Market Day Coordination, Market Size, and Rural Development*

Moritz Poll†

November 21, 2024

Abstract

Market days are the pulse of rural, economic and social life in many parts of the world and millions of people rely for their daily sustenance on weekly markets. I investigate their catchment area size as a tradeoff between agglomeration gains and transport cost. To do so, I identify a natural experiment in Western Kenya in which weekly market schedules over the past century were set quasi-randomly. This induces exogenous variation in the spatial competition over participants between nearby markets on the same day of the week. I find that market schedules causally and lastingly affect present-day market attendance, driven by cross-attendance from other villages, as well as population and nighttime luminosity as a proxy for economic activity. Market consolidation could achieve attendance gains around 20%. Market locations and their schedules have remained nearly unchanged in this setting for half a century now, so finding sizable, unrealized agglomeration gains in this equilibrium is surprising. They are driven by markets that face the fiercest spatial competition and have benefited the most from road building, suggesting that markets have become too spatially fragmented in the face of precipitously falling transport costs.

KEYWORDS: Market days, coordination, agglomeration, market size, rural development, spatial patterns of economic activity, persistence.

JEL CLASSIFICATION: O12, O18, Q13, R11, R12

*I would like to thank the key informants for generously sharing their time and knowledge, Carol Nekesa and the team at REMIT Kenya for data collection support, and Jasmine Vorburger for excellent research assistance. This project has benefitted tremendously from comments by Nava Ashraf, Daniel Björkegren, Marcel Fafchamps, Andrew Foster, Oded Galor, Doug Gollin, Ben Golub, Peter Hull, Matt Jackson, Elisa Macchi, Stelios Michalopoulos, Eduardo Montero, Ameet Morjaria, Nathan Nunn, Jon Roth, Matthew Turner, Winnie van Dijk, and Tillmann von Carnap. I gratefully acknowledge funding from CEPR STEG (SRG #1252 & #3379), the Bravo Center, and the SurveyCTO Primary Data Collection Grant. I also benefited from a Watson Institute fellowship during data collection. This study was approved by Maseno University IRB (MSU/DRPI/MUSERC/01168/22).

†Brown University, Department of Economics, and Busara Center for Behavioral Economics, Nairobi, Kenya. Email: `moritz.poll@brown.edu`. Website: www.moritz-poll.eu.

1 Introduction

In a world with agglomeration gains on the one hand and transport costs on the other, there is a tradeoff between the access to markets and their size. Many small markets scattered across a geographic area have the advantage that buyers and sellers can reach markets easily, procure what they need and bring their wares to market at low transport cost. The probability of finding a trading partner and transacting at a favorable price, however, is greatly diminished in a small market. Reliably finding customers is vital to any business, but to smallholder farmers and entrepreneurs, it is existential. I study how this tradeoff was brokered in the context of rural market days in Western Kenya. Villages in this context are too small to sustain daily trade. Large shares of the consumption basket are perishable, but the absence of refrigeration limits bulk purchases by consumers or storage by the producers. On any given day, a share of consumers need to purchase, while sellers sit on post-harvest perishable stockpiles, or daily fish catch, and sellers of more long-lived products still rely on regular sales for their subsistence. Rotating, periodic market days[1] have emerged here and across the world in response to this challenge and represent an ideal case study for the tradeoff between market size and market access.

The periodic "pulsation of economic activity" that market days spark (Hill, 1966) has been described as "one of the basic life rhythms in all traditional agrarian societies" (Skinner, 1964). At their economic core, they constitute a solution to a coordination problem: Bringing buyers and sellers together in the same place at same time. Rural periodic markets are also the final link in the food supply chain for millions of people. Market days are the site of myriad matching problems and the livelihoods of vulnerable market participants on both sides of the transaction depend on reliably finding someone to trade with at a predictable price. This process is challenging in thin markets with few buyers and sellers and can be eased through market integration that increases market attendance. An age-old, straightforward to implement, and essentially costless way of increasing the attendance to weekly markets, which I study in this paper, is to schedule market days in such a way that they do not clash between neighboring villages, thus allowing buyers and sellers to cross-attend. I investigate the impact of this strategy on present-day trade patterns. To do so, I identify a natural experiment in how market schedules were set in Western Kenya over the past century, which allows me to show that schedule coordination in the distant past meaningfully increases present-day market attendance by shaping market catchment areas.

I measure a market's catchment areas as the area within which it is the closest market to reach on its market day. A simple regression analysis that relates outcomes of interest to market area would not identify the causal effect of market size on these outcomes. There may be other factors such as geographic fundamentals or initial conditions (e.g. in population density) that both induce some markets to synchronize their schedule more with their surroundings while simultaneously affecting the outcomes we are interested in. I provide evidence of this threat in Section 5.3. My goal in this study is to resolve this omitted variable bias and arrive at the causal effect of market

[1] Periodic markets either operate on a non-daily, typically weekly, schedule or on a daily schedule with substantially higher attendance on designated market days.

area.

An in-depth literature review in anthropology, sociology, geography, history, and economics, as well as over 1900 detailed and extensive key informant interviews with village elders and market administrators in the study area allow me to reconstruct the market scheduling process for all 287 weekly markets in my market census. Market day scheduling was a function of the distance to existing markets at the time, region-wide weekday preferences, as well as idiosyncratic preference shocks. Using the method proposed in Borusyak and Hull (2023), I leverage this contextual knowledge to separate the observed variation in market areas into a component that was to be expected given the known geography and scheduling process, and a component of quasi-random deviations from this expectation which are the culmination of a cascade of idiosyncratic weekday preference shocks. In the analysis that follows, I use this latter component to identify the causal effect of market area and frictions on various outcomes of interest.

I find that, indeed, distance to existing markets predicts market day scheduling decisions and that simulations from the estimated coordination model can be used to purge out omitted variable bias in observed market catchment area. The quasi-random component of the scheduling decision model is then used in the remainder of the analysis. I show that quasi-random variation in market area causally impacts market attendance by both buyers and sellers and that this is driven by outsiders cross-attending from other towns. I also show that market towns that are endowed with a larger market area than the coordination model would have us expect have a larger population today and are brighter in nighttime satellite imagery, a proxy for economic activity.

Consider a social planner drawing market catchment areas with the objective to maximize agglomeration gains subject to the distance that market participants are willing to travel. She would make catchment areas so large that those furthest from the market are just made indifferent about attending the market. With this thought experiment in mind, it should come as a surprise that we find agglomeration gains in equilibrium in this setting: Market schedules have at this point been mostly set and highly persistent for over 50 years. Market participants appear willing to travel further if only there were even larger markets to reach. In order to rationalize these gains in equilibrium, I document that my results are driven by markets with small market areas. Consistent with the fact that transport costs have fallen since the inception of these markets. If market catchment areas were optimal at that time, my results suggest that trade activity today is scattered across suboptimally many markets where falling transport costs would enable much larger agglomeration gains.

The optimal size and scope of markets, as well as whether optimality is reached in equilibrium, has been the subject of a longstanding debate in economics (Hotelling, 1929; Tóth, 1953; Lösch, 1954; Mills and Lav, 1964; Stern, 1972; Bollobás and Stern, 1972). These classical papers tend to focus on the location choices of competing firms. Oberfield et al. (2024) study the optimal number, location, and distance between plants of a single firm as a trade-off between transport cost and plants cannibalizing one-another's customer base. In their model, the overarching firm chooses the locations of all its plants to maximize joint profits while in my case – and perhaps even in some of

their own examples of franchise branches – the decision is decentralized without a planner enforcing an optimal allocation. Recent advances by Vitali (2022) and the work cited therein have highlighted the advantages for firms, even those in similar industries, to spatially cluster, rendering it natural to recast the classic location tradeoff into one for markets rather than firms. In this context, the sequential nature of market entry in my paper may also be of interest to readers thinking about how classical static equilibrium concepts can be brought to bear in a dynamic world. Starting with Dixit and Stiglitz (1977), a plethora of models based on a CES functional form, notably among them Melitz (2003), obtain notions of static equilibrium in which differentiated products in product or quality space, or firms or towns in geographic space end up in some form of equidistance from one another. Lösch (1954) and later Stern (1972) warn that the sequential nature of entry is unlikely to always result in such an efficient equilibrium spacing and my paper provides an example of that for the case of marketplaces: Later entrants may undo the schedule optimality of existing markets. In addition, if fundamentals such as transport technology change, a frictionless market system would have markets gradually move further and further apart from one another, but in reality markets are tied to the amenities of the immobile towns that host them.

Food markets in many developing countries are thin (Fafchamps, 1992) and thin markets are volatile (Desmet and Parente, 2010): With few buyers and sellers on either end of the transaction, supply, demand, and prices are likely to fluctuate as match rates are low. This makes it difficult for both buyers and sellers to reap the full potential of market participation. Market integration can improve the performance of price systems and the reliability of markets to all participants (Barrett, 2005; Jensen, 2007; Svensson and Yanagizawa, 2009; Casaburi et al., 2013; Faber, 2014; Donaldson, 2015 and others) and ease matching (Agarwal et al., 2019; Akbarpour et al., 2020; Kapor et al., 2022). In this paper, I study a straightforward means of market integration aimed at increasing market attendance to periodic markets: Coordinating market day schedules with the goal of allowing buyers and sellers to cross-attend several markets is a widely recognized phenomenon in anthropology, sociology, geography, and history (Schurtz, 1900; Thomas, 1924; Fröhlich, 1941; Hill, 1966; Hodder, 1961; Fagerlund and Smith, 1970; Good, 1973; Wood, 1974b; Bromley et al., 1975; Scott, 1978; Smith, 1979, 1980; Geertz, 2000). Interest for them in the social sciences peaked in the 1970s, before the availability of modern GIS and satellite data, detailed maps of virtually every corner of the Earth, or the computing power required for many recent GIS and statistical methods. These earlier papers tend to be small-n case studies focusing on origins rather than impacts of market days. Despite their importance, periodic market days have not attracted broad attention from economists. I revive and build on this rich literature, bringing to bear newly available data and methods, while also departing from the purely descriptive and explanatory scope of earlier work with an attempt at assessing the causal impacts of periodic market schedules.

Two fascinating papers by von Carnap (2022, 2023) are closely related to mine. Using an innovative remote sensing methodology, he exploits the weekly pulsation in activity to detect weekly markets across sixteen Kenyan counties. He relates their location to historical records of marketplaces compiled by Wood (1973b). The natural experiment I describe was largely completed

and market schedules established at that time.[2] Reassuringly – and using fundamentally different methodologies and data sources –, our two studies align closely on the finding that historic market centers are highly predictive of present-day population patterns. I demonstrate that this link is causal.

A number of creative and insightful studies in economics have addressed agricultural markets. Fafchamps and Hill (2005) investigate the role of transport costs for coffee farmers in Uganda in deciding whether to travel to and sell at wholesale markets themselves or whether to accept the lower prices offered by aggregators who come to their farm gate. Jensen (2007) is the classic reference for market integration through information sharing using mobile phone technology and insightful progress has been made since (Svensson and Yanagizawa, 2009; Aker, 2010; Goyal, 2010; Jensen and Miller, 2018). In a study of the road infrastructure connecting the major agricultural markets in Sierra Leone, Casaburi et al. (2013) study market integration through the reduction in travel times and what its effect on crop prices reveals about the competitive structure in these markets. None of the aforementioned studies discuss market attendance as an outcome. In a creative study on Kenyan markets, Bergquist and Dinerstein (2020) investigate the competitive structure of sellers and intermediaries by exogenously inducing firm entry. Burke et al. (2019) discuss the ability of a well-timed microcredit intervention to support farmers to smooth out seasonal price variation. Throughout, market integration has been shown to have meaningful effects on people's lives and livelihoods. While large gains in market integration will certainly be reaped from modern information technology, physical infrastructure, and microcredit, it should be noted that none of these have existed nearly as long as the simple act of synchronizing schedules, which limits our ability to assess their effects in the very long run, and that the latter, if timed at the inception of a new market, can be done essentially costlessly. It should also be noted that the cited studies have focused on markets that tend to be around an order of magnitude larger than the ones I discuss in this paper. While these larger wholesale markets are crucial for the functioning of country-wide food security, the smaller, last-mile markets are the direct touch point of millions of people around the world with the food supply chain, either as consumers who rely on them for their daily sustenance, or as smallholder farmers in an early stage of graduating from subsistence agriculture to marketization – or in fact as both simultaneously (Smith, 1980). These smaller markets outnumber the large wholesale markets many dozen if not hundreds to one.[3] Market periodicity and schedule frictions have not, to my knowledge, been discussed in the economics literature, despite their presence in virtually every agrarian society and their primacy as a locus of

[2] For about two thirds of these historical markets, von Carnap (2023) does not find activity that would be detectable in present-day satellite imagery, which I attribute to the remote sensing methodology being better suited to detect larger markets. Having a data collection team on the ground allows me to be somewhat more confident in having obtained a complete market census than either of these papers and in the counties where we overlap I find over twice as many weekly markets as von Carnap (2023), including virtually all of the 1970s markets (though some of them are small daily trading centers without a market day). The discrepancy lies mostly in the smaller markets being undetectable on satellite data.

