Kenya experienced more "corruption, increasing elite polarization, [and] the rise of militias" with ethnic backing (Branch and Cheeseman, 2008, pg. 11). Ethnic rivalries were often exacerbated precisely because of the strong nature of the executive branch: winner-takes-all politics mean that the spoils for the winner were huge, while the losers became increasingly marginalized. This culminated in the presidential election of 2007, which was marred by violence. The incumbent, Mwai Kibaki (a Kikuyu and member of the Party of National Unity) was declared the winner against opposition leader Raila Odinga (a Luo, and member of the Orange Democratic Movement). Accusations of irregularities were widespread, including from international observers, and the country was soon enveloped by large-scale conflict. The violence ended with the creation of a government of national unity in March 2008, and a pledge to draft a new Constitution that would fundamentally change the way political power is exerted in Kenya.

2.2 The 2013 Devolution Process

In order to fully understand the magnitude of the change brought about by devolution, it is useful to briefly overview the governance structure that came before. Though the country has gone through many phases of governance since it gained independence in 1963 – democracy, autocracy, and a return to multi-party democracy in the 1990s – in all periods the central government remained strong. Under the previous constitution the Provincial Administration (PA) coordinated central government policies and administered development programs at the local level. The PA was a bureaucratic system that had its roots in the British colonial administrative structure, and as such focused on a top-down approach emphasizing law and order and strong executive authority. None of the positions in the PA were democratically elected. The primary role of the PA was to oversee the implementation of central government policies, including the policies of different ministries (Bagaka, 2011; Gertzel, 1966). Throughout the decades, different presidents made efforts to promote community-led development and change the flow of policy from top-down to bottom-up. Some initiatives were more successful than others in achieving this goal, but all fell short of true decentralization of political power.[3]

On 27 August 2010, the Kenyan government ratified a new Constitution outlining its vision for a new Kenya prioritizing democratic governance, transparency, and citizen participation. One of the core reasons for devolving service provision to sub-national elected counties was to "recognize the right of communities to manage their own affairs" and to "promote social and economic development and the provision of proximate, easily accessible services." Thus, the government's stated theory of change driving devolution was that bottom up, community-led, development would lead to enhanced service provision. Furthermore, devolution was created to "protect and promote the interest and rights of minorities and marginalized communities," an especially important priority given the ethnic violence that plagued Kenya in the aftermath of the previous presidential election (Constitution, 2010).

In early 2013, 47 new county governors took office, officially marking the start of Kenya's new devolution policy. The original plan was for county governments to take office in January 2013, however the elections were delayed by a few months. Instead, politicians announced their candidacy and policy platforms in January and elections were held in March; governors and their assemblies took up their posts immediately afterwards. For the purposes of this paper, we use the start of January as the beginning of devolution. At this point candidates were campaigning and holding election rallies, which outlined their plans for how to improve service provision and allocate public goods and services.

The Transition to Devolved Government Act (2012) outlined the intended handover process: over the course of three years, different responsibilities would slowly be devolved from the central government to county governments, commiserate on passing capacity assessments and systems audits (Okech, 2017; McCollum et al., 2018). However this timeline was soon revised. Once county governors took office in March of 2013, they successfully petitioned for the immediate transfer of all authority. As a result, devolution happened much faster than anyone anticipated. Almost overnight the provision of some public services, in particular healthcare, went from being

[3]The three main endeavors include *harambee*, the District Focus for Rural Development (DFRD), and the Constituency Development Fund (CDF). For more information on these, see, for instance, Bagaka (2011); Obosi (2003); Cheeseman et al. (2016).

administered at the province-level by bureaucrats in the PA, to being run by democratically-elected county governors.

Devolution in Kenya is therefore notable for its impact on service provision for three key reasons: (1) sub-national governments were given actual autonomy to dictate policy directives and resource allocation, (2) the leaders of sub-national governments are democratically elected, and (3) the transition process happened much faster than planned, and in some instances counties were given more funding and resources than had been pledged. Taken in sum, this shows that devolution was truly a significant break from the past.

2.3 County Governments

The constitution devolved a number of functions to county governments, including those relating to agriculture, local transport, public works, cultural activities, and importantly for this paper, health services. Governors were now in charge of overseeing county health facilities and pharmacies, ambulance services, the promotion of primary healthcare, food safety, veterinary services, burials and cremation, and refuse removal (solid waste, etc.). The federal government retained control of public education and policing, along with all corporate and income tax collection.

Since devolution, county governments have had significant authority in determining how to allocate their resources. The Governor, in conjunction with his/her appointed County Executive Council, drafts a budget and development plan. This legislative agenda must then be approved by Members of the County Assembly (MCA), who are also directly elected by constituents. Given their budgetary autonomy, governors are considered politically powerful players, and those interested in a career in politics are more interested in running for governor of a county than for a Senate seat (Cheeseman et al., 2016).

County governments are primarily funded by the federal government: (1) 15% of total federal government revenue, evenly distributed between counties, (2) an Equalisation Fund, comprising 0.5% of national revenue, to provide additional resources to historically marginalized and underfunded counties, and (3) conditional grants, at the discretion of the national government. In addition, county governments can raise their own funds via: property and entertainment tax collection, business licenses, and fees for services administered locally (e.g., sanitation services). However these local-level sources only constitute only a small portion of county budgets (Bank, 2012; Aduke, 2013).

2.4 Devolution and Healthcare Provision

Healthcare services are one of the key components of governance to have been devolved to county governors. As is laid out in the Fourth Schedule of the new Constitution, the Ministry of Health retains control over setting national health policy, provides technical assistance to counties, and manages national referral health facilities: everything else relating to healthcare, including recruitment and staffing of clinics, is now under the authority of county governors (Kimathi, 2017). Thus with devolution, budgeting moved from the province to the county level (Oketch et al., 2018).

County governments were given a huge responsibility in managing healthcare services, and almost no time to prepare to do so. As a result, the immediate aftermath of devolution was often chaotic. In a case study of Kilifi county, Tsofa et al. (2017) describe how county governments did not have the capacity to take over control of Human Resources for Health (HRH) and Essential Medicines and Medical Supplies (EMMS) systems management, which led to disruptions in salary payments and a subsequent health worker strike and mass resignations, along with delays in procurement processes leading to stock-outs of important drugs. Other reports show that some counties prioritized spending on highly visible goods – like ambulances – rather than more important services, or essential drugs (RESYST, 2018; Cheeseman et al., 2016).

Other staffing shortages were due to ethnic tensions that became exacerbated after the introduction of county governments. The International Rescue Committee (IRC) conducted a survey in Turkana, and found that in 2013 (directly after devolution) 56% of staff were of the Turkana ethnicity. However by 2015, within 12 health facilities over 92% of the staff were ethnically Turkana. There appears to have been sorting of health personnel based on ethnicity after devolution – as Kimathi (2017) states, "the massive exodus of staff" is partly the result of "ethnic fears" and "political statements made by leaders in the area to the effect that they were discouraging outsiders from employment in the county" (Kimathi, 2017; IRC, 2015). In a separate study, women in Uasin Gishu reported that "tribal discrimination of minorities" led to negative maternal health service access for minorities (Kilonzo et al., 2017).

Other difficulties centered on procurement processes. Prior to devolution health clinics were required to procure supplies from the Kenya Medial Supplies Authority (KEMSA), a monopoly, however county governments are now able to lead competitive procurement processes. While some have been able to cut costs by buying on the open market, instances of corruption and skimming have emerged in a number of counties. For example, in 2015 an Isiolo County audit found that a supposed Ksh 1.2 billion had been spent on drugs and supplies, however spot checks to the clinics themselves showed them to be under-stocked or lacking some of the drugs entirely (Kimathi, 2017; Mwamuye and Nyamu, 2014).

It is worth noting that despite all of the difficulties surrounding the implementation of devolution, it remains a very popular concept among Kenyan citizens. The 2010 Constitution was passed by public referendum with a two thirds majority, and public opinion polls in 2013 (right after the first round of county governor elections) showed that 85% of Kenyans approved of devolution (Cheeseman et al., 2016). These findings appear to be persistent: a 2018 poll shows that 80% of Kenyans prefer the system of devolution to what came before (El Messnaoui et al., 2018).

Finally, it is important to mention a concurrent health policy that is relevant to the outcomes of interest in this paper. In June of 2013, President Kenyatta announced a new program, the Free Maternity Programme, that introduced free maternal healthcare services (free delivery and up to four antenatal visits) at all public health facilities in the country.[4] Implementation was imperfect: there have been many stories of pregnant mothers turned away at some clinics due to delays in reimbursements from the Ministry of Health Okech (2017), or required to purchase their own materials (Oketch et al., 2018). However academic studies into the impact of the policy have shown that it increased the number of births in public facilities, especially for lower income women (Calhoun et al., 2018). This makes it difficult to disentangle the effects of this policy and the overall effects of devolution. However the fee waiver program should only have had a differential impact according to ethnic fractionalization to the extent it was implemented through county governments, and thus can be considered part of the effect we are estimating.

3 Data

This paper primarily uses data from the 2014 Demographic and Health Survey (DHS) in Kenya; this is used to estimate county ethnic shares, as well as to define key outcome variables. For additional health-related outcomes, we also use the 2003 and 2008 waves of the survey, as well as data from the Kenyan Household Health Expenditure and Use Survey (KHHEUS) and the Afrobarometer. Basic summary statistics for the primary outcomes of interest from all main data sources, pre- and post-devolution, are shown in Table 1.

