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► **To cite this version:**

Camille Hémet, Liam Wren-Lewis, Jessica Mahoney. Decentralization, Ethnic Fractionalization, and Public Services: Evidence from Kenyan Healthcare. 2024. halshs-04564267

HAL Id: halshs-04564267

<https://shs.hal.science/halshs-04564267>

Preprint submitted on 30 Apr 2024

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PARIS SCHOOL OF ECONOMICS
ECOLE D'ECONOMIE DE PARIS

WORKING PAPER N° 2024 – 07

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

Keywords:

anr [©]
agence nationale
de la recherche
AU SERVICE DE LA SCIENCE



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

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April 29, 2024

Abstract

This paper examines the impact of ethnic fractionalization on public service use by exploiting 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. Crucially, this changed the ethnic composition of the administrative area responsible for healthcare, while leaving the composition of the local population unchanged. 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. Using within-county variation to investigate mechanisms, we find healthcare use increases were concentrated among individuals of the same ethnicity as members of the new county government executives. Overall, the results suggest that more ethnically homogeneous sub-national jurisdictions can rapidly increase public service use.

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

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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: ytWvTxf0aLf. This working paper shall therefore be cited as Hémet Ⓐ al. (2024). Acknowledgements: We are grateful to Laura Ahlborn for excellent research assistance. We would like to thank Abhijit Banerjee, Luc Behaghel, Denis Cogneau, Juliette Crespín-Boucaud, Esther Duflo, Nathalie Ferrière, Sylvie Lambert, Karen Macours, Bastien Michel, Tavneet Suri, Oliver Vanden Eynde, and Ekaterina Zhuravskaya for their useful comments and suggestions. Funding from the French National Research Agency (ANR-17-EURE-0001, ANR-18-CE22-0013-01, ANR-20-CE41-0014) and from the CEPREMAP is gratefully acknowledged.

1 Introduction

There is a well-documented negative correlation between ethnic diversity and public good provision in both developed and developing countries. This might arise from heterogeneity in preferences for types of public goods (Alesina et al., 1999) or a lack of cooperation across ethnic groups (Miguel and Gugerty, 2005; Algan et al., 2016). Over the past 50 years, many countries have implemented reforms to decentralize government, which is often perceived as an opportunity to form more homogeneous local jurisdictions and alleviate concerns related to inter-ethnic cleavages. However, it remains an open question whether more homogeneous jurisdictions actually provide better local public services.

This paper sets out to answer this question by investigating whether public health services are improved by creating more ethnically homogeneous local administrations. Our study investigates a national decentralization policy that occurred in 2013 in Kenya whereby responsibility for many services were devolved to newly created local authorities.¹ The policy resulted in the creation of 47 new county governments led by a directly-elected governor and county assembly, while the eight provinces that had been in charge beforehand were disbanded. One of the most critical sectors affected was healthcare: the new 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. Crucially, through this decentralization, the reform therefore mechanically changed the ethnic composition of the administrative area responsible for healthcare, while leaving the composition of the local population unchanged.

We take advantage of this decentralization reform to estimate the effect of a change in the ethnic fractionalization of the constituency in charge of the public health service. We look at impacts on various health-related outcomes, ranging from birth in public clinics and other birth-related outcomes to the use of public clinics more generally. More precisely, we measure the change in the correlation between county fractionalization and public healthcare use that occurred during the decentralization process. In a first set of results, using an event-study design 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 decentraliza-

¹To be precise, the political reform was a *devolution*, which 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. While the specific reform in Kenya is an example of devolution, and the process is referred to as such in the country, in this paper we use the more general term *decentralization* to align our research with existing literature.

tion. Consistent with these results, we find that, after decentralization, pregnant women living in less fractionalized counties are more likely to undertake antenatal visits in a public facility and their children receive a larger share of recommended vaccinations. 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 center more generally in less fractionalized counties after decentralization. These results are not driven by observables correlated with fractionalization, and we do not see similar effects when we look at non-decentralized services. Overall, these findings show that public health service use increased significantly in counties where decentralization led to more ethnically homogeneous constituencies.

Interestingly, the various datasets at hand also enable us to look at characteristics of public health provision and to dig into various possible mechanisms. In particular, the KHHEUS and Afrobarometer ask respondents whether they had to make a payment when they visited a public clinic. We find that, in less ethnically fractionalized counties, decentralization saw a reduction in the probability of having to make some form of payment in a public clinic. This is consistent with evidence suggesting better budgeting and less corruption in less fractionalized counties, which may have helped to better implement policies such as a new Free Maternity Programme. Alongside this, we also see important changes in the ethnicity of public sector workers, with their ethnicity becoming more similar to the local population in less fractionalized counties. Strikingly, we also see a differential change in healthcare use *within* counties, with mothers of the same ethnicity as the county government those most likely to change their behavior. This even holds when we allow for clinic-specific decentralization effects, suggesting that part of the result cannot simply be explained by changes in county administration or policy implementation. Instead, at least part of the result must stem from ethnically-related behavioural change, possibly stemming from discrimination or a preference to receive public services provided by co-ethnics.

Our paper contributes to two main strands of the literature. It first and foremost contributes to the literature on the economic and social effects of ethnic diversity, following [Easterly and Levine's](#) (1997) seminal paper.² We add to this literature by investigating public service use in the immediate aftermath of a change in governance, complementing work that has typically focused on longer-run cross-sectional differences in public service provision ([Alesina et al., 1999](#); [Miguel and Gugerty, 2005](#); [Algan et al., 2016](#); [Bazzi et al., 2019](#); [Desmet et al., 2020](#)). We also differ from a large share of the literature by investigating how diversity influences individuals' propensity to *use* public goods and services, thereby potentially including demand-side effects as well as supply-side ones. The specific context also enables us to provide some novel insights about the mechanisms at play. In particular, the variations in ethnic diversity that we leverage

²Beyond public services, this literature has also looked into the relationship with welfare spending ([Luttmer, 2001](#)), trust ([Alesina and La Ferrara, 2002](#)), participation in social activities ([Alesina and La Ferrara, 2000](#)), and economic growth ([Montalvo and Reynal-Querol, 2021](#)).

are not actual population composition changes at the local level, but rather changes in the ethnicities encompassed in the jurisdiction in charge. We can therefore rule out that the negative effects of fractionalization are driven by variations in local social relationships with neighbors or changes in preferences. Instead, we provide suggestive evidence that our results are driven at least in part by the ethnic similarity between constituents and their administration.

This paper also contributes to the broad literature on decentralization by capturing how citizens respond to decentralization in their use of public health services right after devolution occurs. The early theoretical work of [Oates \(1972\)](#) on fiscal federalism argues that decentralized provision of local public goods will be better tailored to the preferences of the local electorate.³ Empirically, recent papers relying on convincing identification of causal effects find mixed effects of decentralization. On public service delivery, [Bianchi et al. \(2023\)](#) find positive impacts of decentralization in Italy, while [Malesky et al. \(2014\)](#) show that public services improved after recentralization in Vietnam and [Mergele and Weber \(2020\)](#) find negative impacts of employment service decentralization in Germany. Related to decentralization reforms, other papers look at ‘district-splitting’, which do something similar by reducing the size of the governing administrative unit. [Cohen \(2024\)](#), [Dahis and Szerman \(2024\)](#), and [Narasimhan and Weaver \(2024\)](#) find that district splitting led to improvements in service delivery in Uganda, Brazil, and India.⁴ On healthcare specifically, [Chaudhary and Iyer \(2022\)](#) show an important negative impact of decentralization in India on both service provision and health outcomes. Compared to this literature, our study focuses on heterogeneity in the effects of decentralization, by measuring the immediate reaction of constituents in counties that are more or less ethnically diverse. In doing so, we also contribute to the literature by providing supportive evidence on the possible mechanisms at play.

Finally, our paper contributes to the discussion on whether decentralization can be used to improve public good provision in ethnically diverse contexts. 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

³Additionally, voters may be 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](#)). In a political economy perspective, [Besley and Coate \(2003\)](#) alternatively argue that because costs are shared in a centralized system, this creates a conflict of interest between citizens in different jurisdictions. Hence, the trade-off between centralized and decentralized provision depends on the decision-making process in the central jurisdiction.

⁴Beyond public service delivery, [Frey and Stutzer \(2000\)](#) and [Flèche \(2021\)](#) show that more local political decision making increases citizens’ utility in Switzerland, while [Traviss and Velayudhan \(2023\)](#) find negative effects of decentralization on economic growth in Indonesia.