[3] Of the several hundred market places I sampled in Siaya County, only Ramba Market in Siaya Town would be considered a wholesale market and it in turn is substantially smaller than any of the markets for which Burke et al. (2019) present seasonal crop price fluctuation data.

exchange prior to industrialization.

There is important path dependence in economic activity, trade patterns and locational economic trajectories (Bleakley and Lin, 2012; Faber, 2014; Storeygard, 2016; Jedwab and Moradi, 2016; Donaldson, 2018; Hornbeck et al., 2024). Wahl (2016) documents a strong role for medieval trade centers in the emergence of modern European cities. Market days are no exception when it comes to persistence (Bromley et al., 1975) and I document that over the past century market schedules in my study area remained mostly unchanged (cf. Table 5). The clearly defined onset of periodic markets, their absence before the arrival of the British, and their persistent organization and effects contribute to the persistence literature.

This paper proceeds as follows. Section 2 reviews the literature about periodic markets in general and in Western Kenya in particular. This section makes the case for the study context being a suitable natural experiment. In section 3 I introduce the data collection exercise, describe the various outcomes of interest, and provide descriptive evidence to support conclusions from the literature review. Section 4 describes the identification argument and empirical strategy in more detail. Section 5 discusses results and section 6 concludes.

2 Background

2.1 Markets in Western Kenya

Western Kenya, which is the focus of this paper, did not have periodic markets until the early twentieth century. The region was "on the whole [...] outside of the major nineteenth century trade routes"and economic exchange was limited to sporadic barter trade that was sparked by encounters between pastoralist (Luo) and farming tribes (Luhya), dictated by specialization and seasonal fluctuations in livelihoods (Hay, 1975). Around the turn of the century, not merely weekly markets, but *the concept of a "week" itself* was introduced to the region (Wood, 1973a). The local tribes did not traditionally have an intermediary unit of timekeeping between the solar day and the lunar month. It was imposed jointly by a coalition of Christian missionaries and the British colonial administration[4] (Dietler and Herbich, 1993). Muslim influence, while present on the Swahili coast for over a millenium, only reached Western Kenya riding on European coattails in the 1880s (Trimingham, 1980 p. 32, 38). In order to organize Christian worship, the missionaries wanted the local population to adopt the seven-day week in order for them to know what day of the week church service was to be attended. The British colonial administration had known periodic rural market days both in Europe and in their colonies in West Africa, where periodic markets were substantially more common than in East Africa (Good, 1973) and where periodicities other

[4]Present-day Kenya was allocated to the British Empire in the Berlin Conference of 1885. It was declared a British Protectorate in 1895 and the Uganda Railway, which allowed the White settlers to make inroads into Western Kenya, was completed in 1901. It connected Mombasa, an important stopover port for Indian Ocean trade routes and the location of the first Christian Mission since 1844, with Kisumu, the regional capital of Western Kenya on the shore of Lake Victoria and already a major settlement at the time. Kenya was declared a British Colony in 1920 and gained independence on 12 December 1963.

than the seven-day week had emerged long before colonialism[5]. The colonial administration's goal of marketization was to encourage division of labor and specialization to lift the local population out of subsistence agriculture and livestock rearing, turn them into more affluent trade partners, and to concentrate the resulting trade in a specific place and time in order to levy taxes. Only Central and Western Kenya appear to have had sufficient population density and economic activity to sustain markets (Wood, 1974a). Both markets and their periodicity were thus introduced about a century ago by outside forces, thus marking an approximate start date for this natural experiment and their schedules were persistent, constituting an opportunity for studying their role in economic development.

3 Data

3.1 Market mapping, history, and attendance

Markets are not presently well mapped in Kenya, especially when it comes to smaller markets. As part of my data collection, my implementing partner REMIT conducted a census of all markets in Siaya, Busia, and Kakamega County in Western Kenya[6]. From scoping activities, it became apparent that the most knowledgeable key informants on market and village history tend to be Village Elders, Market Chiefs/Chairpersons, and Market Incharges. The informational advantage of local leaders is increasingly recognized in the economics literature (Basurto et al., 2020; Balan et al., 2022) and their role has found renewed appreciation across the continent post-independence (Baldwin, 2016). The initial sampling frame comes from triangulating two listing exercises: Villages are part of two parallel administrative structures. Each village is part of a sublocation with an Assistant Chief, which is part of a location with a Chief, which is part of a subcounty with a Deputy Commissioner who reports to the County Commissioner. At the same time each village is part of a ward which has ward administrators and the wards are in turn part of the same subcounties. The location-sublocation structure is determined by Kenya's central government and structures executive power. Finding markets this way avoids missing small markets, but risks duplication if several villages share the same market. The ward structure is determined by the county government and structures taxation and public service delivery. Conducting a census of markets through this structure may miss small markets where no fees are being collected, but is unambiguous when it

[5]The seven-day week appears to be of Babylonian origin and, after entering Judaism through the book of Bereshit/Genesis, it was spread around the world by the more expansionary abrahamic religions of Christianity and Islam. West Africa had and to some extent still has weeks of other periodicities. In contrast to Western Kenya, where the religiously motivated seven-day week dictates market periodicities, the week in West Africa is conjectured to be itself a product of the need to structure trade periodicities (Schurtz, 1900; Thomas, 1924). The outside impetus for market creation and the introduction of a previously unknown weekly periodicity in Western Kenya is crucial for my research design.

[6]The quality of the results of any study suffers when data are missing. This study measures a market's area as a function of the schedules of all of its neighbors. Measurement error in one market therefore spills over into measurement error for all markets. Missing a market that clashes with a neighbor schedule makes surrounding markets appear better coordinated than they really are. Missing a market that does not clash with any neighbors but where two other neighbors clash with each other makes it look like there would have been a way to avoid a clash that was not being used. It is therefore critical to not just obtain a sample but a full census of markets in an area.

comes to uniquely identifying markets. Starting from the top of these two parallel hierarchies, we obtained contacts for every subcounty Deputy Commissioner from the County Commissioner. From those we worked our way down to the location Chiefs and from them to the sublocation Assistant Chiefs who gave us the contacts of Village Elders in each village in their sublocation. Starting from the County Revenue Inspector, we went to the Subcounty Revenue Inspectors who referred us to the Ward Market Incharges who shared contacts for Market Incharges and Market Chairpersons. The majority of our key informants are from these groups, although occasionally, we were referred on to other village members who offered additional insights. Every key informant was also asked to mention neighboring markets to us, ideally with contacts, and the team followed up on every one of those comments to achieve full coverage of all markets. The census was conducted over a period of 20 months in 2023 and 2024.

Geolocations for each market were obtained from Google Maps or Open Street Map (OSM) where available and otherwise an enumerator would visit the village and geocode it. Throughout, whenever we found markets that were not yet mapped, we documented them on OSM, while Google Maps appears to be automatically ingesting our OSM contributions, thus making this public good available much more broadly. In phone surveys, we collected key dates in each market's history, most importantly when it was started and on what day of the week it is being held. If markets operate on several days of the week, we ask whether there is a main market day. I document very strong persistence in weekdays to the present day, even for markets that have been around for a century. I also obtain an estimate of present-day market attendance as well as how this attendance is decomposed into sellers and buyers from within or outside the village and on the market's main versus any other day (cf. Figure 3). In order to guard the data collection against missing some markets entirely, every informant is also asked to list other markets in their area and to provide the contacts of knowledgeable informants. As Table 1 illustrates, the majority of respondents received their information either first-hand as they were alive at the time the market was started or second hand and only for very few markets does my analysis rely on information that was passed through more than one social network link. Village Elders spend years in the company of previous elders, preparing for their role and learning about the local history of their town. Written records are rare in this context and practically non-existant for the pre-colonial era. In collecting these data, we thus also contribute to the preservation of the oral history of Western Kenya. These data form the basis for the empirical strategy described in section 4.

3.2 Outcome data

Ultimately, this study is interested in how market catchment area affected market attendance and rural economic development. Outcomes of interest for my study include village population size and night lights as a proxy for local economic activity. Appendix Table 13 provides more details. These data form the final stage of analysis, described in section 4.5.

Table 1: Source of information

	Count
I was alive at the time the market started	98
From a village elder who **was** "	30
From a village elder who **was not** "	4
From another village member who **was** "	70
From another village member who **was not** "	16
From a family member who **was** "	66
From a family member who **was not** "	1
From a written record	2
Total	287

This table describes how close respondents are to the source of information about the process of market scheduling. Most respondents either experienced the start of their market first hand or learned about it from someone who did. Only a small share of responses relies on data that is more than one network link remote. Written records are rare.

3.3 Pre-treatment controls

Pre-colonial Western Kenya did not have a formalized administration that would have recorded social or economic data in writing. Pre-treatment controls are therefore restricted to geographic controls (location, agricultural suitability, terrain ruggedness, proximity to Lake Victoria, proximity to the regional capital Kisumu, see footnote 4) as well as an estimate by the key informant of the village population in 1920.

3.4 Descriptive evidence

Markets may be open every day of the week, but they tend to be substantially larger on market days (Fröhlich, 1941). In my study area, the majority of markets operate every day, though about a quarter have a dedicated market day, as shown in Table 2. The first map in Figure 1 shows all markets in the study area along with the days on which they operate, while the second map shows only those markets with a main market day, which are studied in this paper. Market days are distributed across days of the week and there appears to be a preference for some days over others (2). A model of market scheduling should therefore allow for weekday fixed effects.

Markets in my sample sport slightly fewer sellers than the hosting village has households. Buyers outnumber sellers more than two to one. These averages mask important heterogeneity. Markets that have a market day are much larger than those that do not (Table 2) and market attendance is substantially higher on market days than on non-market days (Figure 3). The figure illustrates the pulsation that Polly Hill (1966) described: While attendance by locals to their own market roughly doubles or triples on market day, some markets see a five, ten, or even twenty-fold increase in outside attendees.

Anecdotally, from the conducted surveys and scoping interviews, market participants link lower

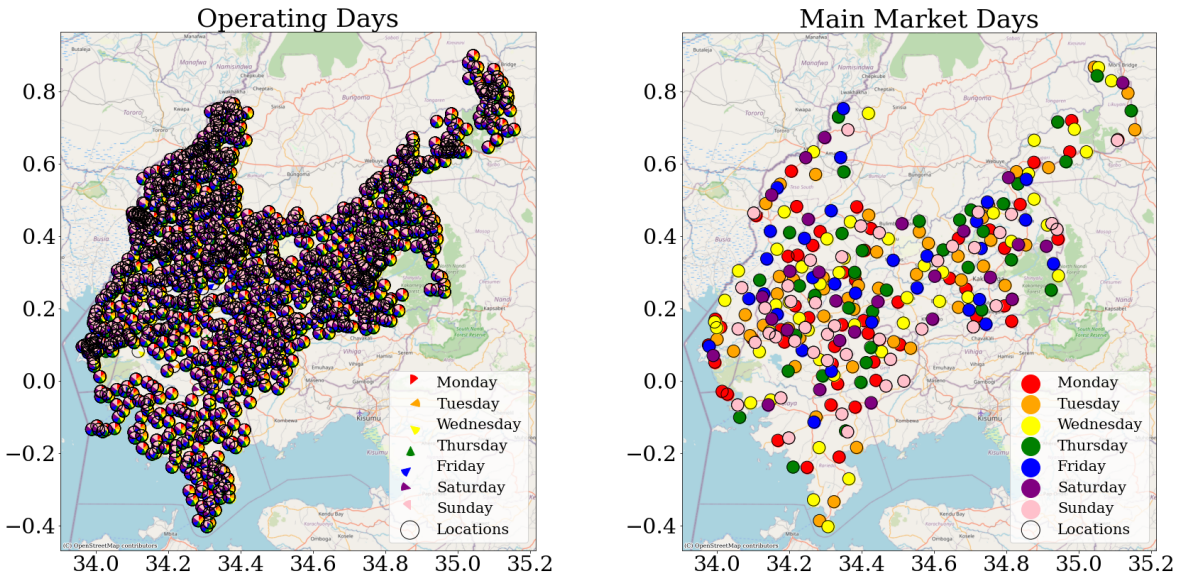


Figure 1: **Map** of markets in Siaya, Busia, and Kakamega County. The left panel shows all markets along with the days on which they operate (often daily), while the right panel shows only those markets with a main market day.