3.1 DHS Data

The Demographic and Health Surveys (DHS) Program collects survey data in over 90 countries around the world, covering topics relating to public heath and health service provision. Data is collected at the household level, with separate surveys for a male and female respondent. We make most use of the 2014 Kenyan DHS, which was conducted from May to October by enumerators from the Kenyan National Bureau of Statistics (KNBS). In addition to providing accurate estimates of key health indicators for Kenya as a whole, the survey was designed to produce representative estimates at the county level. In the first stage, 1,612 enumeration areas (EA) were randomly selected. In the second stage, 25 households within each cluster were randomly selected from a list of all households.

The questionnaires were split into three groups: a household questionnaire, a female survey, and a male survey. The outcomes of interest for this paper focus on female health – pregnancies,

[4]This program was rebranded the Linda Mama Programme and as of 2016 is run through the National Health Insurance Fund (NHIF). The services it covers have expanded to a full antenatal care package, including preventative services that cover malaria prophylaxis, deworming, and iron and folate tablets; and a post natal care package including full sets of vitamins and supplements for mother and newborn, immunizations, and screenings up through 6-weeks post-partum. However in 2013 when first introduced, the program primarily covered the fees associated with giving birth in a public facility.

births, and early childhood healthcare practices – thus the male survey is not used except to generate estimates of the ethnic composition of the county. In total, 36,400 households were successfully interviewed. Within these households, an eligible female between the ages of 15 and 49 was randomly selected to complete the female survey: 31,079 women were successfully interviewed.

The DHS survey asks respondents to report their ethnicity: there are 23 options, including "other." We estimate each ethnicity's share within a county by dividing the total (weighted) number of individuals (both men and women respondents in the DHS survey) of a given ethnic group by the total number of weighted individuals in that county. The ethnic-linguistic fractionalization (ELF) index is computed using the method laid out by Easterly and Levine (1997), which is the following variation of a Herfindahl concentration index:

$$FRAC = 1 - \sum_{i=1}^{N} \pi_i^2$$

where π is the share of individuals belonging to ethnic group i, and N is the total number of groups in the jurisdiction. The index can be interpreted as the probability that two randomly drawn individuals in the county belong to different groups. The index can take values from 0 to 1: it is equal to 0 when the county is completely homogeneous (everyone belongs to the same group) and tends to 1 when the area is entirely heterogeneous (every individual belongs to a different group). The measure of fractionalization in each county is shown in Figure 1.

The county in which the 2014 DHS cluster is located is recorded within the survey, and we use this when we are restricting our analysis to only the 2014 wave of the DHS. Since counties didn't exist prior to 2013, however, when we consider multiple DHS waves we instead approximate the county in which the cluster lies using the GPS coordinates provided by DHS. Note that this adds an element of noise, since clusters are randomly displaced by up to 2km for urban clusters, and up to 5km for 99% of rural clusters. We also use these GPS locations when matching clusters to their nearest health clinic.

It is important to note that devolution led to an overall reduction in ethnic fractionalization in local jurisdictions: post-devolution counties are to a large extent more homogeneous than pre-devolution provinces (only six counties are less homogeneous than the corresponding province). This comes as no surprise, as increased ethnic homogeneity is one of the arguments pushed forward for devolution, and because county borders were initially drawn by the British colonial authorities to house ethnic groups.

3.2 KHHEUS Data

The Kenyan Household Health and Expenditure Survey is a national household survey that explores health seeking behavior, the utilization of health services, health spending, and health

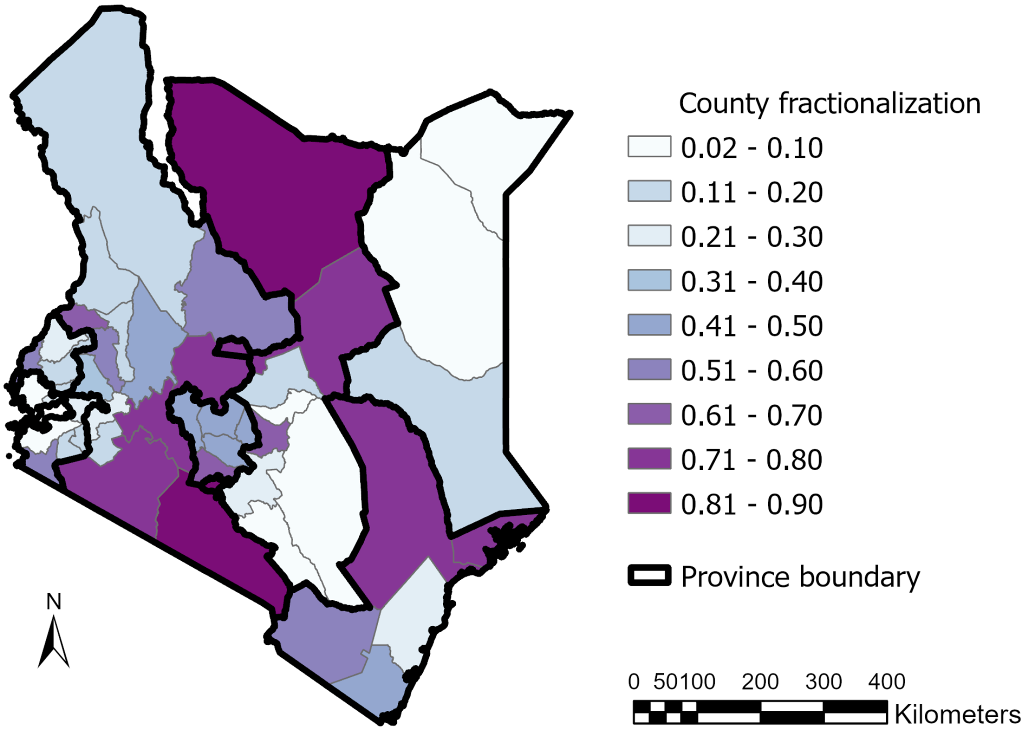


Figure 1:
Note: County fractionalization is measured by the formula $1 - \sum_i s_i^2$, where s_i is the share of ethnicity i within the county population, based on the 2014 DHS.

insurance coverage amongst Kenyan households. Microdata from three waves was obtained from the Kenyan National Bureau of Statistics. These waves were undertaken in 2008, 2013 (between July and August), and 2018. In the two later waves, households' county of residence was recorded, while in the 2008 wave the households' district of residence was recorded, which we can match directly to counties. In each wave, respondents were asked whether each household member was ill within the last four weeks, and if so whether they sought any medical treatment. If they did seek medical treatment, the type of clinic was recorded (i.e. public or private) along with any expenditures they made.

3.3 Afrobarometer Data

Afrobarometer conducts nationally representative opinion surveys throughout Africa. Kenya has participated in 8 rounds, from 2003 to 2019.[5] Topics addressed include opinions on how well the government is performing, quality of local services, and opinions on key policy priorities. We assign each cluster to a county based on the GPS coordinates. This is done even using later

[5]Rounds are not conducted every year. Kenya has participated in every round since round 2: round 2 (2003), round 3 (2005), round 4 (2008), round 5 (2011), round 6 (2014), round 7 (2016) and round 8 (2019).

Table 1: Summary statistics of outcome variables

	Pre-devolution		Post-devolution	
	Obs.	Mean	Obs.	Mean
DHS 2014 birth-level (2009-2014)				
Birth at public clinic	13940	.41	6624	.46
DHS child-level (2003, 2008, 2014)				
Went to public clinic, given case of diarrhea	1624	.31	2646	.48
Went to public clinic, given case of fever or cough	2890	.34	5726	.43
KHHEUS (2007, 2013, 2018)				
Went to public clinic, given sickness	5622	.46	51297	.48
Receivied free care at public clinic, given sickness	5622	.17	51297	.2
Receivied free care, given visited public clinic	2597	.37	24784	.42
Afrobarometer (2005, 2011, 2014,2016, 2019)				
Had contact with public clinic	3663	.82	6386	.72
Had contact and paid no bribe at public clinic	3663	.53	6386	.58
Paid no bribe at public clinic, given contact	3017	.65	4613	.81

Notes:

waves, which contain information on the county of the cluster, in order to ensure consistency across waves.

We primarily make use of answers to the questions 'In the past 12 months, have you had contact with a public clinic or hospital?' and, for those who responded yes, 'how often, if ever, did you have to pay a bribe, give a gift, or do a favour for a health worker or clinic or hospital staff in order to get the medical care you needed?'.[6] We also make use of the question 'do you think your county governor is involved in corruption?' which is asked in rounds 6 and 7.

4 Empirical strategy

Our empirical strategy is essentially a difference-in-difference approach whereby we examine differences over time in how outcomes correlate with ethnic fractionalization. In particular, our baseline estimation involves estimating the coefficients ζ_τ in the following equation:

$$y_{i,c,p,t} = \sum_{\tau} \zeta_\tau(\mathbb{1}(t = \tau) \times FRAC_c) + \beta X_i + \gamma_{p,t} + \eta_c + \epsilon_i \tag{1}$$

where $y_{i,c,r,t}$ is the outcome of individual i observed in year t, living in county c, within province p and X_i is a vector of controls. $FRAC_c$ is the ethnic fractionalization in county c, $\gamma_{p,t}$ are province-year fixed effects and η_c are county-level fixed effects. The exact set of years τ considered depends on the availability of data on the outcome variable, but in each case we drop the last pre-devolution year since county fixed effects are included. Plotting the annual coefficients in this 'event-study' style analysis allows us to look for evidence of changes in the correlation between fractionalization and our outcome variable over time. We include province-

[6] Note that, as we can see in Table 1, reported contact with public clinics decreases after devolution in Afrobarometer, which contrasts with contact measured by the other datasets. This stems from a change in the way in which the question was asked across waves which we discuss in more detail in 5.2.3.

year fixed effects to control for variation over time between different provinces, which are the larger administrative unit within which counties are contained and were previously responsible for healthcare.