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 paper by Seidel (2023), 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 findings also echo Swee (2015), who shows that partitioning political jurisdictions into more ethnically homogeneous units in the aftermath of the Bosnian war led to an improvement in the provision of public schooling. Beyond the very different contexts and nature of the reforms, the case studied in their paper is substantially different from ours since public schooling is deliberately ethnically oriented in Bosnia. In contrast, there is no specific ethnic component to Kenyan public health services, which makes this type of public good less obviously influenced by administrative ethnic composition.

More generally, our paper relates to the literature on how decentralization can be used to alleviate issues related to large levels of ethnic fractionalization. Bazzi and Gudgeon (2021) look at district splitting in Indonesia to study how redefining political boundaries may influence social conflict. They show that violence is reduced when the new boundaries follow ethnic divisions, while ethnic tensions may be exacerbated when re-districting leads to increased polarization. Also in Indonesia, Alesina et al. (2019) provide evidence that a reduction in diversity due to decentralization leads to a reduction in deforestation. Unlike these papers, our analysis doesn't study the splitting of a subset of existing political jurisdictions, but instead the wholesale creation of a new layer of governance across the country. Our work is closely linked to a recent working paper by Bluhm et al. (2021) that uses the same 2010 Kenyan constitutional reform as us to investigate how the associated redistricting of local administration impacted ethnic voting. They find that ethnofederalism (when local jurisdictions tend to be defined along ethnic group borders, rather than across them) reduces the salience of ethnicity and the extent of ethnic voting in national politics. None of these papers look at public service provision, but their results are consistent with ours in that a reduction in ethnic tension may be one of the mechanisms underpinning 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 decentralization process, the role of newly formed county governments, and the post-decentralization provision of healthcare. Section 3 describes the data sources used, and section 4 outlines 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 made up 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, Luhya, 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 Decentralization Process

In order to fully understand the magnitude of the change brought about by decentralization, 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.⁵

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 decentralization was that bottom up, community-led, development would lead to enhanced service provision. Furthermore, decentralization 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 decentralization 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 decentralization. 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 decentralized 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, decentralization happened much faster than anyone anticipated. Almost overnight the provision of some public services, in particular healthcare, went from being administered at the province-level by bureaucrats in the PA, to being run by democratically-elected county governors.

Decentralization in Kenya is therefore notable for its impact on service provision for three key reasons: (1) sub-national governments are 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 decentralization was truly a significant break from the past.

⁵The 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).

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. County governments 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 decentralization, 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 (World Bank, 2012; Aduke, 2013).

2.4 Decentralization 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 decentralization, 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 decentralization was often chaotic. As a further strain on capacity, counties were tasked with implementing a new Free Maternity Programme, announced by President Kenyatta in June of 2013, only a few months after governors took office. This program introduced free maternal healthcare services

(free delivery and up to four antenatal visits) at all public health facilities in the country. The program was effective in increasing the number of overall births taking place in public facilities, especially for lower income women (Calhoun et al., 2018; Masaba and Mmusi-Phetoe, 2020; Gitobu et al., 2018): this means that we are unable to make statements on the impact of devolution on the *overall* prevalence of giving birth in a public clinic. 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. Indeed, numerous studies have highlighted the implementation challenges associated with the program roll-out, including inadequate stock of medical supplies, disrupted or delayed financial flows, and insufficient staffing (Okech, 2017; Oketch et al., 2018; Lang’at et al., 2019; Orangi et al., 2021; Tama et al., 2017; Lang’at and Mwanri, 2015), with decentralization directly cited as a key contributing factor to not only these challenges, but also to variations in how effectively the policy was implemented in different counties (Pyone et al., 2017; Lang’at and Mwanri, 2015).

The issues afflicting the Free Maternity Programme were not unique to it, and the implementation of healthcare services in general was plagued by irregularities and capacity constraints (Kagwanja et al., 2020). Budgeting processes and financial flows were overhauled, and despite the new protocols being outlined in the Public Finance Management Act of 2012, counties interpreted the PFMA differently. In many, county governments retained all funds received from the central government in a county revenue fund (CRF) and allocated to health centres and clinics at the discretion of the county government (in some extreme cases, hospitals no longer retained their own bank accounts (Pyone et al., 2017)); in others, health centres retained some degree of financial autonomy (Kairu et al., 2021; Tama et al., 2017).

County governments were also expected to oversee the procurement of medical supplies. Prior to decentralization health clinics were required to procure supplies from the Kenya Medial Supplies Authority (KEMSA), a monopoly, however county governments are able to lead competitive procurement processes. While some were able to cut costs by buying on the open market, instances of corruption and skimming 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). 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).

Human resource management was another area that saw significant disruptions in the early months of decentralization. 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 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 decentralization) 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 decentralization – 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).⁶ 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).

It is worth noting that despite all of the difficulties surrounding the implementation of decentralization, 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 decentralization (Cheeseman et al., 2016). These findings appear to be persistent: a 2018 poll shows that 80% of Kenyans prefer the system of decentralization to what came before (El Messnaoui et al., 2018).

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-decentralization, 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 health 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

⁶Turkana is the largest and one of the poorest counties in Kenya, beset by conflict between different pastoral groups particularly since the discovery of oil since 2013 - the situation there may therefore not be representative of the country more broadly.

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, 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:

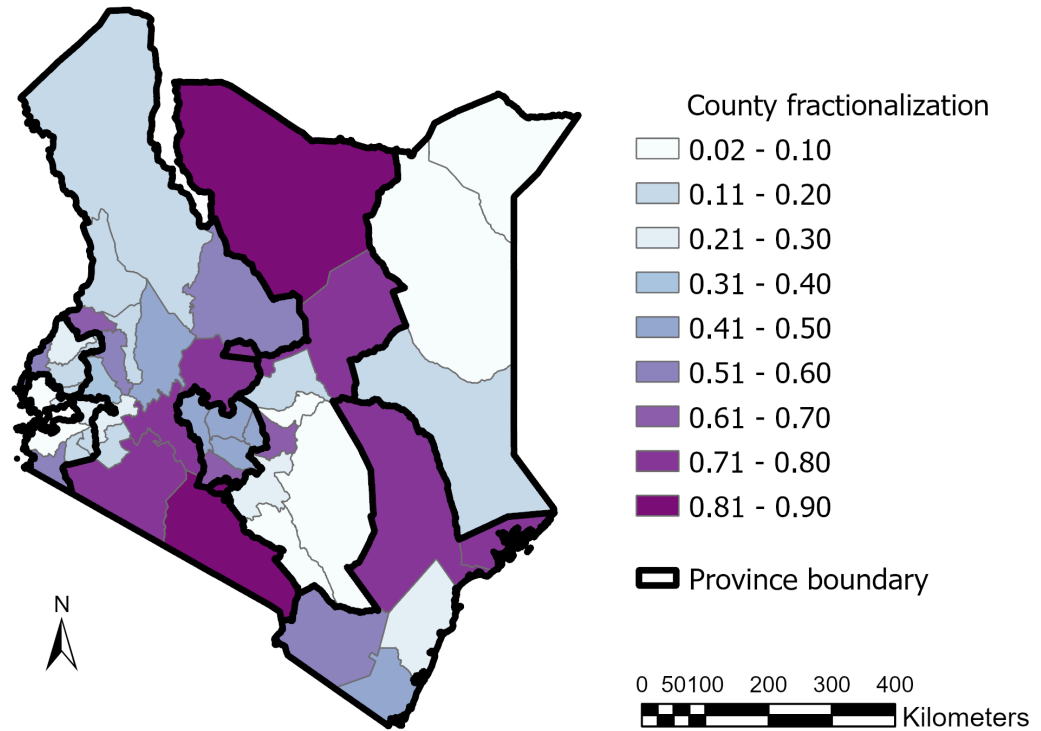
$$FRAC = 1 - \sum_{i=1}^N \pi_i^2$$

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 did not 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 decentralization led to an overall reduction in ethnic fractionalization in local jurisdictions: post-decentralization counties are to a large extent more homogeneous than pre-decentralization provinces (only six counties are less homogeneous than the corresponding province). This comes as no surprise, as increased ethnic homogeneity is one

Figure 1: Fractionalization index



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

of the arguments pushed forward for decentralization, and because the precursors to what became modern-day county borders were initially drawn by the British colonial authorities around historic ethnic homelands. ⁷

As a final note, we acknowledge that fractionalization indices are influenced by the ways in which different categories are grouped and defined, and indeed much of the technical literature on these indices emphasizes the importance of measurement issues (Fearon, 2003; Bossert et al., 2011). Kenya is commonly considered to have 42 officially recognized ethnic groups.⁸ Some ethnic groups are closely linked, in terms of socio-linguistic similarities, or religious background, meaning respondents may not see a clear delineation between groups when self-identifying; other groups are more distinct. The 2014 DHS survey lists 23 different ethnic groups including “other.” The survey questionnaire – and corresponding answer options – was designed with input from the Kenya National Bureau of Statistics, and thus the ethnicity categories come from official

⁷The homogeneity of these so-called native reserves was artificially enhanced by the British, in their grouping of co-ethnics together (Morgan, 2000).