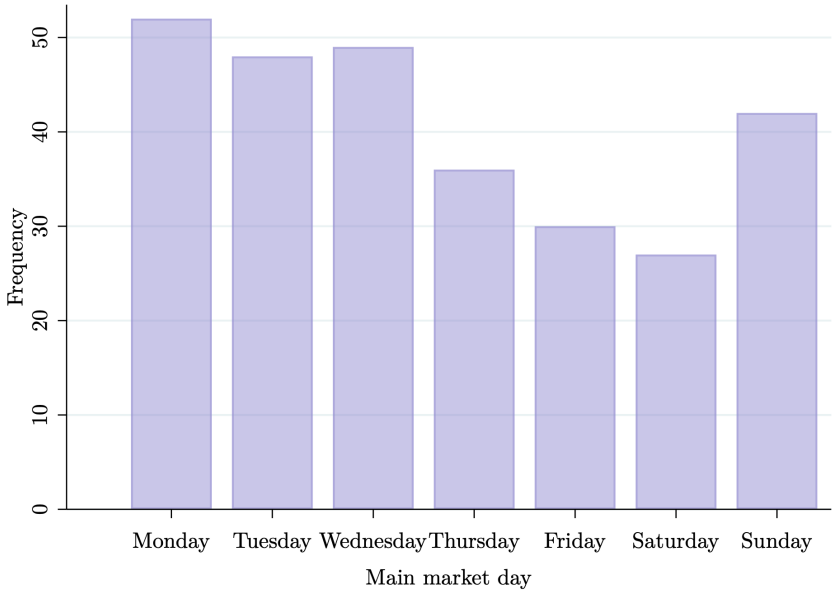


Figure 2: **Market days** across the different weekdays.

Table 2: Market attendance

	Average	Count
Number of sellers	180	1,198
” in markets with main market day	632	279
” in markets without main market day	43	919
Number of buyers	386	1,198
” in markets with main market day	1,148	279
” in markets without main market day	155	919
Population (HHs) around 1920	3	1,054
Population (HHs) when market was first started	76	1,139
Population (HHs) today	212	1,245

This table describes the market attendance and the population size of the towns in/near which they operate. Markets with market days are substantially larger than those without. The left column describes sample averages and the right column the number of markets over which the averages are formed.

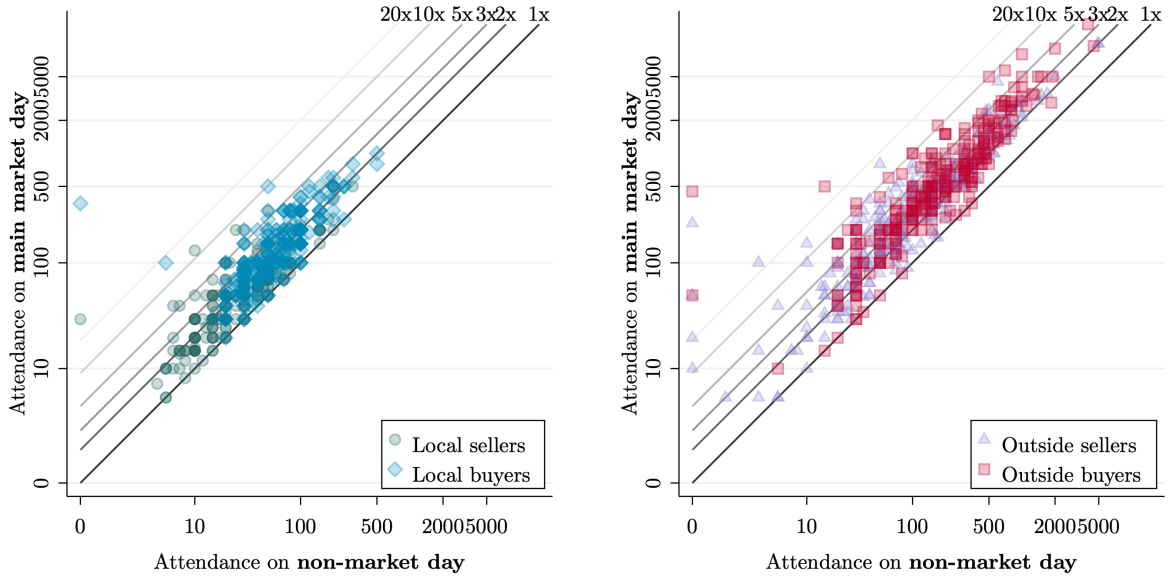


Figure 3: **Market attendance**, shown here on a $\log(x+1)$ scale by market, broken down by attendant category, is substantially higher on market day than on other days of the week, especially among participants from outside the town or village (right panel). But even local attendance is higher on market day.

attendance at their own market to the emergence of nearby markets on the same day of the week. I therefore inquire about the scheduling process for these market days. Historical sources suggest that while the Europeans pushed for the introduction of markets following a seven-day periodicity, they left the precise scheduling to local authorities (Wood, 1973a) – a fact I confirm for the study area. Market days were initially set by the Village Elders, local authorities, and local stakeholders (Table 3) with a *coordination motive* and with knowledge of already existing nearby markets, though in some cases local idiosyncrasies led to the adoption of particular days or they emerged organically (Table 4). Notably, these concern pre-existing village-internal community meetings ("chief barazas") or local customs such as the weekday on which the local butcher used to slaughter. There is no evidence that higher levels of government, the church, or another social planner-type actor held any sway over the schedule. We can therefore think of the coordination process as decentralized, which introduces the possibility of inefficiencies.

Table 3: Decision makers

	Percent
Village elder(s)	20.7
Local council	42.9
Traders from the village	65.8
Traders from outside the village	37.5
Emerged organically	7.3
Sublocation chief	8.4
Location chief	15.6
Ward administration	0.7
County government	22.0
Central government	0.0
Colonial government	2.5
Don't know	2.2
Other	0.0
Observations	287

This table describes who was (and who wasn't) involved in the schedule setting of the main market day. It highlights that market scheduling was a decentralized coordination process that was not implemented by a social planner.

Once set, market schedules and activities have been remarkably persistent (cf. Table 5). Only a small share of markets have ever seen a change to their schedule and of the few observed shifts, some are accounted for by adding a day or dropping one of several. Survey respondents also indicate that few if any markets have ever been interrupted in their activities for any meaningful amount of time, especially for reasons other than the COVID-19 pandemic, which does not appear to have caused lasting closures or schedule shifts.

Markets were first started in the colonial period with an acceleration around Kenyan Independence in 1963. Most markets since around 1975 are smaller markets without main market days (cf.

Table 4: Coordination motive

	Percent
Scheduling motives	
To not clash with the schedule of another market	69.5
Outside traders visited regularly on this day	13.8
Idiosyncratic day preference	34.8
To align with the church schedule	8.0
Don't know	9.1
Other	0.4
Obervations	287
Hypothetical coordination of new markets	
Mention schedule coordination	86.3
Mention idiosyncratic day preference	12.5
Observations	328

This table describes what factors determined schedule setting of the main market day. It highlights that market scheduling was driven by a coordination motive as well as local idiosyncratic preferences over week days. The bottom panel shows that the majority of towns without a market but that entertain the possibility of starting one also mention the need for schedule coordination. These data are manually coded from open-ended answers.

Table 5: Market descriptives and persistence

	Percent
All trading centers	
... operates daily	96.4
... has main market day	23.0
Markets with market day	
Road access in 1975	12.5
Road access today	48.1
Schedule persistence	
Market schedule never changed	89.1
Shifted to different market day	8.7
Added or dropped a market day	2.2
Rather close than change market day	58.2
Operational persistence	
Market never interrupted	77.7
Interrupted: COVID	18.8
Interrupted: Other reason	3.5
Observations	1248

This table describes the sample of markets and their schedule and operational persistence.

Figure 4). In evaluating the effects of market catchment area, this study thus takes a long-term view of the cumulative effects over the past century, where the regional market schedule was mostly set over half a century ago. Over the same period, the average distance from points in the study area to the nearest market fell sharply and stabilized over the past half century.

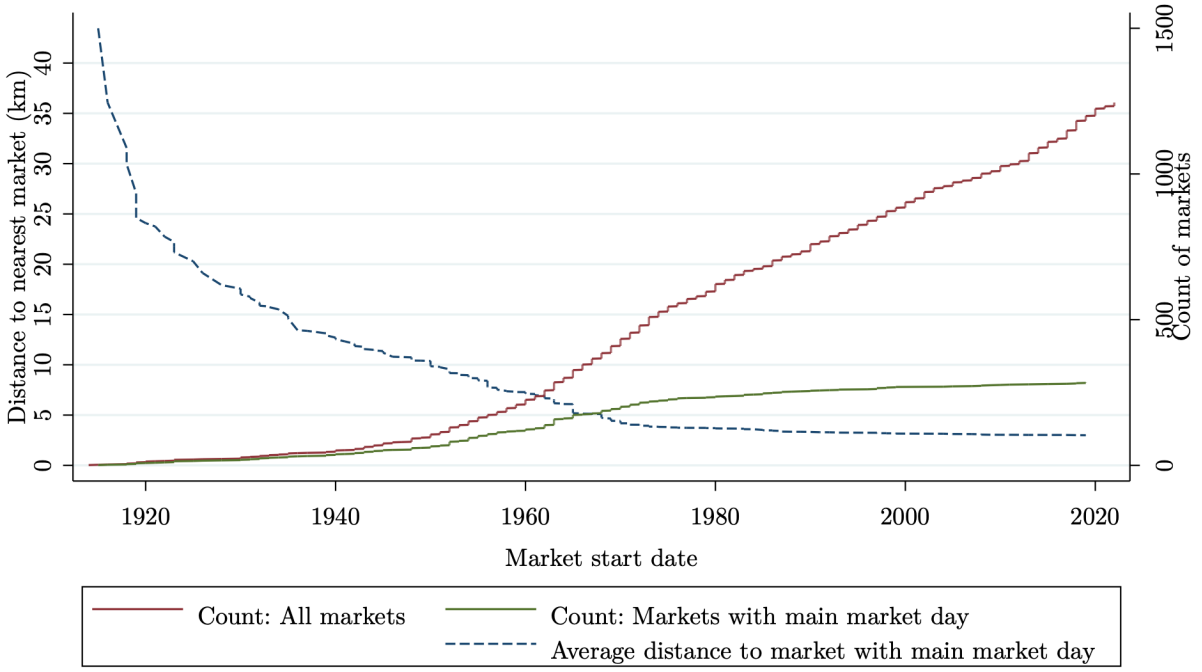


Figure 4: **Markets** were first started in the colonial period with an acceleration around Kenyan Independence in 1963 (left axis). Most markets since around 1975 are smaller markets without main market days (left axis). The average distance to a market with a main market day similarly fell rapidly until around 1975 (right axis) to a walkable distance.