As a secondary analysis, we then additionally estimate a simpler diff-in-diff style equation:

$$y_{i,c,p,t} = Post_t \times FRAC_c + \beta X_i + \gamma_{p,t} + \eta_c + \epsilon_i \tag{2}$$

where $Post_t$ is an indicator for whether t is after devolution - i.e. the year is 2013 or later. In all cases standard errors are clustered at the county level.

5 Results

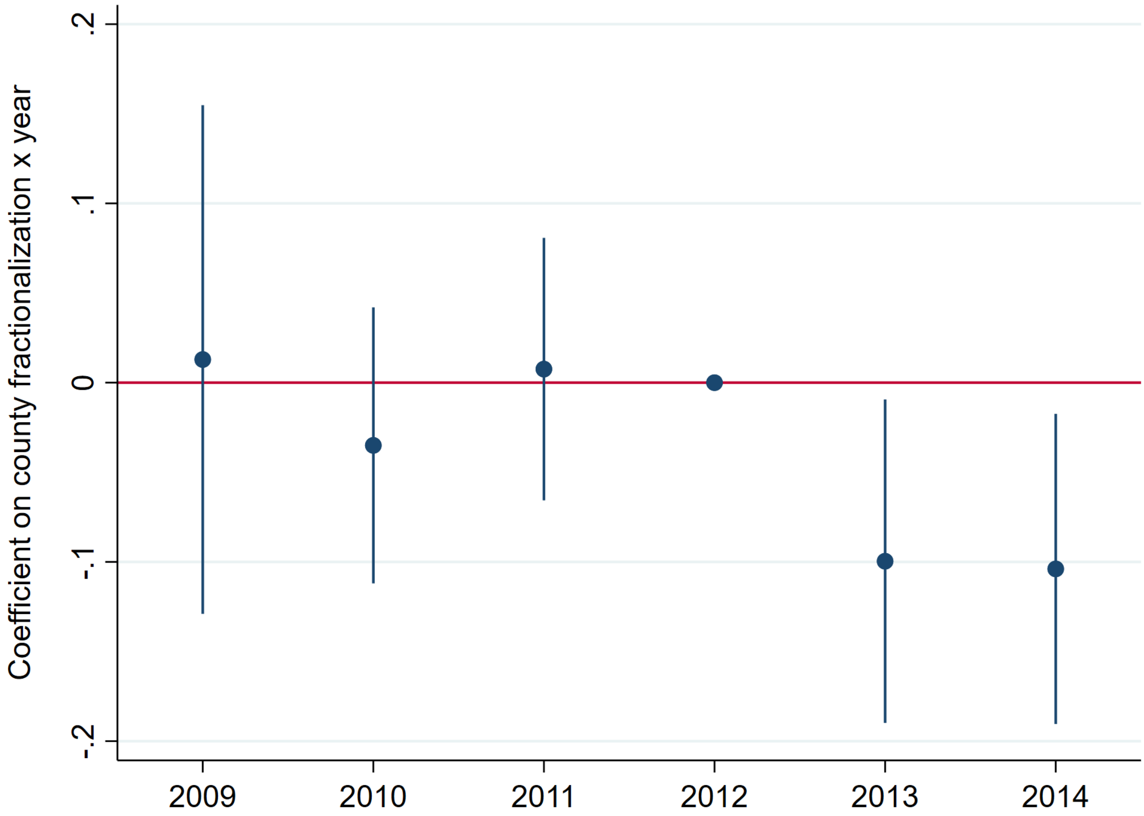
5.1 Births in public clinics

We begin by presenting results on whether births recorded in DHS took place in public clinics. Giving birth in a health facility (either private or public) is a stated priority for the Ministry of Health: should complications arise during pregnancy, both mother and baby are more likely to survive without long-term effects (DHS, 2015). A key advantage of this outcome variable is that we have births reported for each year over the period including devolution, allowing us to undertake an event-study style analysis. We estimate equation (1) for births in the years 2009-2014, with the interaction with 2012 omitted since we include county fixed-effects and this is the last year before devolution.

The coefficients on the year dummies interacted with county fractionalization are displayed in Figure 2. We note that the coefficients on the post-devolution terms are significantly negative, meaning that in less fractionalized counties births are more likely to occur in public clinics after 2013. The magnitude is sizeable - going from the fractionalization level of the most to the least fractionalized county would increase the share of births in public clinics by around 8 percentage points, about 17 % of the mean. We can also see this result in the raw data if we simply plot the change in public birth share after devolution against county fractionalization (Figure A1). Here we can see that in the most fractionalized counties, the share of births taking place in clinics stayed pretty much unchanged in the most fractionalized counties, while there was an increase of up to 20 percentage points in the less fractionalized counties.

We can therefore conclude that births were more likely to take place in public clinics after devolution in less fractionalized counties. One reason we might be cautious in interpreting this as a causal impact of fractionalization, however, is that fractionalization may be correlated with omitted variables which independently impact changes in public clinic use. In Table 2 we therefore test the robustness of this result to including additional control variables. In column 1 we present the results of estimating equation (2), where instead of interacting county fractionalization with year dummies (as in Figure 2) we interact it with a simple dummy indicating whether

Figure 2: Birth at public clinic by birth year



Notes: Points represent coefficients from regressing a dummy for whether a birth took place a public clinic on county fractionalization interacted with year dummies - i.e. equation (1). The lines represent the 95 % confidence intervals. Controls include province-year fixed effects, county fixed effects, birth order, birth month, the sex of the child, whether the mother lives in an urban area, and categorical variables for the mother's age, education, and asset index. Standard errors are clustered at the county level.

the birth took place after devolution (i.e. in 2013 or 2014). In column 2, we include year fixed-effects interacted with a number of county-level controls, including the county population, population density, night lights in 2012, area, urbanization rate, the log of the average distance to a clinic, and the average education level. We can note that our coefficient of interest decreases only very slightly in magnitude and remains highly significant, meaning that our result is not being driven by variation in these variables.

In order to understand which variation is driving our result, we can also add a number of further fixed effects to the regression. It would be concerning, for instance, if our result stemmed from differences in the characteristics of mothers which give birth over time across counties, since this would be unlikely to be driven by devolution. To assuage this concern, in column 3 we include mother-level FEs. This substantially reduces our sample, since we are now only considering mothers who had two or more children between 2009 and 2014, but our result remains significant

Table 2: Robustness of birth result

	(1)	(2)	(3)	(4)	(5)
County fractionalization	-.095***	-.083***	-.077**	-.099**	-.11***
× Post-devolution	(.029)	(.027)	(.032)	(.045)	(.034)
County FEs	Yes	Yes	No	No	Yes
Province-year FEs	Yes	Yes	Yes	Yes	Yes
Controls × year FEs	No	Yes	No	No	No
Mother FEs	No	No	Yes	Yes	No
Ethnicity-year FEs	No	No	No	Yes	No
R^2	.18	.18	.77	.78	.18
Observations	20564	20564	10634	10630	20564
Clusters	47	47	47	47	47
Frac. measured in	2014	2014	2014	2014	2008

Notes: The table presents results of estimating equation (2). Controls include province-year fixed effects, county fixed effects, birth order, birth month, the sex of the child, whether the mother lives in an urban area, and categorical variables for the mother's age, education, and asset index. In column (2) we include year fixed-effects interacted with county-level variables including the county population, population density, night lights in 2012, area, urbanization rate, the log of the average distance to a clinic, and the average education level. County fractionzaliztion is measured using the 2014 DHS in columns (1) to (4), and using the 2008 DHS in column (5). Since a birth is assigned to a county based on the location of the mother at the time of the survey, county fixed-effects are dropped when mother fixed-effects are included in colums (3) and (4). Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

with a similar coefficient. In column 4 of Table 2, we additionally add ethnicity-year fixed effects, allowing for different ethnicities to exhibit different changes in public clinic use over time. Since one's ethnicity is highly correlated with county fractionalization (with, for instance, some ethnicities concentrated in relatively non-fractionalized counties), including these fixed-effects substantially reduces power, but our coefficient of interest remains significant.

A final concern which we consider is that our measure of county fractionalization comes from the 2014 DHS, which obviously took place after devolution. If county fractionalization changed substantially over the period, then our result could be biased due to measurement error - i.e. we will be approximating county fractionalization better in 2014 than in 2009. To mitigate this concern, we recalculate county fractionalization levels using the 2008 DHS wave. Given that the difference in time is relatively short, we unsurprisingly find the measures are highly correlated, and when we use the 2008 measure instead of the 2014 one (in column 5 of Table 2), our results are very similar.