⁸The exact number of groups included in official statistics has varied over the years, and across census collections. Between 1948 and 1988, the number of ethnic groups classified by official statistics ranged from 38 to 47, but in 2009 the amount close to tripled (if including sub-tribes) (Balaton-Chrimes, 2019). The most recent census lists 45 main ethnic groups, with additional sub-groups listed for seven (Orinde, 2019).

Table 1: Summary statistics of outcome variables

	Pre-decentralization		Post-decentralization	
	Obs.	Mean	Obs.	Mean
<i>DHS 2014 birth-level (2009–2014)</i>				
Birth at public clinic	13940	.41	6624	.46
<i>DHS child-level (2003, 2008, 2014)</i>				
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
<i>KHHEUS (2007, 2013, 2018)</i>				
Went to public clinic, given sickness	5622	.46	51297	.48
Received free care at public clinic, given sickness	5622	.17	51297	.2
Received free care, given visited public clinic	2597	.37	24784	.42
<i>Afrobarometer (2005, 2011, 2014, 2016, 2019)</i>				
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: The pre-decentralization period includes all years up to and including 2012. Questions are consistent across survey waves, except for in the Afrobarometer where a small change was introduced after 2011 - see Section 5.2.3 for more detail.

sources (i.e., they are not created by outside researchers) and reflect the largest ethnic groups in the country in terms of population share. If the way we have constructed the variable means that we are mismeasuring fractionalization in some way, this is likely to bias our results toward zero.

To take into account that some ethnic groups may be relatively close to each other, we additionally go beyond a simple measure of ethnic fractionalization in Section 6. In particular, in Table 5 we use measures of similarity between individuals and groups and the ethnic make-up of members of the County Executive Committee (CEC). In situations in which members of two ethnic groups are in a coalition, they are more likely to share power on a CEC than if there is high level of animosity between the groups. In this way, the ethnic make-up of the CEC can partially address the “closeness” of different ethnic groups to one another.

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 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 2019.⁹ 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 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 favor for a health worker or clinic or hospital staff in order to get the medical care you needed?’¹⁰ 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 examines differences over time in how outcomes correlate with county ethnic fractionalization. In particular, our baseline estimation involves estimating the coefficients ζ_τ in the following equation:

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

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.¹¹ 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-decentralization 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-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

⁹Rounds 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).

¹⁰Note that, as we can see in Table 1, reported contact with public clinics decreases after decentralization 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

¹¹Although counties were only formed in 2013 as political units, for the empirical analysis we also assign individuals to a county prior to this date based on their geographic location (see the relevant data section for details on how we do this for each dataset). Each individual is assigned to a single county, which doesn’t change over time - i.e. when we use recall data from the 2014 DHS, we assign individuals to their county of residence in 2014 since we don’t have data on previous counties of residence

responsible for healthcare. This allows us to control for any unobservable factors which may impact healthcare use differentially across Kenya. This means, for instance, that we are never comparing counties in North-Eastern Kenya to those in the South-West, but rather all inference comes from within-province variation (see Figure 1 for a map of the provinces of Kenya). One notable impact of this is that Nairobi is dropped from our analysis, since it is the only province to contain just a single county.

As a secondary analysis, we then additionally estimate a simpler equation where we aggregate the pre- and post- periods:

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

where $Post_t$ is an indicator for whether t is after decentralization - i.e. the year is 2013 or later. Compared to the event-study style set out in equation (1), this increases our power by aggregating the pre- and post- periods, and also provides a single point estimate which simplifies robustness checks and comparability across datasets. In all cases standard errors are clustered at the county level.

To infer causality on the impact of ethnic fractionalization and decentralization, we must make two important identification assumptions. First, we assume that any change over time in the within-province correlation between county fractionalization and our outcome variables is the result of decentralization. We include time fixed-effects since there are likely other changes occurring in this period, including changes in healthcare policy, which prevent us from cleanly estimating the average overall impact of decentralization. Importantly, however, we do not believe these changes should impact counties differentially according to their fractionalization, except through the channel of decentralized governance. To support this assumption, wherever possible we show that there were no significant changes over time in the correlation between fractionalization and the relevant outcome of interest prior to decentralization.¹² Where possible, we also show that there is no significant variation over time in the correlation between country fractionalization and the performance of non-decentralized services such as schools and police, and in Appendix Figure [A3](#) we show there is no such correlation with other variables such as night lights or conflict. Our second assumption requires that the relationships between public healthcare use and other variables correlated with county fractionalization do not change over the same period. We may be concerned, for instance, that healthcare services in urban areas are changing at a different rate to rural ones, and that more fractionalized counties are typically more urban. We cannot test this assumption directly since many correlates of fractionalization are unobservable, but we can partially address it by including time fixed effects

¹²It is worth noting that before 2013 there is no significant correlation between the share of births that occur in a public clinic and the county level of fractionalization (see Table [B7](#)). This is consistent with the fact that, prior to decentralization, the areas that became counties did not play an important role in administering public services.

interacted with observed correlates as a robustness check. We therefore provide such a check for all our main results either in the main paper or the appendix.

5 Results

5.1 Births in public clinics

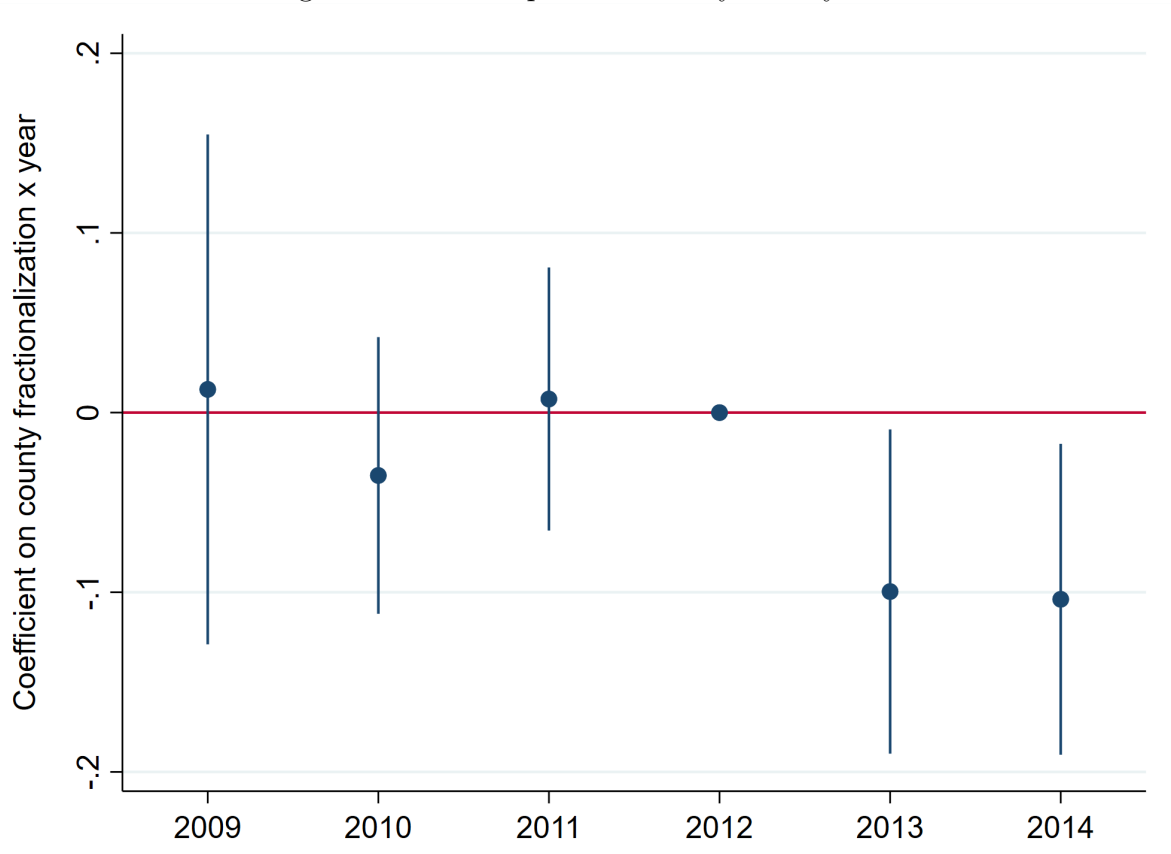
We begin by presenting results on whether births recorded in DHS took place in public clinics. Giving birth in a health facility (either private or public) is a stated priority for the Ministry of Health: should complications arise during pregnancy, both mother and baby are more likely to survive without 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 decentralization, 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 decentralization.