4 Identification and empirical strategy

The goal of this paper is to estimate the causal effect of market catchment area differences that arose from scheduling frictions over the past century on market attendance and, in turn, on rural economic development today. If the area over which a market is the nearest operating one on its market day is larger, how many more sellers and buyers can it attract? If by contrast, two nearby markets are splitting their surrounding area between each other on market day, how much does this hurt their attendance? Are other measures of economic development affected by this? I will argue that scheduling frictions are at least in part the product of chance. Yet, simply regressing outcomes of interest on some measure of how well market schedules are coordinated would be biased if for example new markets coordinated better with existing larger markets than with existing smaller markets and market size in the past is predictive of market size (or other outcomes of interest) today. Evidence for that would be an imbalance in pre-treatment controls (such as population

size a century ago or geographic fundamentals) with respect to market area, which I present in Section 5.3.

The following model illustrates how the bias arrises. It relates market area A_l in a location l to some outcome Y_l where ε_l is an error term that contains other factors such as geography or lagged values of Y_l that are potentially correlated with A_l:

$$Y_l = \beta_0 + \beta_{\mathrm{A}} \mathrm{A}_l + \varepsilon_l, \qquad \text{where } \mathbb{E}\left[\sum_l \mathrm{A}_l \, \varepsilon_l\right] \neq 0. \tag{1}$$

The coefficient β_{A}, which I seek to estimate, is the causal effect of scheduling frictions on outcomes of interest. Estimating equation (1) with simple OLS would yield a bias because of the omitted variables in ε_l that are correlated with market area.

The contextual insights from the key informant interviews and literature review in anthropology, sociology, history, and geography allow for a design-based approach to resolving this causal inference challenge in which I separate the schedule assignment process into its endogenous, fixed-by-design, as well as its exogenous, quasi-random component. As evidenced in Table 4, market scheduling (which produced today's market catchment areas A_l) was a function of the schedules and locations of already existing nearby markets (the known geography Δ) as well as some local idiosyncratic preferences by market stakeholders (ξ).

$$\mathrm{A}_l = f_l(\xi, \Delta)$$

The following three assumptions allow me to exploit the scheduling process as a natural experiment for causal identification of the effects of market catchment area, effectively holding Δ fixed and pinning down changes in A_l only as a function of ξ:

> **Assumption A1**: Market scheduling decisions were made without foresight over the entry or scheduling choices of future entrants. In other words, scheduling choices are optimal relative to the geography Δ_t that existed at the time $t(l)$ at which market l was started.
>
> **Assumption A2**: I assume that preferences over weekdays ξ are independent of other factors contained in ε and therefore affect outcomes of interest only through the variation in market area that results from them: $\xi \perp\!\!\!\perp \varepsilon$. Concretely, I parameterize idiosyncratic weekday preferences as iid draws from a Type-1 Extreme Value distribution (one for each market and weekday): $\xi_l = (\xi_l^{\text{Monday}}, ..., \xi_l^{\text{Sunday}}) \overset{\text{iid}}{\sim} \text{T1EV}$[7]
>
> **Assumption A3**: Market entry order is fixed and does not depend on the schedule of existing ones. Suppose we label markets $l = 1, ..., L$ in the order in which we observe them start in the data, i.e. $t(1) < ... < t(L)$. **A3** says that $(t(1), ..., t(L)) \perp\!\!\!\perp (\xi, \Delta)$. In a counterfactual world in which market day scheduling may have played out differently, the order of entry would have been the same.[7]

[7] Assumption **A3** deserves particular discussion. It describes a decision process in which a town decides that it

Taken together, these assumptions produce the following decision problem: Markets enter sequentially in their observed order (**A3**). Every market chooses one of seven possible weekdays to hold its market. I explore two closely related scheduling approaches: In the first, market stakeholders maximize the size of the catchment area that a market can capture at the time of its inception conditional on the locations and schedules of existing markets (but no foresight over the identity or actions of potential future entrants, **A1**) and on idiosyncratic local preferences (**A2**). The second approach instead minimizes the distance to other existing markets that are already happening on the same day (which is more akin to the decision rule key informants described in the interviews). The former consitutes a more competitive scheduling motive under which one market might cut the other one off its catchment area, whereas the latter would seem like a more easily implementable heuristic by the decision makers. Concretely, a town l chooses a day $d_l \in \{1, ..., 7\}$ at time t with idiosyncratic location-day-specific preference ξ_l^d (**A2**) and either a catchment area or a distance to the closest existing market on a given day d, $\Delta_{ldt(l)} \equiv \min \text{distance}_{ldt(l)}$ and weighted by some utility weight δ_Δ. The term δ_d allows the T1EV distributions to have different means, should particular weekdays be overall more popular than others. The time subscript captures the fact that entry order matters and the establishment of new markets changes the distances and schedule clashes considered by later markets. Entrant markets maximize the utility from each day d_l

$$U_{lt(l)}(d_l) = \delta_d + \delta_\Delta \Delta_{ldt(l)} + \xi_{ldt(l)} \tag{2}$$

and present-day market area A_l is computed from the resulting schedule $\{\arg\max_{d_l} U_{lt(l)}(d_l)\}_{l=1}^{L}$. **A2** imposes logit substitution patterns, meaning that if a particular day of the week were no longer available for a market, those markets would substitute to other days according to the overall market day distribution. I test this with hypothetical questions to respondents in Appendix Figure 8 and cannot reject that the observed and substitution distribution are identical.

Borusyak and Hull (2023) show that knowledge of $f(\xi_l, \Delta_l)$ suffices to decompose $\text{A}_l = \mathbb{E}[\text{A}_l] + \widetilde{\text{A}}_l$ in such a way that the expected market area has the exact same correlation with the error term ε_l as A_l:

$$\mathbb{E}\left[\sum_l \mathbb{E}[\text{A}_l]\ \varepsilon_l\right] = \mathbb{E}\left[\sum_l \text{A}_l\ \varepsilon_l\right]$$

This powerful result implies that adding $\mathbb{E}[\text{A}_l]$ to equation (1) resolves the omitted variable bias.

wants to start a market without anticipating the scheduling problem. This is not an innocuous assumption. There are a few reasons to believe that it might still be a reasonable approximation to the truth. First, the assumption is likely plausible early on in the process when markets are few and far between and only starts to be become implausible as the map gets more crowded, which would explain the pattern in Figure 4 that most markets with market days were started prior to 1975 and very few since. Second, the assumption becomes more palatable, the more uncertainty there is around the success of any particular weekday as a market day. Third, Hodder (1965) conjectures that population pressure is the main driver of the decision to start a market. In this view, locals need to first form a critical mass of attendance to then attract outsiders on a particular day. We lack the historical records that would tell us about the population and economic conditions at the time most of these markets started, but to the extent that those mattered for the decision of starting a market, this information is encoded in the entry order, which is another reason to keep it fixed.

Importantly, if like in my case, more than one plausible mechanism (maximizing catchment area or minimizing distance to the nearest schedule clash) may have produced the observed data, the Borusyak and Hull (2023) approach allows me to add both of them to my regression and only one of them needs to be correct for the bias to be removed.

Figure 5 builds intuition for the identification strategy in this natural experiment. Suppose eight villages, depicted by nodes, start markets sequentially ($t = 1, ..., 8$) and decide on what day of the week (indicated by colors) to hold their market day. In the top four panels, we observe the first seven villages choosing their market days in a certain way and the eighth village finds it optimal to host its market on Wednesday, since it is relatively further away from the next Wednesday market than from any other market. In a world where attendees from surrounding villages attend their closest market, the eighth market would capture the attendees from most of the other villages on its Wednesday market day. The shading indicates the market area of each market. In my first scheduling model, markets maximize this shaded area, while they minimize the distance to the nearest market on the same day in the second model. In the bottom four panels, the same coordination process unfolds with one small deviation: Village 5 chooses Wednesday instead of Tuesday, perhaps because the local chief was traditionally holding a village gathering on this day, and village 8 therefore subsequently finds it optimal to host its market on a Tuesday. The resulting cross-attendance patterns on Wednesdays look very different in this counterfactual world. In this paper, I leverage variation in trade patterns caused by small and arguably quasi-random perturbations like this and I provide evidence of their role in scheduling in Table 4. If most counterfactual coordination outcomes look more like the bottom panel, then under the realized coordination pattern in the top panel, a place like village 4 suffers more strongly under the spatial competition from village 8 than the fundamentals of geography and the coordination process would have us expect. This difference between how favorable we would have expected the neighboring market schedules to be for cross-attendance versus how favorable they turned out to be is the treatment in this natural experiment. The effects of that should then be detectable in market attendance and other measures of rural economic development.

My empirical strategy proceeds in six steps, described in more detail below:

1. Measure present-day market areas.

2. Reconstruct the decision problem that each market town faced when starting its market (Figure 5, top).

3. Simulate many counterfactual coordination processes and measure their resulting market areas (Figure 5, bottom).

4. Following Borusyak and Hull (2023), control for each market's *expected* market area. The remaining variation in market area becomes the treatment assignment, which depends on how ties between similarly attractive scheduling choices were broken plausibly randomly.

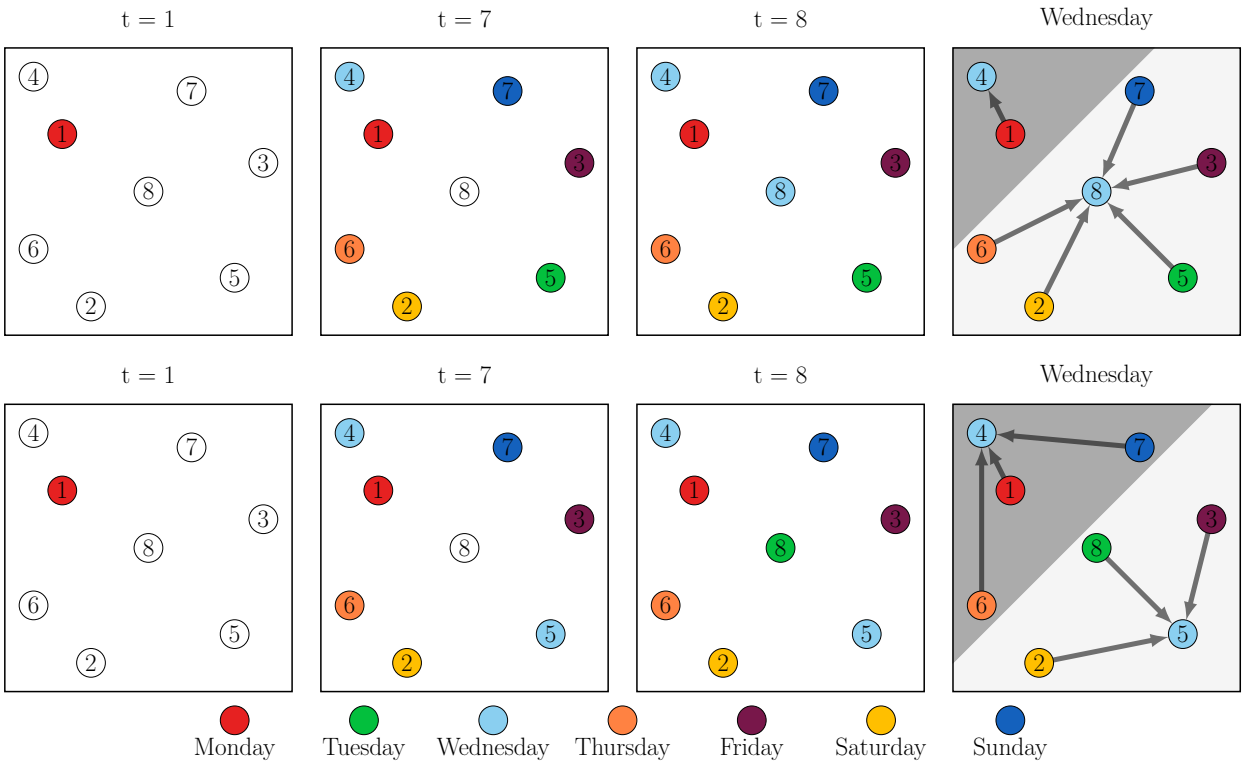


Figure 5: **Counterfactual coordination**: Each node is a town. They sequentially choose market days in the order of their numbering ($t = 1, ..., 8$). In the top four panels the last town to pick a market chooses to host its market on a Wednesday in order to avoid clashing with its close neighbors. This makes it the closest Wednesday market for the majority of towns. The bottom four panels show that a small local deviation in the scheduling process (town 5 choosing Wednesday over Tuesday) changes the market cross-attendance pattern. Simulating many such small perturbations in the scheduling process can give us a sense of the potential for market cross-attendance for each market, indicated by arrows. The shading indicates each market's area.