In order to understand this change in public clinic use further, in Table 3 we undertake a similar analysis for other birth-related variables. In columns 1 and 2 of the table, we show that the increase in births in public clinics generally substitutes for home-births rather than births in private clinics. Presumably as a result, column 3 then shows that these births are more likely to be attended by a nurse or midwife after devolution in more homogeneous counties. A subset of mothers are also asked about whether or not they attended antenatal visits for their most recent birth. In column 4 we therefore undertake the same analysis as we do for births only looking at whether the mother attended at least one antenatal visit at a public clinic. As with births, we find women in less fractionalized counties are more likely to attend a public clinic after devolution.[7]

Table 3: Birth related outcomes

	Birth at private clinic (1)	Birth at home (2)	Nurse or midwife attended (3)	Antenatal visit at public clinic (4)	Share of vaccines received (5)	Died within 1 week (6)
County fractionalization	0.0237	0.0703**	-0.0708*	-0.0675*	-0.0324*	0.00455
× Post-devolution	(0.0150)	(0.0296)	(0.0354)	(0.0399)	(0.0186)	(0.00962)
Observations	20564	20564	20564	6756	19271	20564
Adjusted ^{2}	0.156	0.336	0.190	0.115	0.179	0.00234
Dep. var mean	0.108	0.453	0.412	0.763	0.882	0.0164

Notes: The table presents results of estimating equation (2). Antenatal visits - the dependent variable in column (3) are only recorded for the most recent birth of each mother. In column (5) the dependent variable is the number of vaccines that the child received by the time of the survey, out of those which we would have expected to be administered by this point - see the notes to Table A1 for details. Children aged one month and below are therefore excluded from this regression. Controls include province-year fixed effects, county fixed effects, birth order, birth month, the sex of the child, whether the mother lives in an urban area, and categorical variables for the mother's age, education, and asset index. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

An important question is whether this increased attendance of public clinics improved health outcomes. Unfortunately, this is difficult to measure using DHS, since it is not well adapted to measure maternal mortality and there are few relevant outcomes for historic births. One could imagine, for instance, an impact on birth weight, but this is only recorded systematically when the birth took place in a facility. One related outcome it is possible to look at is vaccinations, since these are recorded for all relevant children. In column 5 of Table 3, we use as a dependent variable the number of vaccinations which the child has received at the time of the survey out of the set of vaccines which we would expect them to have received.[8] We find that children born in less fractionalized counties after devolution receive a greater share of the recommended vaccines. We also look, in column 6, at whether the child born died at birth or within the next week. Here we find no significant effect, but the outcome is sufficiently rare that we are not powered to make strong conclusions here. Finally, in Table A2 we undertake the same regressions including year fixed-effects interacted with county-level controls and find broadly similar results.

[7] When undertaking this analysis, we exclude from the sample births which took place before July 2013, since potential antenatal visits would cover both the pre-devolution and post-devolution periods.

[8] Children 1 month or less are not included in this sample as it is quite likely they will receive all of the relevant vaccines after the time of survey. We also look at the individual vaccinations that contribute to this total in Appendix Table A1 - this shows that there isn't a particular vaccine driving this result, but rather each vaccine is less likely to be given in more fractionalized counties after devolution.

5.2 General use of public clinics

The previous section showed evidence that, after devolution, mothers in less fractionalized counties were more likely to give birth in public clinics. It is therefore natural to ask whether we see use of public clinics for other purposes also change after devolution in a similar way. While we don't have similar annual data for other healthcare issues, we can exploit the fact we have several waves of DHS, KHHEUS, and Afrobarometer surveys to look at how behavior changed across waves.

5.2.1 Evidence from multiple waves of the DHS

In the DHS, mothers are asked if they took their child to a public clinic in two cases: when their child had a case of diarrhea, and when their child had a fever or cough. We can therefore restrict our sample to mothers who report a case of either illness, and then use whether they took the child in question to a public clinic as the outcome variable.[9] We then estimate equation (1) for these two outcomes and present our results in Figure 3. As in the case of births, we see that differential use of public clinics by county fractionalization increases after devolution for both types of illness. In Table A3. we show that these results are robust to including year fixed-effects interacted with county-level variables.

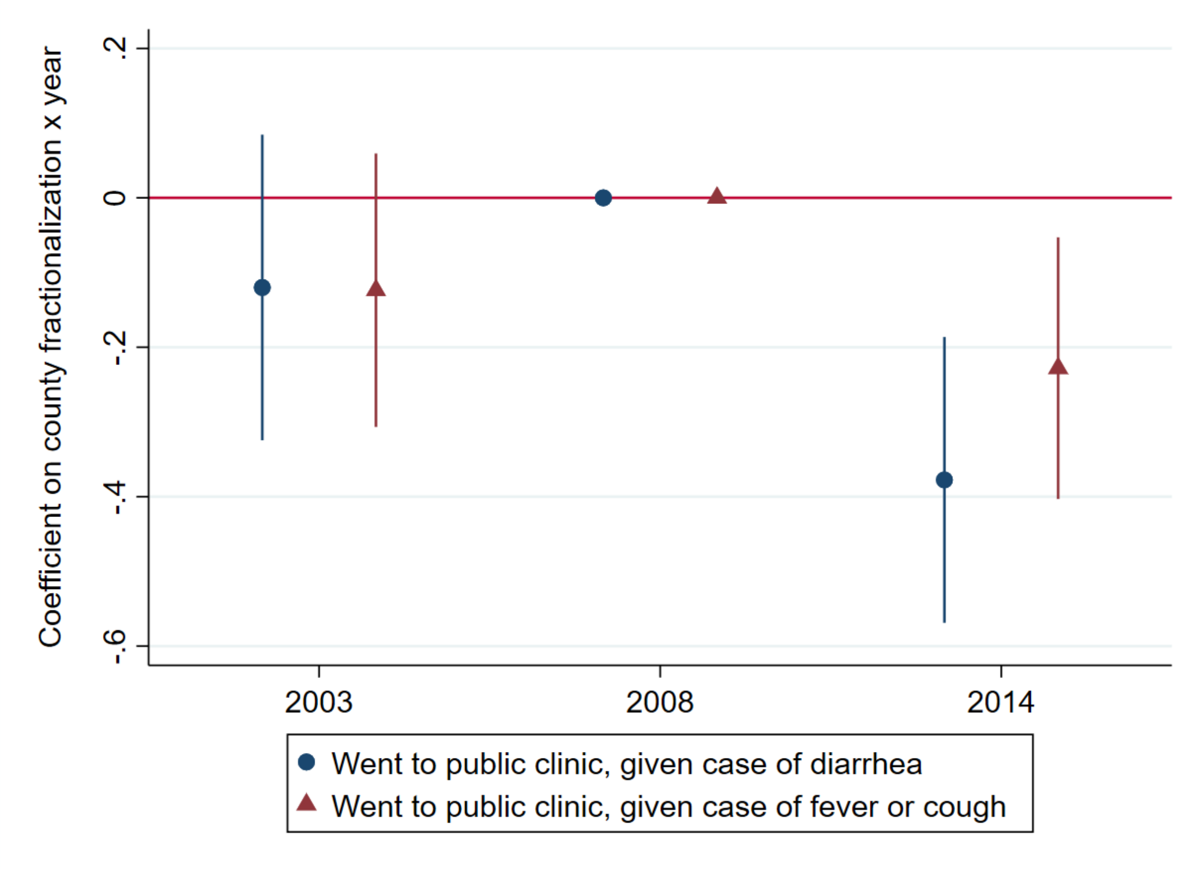
5.2.2 Evidence from the KHHEUS

In the Kenyan Household Health Expendiutre and Use Survey (KHHEUS), the respondent is asked whether each household member was ill in the last four weeks, and whether they sought medical treatment. In a similar manner to with the DHS, we therefore restrict our sample to household members who were reported as being ill. Our first outcome variable is then whether they visited a public clinic to seek help with their illness. We again estimate a version of equation (1), omitting the interaction between county fractionalization and the 2008 dummy, which is our only pre-treamtent wave. The results are shown as the blue circles in Figure 4 - visiting a public clinic is significantly negatively correlated with visiting a public clinic after devolution.

One advantage of the KHHEUS is that respondents are also asked about their health expenditures. This is an interesting aspect to explore since, for some healthcare services, individuals should be able to access them for free, but in practice may end up paying. Accessing public clinics without payment can therefore be seen as an important measure of the performance of public healthcare services. We thus construct an additional indicator variable which takes the value one if an individual received treatment at a public clinic and made no payment. When we take this as our outcome variable, we observe a coefficient very similar to that on visiting

[9] We also check in Table A6 whether the probability of reporting such an illness changes as a function of fractionalization after devolution. We find no significant impact on the probability of reporting a case of fever or cough and a slightly significant impact of reporting a case of diarrhea.

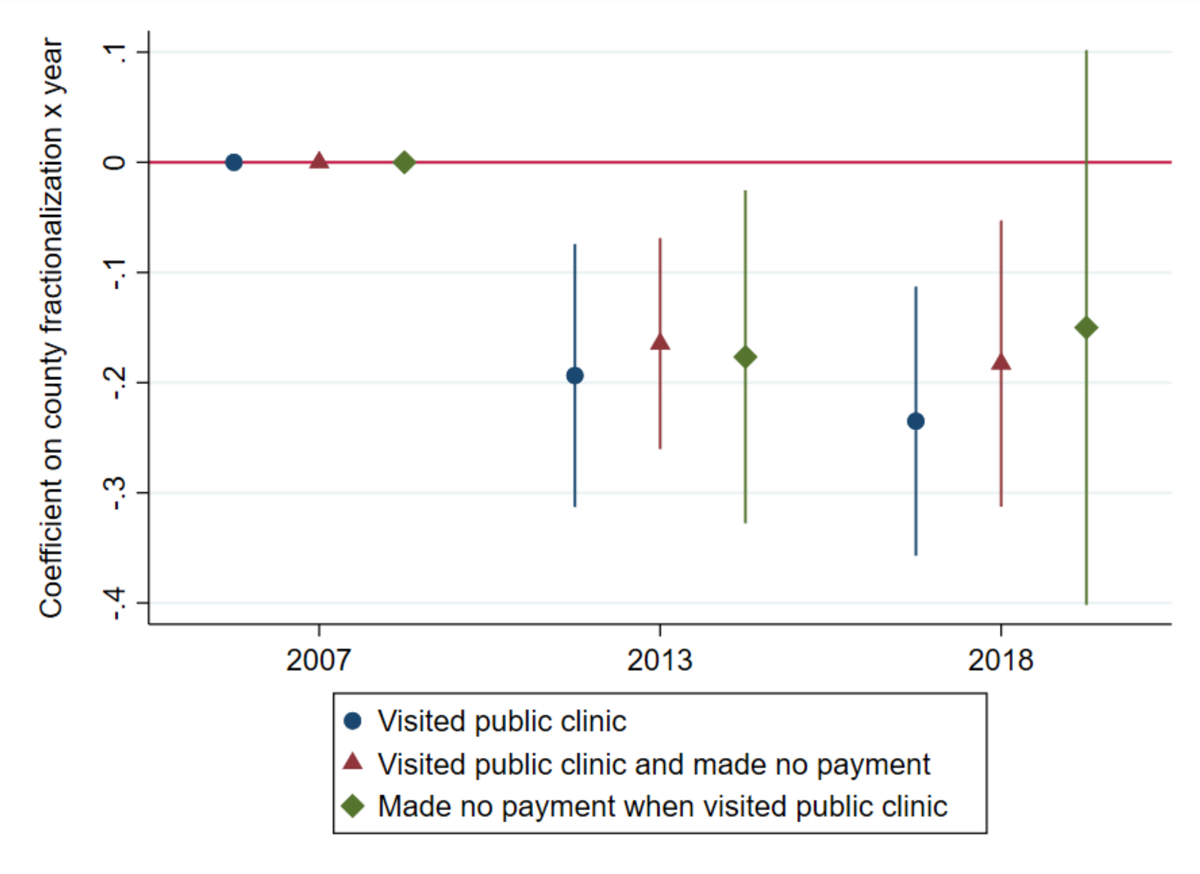
Figure 3: Use of public clinics in three waves of the DHS