The coefficients on the year dummies interacted with county fractionalization are displayed in Figure 2. We note that the coefficients on the post-decentralization 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 decentralization 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 decentralization 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 the birth took place after decentralization (i.e. in 2013 or 2014). In column 2, we then add to this regression the same dummy interacted with eighteen county-level control variables. This includes, for instance, the share of the population living in an urban area and the share of births in public clinics at baseline.¹³ Since this number of variables is large compared to

¹³A full list of the control variables is given in Appendix Table B7. This table also shows the partial correlation of each variable with county fractionalization, and the coefficients when we include each

Figure 2: Birth at public clinic by birth year



Notes: Points represent coefficients from regressing a dummy for whether a birth took place at 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 number of counties we have, in column 3 we select the most relevant among these using post-double selection lasso - in this case, only the county urbanisation rate is retained. In both columns we can note that our coefficient of interest remains similar in magnitude and is still highly significant, meaning that our result is not being driven by these other county-level variables.

One concern we might have is that our measure of county fractionalization comes from the 2014 DHS, which obviously took place after decentralization. If county fractionalization changed substantially over the period, then our result could be biased due to measurement error - i.e.

variable individually rather than simultaneously. The main lesson from this table is that most of the variables strongly correlated with fractionalization, such as urbanisation, wealth, and ruggedness, are not significantly correlated with the change in birth location once we control for county fractionalization. All variables are taken from the 2014 DHS or from Goodman et al. (2019), except for data on the political party of the county governor which is taken from Marx et al. (2021b).

Table 2: Robustness of birth result

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
County fractionalization × Post-decentralization	-.095*** (.029)	-.13*** (.039)	-.093*** (.029)	-.11*** (.034)	-.15*** (.037)	-.077** (.032)	-.099** (.045)
County polarization × Post-decentralization					.083 (.054)		
County FEs	Yes	Yes	No	Yes	Yes	No	No
Province-year FEs	Yes	Yes	No	Yes	Yes	Yes	Yes
Controls × Post	No	Yes	No	No	No	No	No
Selected controls × Post	No	No	Yes	No	No	No	No
Mother FEs	No	No	No	No	No	Yes	Yes
Ethnicity-year FEs	No	No	No	No	No	No	Yes
R^2	.18	.18	.18	.18	.18	.77	.78
Observations	20564	20564	20564	20564	20564	10634	10630
Clusters	47	47	47	47	47	47	47
Frac. measured in	2014	2014	2014	2008	2014	2014	2014

Notes: The table presents results of estimating equation (2). 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. In column (2) we include the post-decentralization dummy interacted with other county-level variables, a list of which can be found in Appendix Table B7. Column (3) then includes a subset of these county-level interactions selected using post-double selection Lasso. County fractionalization is measured using the 2014 DHS in all column except (4), which uses the 2008 DHS. 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 columns (6) and (7). Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

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 4 of Table 2), our results are very similar. We may also wonder whether our result is not driven by the level of ethnic *fractionalization* within a county, but instead the level of ethnic *polarization*, as defined by Montalvo and Reynal-Querol (2005). We therefore add this variable interacted with the post-decentralization dummy in column 5 - the variable is, however, insignificant, with the coefficient on the fractionalization interaction increasing in magnitude.¹⁴

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 who give birth over time across counties, since

¹⁴Since fractionalization and polarization are highly correlated (i.e. the correlation coefficient is .78) it is of course difficult to distinguish between the two. Nonetheless, if we replace fractionalization with polarization, the latter isn’t significant, also suggestive that fractionalization is the more relevant variable here.

this would be unlikely to be driven by decentralization. To assuage this concern, in column 6 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 with a similar coefficient. In column 7 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.

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 decentralization 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 decentralization.¹⁵

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 × Post-decentralization	0.0237 (0.0150)	0.0703** (0.0296)	-0.0708* (0.0354)	-0.0675* (0.0399)	-0.0324* (0.0186)	0.00455 (0.00962)
Observations	20564	20564	20564	6756	19271	20564
Adjusted R^2	0.156	0.336	0.190	0.115	0.179	0.00239
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 (4) 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 B1 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

¹⁵When undertaking this analysis, we exclude from the sample births which took place before July 2013, since potential antenatal visits would cover both the pre-decentralization and post-decentralization periods.

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.¹⁶ We find that children born in less fractionalized counties after decentralization 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 [B2](#) we undertake the same regressions including year fixed-effects interacted with county-level controls and find broadly similar results.

5.2 General use of public clinics

The previous section showed evidence that, after decentralization, 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 decentralization 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.

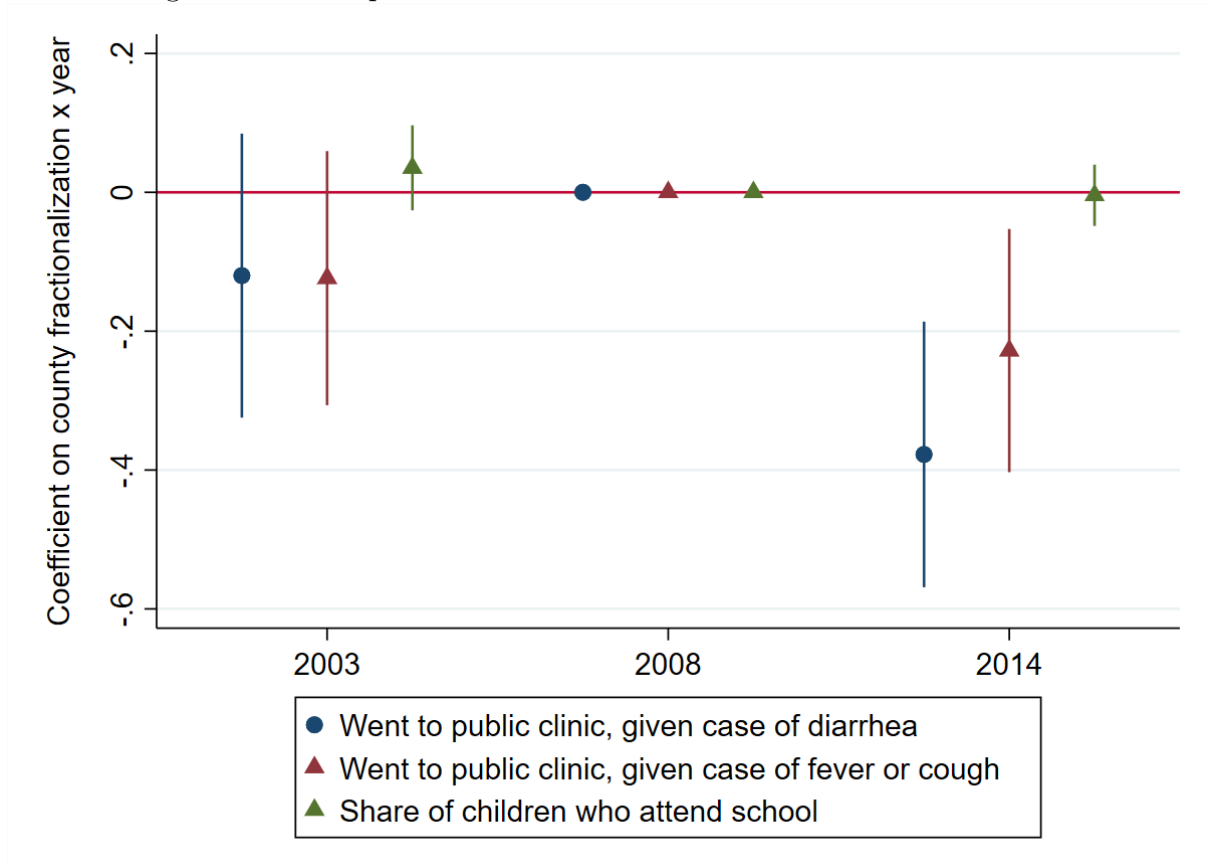
5.2.1 Evidence from multiple waves of the DHS

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.¹⁷ 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 decentralization for both types of illness. In Table [B3](#) we show that the diarrhea result is robust to including year fixed effects interacted with county controls, while the fever or cough result becomes marginally insignificant. Finally, in Figure [3](#) graph we also show the results when the dependent variable is the share of a mother's children who attend school. We note here that there is no significant change in the correlation of this variable with county fractionalization over time, consistent with schooling not being a devolved service.