5. Estimate the effects of market areas on present-day market attendance and rural development more broadly after purging out OVB by controlling for expected market areas.

4.1 Measure market catchment areas

To assess coordination, I formalize what the geography literature calls market area (Skinner, 1964; Hodder, 1965; Wood, 1974a,b). I compute the area of the map for which a particular market is the closest market *on the weekday on which this market holds its market day*. This can be thought of as a geographic measure of market potential. Formally, call Q the set that contains all points q_k in the two-dimensional plane that constitutes the study area. The set $P_d \subset Q$ contains the locations of all market places p_{ld} that have their main market day on day d. A market area A_l is defined as the set of points q_k that are closer to p_{ld} in Euclidean distance than to any other market p_{dm} that holds its market day on the same day d:

$$A_l = \{q_k \in Q \mid d(q_k, p_{ld}) \leq d(q_k, p_{dm}) \, \forall \, p_{dm} \in P_d, m \neq l\}$$

In practice, it is calculated as a day-specific Voronoi tesselation (referred to in different contexts as Descartes, 1664; Lejeune Dirichlet, 1850; Voronoï, 1908a,b; Thiessen, 1911 polygons), up to a distance of 20km, and removing the area covered by Lake Victoria and Uganda.

Arguably, a more economically meaningful measure of the potential trade activity that a market can capture would be the population of the catchment, not its area. However, there are two important reasons prefer this area measure: First, there are no reliable estimates of population density prior to market establishment that would be granular enough for this exercise and present-day population density patterns may themselves be a product of the treatment I am studying, i.e. they are endogenous to the process under study through migration toward market towns over the past century or varying fertility and child survival. Second, the purely spatial definition of catchment areas makes it straightforward to identify and deal with sources of bias. The catchment area of each market depends purely on the location of each of the other markets (who entered) and the day of the week they entered on. My understanding of scheduling process allows me to reconstruct alternative, plausible schedules under the same entry process which thus share the same bias. This constitutes an important advantage over more complex measures of market catchment area.

4.2 Reconstruct coordination process

Following the distributional assumption in **A2**, I implement the decision problem of maximizing the above utility as a logit across the seven days of the week, accounting for alternative-specific characteristics (distance to other markets vary by the day of the week). The day-specific intercept allows for the possibility that some days of the week might be inherently more appealing for markets than others. I estimate seven parameters: Six day-specific intercepts $\hat{\delta}_d$ (relative to the seventh) as well as $\hat{\delta}_\Delta$ which translates distance to a competing market on the same day relative

to those on other days into utils. Only markets within a travel distance of 20km are taken into consideration here.[8] While in some contexts, the logit model's property of proportional substitution is unrealistic, it does not appear to be unreasonable in my context to assume that if e.g. Mondays did not exist, the Monday markets would instead distribute across other days roughly according to relative preference over those days.

4.3 Simulate counterfactual coordination outcomes

Using the parameters $\hat{\delta}_d$ and $\hat{\delta}_\Delta$ backed out above, I simulate how towns *could have coordinated*, by redrawing iid Type-1 EV preference shocks (**A2**) for each town and facing them in their same order (**A3**) with their respective decision problems under the new idiosyncratic shocks. After each decision τ, the distance measures $\Delta_{ldt(l)}$ for all future entrants l for which $t(l) > \tau$ are updated based on the last decision. Decisions take the current distances as given without foresight of future entrants or their scheduling decisions (**A1**). When all market days are assigned I calculate the coordination measure from section 4.1. I repeat this process 1,000 times.

4.4 Recentered coordination treatment assignment, counterfactual validity, and baseline balance

Following Borusyak and Hull (2023), I average the market area I obtain across the 1,000 simulations described in section 4.3 at the market level. These can be interpreted as the expected market area for each market $\mathbb{E}[\mathrm{A}_l]$. Borusyak and Hull (2023) suggest that under a correctly specified shock assignment process, the slope of a regression of A_l on $\mathbb{E}[\mathrm{A}_l]$ should be close to 1 and the intercept close to 0, which I confirm. In order to scrutinize whether the residual A_l is indeed quasi-random conditional on $\mathbb{E}[\mathrm{A}_l]$, I further check baseline balance of pre-treatment control variables, discussed in section 3.3, using the below OLS specification:

$$X_l = \theta_0 + \theta_{\mathrm{A}}\mathrm{A}_l + \theta_E\mathbb{E}[\mathrm{A}_l] + \varepsilon_l$$

4.5 Effect of market catchment area on attendance and economic development

I am interested in the effect of market area on market attendance and economic development. Simply regressing these outcomes of interest on the market area calculated in section 4.1 is potentially confounded. Following Borusyak and Hull (2023), I control for each market's expected area, thus recentering the observed market area by the market area that the coordination model would have led us to expect. The below equation (3) illustrates this approach: After controlling for the expected market area $\mathbb{E}[\mathrm{A}_l]$ (computed in two different ways) and pre-treatment control variables $\mathbf{X}$, the coefficient γ_{A} captures the effect of only the observed market area's random component in how the market scheduling actually played out on our outcome of interest.

[8] Otherwise, as the map of markets grows unboundedly, very distant market schedules (which would be highly leveraged in this estimation) would have arbitrary sway on the estimated relationship.

$$Y_l = \beta_0 + \beta_{\mathrm{A}} \mathrm{A}_l + \beta_{E|a} \mathbb{E}[\mathrm{A}_l \mid \text{area}] + \beta_{E|d} \mathbb{E}[\mathrm{A}_l \mid \text{distance}] + \beta_X X_l + \varepsilon_l \tag{3}$$

Conditional on $\mathbb{E}[\mathrm{A}_l]$, the treatment in this natural experiment is assigned at the market level, so I will not cluster standard errors (Abadie et al., 2017). The concern of outcomes being spatially correlated instead suggests the use of Conley (1999) standard errors.[9] This specification has another advantage worth noting: To the extent that the effect of market catchment area on our outcomes of interest per se might non-linear, controlling for the expected market area redefines the coefficient β_{A} as the effect of only the deviations in market catchment area due to scheduling idiosyncrasies, which is a better measure or the persistent effects of scheduling-induced differences in catchment areas.

4.6 Bias simulation

In Table 14, I simulate omitted variables such as initial conditions or intrinsic suitability of a location for commerce. These factors may deter a market's nearby competing entrants (increasing catchment area) and at the same time be the true reason for better present-day performance of the market. This would bias the simple OLS coefficient in equation (1) upward. Backing out the parameters that guide scheduling behavior, I show that the bias can be removed using the Borusyak and Hull (2023) method. I first simulate the bias many times. The exact parameters of the simulation can be found in the table note. A regular grid of potential markets is generated with distance metrics matching those observed in the real data. A share of them is randomly selected to be intrinsically more suitable for market activities and economic development more broadly. This deters markets within some distance from entering which mechanically endows suitable markets with a larger market area. Simultaneously these markets find themselves with better present-day outcomes beyond the imposed true effect β of market area in column (1). Column (2) shows that this would bias the coefficient in equation (1) upward. Market scheduling in my simulations was governed by the parameter δ in column (1) and followed equation (2). In the Scheduling panel, I show that I can recover this parameter under the assumption that my scheduling model is correctly specified. Employing this information to compute expected market catchment areas for the markets in the median bias scenario, I show that controlling for expected market catchment area can purge out the introduced bias from deterred entry and recover the true β parameter in column (3).

5 Results

5.1 Reconstructing the scheduling process

Non-parametric, descriptive evidence of the coordination motive is presented in the binscatter in Figure 6. Weekday clashes are less likely in the near vicinity than at longer distances.

[9] Conley (1999) standard error adjustments follow the code implementation by Hsiang (2010).

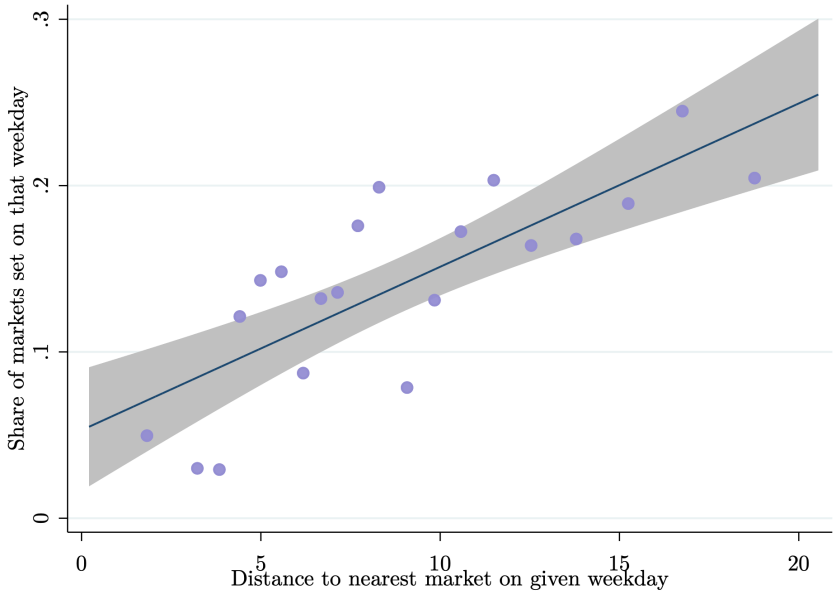


Figure 6: **Binscatter** of the share of markets with clashing weekday schedules at different distances.

Table 6 presents the results from the discrete choice scheduling problem in Section 4.2, where markets decide on their market day based on either the market area they can capture or the distance to other already existing markets at the time they start their own markets, as well as day fixed effects. The area and distance parameters enter significantly positively, indicating that markets are more likely to be scheduled on a particular day of the week if a larger market area can be captured and the nearest existing market with the same market day is further away. At the sample-wide average distance between two markets happening on the same day of 8.9km (Table 4), the probability of two markets that are exactly this far apart to share the same market day is 14% (Figure 6).[10] The estimated coefficient on distance $\hat{\delta}_{\Delta}$ implies that halving the distance between the two markets would reduce that probability to 11.1%. The coefficients on the weekday fixed effects mirror Figure 2.

It is worth recalling Assumption **A3** here, that after accounting for distance and weekday fixed effects, the remaining variation in weekday choices can indeed be attributed to idiosyncratic preference shocks $\xi_{ldt(l)}$ that may have materialized differently. Concretely, they cannot be related to the error term ε_l for outcomes in equation (1). This assumption would be violated if for example village elders chose to purposefully compete with certain markets rather than others based on knowledge unobserved by me, the econometrician. If they had accurate foresight over which market would pose a lesser degree of competition to their own market, that would reintroduce omitted variable bias I am trying to purge out. While readers may be reassured to know that none of the key informants mentioned such scheduling motives, it may still be more convincing to test this

[10] For reference, under completely random weekday assignment we would expect the probability of a clash at any distance to be about $1/7 = 14.3\%$.

assumption empirically. Fortunately, I have some means of testing this assumption. In Table 15, I add three candidate variables of the kind of information village elders may have had in addition to the location and schedules of existing markets that should be correlated with any measures of competitiveness that we may be worried about: The age of the neighboring market at the time, the population of its hosting town when that market started, as well as whether it was at the time connected to a paved road. Reassuringly, including these controls barely changes the coefficients of interest and only one of the controls appears significant and not in the direction one might expect: Village elders appear slightly more likely to compete with the market of a larger town holding location fixed. I interpret this as evidence that the two error terms are indeed orthogonal.