Notes: Points represent coefficients from regressing a dummy for whether a mother took their sick child to a a public clinic on county fractionalization interacted with year dummies - i.e. equation (1). Years correspond to rounds of the DHS survey. The lines represent the 95 % confidence intervals. Controls include province-year fixed effects, county fixed effects, whether the mother lives in an urban area, and categorical variables for the mother's age, education, and asset index. Standard errors are clustered at the county level.

a public clinic (see the red triangles in Figure 4). This suggests that the vast majority of the additional visits made in less fractionalized counties do not require payment. Additionally, we also restrict to the set of people who visited public clinics, and then use as our outcome variable whether or not they made a payment. The green diamonds in Figure 4 show us that again coefficients are negative, suggesting that public clinics were less likely to require payments after devolution in less fractionalized counties. These results are displayed in diff-in-diff form in Table A4, which also shows that they are robust to the inclusion of county-level controls interacted with year FEs.

Figure 4: Use of public clinics in the Kenyan Household Health Expenditure and Usage Survey



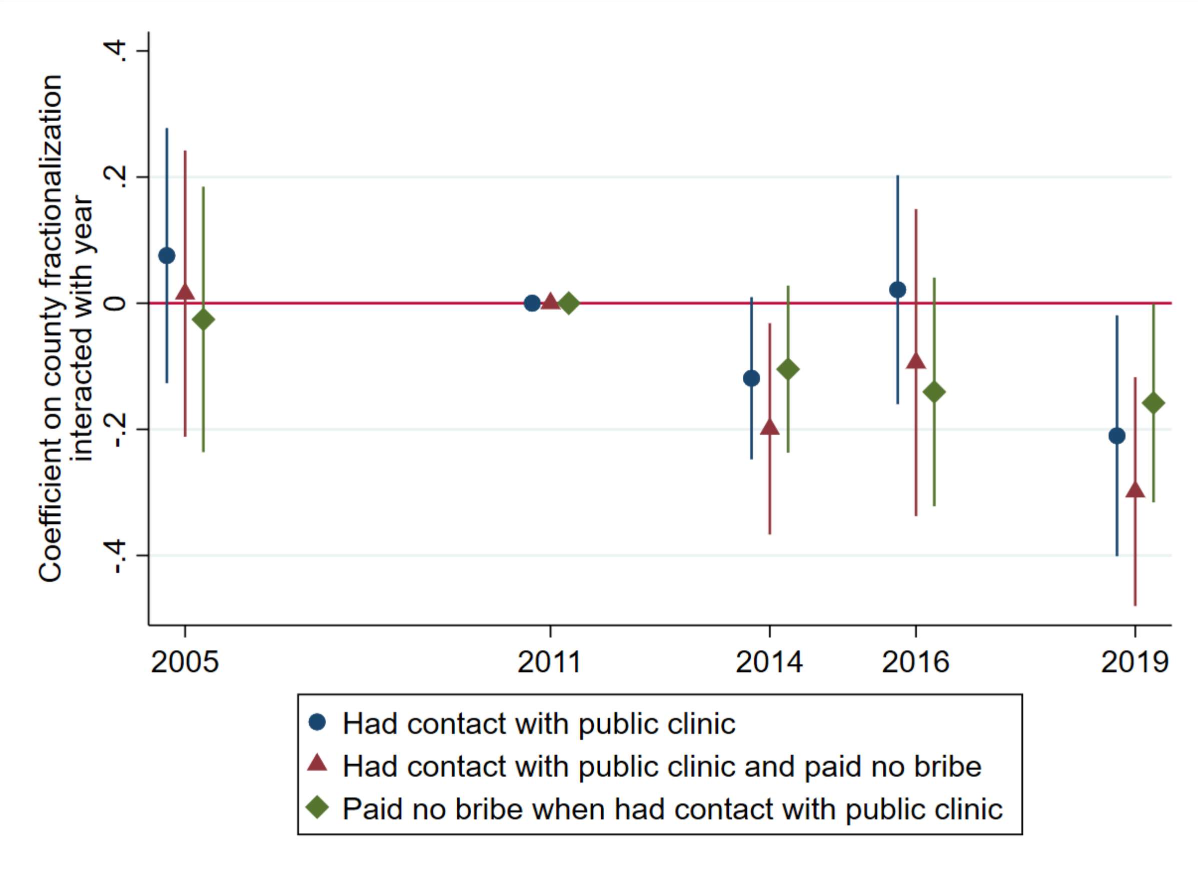
Notes: The points represent coefficients from regressing the relevant variable on county fractionalization interacted with year dummies - i.e. equation (1). An observation corresponds to a household member who is reported as having an illness in the last four weeks. Years correspond to rounds of the KHHEUS survey. The lines represent the 95 % confidence intervals. Controls include province-year fixed effects and county fixed effects. Standard errors are clustered at the county level.

5.2.3 Evidence from Afrobarometer

Although not focused on healthcare, several waves of the Afrobarometer surveys ask respondents whether they had any contact with a public clinic. Since the form of contact is not elicited and this is not the focus of the survey, it is likely to be a noisier measure of public healthcare use than in the previous two surveys, but it is valuable to look at the survey in this way for two reasons. First, the question has been asked in five different waves between 2005 and 2019, giving us a larger number of observations over time than either of the other surveys. Second, the survey asks whether respondents paid a bribe when they were in contact with the public clinic, which can be viewed as an important aspect of public healthcare performance.

In Figure 5, we therefore plot our standard event-study figure with three different outcome variables. First, we use an indicator of simply whether an individual had contact with a public clinic.[10] Second, we construct an indicator that takes the value one only if they had contact with a public clinic and didn't pay a bribe. Third, we then restrict our sample to individuals who reported having had contact with a public clinic and then take as an outcome variable whether or not they paid a bribe.

Figure 5: Contact and bribe paying public clinics, from Afrobarometer



Notes: The points represent coefficients from regressing the relevant variable on county fractionalization interacted with year dummies - i.e. equation (1). Years correspond to rounds of the Afrobarometer survey. The lines represent the 95 % confidence intervals. Controls include province-year fixed effects, county fixed effects, and respondents language, gender, education, and age. Standard errors are clustered at the county level.

From Figure 5, we can again note that there appears to be a shift in the correlation between ethnic fractionalization and contact with public clinics after devolution. This is even more pronounced when we look at bribe-free contact with public clinics. Consistent with this, those who had contact with public clinics are less likely to pay bribes in less fractionalized counties

[10]Note that the exact question phrasing changed after 2011. In particular, for later waves, the question was formulated in a way that was more likely to have respondents answer that they had not had contact with a public clinic. To test that the question change does not introduce bias into our findings, in Figure A2 we use services that were not devolved to county governments (i.e. policing end schooling), for which the same question change issue also applies, to serve as a placebo. We can note that we see no similar change in our outcome for these other services, meaning that measurement issues are unlikely to be driving the result.

after devolution. Although some of the individual coefficients are insignificant, each of these results is significant when we aggregate the years in a diff-in-diff analysis in Table A5. This table also shows that results remain largely unchanged when we include county-level controls interacted with year fixed effects.

6 Discussion of possible mechanisms

The previous section has demonstrated that public clinic use became more negatively correlated with county fractionalization after devolution. Moreover, we found some results suggesting that users were less likely to pay to use such services, suggesting that after devolution less fractionalized counties may have been more successful in providing free healthcare. While we have limited data to understand the mechanisms behind these results, in this section we discuss possible mechanisms and provide some supportive evidence where possible.

On the supply side, let us consider the possibility that changes in infrastructure, budget allocation, or staffing composition may be driving our results. Though new hospitals or clinics could not have been constructed in time to impact clinic use in 2013 or 2014, existing clinics may have received a greater budget. While budget information is not available, we can explore cross-sectional information on some indicators related to budget provision.[11] The first column of Table 4 shows that the number of hospital beds per capita decreased relatively more in more fractionalized counties from 2012 to 2018. This could reflect the fact that more new clinics were opened in homogenous counties in the years following devolution, but could also be a reflection of the fact that healthcare funding is more efficiently allocated, with less leakage and corruption, in homogenous counties. On the latter point, columns 2 and 3 of Table 4 show that homogenous counties receive more favorable opinions from the Auditor General, and citizens in these counties are less likely to report that their governor is corrupt. Indeed, qualitative interviews undertaken in tandem with the 2014 DHS data collection in Kenya suggest that corruption, or different levels of service quality based on ethnicity, did play a factor in healthcare.