¹⁶Children 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 [B1](#) - this shows that there is not a particular vaccine driving this result, but rather that each vaccine is less likely to be given in more fractionalized counties after decentralization.

¹⁷We also check in Table [B6](#) whether the probability of reporting such an illness changes as a function of fractionalization after decentralization. We find no significant impact on the probability of reporting a case of fever or cough and a slightly significant increase in the probability of reporting a case of diarrhea (consistent with child health improving in less fractionalized counties).

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



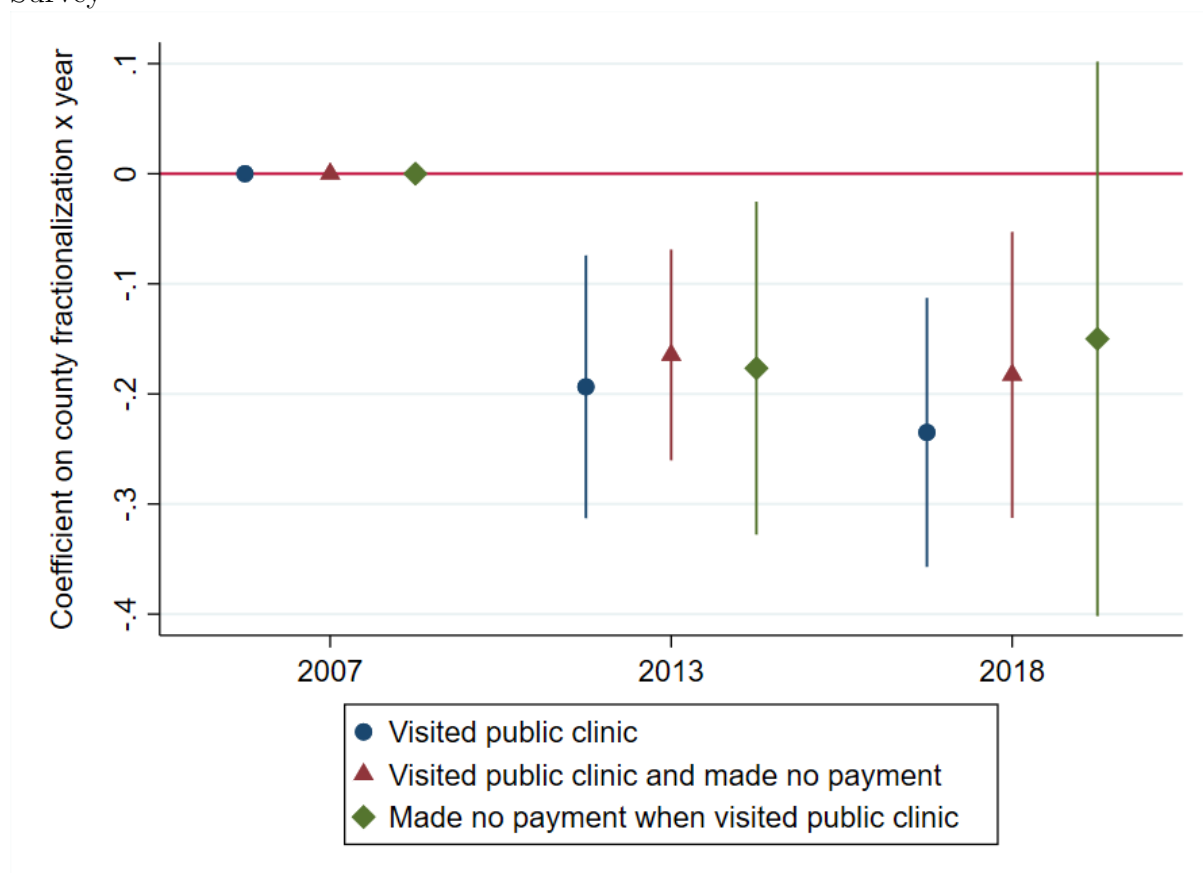
Notes: Points represent coefficients from regressing a dummy for whether a mother took their sick child to a public clinic on county fractionalization interacted with year dummies - i.e. equation (1). Years correspond to rounds of the DHS survey. The lines represent the 95 % confidence intervals. Controls 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.

5.2.2 Evidence from the KHHEUS

In the Kenyan Household Health Expenditure 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 our approach with the DHS, we therefore restrict our sample to household members who were reported being ill.¹⁸ 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-treatment wave. The results are shown as the blue circles in Figure 4 - visiting a public clinic is significantly more negatively correlated with fractionalization after decentralization.

¹⁸Table B6 shows there’s no significant impact of country fractionalization interacted with the post-decentralization dummy on reporting an illness.

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.

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 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 decentralization in less fractionalized counties. These results are displayed in diff-in-diff form

in Table [B4](#), which also shows that they are generally robust to the inclusion of county-level controls interacted with year FEs.

5.2.3 Evidence from Afrobarometer

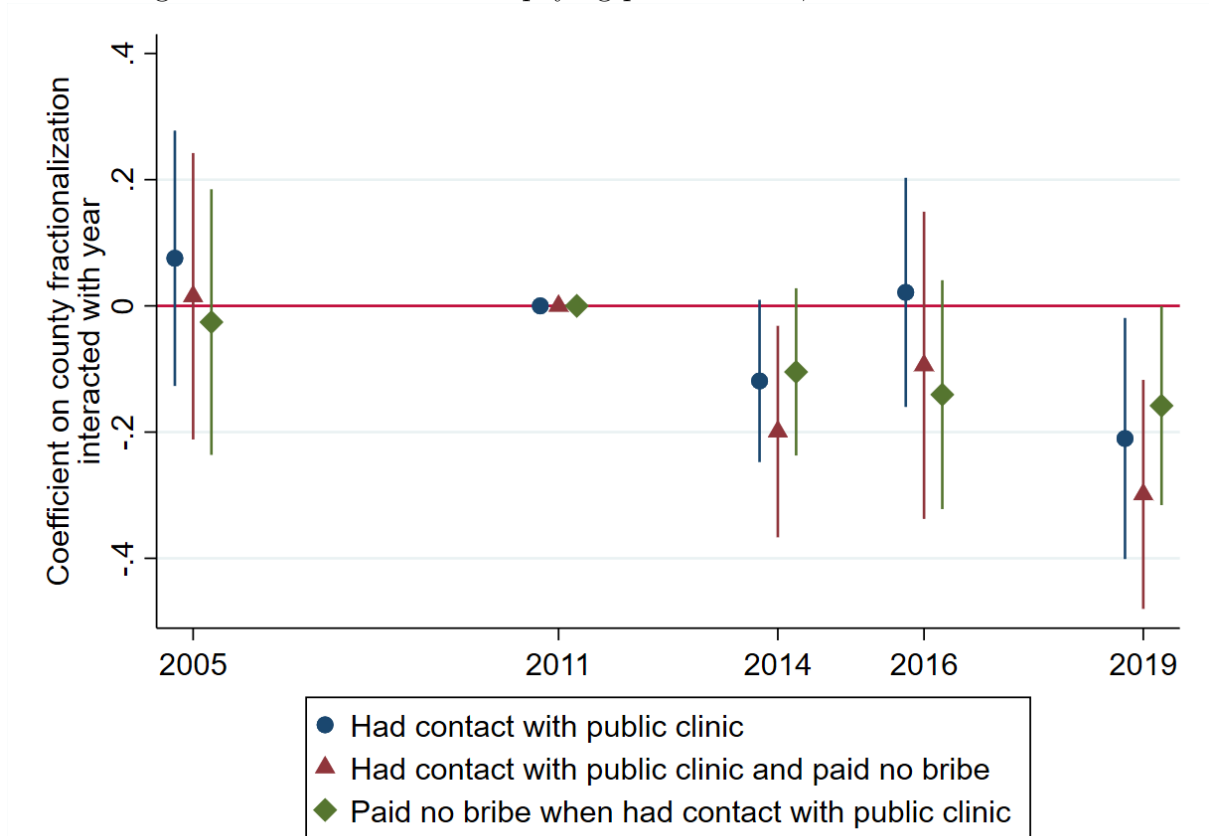
Although not focused on healthcare, several waves of the Afrobarometer surveys ask respondents whether they had any contact with a public clinic. Since the form of contact is not elicited and this is not the focus of the survey, it is likely to be a noisier measure of public healthcare use than in the 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.¹⁹ 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.