Table 6: Weekday choice

	(1)	(2)
Area	.002***	
	(.000398)	
Distance		.0895***
		(.0156)
Day FEs		
Tuesday	-.249	-.152
	(.206)	(.203)
Wednesday	-.0324	-.00634
	(.199)	(.201)
Thursday	-.393*	-.421*
	(.217)	(.218)
Friday	-.595***	-.558**
	(.229)	(.227)
Saturday	-1.06***	-.936***
	(.255)	(.248)
Sunday	-.297	-.275
	(.209)	(.209)
Observations	2009	2009

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Expected market area

After parameterizing the coordination process in Table 6, I simulate 1,000 new runs of it under different Type-1 EV draws. Borusyak and Hull (2023) suggest that under a correctly specified shock assignment process, the slope of a regression of A_l on $\mathbb{E}[A_l]$ should be close to 1 and the intercept close to 0. I provide evidence of this in the top panel of Figure 7 for both the area and distance method and the results are very similar. The bottom panel shows the distribution of residualized market area, which will be useful in interpreting the results. Holding geography and market entry order (and therefore the expected market area) fixed and moving a village from the

10^{th} to the 50^{th} percentile of the realized market area distribution (which can be thought of as preventing unnecessary schedule clashes) coincides with adding about 95 km^2 of market area and from the 50^{th} to the 90^{th} percentile (akin to assigning a market a spatio-temporal monopoly) about an additional 142 km^2. For comparison, the area of Manhattan is about 59.1 km^2, Paris inside the Boulevard Périphérique measures about 87 km^2, while the Bronx measures about 110 km^2, and the District of Columbia is about 158 km^2. Reassuringly, the simulations match other moments of the observed data well. For example, similar to the finding in Table 4, I find an average distance to the nearest market with a clashing market day of 8.78 km.

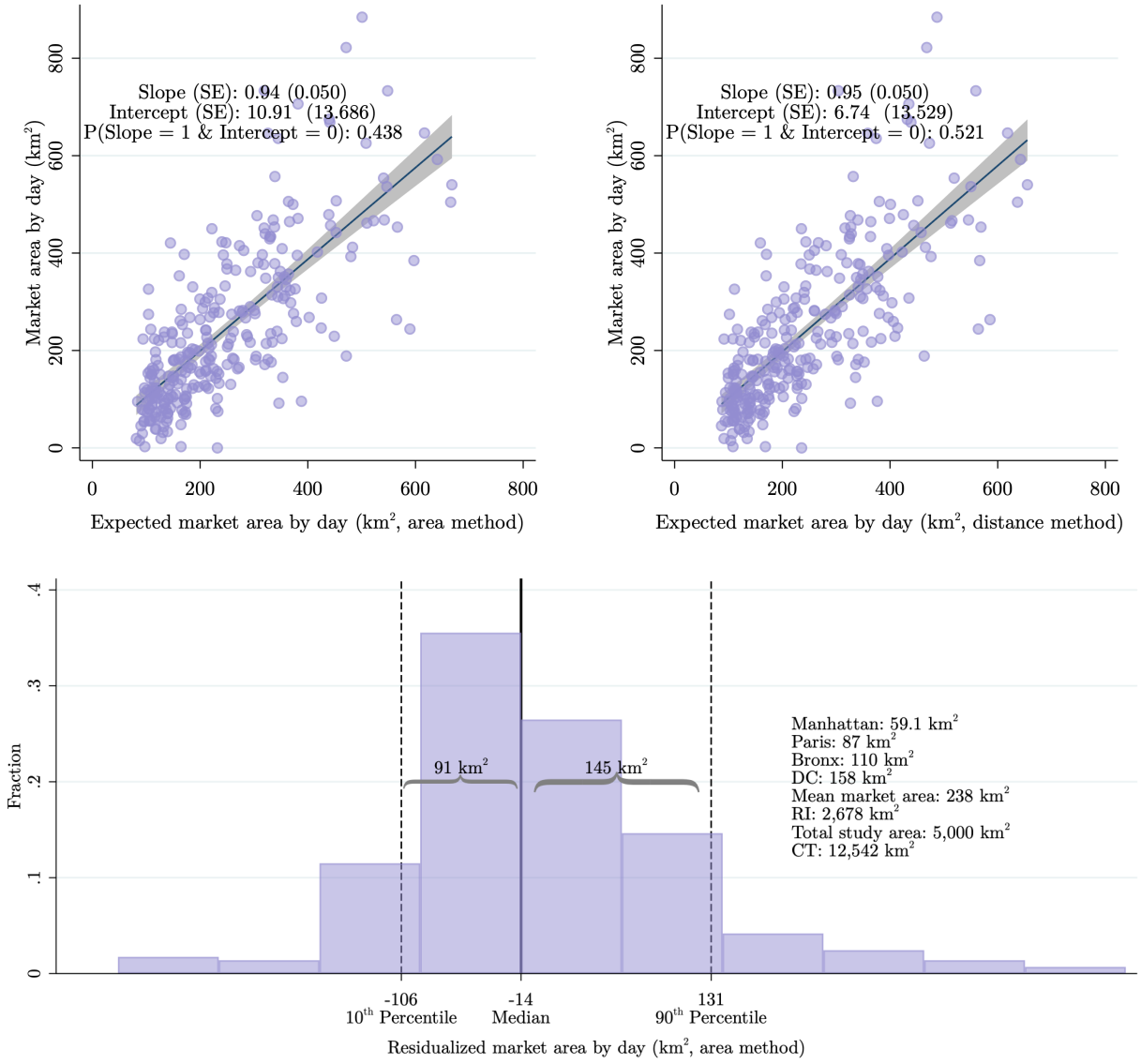


Figure 7: **Expected market area** predicts realized market area.

5.3 Balance

With market area as the treatment in this natural experiment, I now proceed to testing for baseline balance on the pre-treatment control variables I described in section 3.3. Column (1) of Table 7 shows strong imbalances in the pre-determined control variables with respect to the market area in a simple regression. Markets further North and East and further away from Lake Victoria and in more rugged terrain appear to have larger market areas. In a regression in which all of the controls are used to predict market area, I strongly reject the hypothesis that the controls are irrelevant (see the F-test at the bottom). Imbalances in the treatment would indicate that estimated effects are not causal and potentially systematically biased, confounding the effect of market coordination with that of the imbalanced pre-determined variables and geographic fundamentals. The Borusyak and Hull (2023) methodology provides a solution to this problem: By purging out the non-random component of market coordination, it allows me to obtain market coordination deviations from the expectation that are driven purely by random idiosyncratic weekday preference. Under my model, controlling for the expectation of market schedule market area purges out potential omitted variable bias, not only of the variables presented in the sample balance analysis but any other unobservable variable as well. I provide evidence that the sample imbalance is indeed ameliorated after accounting for expected market area in column (2) of Table 7. Reassuringly, the loss in significance appears to be driven by a reduction in coefficient size rather than an inflation of standard errors.

5.4 Market attendance

I estimate equation (3) for analyzing the effects of scheduling frictions on seller and buyer attendance in Tables 8 and 9. An additional square kilometer of market area (beyond what the reconstructed coordination process would have us expect) induces the market size to increase by about 0.4981 sellers and 0.8595 buyers. Moving a village from the 10^{th} to the 50^{th} percentile of the market area distribution translates into an increased market attendance of 153 sellers and 243 buyers and moving it from the 50^{th} to the 90^{th} percentile leads to an additional 234 sellers and 371 buyers respectively, relative to an average main market day attendance of 632 sellers and 1148 buyers (after accounting for rounding precision loss). Decomposing attendance in local and outside attendance, both seem to mainly be driven by cross-attendees from outside, although both increase significantly in the case of buyers. All of these results are robust to the inclusion of baseline controls.

5.5 Economic development

In Table 10, I estimate equation (3) for the outcomes discussed in Section 3.2. Even after adjusting for its expectation, market area has an effect on present-day population of the villages that host markets. An additional square kilometer of market area (relative to its expectation) induces a population increase in the hosting village of 0.4244 households. Moving a village from the 10^{th} to the 50^{th} percentile of the market area distribution translates into an effect size of 33 additional households and moving it from the 50^{th} to the 90^{th} percentile leads to 50 additional households

Table 7: Sample balance

	(1) Mean (SD)	(2) Market area	(3) Recentered Market area
Latitude	0.3	.000525***	.000085
	(0.3)	(.0000895)	(.000147)
Longitude	34.4	.000829***	3.00e-06
	(0.3)	(.0000967)	(.000133)
Distance: Lake Victoria	39,331.4	68.1***	4.52
	(24,577.2)	(8.77)	(14.1)
Distance: Kisumu	65,268.4	4.13	-6.14
	(18,851.8)	(7.47)	(11.7)
Population 1920 (HHs)	2.3	-.00549	.00882*
	(7.5)	(.00371)	(.0051)
Agricultural suitability	-47.6	.331	.392
	(1,024.7)	(.296)	(.493)
Ruggedness	30,614.1	31.4**	-19.8
	(37,656.0)	(15.4)	(20.1)
Observations		287	287
F		10.89	1.19
$p(F = 0)$		3.8e-12***	.31

This table describes the sample balance of the measure of market area with respect to several pre-determined variables. The main panel reports the sample means and coefficients of the area measure in a regression predicting each control variable. At the bottom of the table, an F statistic is reported for a regression in which all controls jointly predict the treatment. The first column shows sample means and standard deviations. In the second column, the coordination measure is used at face value while in the third column I partial out the expectation of the coordination measure. Standard errors are reported in parentheses. Significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

respectively, relative to an average village size of 212 households. Assuming an average household size of 7 people, this corresponds to headcount increases of 230 and 352, respectively. Note that this is not a purely mechanical result, as the outcome variable in question is not the population of the market area, but that of the village hosting the market . Even after adjusting for its expectation, market area has an effect on present-day nighttime luminosity, as Table 10 shows. This suggests that market day scheduling has impacts not just on market attendance but more broadly on economic activity in the area. All of these results are robust to including baseline controls into the regression.

5.6 A comment on methodology

Before discussing the substantive results of this paper, it is worth briefly reviewing how the balance Table 7 differs from the results Tables 8 – 10. While the shifts in coefficients in geographic fundamentals from including the expected market catchment area are large and meaningfully change their interpretation in the balance Table 7 (and somewhat in the broader development outcomes in Table 10), the attendance results in Tables 8 and 9 barely change. This suggests that while the former appear to have suffered from omitted variable bias, market attendance appears not to. Of course while it may be ex post reassuring that the same bias removal technique that cleans up the balance table has relatively little effects on the naive OLS regression results of market attendance on catchment area, this was not ex ante obvious.

6 Discussion

As Figure 4 shows, the number of markets with a main market day has been fairly stable for fifty years and their schedules and with those their catchment areas have been largely unchanged (Table 5), suggesting that the local markets are in equilibrium. Consider a social planner drawing market catchment areas with the objective to maximize agglomeration gains subject to the distance that market participants are willing to travel. A catchment area would be defined in such a way that those living on its boundary are indifferent about attending the market when weighing their transport cost. Considering the long-term horizon of this quasi-experiment, finding significantly positive average treatment effects may be surprising as it suggests agglomeration gains in equilibrium. Since villages cannot readily move to achieve gradual gains, agglomeration would have to happen on the extensive margin, but I find little evidence of markets disappearing or merging, suggesting that the situation is not sufficiently suboptimal for such a large-scale restructuring either. In an equilibrium that maximizes agglomeration, market catchment areas should be so large that further expansion of market catchment areas should not induce higher attendance.

This does not appear to be the equilibrium that we are in. While the previous literature on market integration through roads or information technology does not provide reference points for the effect on market attendance, the results in this study seem large. Exploring these results, I split markets by their median day-specific catchment area and show in Table 11 that the gains are concentrated among the markets with the smallest catchment area. This suggests that from an

agglomeration perspective these smaller markets are too fragmented: Potential market participants would be willing to travel to larger, further-away markets if those existed, but smaller, closer markets are splitting the crowds amongst each other.

I rationalize this finding through a combination of misaligned incentives and uninternalized externalities on the one hand leading to persistence in an equilibrium made suboptimal by technological advance: As documented in Table 5, schedule persistence is very high. The absence of a social planner implies that two kinds of externalities are not internalized: First, markets choose their day optimally given the market schedule that prevailed at the time of market inception. This may undo the optimality of the schedule for other markets. Why do markets not change their schedules or cease to exist? Market attendants do not internalize the market thickness they contribute to the market they shop at (and withhold from the one they do not attend). They might privately optimally decide to attend a nearer-by market with lower transport cost (thus keeping that market alive), disregarding that if they went to a bigger, further-away market, that would motivate others to follow suit and in turn make that market worth the longer travel. A political economy version of this is the question: If two markets are in suboptimal spatial competition with each other, which of them should give up their market in favor of the other? Even if the joint market were appealing enough for everybody to attend even for the villagers who no longer have their own village market, the immediate increased travel cost may outweigh or at least be more salient than the agglomeration gains. The gains from market consolidation accrue to the attendants of the surviving market gaining market thickness while the costs are born by the attendants of the dying market that are now traveling further, leading to misaligned incentives. It may be locally optimal to keep a small market operational. Even schedule adjustments are hampered by this logic: When asked what they would do if holding a market on their current market day were no longer possible, a non-negligible share of market stakeholders indicate that shifting their market day would have such adverse effects on market attendance that they might as well close the market altogether (Table 5).