An additional supply-side mechanism we are able to test is whether county governments made decisions on staffing that resulted in changes to the ethnic composition of the workforce following devolution. We do not have data on the ethnic composition of healthcare workers to test this directly, but we can make use of data on public servants more generally collected by the NCIC (2016). They measure the ethnic composition of both the stock of public servants employed by

[11] Despite the obligation of counties – by both the 2010 Constitution and the 2012 Public Finance Act – to publish budget information throughout the entire process, very few do. Data from the International Budget Partnership (IPB) in 2015 (the first year for which data were collected) show that of the 47 counties, 19 had zero documents and 15 had only one (IPB, 2015b). Things have improved over time, though marginally; by 2021, only three counties had published the full set of budgeting documents online (IPB, 2022). The lack of available online information may belie larger problems in transparency and access. As noted by the IPB, "Given how easy it is [to upload documents to existing websites], if a document is unavailable online it may suggest that it is not being made available at all" (IPB, 2015a).

Table 4: Cross-sectional post-devolution county-level outcomes

	Δ Log of number of beds in county, 2012 to 2018	Auditor-General's opinion of County Executive, 2017-18	Average corruption rating of County Governor, Afrobarometer	Δ county public service fraction-alization	Δ county pop.- county public service dissimilarity
	(1)	(2)	(3)	(4)	(5)
County fractionalization	-0.818*	-0.743*	0.203**	0.304***	0.149***
	(0.448)	(0.399)	(0.0984)	(0.105)	(0.0439)
Observations	44	46	46	46	46
Adjusted ^{2}	0.108	0.179	0.371	0.216	0.359
Dep. var mean	-0.692	2.783	1.439	-0.111	-0.0540

Notes: The dependent variable in column (1) is the change in the ethnic dissimilarity between the county population (as measured using the 2014 DHS) and the public service employees working in the county. This latter variable is estimated using data from NCIC (2016), notably on the ethnic breakdown of county public service employees and new appointments. The dependent variable in column (2) is the change in the log of beds per 10000 people constructed from data from Moses et al. (2021) for 2018 and from World Bank (2014) for 2012. The dependent variable in column (3) is a score given between 1 and 4, with 1 representing a lower opinion. The dependent variable in column 4 is the average over rounds 6 and 7 of the Afrobarometer. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

the county, and those recruited after 2013. In column 4 of Table 4 we see that average workforce fractionalization fell following devolution, but this hides a lot of heterogeneity: the workforce became more fractionalized in the most fractionalized counties, and less so in the most homogenous counties. This may in turn have had an impact on productivity.[12] Using this same data, we can also estimate the change in ethnic dissimilarity between the county population (estimated from the DHS) and the county employees before and after devolution (estimated from NCIC (2016)). Here 'dissimilarity' is constructed in an equivalent way to county fractionalization, and measures the probability that a randomly chosen county employee is the same ethnicity as a randomly chosen county resident. In the fifth column of Table 4, we regress this change on our measure of county fractionalization. We can first note that the mean of the dependent variable is negative – in other words, on average, the ethnic composition of county employees did indeed become more similar to the county population. We also note, however, that the coefficient on county fractionalization is positive and significant: this process of increased similarity, therefore, took place to a much larger extent in less fractionalized counties. Qualitative evidence supports these findings that the workforce in devolved services became closer in ethnic composition to the population of the county (Kimathi, 2017; IRC, 2015). In a qualitative study of hospital workers, for instance, a senior hospital manager from Kilifi reported that some hospital workers were hired "because of ethnicity", rather than qualifications (Barasa et al., 2017). This may

[12]Evidence from the private sector in Kenya suggests that interethnic rivalry can impede efficiency, leading to lower overall productivity (Hjort, 2014). Separate evidence from Kenya on non-profit voter canvassing organizations tells a more nuanced story: researchers found that more homogeneity in ethnicity between colleagues of the same level ("horizontal" homogeneity) resulted in greater efficiency, however ethnic homogeneity between employees and management ("vertical" homogeneity) led to reduced productivity (Marx et al., 2021). The dynamics of these interactions in the Kenyan healthcare sector have not been directly tested, to our knowledge.

have impacted supply, since DHS interviews revelated that co-ethnics were reportedly receiving preferential treatment in health clinics, including jumping to the head of lines, having reduced waiting times and overall better interactions with health care providers (i.e., greater patience) (Pietrzyk et al., 2018).

These observed staffing changes may also drive changes on the demand side if patients feel more comfortable receiving care from medical professionals from a similar background. Research in the United States has shown that patients prefer receiving care from healthcare workers of the same race and ethnicity (Takeshita et al., 2020), and are more likely to pursue preventative care if they are treated by a doctor of the same race (Alsan et al., 2019). Qualitative interviews from the 2014 DHS survey show that similar dynamics may be at play in Kenya, specifically regarding maternal healthcare. Women reported that stigma and discrimination may occur at health facilities, stemming from a variety of biases including ethnicity. As a result, these women stated that the ethnic, cultural and religious backgrounds of expectant mothers weighed in on their decision as to where they planned to give birth (Pietrzyk et al., 2018). In a different study, women expressed a preference for a birth attendant who is from the same ethnic background; if they perceive it unlikely to find such support in the formal healthcare sector, they may instead choose a home birth with a traditional birth attendant (TBA) who is of the same ethnicity (Warren et al., 2017).

One way of getting at whether increased demand could be a credible mechanism for our result is to exploit individual-level heterogeneity in ethnicity in the DHS data. If it is the case, for instance, that individuals are more likely to use public services when they feel closer to the county government, we might expect this effect to be strongest among the ethnic groups who are most represented within the county government. Similarly, if individuals prefer using public services when the employees are of the same ethnicity, this will affect most those whose ethnicity comes to be most represented among public employees. We test for this effect in columns 1 to 3 of Table 5. In this table, we return to our baseline outcome on births in public clinics, as considered in an event-study style framework in Figure 2 – in other words, our sample is children under-5 of mothers surveyed in the 2014 DHS, and we consider whether the birth took place in a public clinic. In column 1, for comparative purposes, we present the diff-in-diff version of our baseline result on whether births take place in public clinics, which shows a shift towards more births in public clinics in less fractionalized counties after devolution. In column 2, we then add an indicator variable which, for each individual, measures the share of the County Executive Committee (CEC) which is of the same ethnicity as the individual, along with this variable interacted with a post-devolution indicator. We can think of this variable as a measure of similarity between the individual and the county government, and indeed we obtain similar results if we use other measures such as the share of county employees.

From the results of column 2 of Table 5, we can see that individuals who are ethnically similar to the county government are more likely to give birth in a public hospital after devolution. Since

Table 5: Impacts of within county variation on place of birth

	(1)	(2)	(3)	(4)	(5)	(6)
County fractionalization	-.095***	-.048		.074		
× Post-devolution	(.029)	(.041)		(.1)		
Share same ethnicity on CEC		-.028	-.028			-.035
		(.033)	(.032)			(.026)
Share same ethnicity on CEC		.049*	.049*			.037
× Post-devolution		(.027)	(.028)			(.027)
Nearest clinic county				-.18*	-.046	
fractionalization × Post-devolution				(.1)	(.044)	
Clinic population ethnic					.019	.025
dissimilarity w/ CEC					(.057)	(.062)
Clinic population ethnic					-.062*	-.061*
dissimilarity with CEC × Post-devolution					(.033)	(.034)
County FEs	Yes	Yes	Yes	Yes	No	Yes
County-year FEs	No	No	Yes	No	No	No
Province-year FEs	Yes	Yes	Yes	Yes	No	Yes
Nearest clinic county FEs	No	No	No	Yes	Yes	Yes
Nearest clinic province-year FEs	No	No	No	Yes	Yes	Yes
R^2	.18	.18	.19	.19	.18	.19
Observations	20564	20521	20521	20564	20564	20521
Clusters	47	47	47	47	47	47

Notes: The table presents results of estimating versions of equation (2). Column (1) is identical to the baseline result in column (1) of Table 2 and is given for reference. In columns (2) and (3) we include a variable which measures the share of the County Executive Committee which is the same ethnicity as the mother, along with its interaction with the post-devolution time dummy. In columns (4) and (5) we include the post-devolution time dummy interacted with the county fractionalization of the county of the nearest public clinic to the DHS cluster (as opposed to the county of the DHS cluster itself). In these regressions, we replace fixed-effects corresponding to the county that the DHS cluster lies in with fixed-effects corresponding to the county that the nearest clinic lies in. In columns (5) and (6) we include a measure of 'dissimilarity' between the County Executive Committee and the DHS clusters within 10km of the public clinic nearest to the mother's cluster, along with its interaction with the post-devolution time dummy. Controls in all columns include province-year fixed effects, county fixed effects, birth order, birth month, the sex of the child, whether the mother lives in an urban area, and categorical variables for the mother's age, education, and asset index. Standard errors are clustered at the level of the county the DHS cluster lies in in columns (1)-(3), at the level of the county of the nearest public clinic in column (5), and at both levels in columns (4) and (6). * $p < .10$, ** $p < .05$, *** $p < .01$

this is a measure of ethnic similarity, it is clearly highly correlated with county fractionalization, and indeed the coefficient on the interaction between county-fractionalization and the post-devolution dummy falls by a half. While it is difficult to disentangle the two variables, in column 3 we show that the coefficient on the new interaction term remains significant when we include county-year fixed effects, showing us that this variable explains some within-county-year variation in public-clinic use in addition to the across-county-year variation which our main variable of interest captures. This is therefore consistent with individual 'demand' effects playing some role in explaining our result.