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 decentralization. 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 after decentralization. Although some of the individual coefficients are insignificant, the results on the outcomes involving bribery are significant when we aggregate the years in a diff-in-diff analysis in Table [B5](#). This table also shows that results remain largely unchanged when we include county-level controls interacted with year fixed effects. Consistent with this result being about decentralization, we find no similar pattern when we conduct the same analysis with services that were not decentralized (Figure [A2](#)).

¹⁹Note 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 and 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.

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 respondent’s language, gender, education, and age. Standard errors are clustered at the county level.

6 Discussion of possible mechanisms

The previous section has demonstrated that public clinic use became more negatively correlated with county fractionalization after decentralization. Moreover, users in less fractionalized counties were less likely to pay to use such services. While we have limited data to understand the mechanisms behind these results, in this section we discuss possible mechanisms and provide supportive evidence where possible. We consider two main possible mechanisms that may be behind the effects we observe: changes in budgeting, and changes in staffing.

Although 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.²⁰ The first column of Table 4 shows that the number of hospital beds per capita

²⁰Despite 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

decreased at a relatively higher pace in more fractionalized counties from 2012 to 2018. This could reflect the fact that more new clinics were opened in homogeneous counties in the years following decentralization, but could also be a reflection of the fact that healthcare funding is more efficiently allocated, with less leakage and corruption, in homogeneous counties. On the latter point, columns 2 and 3 of Table 4 show that homogeneous 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 (Pietrzyk et al., 2018). Another study shows that elected officials at the county level could directly influence operations at the hospital level by, for example, asking for certain patients to be prioritized for receiving care, waiving bills, or insisting that favored patients be referred for treatment at specialized facilities (Kagwanja et al., 2020).²¹ Consistent with better performance of county governors in less fractionalized counties, column 4 shows that they are more trusted.

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

	Δ Log of number of beds in county, 2012 to 2018 (1)	Auditor- General's opinion of County Executive, 2017-18 (2)	Average corruption rating of County Governor (3)	Average trust in County Governor (4)	Δ county public service fraction- alization (5)	Δ county pop. - county public service dissimilarity (6)
County fractionalization	-0.818* (0.448)	-0.743* (0.399)	0.203** (0.0984)	-0.0960* (0.0547)	0.304*** (0.105)	0.149*** (0.0439)
Observations	44	46	46	46	46	46
Adjusted R^2	0.108	0.179	0.371	0.485	0.216	0.359
Dep. var mean	-0.692	2.783	1.439	0.804	-0.111	-0.0540

Notes: The dependent variable in column (1) 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 (2) is a score given between 1 and 4, with 1 representing a lower opinion. change in the ethnic dissimilarity between the county population (as measured using the 2014 DHS) and the public service employees working in the county. The dependent variable in columns (3) and (4) are the average over rounds 6 and 7 of the Afrobarometer. The dependent variable in column (6) 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 and the dependent variable in column (5) are estimated using data from NCIC (2016), notably on the ethnic breakdown of county public service employees and new appointments. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

A second mechanism could be through county governments making staffing decisions that resulted in changes to the ethnic composition of the workforce. We do not have data on the ethnic composition of healthcare workers to test this directly, but we can make use of data

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, 2015). Things have improved over time, though marginally; by 2021, only three counties had published the full set of budgeting documents online (IPB, 2022).

²¹On a related note, Coşgel et al. (2023) document that leaders may tend to favor individuals from the same religious group in fragmented societies, which can have long-run consequences for ethnic conflict. Kenya is a majority Christian country, and ethnicity tends to be correlated with religious affiliation, though the correlation is not perfect.

on public servants more generally collected by the [NCIC \(2016\)](#). They measure the ethnic composition of both the stock of public servants employed by the county, and those recruited after 2013. In column 5 of [Table 4](#) we see that average workforce fractionalization fell following decentralization, but this hides a lot of heterogeneity: the workforce became more fractionalized in the most fractionalized counties, and less fractionalized in the most homogeneous counties. This may in turn have had an impact on productivity.²² 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 decentralization (estimated from the [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 sixth 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 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 the finding that the workforce in decentralized 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 have impacted supply, since DHS interviews revealed 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](#)). There is also evidence of county officials directly involving themselves in the appointment of health care staff, for example by demanding that some staff be transferred to different facilities ([Kagwanja et al., 2020](#)). In other instances, county government actions (or lack thereof) influenced staffing indirectly: delays in promotions or trainings led hospital staff to leave for counties with better paid opportunities ([Kagwanja et al., 2020](#); [Tsofa et al., 2017](#)).

These observed staffing changes may also drive behavioral responses from patients if they 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

²²Evidence from the private sector in Kenya suggests that inter-ethnic 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., 2021a](#)). The dynamics of these interactions in the Kenyan healthcare sector have not been directly tested, to our knowledge.

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). It should be noted that while staffing changes would have taken time to take place, related staff behaviour may have changed rapidly. Vanden Eynde et al. (2018) show, for instance, that the behaviour of public servants in Kenya changed in response to co-ethnic leadership in the post-independence period. It may also be the case that the health services simply being administered by co-ethnics was sufficient to change demand from users, particularly if they expected more favourable treatment as a result. Finally, it could be that those of the same ethnicity as the government may be more likely to receive information about healthcare (Gomes, 2020).

If part of the mechanism comes through the anticipation of better treatment of those with the same ethnicity as the county government, we should expect to see variation in behaviour *within* counties. To test for this, in Table 5 we return to our baseline outcome on births in public clinics. Column 1 reports our baseline specification. In column 2, we then add in a dummy for whether the mother is of the same ethnicity as someone on the County Executive Committee (CEC). We can note that, although this had no significant impact on whether a mother gave birth in a public clinic prior to fractionalization, afterwards such mothers are significantly more likely to use public clinics. In column 3 we note that this holds even when we control for county fixed effects interacted with a post-decentralization dummy, confriming that it is driven by within-county variation. Moreover, in column 4 we include a set of over 1000 fixed effects based on which clinic each DHS cluster is closest to.²³ The result on mother’s ethnicity remains positive and significant, meaning that, post-decentralization, a mother who is of the same ethnicity as someone on the CEC is more likely to give birth at a public clinic than one of another ethnicity even when they live near the same clinic. This suggests that at least part of the mechanism cannot be coming through budgeting or policy decisions, since these cannot discriminate by ethnicity within a clinic.

²³Since there are roughly 1500 DHS clusters in our sample, most clinics are therefore linked to a unique cluster.

Table 5: Impacts of mother’s ethnicity on place of birth

	(1)	(2)	(3)	(4)
County fractionalization × Post-decentralization	-0.09*** (0.03)	-0.08** (0.03)		
Mother’s ethnicity is on CEC		-0.01 (0.02)	-0.01 (0.02)	-0.05** (0.02)
Mother’s ethnicity is on CEC × post-decentralization		0.04** (0.02)	0.04** (0.02)	0.07** (0.03)
County FEs	Yes	Yes	Yes	Yes
Province-year FEs	Yes	Yes	Yes	Yes
County FEs × Post	No	No	Yes	Yes
Clinic FEs × Post	No	No	No	Yes
R^2	.18	.18	.18	.34
Observations	20564	20564	20564	20472
Clusters	47	47	47	47

7 Conclusion

The introduction of decentralization 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, decentralization 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 decentralization. In this paper, we partly fill this gap by analyzing the differential impacts of decentralization on public health services, depending on the level of ethnic fractionalization in the local jurisdictions in charge of providing healthcare. Using event-study style estimations, we are able to investigate how ethnic fractionalization plays a role after decentralization. Our results reveal that individuals tend to use public clinics more after decentralization in less diverse communities, whether it be 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 constituents change their behavior in response to the local political context, while the extant literature has more to say on the actions taken by local political leaders. We also observe that access to free health care is more available in less diverse areas after decentralization.