Further, consider that optimal catchment area size increases as transport costs fall and the introduction of markets in this area predates the mass adoption of even the bicycle, while motorized public transport on paved roads is a relatively recent phenomenon. In 1975, when the market schedule had mostly settled to what it is today, only about 12% of the markets in my census were connected to a paved road while the share has increased to 49% today. It is precisely the markets with road access that would benefit from consolidation (Table 12). It therefore appears that markets in this area proliferated when participants were walking and transport costs were prohibitive and that trade activity today is scattered across suboptimally many markets, leaving agglomeration gains on the table.

In this paper, I have described and evaluated a natural experiment in how market days in Western Kenya were scheduled. I found that while a simple regression analysis of outcomes of interest on present-day market catchment area may be biased, this bias can be purged out by leveraging detailed contextual knowledge of the coordination process. Doing so allows me to conclude that

market catchment areas indeed have a sizable and lasting causal impact on market attendance, particularly cross-attendance from other towns and that it can also partly explain the population size and night time luminosity of the towns that host the market. Market areas in Western Kenya, while perhaps optimal in an age when its participants were exclusively walking, appear to be too fragmented in light of advances in transport technology. Yet, strong persistence in market locations and their schedules as well as misaligned incentives on which town should give up its market, appear to be preventing a consolidation. I hasten to add, however, that policy intervention in these immensely fragile food and livelihood systems requires caution and local stakeholder involvement. While my results suggest agglomeration gains from market consolidation *on average*, they do not imply that there wouldn't be both winners and losers. This is especially true if we believe that transport cost is heterogeneous and poorer market participants would disproportionately be excluded from market participation if their local market closed in favor of a larger, more distant commercial center.

Table 8: Market attendance: Sellers

	Seller attendance			Seller attendance (local)			Seller attendance (outside)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market area	1.485***	1.590***	1.410***	0.0763*	0.0997	0.0792	1.413***	1.486***	1.324***
	(0.334)	(0.466)	(0.466)	(0.0393)	(0.0613)	(0.0572)	(0.314)	(0.431)	(0.437)
$\mathbb{E}$[Market area | Area]		-7.226	-9.089*		-0.0811	-0.440		-7.064	-8.495*
		(4.624)	(4.709)		(0.327)	(0.294)		(4.716)	(4.818)
$\mathbb{E}$[Market area | Distance]		6.970	8.252*		0.0404	0.493*		6.857	7.646
		(4.717)	(4.942)		(0.326)	(0.294)		(4.808)	(5.064)
Baseline controls	×	×	✓	×	×	✓	×	×	✓
Observations	279	279	279	275	275	275	277	277	277

This table describes the effects of market area induced by scheduling on the outcome variable indicated at the top. Columns (1), (4), and (7) describe the results of the naive OLS regression of the outcome on market area, while columns (2), (5), and (8) remove omitted variable bias by controling for the expected market area. Columns (3), (6), and (9) add baseline controls to the regression. Conley (1999) standard errors with a distance cutoff of 5km are reported in parentheses. Significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Market attendance: Buyers

	Buyer attendance			Buyer attendance (local)			Buyer attendance (outside)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market area	2.631***	2.527***	2.185***	0.213***	0.274***	0.240***	2.423***	2.267***	1.960***
	(0.546)	(0.709)	(0.720)	(0.0692)	(0.0956)	(0.0877)	(0.509)	(0.653)	(0.666)
$\mathbb{E}$[Market area | Area]		-12.91	-15.95*		-0.211	-0.919*		-12.96	-15.30*
		(8.034)	(8.104)		(0.561)	(0.534)		(8.006)	(8.046)
$\mathbb{E}$[Market area | Distance]		12.95	15.20*		0.105	1.030*		13.08	14.43*
		(8.184)	(8.457)		(0.574)	(0.550)		(8.151)	(8.414)
Baseline controls	×	×	✓	×	×	✓	×	×	✓
Observations	279	279	279	275	275	275	276	276	276

This table describes the effects of market area induced by scheduling on the outcome variable indicated at the top. Columns (1), (4), and (7) describe the results of the naive OLS regression of the outcome on market area, while columns (2), (5), and (8) remove omitted variable bias by controling for the expected market area. Columns (3), (6), and (9) add baseline controls to the regression. Conley (1999) standard errors with a distance cutoff of 5km are reported in parentheses. Significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Economic development

	Population (HHs)			Nightlights			Log nightlights		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market area	0.159	0.342**	0.277*	0.122***	0.234***	0.228***	0.0132***	0.0169***	0.0158***
	(0.100)	(0.149)	(0.142)	(0.0413)	(0.0744)	(0.0772)	(0.00361)	(0.00516)	(0.00542)
$\mathbb{E}$[Market area | Area]		-2.378	-2.754		-0.184	-0.288		-0.0773	-0.103*
		(1.900)	(1.704)		(0.801)	(0.785)		(0.0576)	(0.0582)
$\mathbb{E}$[Market area | Distance]		2.045	2.685		-0.00826	0.0455		0.0702	0.0952
		(1.844)	(1.713)		(0.811)	(0.847)		(0.0582)	(0.0592)
Baseline controls	×	×	✓	×	×	✓	×	×	✓
Observations	285	285	285	287	287	287	287	287	287

This table describes the effects of market area induced by scheduling on the outcome variable indicated at the top. Columns (1), (4), and (7) describe the results of the naive OLS regression of the outcome on market area, while columns (2), (5), and (8) remove omitted variable bias by controling for the expected market area. Columns (3), (6), and (9) add baseline controls to the regression. Conley (1999) standard errors with a distance cutoff of 5km are reported in parentheses. Significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Heterogeneous effects by catchment area size

	Sellers w/ small catchment			Sellers w/ large catchment			Buyers w/ small catchment			Buyers w/ large catchment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market area	2.686***	2.402***	1.722*	0.735	1.091	1.108	4.885***	4.687***	3.328**	1.864	1.999*	2.054*
	(0.626)	(0.639)	(0.879)	(0.780)	(0.745)	(0.684)	(1.136)	(1.163)	(1.459)	(1.195)	(1.178)	(1.128)
$\mathbb{E}$[Market area | Area]		-6.959*	-7.996*		-6.829	-7.876		-12.65	-14.06*		-12.86	-14.54
		(4.115)	(4.136)		(6.293)	(6.669)		(7.723)	(7.701)		(10.84)	(11.18)
$\mathbb{E}$[Market area | Distance]		7.574*	8.336*		6.153	6.468		13.25*	14.52*		12.60	13.35
		(4.099)	(4.259)		(6.504)	(7.137)		(7.784)	(7.887)		(11.15)	(11.93)
Baseline controls	×	×	✓	×	×	✓	×	×	✓	×	×	✓
Observations	138	138	138	141	141	141	138	138	138	141	141	141

This table describes the effects of market area induced by scheduling on the outcome variable indicated at the top. Columns (1), (4), and (7) describe the results of the naive OLS regression of the outcome on market area, while columns (2), (5), and (8) remove omitted variable bias by controling for the expected market area. Columns (3), (6), and (9) add baseline controls to the regression. Conley (1999) standard errors with a distance cutoff of 5km are reported in parentheses. Significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Heterogeneous effects by road access

	Sellers in markets w/o road			Sellers in markets w/ road			Buyers in markets w/o road			Buyers in markets w/ road		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market area	0.519***	-0.0233	-0.170	1.559***	2.130***	2.124***	0.957***	0.0582	-0.144	2.813***	3.306***	3.265***
	(0.163)	(0.239)	(0.230)	(0.527)	(0.723)	(0.725)	(0.280)	(0.440)	(0.432)	(0.866)	(1.113)	(1.152)
$\mathbb{E}$[Market area | Area]		-2.156	-4.513**		-5.618	-1.131		-1.039	-4.729		-13.09	-4.285
		(1.872)	(2.042)		(8.423)	(10.64)		(2.875)	(3.298)		(14.37)	(16.73)
$\mathbb{E}$[Market area | Distance]		2.920	5.176**		4.484	-2.915		2.325	6.025*		12.06	-1.283
		(1.869)	(2.088)		(8.577)	(11.49)		(2.844)	(3.378)		(14.58)	(17.97)
Baseline controls	×	×	✓	×	×	✓	×	×	✓	×	×	✓
Observations	143	143	143	136	136	136	143	143	143	136	136	136

This table describes the effects of market area induced by scheduling on the outcome variable indicated at the top. Columns (1), (4), and (7) describe the results of the naive OLS regression of the outcome on market area, while columns (2), (5), and (8) remove omitted variable bias by controling for the expected market area. Columns (3), (6), and (9) add baseline controls to the regression. Conley (1999) standard errors with a distance cutoff of 5km are reported in parentheses. Significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey Wooldridge, "When should you adjust standard errors for clustering?," Technical Report, National Bureau of Economic Research 2017.

Agarwal, Nikhil, Itai Ashlagi, Eduardo Azevedo, Clayton R Featherstone, and Ömer Karaduman, "Market failure in kidney exchange," *American Economic Review*, 2019, *109* (11), 4026–4070.

Akbarpour, Mohammad, Shengwu Li, and Shayan Oveis Gharan, "Thickness and information in dynamic matching markets," *Journal of Political Economy*, 2020, *128* (3), 783–815.

Aker, Jenny C, "Information from markets near and far: Mobile phones and agricultural markets in Niger," *American Economic Journal: Applied Economics*, 2010, *2* (3), 46–59.

Balan, Pablo, Augustin Bergeron, Gabriel Tourek, and Jonathan L Weigel, "Local elites as state capacity: How city chiefs use local information to increase tax compliance in the democratic republic of the Congo," *American Economic Review*, 2022, *112* (3), 762–797.

Baldwin, Kate, *The paradox of traditional chiefs in democratic Africa*, Cambridge University Press, 2016.

Barrett, Christopher B., "Spatial Market Integration," in Steven N. Durlauf Lawrence E. Blume, ed., *The New Palgrave Dictionary of Economics*, 2nd ed., London: Palgrave Macmillan, 2005, pp. 115–168.

Basurto, Maria Pia, Pascaline Dupas, and Jonathan Robinson, "Decentralization and efficiency of subsidy targeting: Evidence from chiefs in rural Malawi," *Journal of public economics*, 2020, *185*, 104047.

Bergquist, Lauren Falcao and Michael Dinerstein, "Competition and entry in agricultural markets: Experimental evidence from Kenya," *American Economic Review*, 2020, *110* (12), 3705–3747.

Bleakley, Hoyt and Jeffrey Lin, "Portage and path dependence," *The Quarterly Journal of Economics*, 2012, *127* (2), 587–644.

Bollobás, Bela and Nicholas Stern, "The optimal structure of market areas," *Journal of Economic Theory*, 1972, *4* (2), 174–179.

Borusyak, Kirill and Peter Hull, "Nonrandom Exposure to Exogenous Shocks," *Econometrica*, 2023, *91* (6), 2155–2185.

Bromley, Rose J, Richard Symanski, and Charles M Good, "The rationale of periodic markets," *Annals of the Association of American Geographers*, 1975, *65* (4), 530–537.

Burke, Marshall, Lauren Falcao Bergquist, and Edward Miguel, "Sell low and buy high: Arbitrage and local price effects in Kenyan markets," *The Quarterly Journal of Economics*, 2019, *134* (2), 785–842.

Casaburi, Lorenzo, Rachel Glennerster, and Tavneet Suri, "Rural roads and intermediated trade: Regression discontinuity evidence from Sierra Leone," *Available at SSRN 2161643*, 2013.

Conley, Timothy G, "GMM estimation with cross-sectional dependence," *Journal of Econometrics*, 1999, *92* (1), 1–45.