One implication of such mechanisms is that individuals' healthcare use should be more impacted by the county which runs their nearest clinic than their county of residence. Of course, for most of our sample these counties are the same, but for clusters near county borders this may not be the case. Unfortunately we could not find a map of clinics which changes over time, so we approximate the location of public clinics based on a publicly available map (Seje, 2020). For 6 % of our sample, the nearest clinic is in a different county. In column 4 of Table 5 we therefore undertake a horse-race by simultaneously including the relevant interactions of the fractionalization of one's county of residence (as in baseline) and the fractionalization of the county of the nearest clinic. Though the two are highly correlated, it is the fractionalization of the county of the nearest clinic which remains significantly negative, suggesting that it is indeed the characteristics of the nearest clinic that are driving our result.

Above, when discussing supply-side mechanisms, we posited that one possible driver of our main result is that counties provide better healthcare in areas which have the same ethnicity as those running the government. However, the perception of care quality (i.e., a demand-side driver) – independent of objective measures of quality – could be driving patient behavior. Though we cannot test whether it is objective quality or the perceptions of quality driving behavior, we can test whether behavior changes are the strongest in more homogeneous areas within a county. In less fractionalized counties, this will be most of the geographic area of the county, while in more fractionalized counties this is likely to exclude some areas if ethnic groups are clustered geographically. To test for this, we estimate the ethnic composition of the area surrounding each public clinic using those DHS clusters located within 10km. We then construct a measure of ethnic dissimilarity between this area and the County Executive Committee (CEC) and assign each DHS cluster to its nearest clinic. We enter this variable into the regression in column 5 of Table 5 alongside its interaction with the post-devolution indicator. The coefficient is negative and significant even though the county fractionalization of the nearest clinic is also included, suggesting that an important part of the result may stem from the ethnicity of areas below the county level. Finally, in column 6, we add to this regression the individual-level measure of ethnic similarity, since this is clearly correlated with our clinic-level measure. Both terms retain similar values, suggesting both potential mechanisms could be playing a role, though we are now at the limits in terms of statistical power.

7 Conclusion

The introduction of devolution in 2013 brought about sweeping changes to the political landscape in Kenya. Almost overnight, the responsibility for local service provision was moved from eight provinces led by the bureaucratic Provincial Administration, to 47 democratically elected county governments. The government of Kenya was explicit in its hopes that devolving authority to sub-national jurisdictions would increase transparency, further citizen engagement with policy making, and improve the provision of local public services. In a context where ethnic cleavages are particularly salient, devolution was also expected to alleviate the difficulties raised by a highly ethnically diverse country. In particular, the provision and use of local public services is expected to benefit from decentralization, to the extent that it brings about more homogeneous decision making and preferences.

Despite these important expectations, there is little evidence documenting the interplay between ethnic diversity and devolution. In this paper, we partly fill this gap by analyzing the differential impacts of devolution on public health services, depending on the level of ethnic fractionalization in the local jurisdictions in charge of providing healthcare. Using difference-in-differences estimations, we are able to investigate how public health services are impacted after devolution, based on their level of ethnic fractionalization. Our results reveal that individuals tend to use public clinics more after devolution in less diverse communities, whether be it for childbirth, for perinatal care more generally, or for other reasons related to illness. This set of results is a first contribution of this paper, as it shows how the constituents change their behavior in response to the local and political context, while the extant literature has more to say on the actions taken by local political leaders. Nonetheless, we also dig into supply side responses to devolution, and observe that access to free health care is more available in less diverse areas after devolution, which is consistent with previous studies.

Various mechanisms could be underlying our findings. Although our data do not allow us to directly test them, we provide suggestive evidence of which may be at play and which may be discarded. Given that we observe significant effects on health care service utilization in the immediate aftermath of devolution, we can rule out any impact related to changes in infrastructure, such as hospitals. We provide evidence that the ethnic composition of public employees became more homogeneous after devolution in more homogeneous counties, reducing the ethnic distance between patients and health care workers. This alternative supply effect of devolution may have triggered the increased demand in health care services in more homogeneous counties.

All in all, our results support the prior that devolution is one way to mitigate negative impacts of diversity. Our paper therefore adds to a literature investigating how institutions, such as a common language (Miguel, 2004), well-defined electoral rules (Posner, 2004), cross-cutting cleavages (Dunning and Harrison, 2010) or strong chiefs (Glennerster et al., 2013) may alleviate ethnic cleavages. Even though we are not able to investigate the persistence of these effects in the longer run, we think that observing immediate responses is encouraging. It suggests that the mere fact of having a devolved government has an impact, even before this new form of government has time to undertake significant investments in public services.

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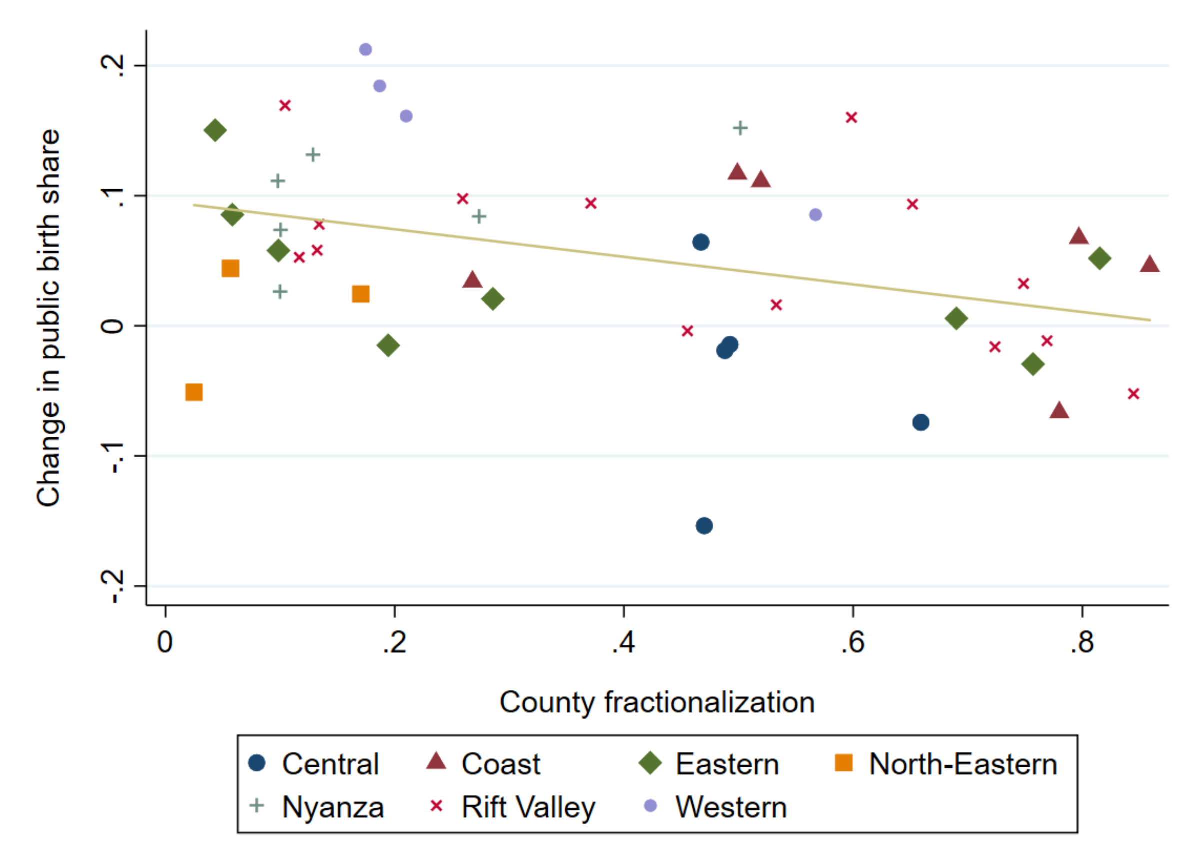
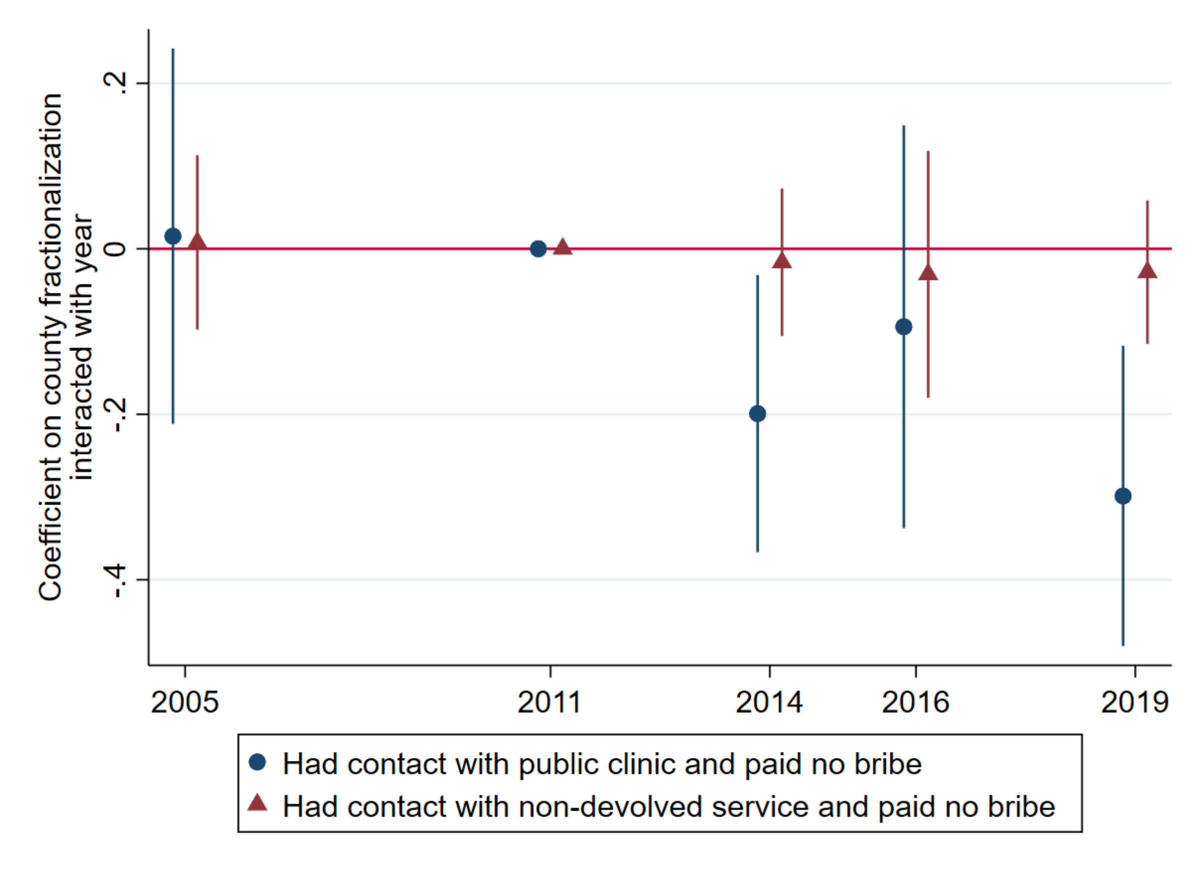
Appendix A Appendix: Additional tables and figures