Various mechanisms could be underlying our findings. Although our data do not allow us to directly test them, we provide suggestive evidence of those that may be at play and those that can be discarded. Given that we observe significant effects on health care service utilization in the immediate aftermath of decentralization, we can rule out any impact related to changes in infrastructure, such as hospital or clinic construction. Instead, within-county variation suggests that the impact of decentralization is strongest for individuals of the same ethnicity of the county government, consistent with ethnic discrimination or preferences to be treated by coethnics.

All in all, our results support the prior that decentralization is one way to mitigate the negative impacts of diversity. Our paper therefore adds to a literature that investigates 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 (Glennster et al., 2013) may alleviate ethnic divisions. 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 decentralization can have an impact, even before this new form of government has time to undertake significant investments in public services.

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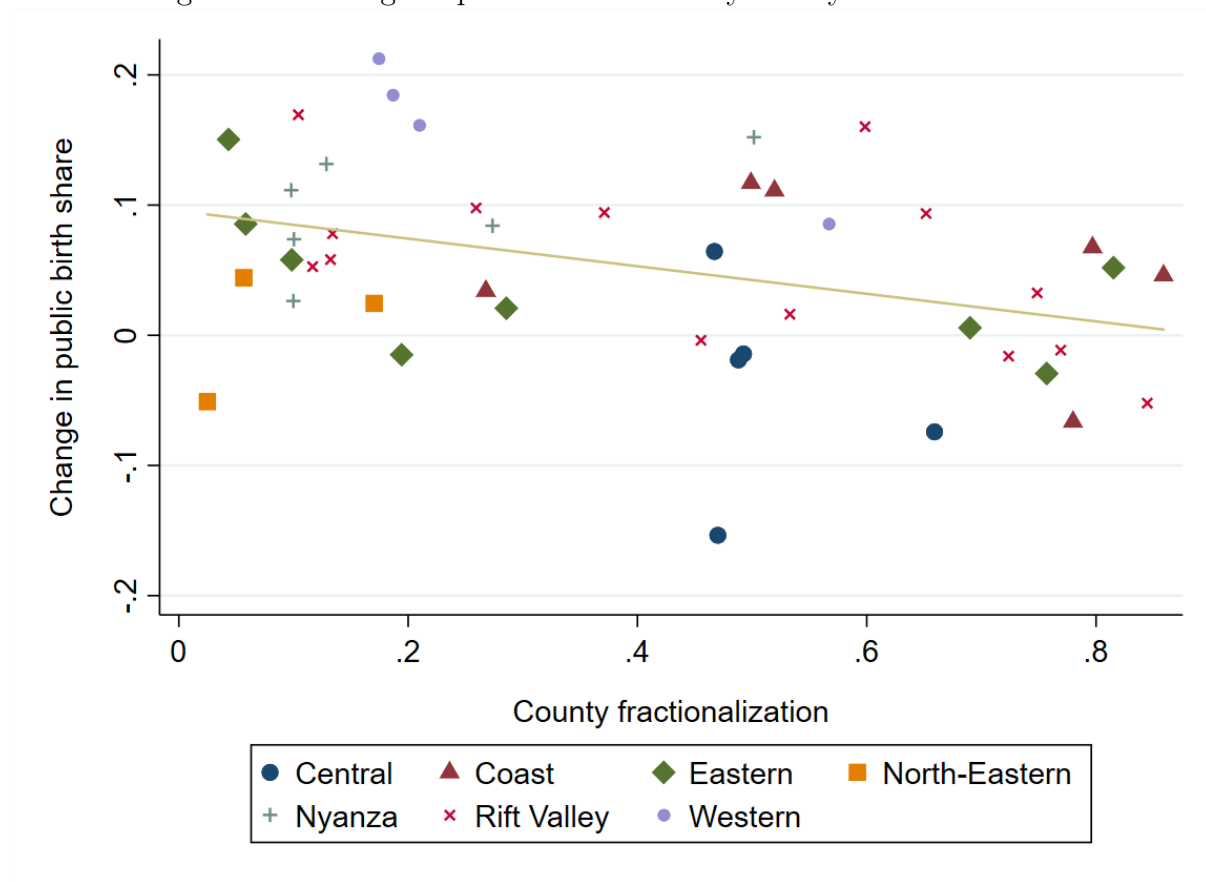
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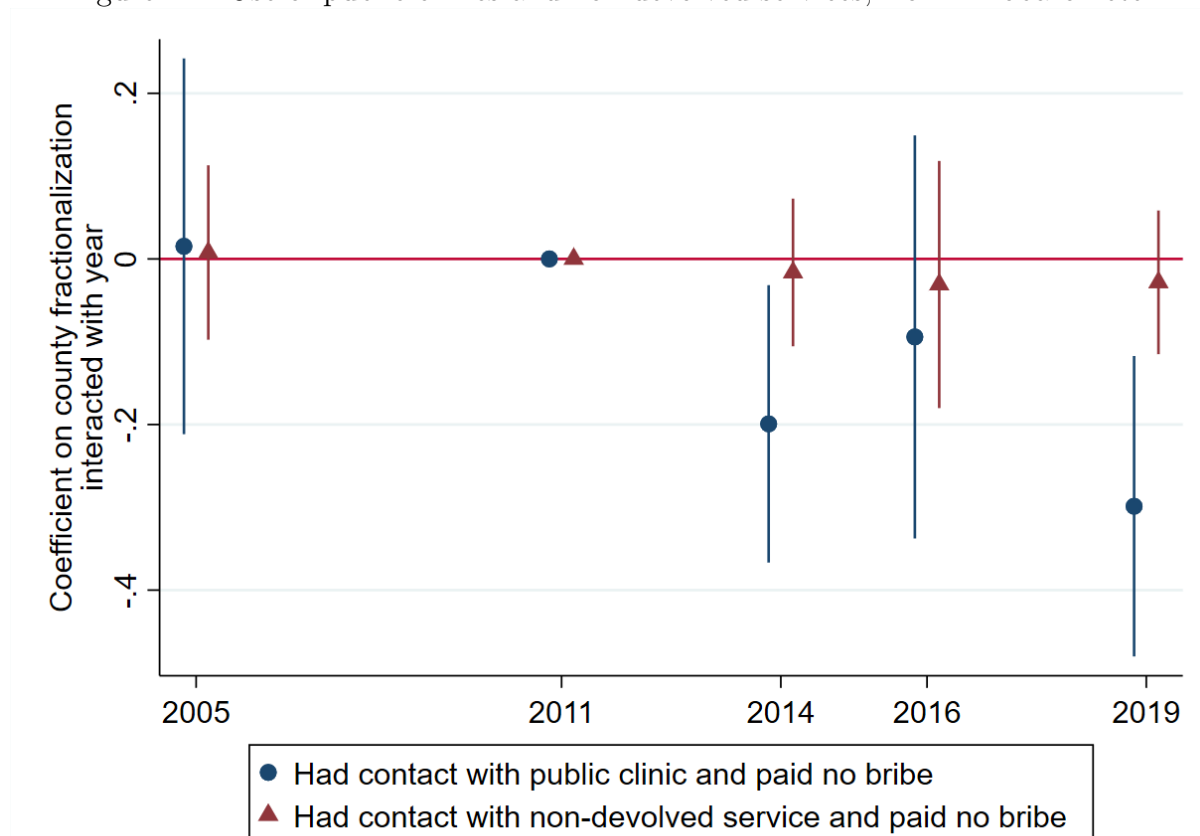
Appendix A Additional figures

Figure A1: Change in public birth share by county fractionalization



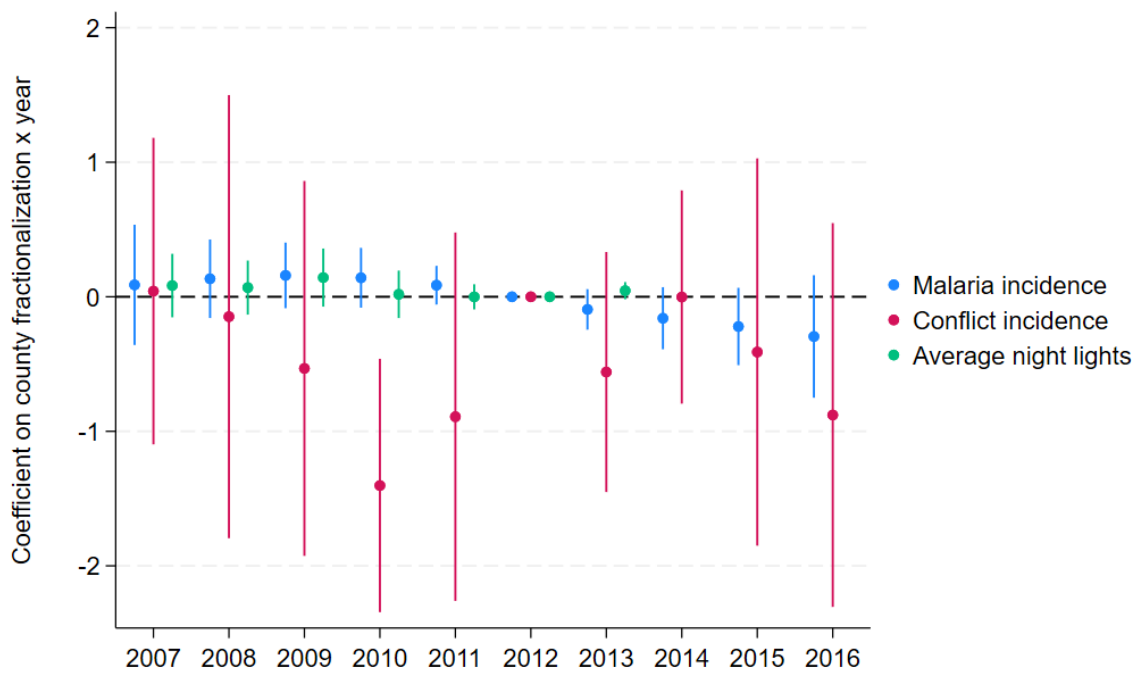
Notes: Each point represents a different county, with the different symbols representing different provinces. The x-axis measures ethnic fractionalization within the county, estimated using DHS 2014. The y-axis measures the difference in the share of births which take place in public clinics when we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

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

Figure A3: No similar time patterns in non-impacted variables



Notes: The points represent coefficients from regressing the relevant variable on county fractionalization interacted with year dummies - i.e. equation (1). Controls include province-year fixed effects and county fixed effects. Standard errors are clustered at the county level. All variables are taken from [Goodman et al. \(2019\)](#).

Appendix B Additional tables

Table B1: Vaccines

	Polio 0 (1)	Bcg (2)	Dpt 1 (3)	Polio 1 (4)	Dpt 2 (5)	Polio 2 (6)	Dpt 3 (7)	Polio 3 (8)	Measles (9)
County fractionalization × Post-decentralization	-.053 (.033)	-.0056 (.012)	-.031* (.016)	-.018 (.014)	-.028 (.018)	-.021 (.013)	-.036 (.032)	-.04 (.03)	-.014 (.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 B2: Birth related outcomes, with county-level controls interacted with post-decentralization dummy

	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 × Post-decentralization	0.0122 (0.0154)	0.0723** (0.0338)	-0.0730* (0.0426)	-0.0624 (0.0430)	-0.0559*** (0.0171)	0.00506 (0.0103)
Observations	20564	20564	20564	6756	19271	20564
Adjusted R^2	0.156	0.336	0.190	0.114	0.180	0.00234
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 B3 only with the inclusion of various county-level variables interacted with a post-decentralization dummy - please see the notes to that table. The county-level variables included are chosen by post-double selection Lasso from the list in Appendix Table B7. * $p < .10$, ** $p < .05$, *** $p < .01$

Table B3: 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 × Post-devolution	-0.325*** (0.0762)	-0.348*** (0.0879)	-0.165** (0.0669)	-0.193** (0.0754)
Controls × year FEs	No	Yes	No	Yes
Observations	4270	4270	8616	8616
Adjusted R^2	0.0795	0.0793	0.0473	0.0473
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-decentralization. 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 a post-decentralization dummy interacted with county-level variables. The county-level variables included are chosen by post-double selection Lasso from the list in Appendix Table B7. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table B4: Public clinic use in KHHEUS with county-level controls interacted with post-decentralization dummy

	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 × Post-devolution	-0.215*** (0.0546)	-0.271*** (0.0601)	-0.174*** (0.0471)	-0.165*** (0.0521)	-0.163* (0.0879)	-0.109 (0.0891)
Controls × year FEs	No	Yes	No	Yes	No	Yes
Observations	56919	56919	56919	56919	27381	27381
Adjusted R^2	0.0478	0.0480	0.0417	0.0417	0.0855	0.0857
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-decentralization. Controls include province-year fixed effects and county fixed effects. In columns (2), (4), and (6) we include a post-decentralization dummy interacted with county-level variables. The county-level variables included are chosen by post-double selection Lasso from the list in Appendix Table B7. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table B5: Afrobarometer results with county-level controls interacted with post-decentralization dummy

	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 × Post-devolution	-0.0759 (0.0483)	-0.0614 (0.0694)	-0.257*** (0.0685)	-0.265*** (0.0861)	-0.208** (0.0882)	-0.338*** (0.0970)
Controls × year FEs	No	Yes	No	Yes	No	Yes
Observations	10048	10048	10073	10073	7628	7628
Adjusted R^2	0.0512	0.0511	0.0447	0.0452	0.0901	0.0971
Dep. var mean	0.759	0.759	0.564	0.564	0.745	0.745

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 Afrobarometer 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-decentralization. Controls include province-year fixed effects, county fixed effects, and respondents language, gender, education, and age. In columns (2), (4), and (6) we include a post-decentralization dummy interacted with county-level variables. The county-level variables included are chosen by post-double selection Lasso from the list in Appendix Table B7. Standard errors are clustered at the county level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table B6: Probability of reporting birth or sickness

	Reports birth, DHS (1)	Reports case of diarrhea, DHS (2)	Reports case of fever or cough, DHS (3)	Reports case of illness, KHEUS (4)
County fractionalization × Post-devolution	-0.00134 (0.00928)	0.0929* (0.0526)	0.165 (0.104)	-0.0419 (0.0339)
Observations	285898	21452	21452	309055
Adjusted R^2	0.113	0.0298	0.0522	0.0150
Dep. var mean	0.0922	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 the 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. * $p < .10$, ** $p < .05$, *** $p < .01$

Table B7: Correlations and coefficients relating to adding control variables interacted with post-devolution dummy

	(1)	(2)	(3)
	Partial correlation with county fractionalization with region FEs	Coef. on fractionalization when adding only this control to baseline	Coef. on control variable when adding only this control to baseline
Average education level	-0.038 (0.053)	-0.093*** (0.029)	0.005 (0.008)
Average elevation	-0.052 (0.072)	-0.090*** (0.029)	0.024* (0.012)
Average night lights, 2008	0.065 (0.050)	-0.093*** (0.030)	-0.003 (0.007)
Average precipitation, 2008	-0.128** (0.058)	-0.074*** (0.028)	0.022*** (0.008)
Average wealth index	0.090** (0.045)	-0.095*** (0.032)	0.000 (0.008)
Governor's party in jubilee coalition	0.005 (0.045)	-0.095*** (0.030)	-0.015** (0.007)
Governor's party supported president	0.026 (0.048)	-0.092*** (0.031)	-0.008 (0.008)
Log area	0.034 (0.049)	-0.092*** (0.029)	-0.005 (0.007)
Log malairia incidence rate, 2008	0.033 (0.057)	-0.093*** (0.029)	-0.009 (0.010)
Log of average distance to clinic	0.007 (0.053)	-0.094*** (0.029)	-0.005 (0.007)
Log of conflict events, 2000–2008	0.044 (0.041)	-0.093*** (0.030)	-0.004 (0.006)
Log of distance to road	0.045 (0.048)	-0.086*** (0.029)	-0.015* (0.008)
Log population, 2008	-0.066 (0.041)	-0.093*** (0.030)	0.001 (0.007)
Ruggedness	-0.146*** (0.045)	-0.115*** (0.034)	-0.014 (0.009)
Share employed in agriculture	-0.110*** (0.037)	-0.091*** (0.032)	0.002 (0.008)
Share of births in public clinic, 2008	0.007 (0.046)	-0.094*** (0.028)	-0.008 (0.006)
Share of population urban, 2014	0.121*** (0.039)	-0.084*** (0.031)	-0.007 (0.007)
Travel time to nearest city	0.008 (0.046)	-0.093*** (0.030)	-0.009 (0.008)

Notes: In column 1, each coefficient comes from a separate county-level regression where we regress county fractionalization on the control variable and region fixed effects. Pairs of coefficients in columns 2 and 3 come from separate regressions where we add each control variable interacted with a post-devolution dummy to our baseline regression, i.e. column 1 of Table 2. Column 2 then reports our main coefficient of interest, that on the interaction of county fractionalization and the post-devolution dummy, while column 3 reports the coefficient on the newly introduced control.