Figure A1: Change in public birth share by county fractionalization



Notes: Each point represents a different county, with the different symbols representing different provinces. The x-axis measures ethnic fractionalization within the county, estimated using DHS 2014. The y-axis measures the difference in the share of births which take place in public clinics when we divide births reported in DHS 2014 into two periods, pre-devolution (2009-2012) and post-devolution (2013-2014).

Figure A2: Use of public clinics and non-devolved services, from Afrobarometer



Notes: Notes: The points represent coefficients from regressing the relevant variable on county fractionalization interacted with year dummies - i.e. equation (1). Years correspond to rounds of the Afrobarometer survey. The lines represent the 95 % confidence intervals. Non-devolved services are schools and the police. Controls include province-year fixed effects, county fixed effects, and respondents language, gender, education, and age. Standard errors are clustered at the county level.

Table A1: Vaccines

	Polio 0	Bcg	Dpt 1	Polio 1	Dpt 2	Polio 2	Dpt 3	Polio 3	Measles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
County fractionalization	-.053	-.0056	-.031*	-.018	-.028	-.021	-.036	-.04	-.014
× Post-devolution	(.033)	(.012)	(.016)	(.014)	(.018)	(.013)	(.032)	(.03)	(.034)
R^2	.2	.12	.11	.1	.1	.086	.095	.098	.089
Observations	19262	18916	18889	18878	18251	18229	17566	17544	15520
Clusters	47	47	47	47	47	47	47	47	47
Dep. var mean	.71	.95	.95	.95	.94	.92	.87	.79	.87
Median age, months	0	0	2	2	3	3	4	4	9
90th percentile age, months	1	2	2	2	4	4	6	6	12

Notes: The table presents results of estimating equation (2). The sample in each column is children above the age at which we would expect the relevant vaccine to have been administered by, as measured by the 90th percentile of those who received the vaccine (displayed in the last row of the table). The dependent variable is then whether the child has had the respective vaccine. Controls include province-year fixed effects, county fixed effects, birth order, birth month, the sex of the child, whether the mother lives in an urban area, and categorical variables for the mother's age, education, and asset index. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A2: Birth related outcomes, with county-level controls interacted with year FEs

	Birth at private clinic	Birth at home	Nurse or midwife attended	Antenatal visit at public clinic	Share of vaccines received	Died within 1 week
	(1)	(2)	(3)	(4)	(5)	(6)
County fractionalization	0.0172	0.0699**	-0.0862**	-0.0841**	-0.0428**	0.00195
× Post-devolution	(0.0153)	(0.0295)	(0.0387)	(0.0345)	(0.0183)	(0.00839)
Observations	20564	20564	20564	6756	19271	20564
Adjusted ^{2}	0.156	0.336	0.190	0.116	0.180	0.00139
Dep. var mean	0.108	0.453	0.412	0.763	0.882	0.0164

Notes: This table presents the same regressions as displayed in table 3 only with the inclusion of various county-level variables interacted with year fixed-effects - please see the notes to that table. These county-level variables include the county population, population density, night lights in 2012, area, urbanization rate, the log of the average distance to a clinic, and the average education level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A3: Robustness of results on use of public clinics in three waves of the DHS

	Went to public clinic, given case of diarrhea		Went to public clinic, given fever or cough	
	(1)	(2)	(3)	(4)
County fractionalization	-0.325***	-0.347***	-0.165**	-0.118
× Post-devolution	(0.0762)	(0.0784)	(0.0669)	(0.0718)
Controls × year FEs	No	Yes	No	Yes
Observations	4270	4270	8616	8616
Adjusted ^{2}	0.0792	0.0765	0.0472	0.0476
Dep. var mean	0.419	0.419	0.400	0.400

Notes: This table presents regressions with the same dependent variables as the regression results displayed in Figure 3. The sample in columns (1) and (2) are children who have a reported case of diarrhea, while in columns (3) and (4) are those who have a reported case of a fever or cough. In each case we take observations from DHS 2003, 2008, and 2014, with only the last one categorized as post-devolution. Controls include province-year fixed effects, county fixed effects, whether the mother lives in an urban area, and categorical variables for the mother's age, education, and asset index. In columns (2) and (4) we include year fixed-effects interacted with county-level variables including the county population, population density, night lights in 2012, area, urbanization rate, the log of the average distance to a clinic, and the average education level. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A4: Public clinic use in KHHEUS with county-level controls interacted with year FEs

	Visited public clinic		Visited public clinic and made no payment		Made no payment when visited public clinic	
	(1)	(2)	(3)	(4)	(5)	(6)
County fractionalization	-0.215***	-0.295***	-0.174***	-0.177***	-0.163*	-0.125
× Post-devolution	(0.0546)	(0.0504)	(0.0471)	(0.0475)	(0.0879)	(0.0959)
Controls × year FEs	No	Yes	No	Yes	No	Yes
Observations	56919	56919	56919	56919	27381	27381
Adjusted ^{2}	0.0478	0.0492	0.0417	0.0429	0.0855	0.0880
Dep. var mean	0.481	0.481	0.199	0.199	0.413	0.413

Notes: This table presents regressions with the same dependent variables as the regression results displayed in Figure 4. The sample in columns (1)-(4) are household members who are reported to have been ill in the KHHEUS, while in columns (5) and (6) they are those who reported being ill and having visited a public clinic. In each case we take observations from KHHEUS 2008, 2013, and 2018, with the last two categorized as post-devolution. Controls include province-year fixed effects and county fixed effects. In columns (2), (4), and (6) we include year fixed-effects interacted with county-level variables including the county population, population density, night lights in 2012, area, urbanization rate, the log of the average distance to a clinic, and the average education level. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A5: Afrobarometer results with county-level controls interacted with year FEs

	Had contact w/ public clinic		Had contact w/ public clinic and paid no bribe		Paid no bribe when had contact w/ public clinic	
	(1)	(2)	(3)	(4)	(5)	(6)
County fractionalization	-0.0764	-0.00292	-0.257***	-0.278***	-0.211**	-0.308**
× Post-devolution	(0.0483)	(0.0624)	(0.0681)	(0.0981)	(0.0893)	(0.120)
Controls × year FEs	No	Yes	No	Yes	No	Yes
Observations	10048	10048	10073	10073	7653	7653
Adjusted ^{2}	0.0511	0.0550	0.0445	0.0460	0.0942	0.101
Dep. var mean	0.759	0.759	0.564	0.564	0.742	0.742

Notes: This table presents regressions with the same dependent variables as the regression results displayed in Figure 5. The sample in columns (1)-(4) are all afrobaromater respondents, while in columns (5) and (6) they are those who reported having been in contact with a public clinic. In each case we take observations from the rounds of the Afrobarometer conducted in 2005, 2011, 2014, 2016, and 2019, with the last three categorized as post-devolution. Controls include province-year fixed effects, county fixed effects, and respondents language, gender, education, and age. In columns (2), (4), and (6) we include year fixed-effects interacted with county-level variables including the county population, population density, night lights in 2012, area, urbanization rate, the log of the average distance to a clinic, and the average education level. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A6: Probability of reporting birth or sickness

	Reports birth, DHS	Reports case of diarrhea, DHS	Reports case of fever or cough, DHS	Reports case of illness, KHEUS
	(1)	(2)	(3)	(4)
County fractionalization	0.00588	0.0929*	0.165	-0.0419
× Post-devolution	(0.0131)	(0.0526)	(0.104)	(0.0339)
Observations	89568	21452	21452	309055
Adjusted ^{2}	0.0359	0.0298	0.0521	0.0150
Dep. var mean	0.230	0.199	0.402	0.184

Notes: The table presents results of estimating equation (2), where the dependent variables are indicators for whether respondents are in our sample in a given year. In column (1), the dependent variable is whether a mother in teh 2014 DHS reports a birth in a given year - observations are at the mother-year level for years 2009-2014. In columns (2) and (3), the dependent variables are whether a mother reports a case of diarrhea/fever or cough - there is therefore one observation per child under-5 asked about in each wave of the DHS (i.e. 2003, 2008, and 2014). In column (4), the dependent variable is whether a household member is reported to have had an illness - there is therefore one observation per household member asked about in each wave of the KHHEUS (i.e. 2008, 2013, and 2018). Controls include province-year fixed effects and county-level fixed effects. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$