Descartes, René, *Principia Philosophiae* 1664.

Desmet, Klaus and Stephen L Parente, "Bigger is better: Market size, demand elasticity, and innovation," *International Economic Review*, 2010, *51* (2), 319–333.

Dietler, Michael and Ingrid Herbich, "Living on Luo time: Reckoning sequence, duration, history and biography in a rural African society," *World Archaeology*, 1993, *25* (2), 248–260.

Dirichlet, Gustav Lejeune, "Über die Reduction der positiven quadratischen Formen mit drei unbestimmten ganzen Zahlen.," *Journal für die reine und angewandte Mathematik (Crelles Journal)*, 1850, *1850* (40), 209–227.

Dixit, Avinash K and Joseph E Stiglitz, "Monopolistic competition and optimum product diversity," *The American economic review*, 1977, *67* (3), 297–308.

Donaldson, Dave, "The gains from market integration," *economics*, 2015, *7* (1), 619–647.

_ , "Railroads of the Raj: Estimating the impact of transportation infrastructure," *American Economic Review*, 2018, *108* (4-5), 899–934.

Faber, Benjamin, "Trade integration, market size, and industrialization: Evidence from China's National Trunk Highway System," *Review of Economic Studies*, 2014, *81* (3), 1046–1070.

Fafchamps, Marcel, "Cash crop production, food price volatility, and rural market integration in the third world," *American Journal of Agricultural Economics*, 1992, *74* (1), 90–99.

_ **and Ruth Vargas Hill**, "Selling at the farmgate or traveling to market," *American Journal of Agricultural Economics*, 2005, *87* (3), 717–734.

Fagerlund, Vernon G and Robert HT Smith, "A preliminary map of market periodicities in Ghana," *The Journal of Developing Areas*, 1970, pp. 333–348.

Fröhlich, Willy, *Das afrikanische Marktwesen*, Springer, 1941.

Geertz, Clifford, *Deep play: Notes on the Balinese cockfight*, Springer, 2000.

Good, Charles M, "Markets in Africa: A Review of Research Themes and the Question of Market Origins (Marchés africains: recension des thèmes de recherche et de la question de l'origine des marchés)," *Cahiers d'études africaines*, 1973, pp. 769–780.

Goyal, Aparajita, "Information, direct access to farmers, and rural market performance in central India," *American Economic Journal: Applied Economics*, 2010, *2* (3), 22–45.

Hay, Margaret, "Local trade and ethnicity in western Kenya," *African Economic History Review*, 1975, *2* (1), 7–12.

Hill, Polly, "Notes on Traditional Market Authority and Market Periodicity in West Africa," *The Journal of African History*, 1966, *7* (2), 295–311.

Hodder, Bromwell W, "Rural periodic day markets in part of Yorubaland," *Transactions and Papers (Institute of British Geographers)*, 1961, (29), 149–159.

_ , "Distribution of markets in Yorubaland," *Scottish Geographical Magazine*, 1965, *81* (1), 48–58.

Hornbeck, Richard, Guy Michaels, and Ferdinand Rauch, "Identifying agglomeration shadows: Long-run evidence from ancient ports," Technical Report, National Bureau of Economic Research 2024.

Hotelling, Harold, "Stability in competition," *The Economic Journal*, 1929, *39* (153), 41–57.

Hsiang, Solomon M, "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America," *Proceedings of the National Academy of sciences*, 2010, *107* (35), 15367–15372.

Jedwab, Remi and Alexander Moradi, "The permanent effects of transportation revolutions in poor countries: Evidence from Africa," *Review of Economics and Statistics*, 2016, *98* (2), 268–284.

Jensen, Robert, "The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector," *The Quarterly Journal of Economics*, 2007, *122* (3), 879–924.

_ **and Nolan H Miller**, "Market Integration, Demand, and the Growth of Firms: Evidence from a Natural Experiment in India," *American Economic Review*, 2018, *108* (12), 3583–3625.

Kapor, Adam, Mohit Karnani, and Christopher Neilson, "Aftermarket Frictions and the Cost of Off-Platform Options in Centralized Assignment Mechanisms," Working Paper 30257, National Bureau of Economic Research July 2022.

Lösch, August, *The Economics of Location*, Yale University Press, New Haven, Conn., 1954.

Melitz, Marc J, "The impact of trade on intra-industry reallocations and aggregate industry productivity," *Econometrica*, 2003, *71* (6), 1695–1725.

Mills, Edwin S and Michael R Lav, "A model of market areas with free entry," *Journal of Political Economy*, 1964, *72* (3), 278–288.

Oberfield, Ezra, Esteban Rossi-Hansberg, Pierre-Daniel Sarte, and Nicholas Trachter, "Plants in space," *Journal of Political Economy*, 2024, *132* (3), 867–909.

Román, Miguel O, Zhuosen Wang, Qingsong Sun, Virginia Kalb, Steven D Miller, Andrew Molthan, Lori Schultz, Jordan Bell, Eleanor C Stokes, Bhartendu Pandey et al., "NASA's Black Marble nighttime lights product suite," *Remote Sensing of Environment*, 2018, *210*, 113–143.

Schurtz, H, "Das afrikanische Gewerbe. 35," *Preisschrift der Fürstlich Jablonowskischen Gesellschaft zu Leipzig*, 1900.

Scott, Earl P, "Subsistence, markets, and rural development in Hausaland," *The Journal of Developing Areas*, 1978, *12* (4), 449–469.

Skinner, G William, "Marketing and social structure in rural China, Part I," *The Journal of Asian Studies*, 1964, *24* (1), 3–43.

Smith, Robert HT, "Periodic market-places and periodic marketing: Review and prospect—I," *Progress in Human Geography*, 1979, *3* (4), 471–505.

_ , "Periodic market-places and periodic marketing: Review and prospect—II," *Progress in Human Geography*, 1980, *4* (1), 1–31.

Stern, Nicholas, "The optimal size of market areas," *Journal of Economic Theory*, 1972, *4* (2), 154–173.

Storeygard, Adam, "Farther on down the road: Transport costs, trade and urban growth in sub-Saharan Africa," *The Review of Economic Studies*, 2016, *83* (3), 1263–1295.

Svensson, Jakob and David Yanagizawa, "Getting prices right: The impact of the market information service in Uganda," *Journal of the European Economic Association*, 2009, *7* (2-3), 435–445.

Thiessen, Alfred H, "Precipitation averages for large areas," *Monthly Weather Review*, 1911, *39* (7), 1082–1089.

Thomas, Northcote W, "The Week in West Africa," *The Journal of the Royal Anthropological Institute of Great Britain and Ireland*, 1924, *54*, 183–209.

Tóth, L Fejes, *Lagerungen in der Ebene auf der Kugel und im Raum*, Vol. 65, Springer Verlag, 1953.

Trimingham, J. Spencer, *The Influence of Islam upon Africa*, 2nd ed. 1980.

Vitali, Anna, "Consumer search and firm location: Theory and evidence from the garment sector in Uganda," *Working Paper*, 2022.

von Carnap, Tillmann, "Remotely-sensed market activity as a short-run economic indicator in rural areas of developing countries," *Available at SSRN 3980969*, 2022.

_ , "Rural marketplaces and local development," 2023.

Voronoï, Georges, "Nouvelles applications des paramètres continus à la théorie des formes quadratiques. 1$^{\text{er}}$ mémoire. Sur quelques propriétés des formes quadratiques positives parfaites.," *Journal für die reine und angewandte Mathematik (Crelles Journal)*, 1908, (133), 97–102.

_ , "Nouvelles applications des paramètres continus à la théorie des formes quadratiques. 2$^{\text{ème}}$ mémoire. Recherches sur les parallélloèdres primitifs.," *Journal für die reine und angewandte Mathematik (Crelles Journal)*, 1908, (134), 198–287.

Wahl, Fabian, "Does medieval trade still matter? Historical trade centers, agglomeration and contemporary economic development," *Regional Science and Urban Economics*, 2016, *60*, 50–60.

Wood, Leslie J, "The temporal efficiency of the rural market system in Kenya," *East African Geographical Review*, 1973, *1973* (11), 65–70.

_ , "Unpublished Ph.D. thesis," 1973.

_ , "Population Density and Rural Market Provision (Densité de population et marchés ruraux)," *Cahiers d'études Africaines*, 1974, pp. 715–726.

_ , "Spatial interaction and partitions of rural market space," *Tijdschrift voor economische en sociale geografie*, 1974, *65* (1), 23–34.

Appendix

Table 13: Outcome Variables

Name	**Definition**	**Source**	**Spatial resolution**	**Temporal resolution**	**Citation**
Attendance	Attendance estimates of sellers and buyers on the main market day	Phone survey	Market	2023–2024	This paper
Population	Number of households presently living in the village	Phone survey	Market	2023–2024	This paper
Nighttime lights	Lunar-adjusted top of atmosphere radiance	NASA BlackMarble	∼500m	January 2023 (composite)	Román et al. (2018)

Note: This table summarizes the outcome data sources used in this paper, alongside with definitions, sources, applicable resolution and useful citations.

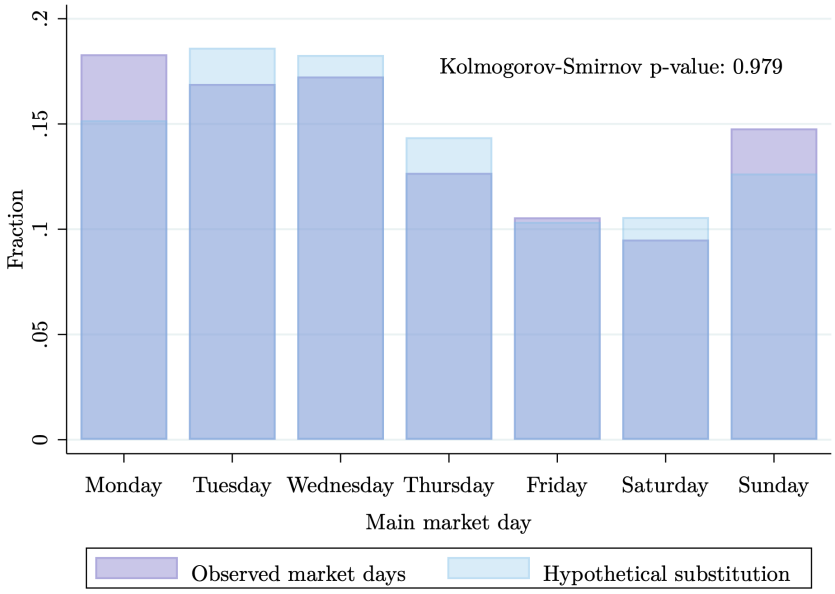


Figure 8: **Market days** hypothetically chosen if current day were no longer feasible.

Table 14: Bias simulation

	(1) True value	(2) Naive estimate	(3) BH estimate
Outcome regression equations (1) **&** (3)			
Market Area (β)	1.000	1.451	1.041
		(0.170)	(0.439)
		[0.000]	[0.071]
Expected Market area			0.408
			(0.479)
			[0.395]
Scheduling equation (2)			
Distance (δ)	1.000		0.998
			(0.091)
			[0.000]
$P(\delta = 1)$			0.499
$P(\beta = 1)$		0.097	0.547
Observations		272	272

Note: This table shows results from simulating and then removing bias in the estimation using the Borusyak and Hull (2023) method. A regular grid of 1,024 potential markets is generated with distance metrics matching those observed in the real data. A share of 10% of them is randomly selected to be intrinsically more suitable for market activities and economic development more broadly. This deters markets within a 10,000m distance from entering which mechanically endows suitable markets with a larger market area. Simultaneously these markets find themselves with better present-day outcomes beyond the imposed true effect β of market area in column (1). Column (2) shows that this would bias the coefficient in equation (1) upward. Market scheduling was governed by the parameter δ in column (1). In the Scheduling panel, using 101 simulations I show that I can recover this parameter under the assumption that my scheduling model is correctly specified. Employing this information to compute expected market catchment areas for the markets in each bias scenario over 100 simulations, I show that controlling for expected market catchment area can purge out the introduced bias from deterred entry and recover the true β parameter.

Table 15: Scheduling: Robustness given other local knowledge

	(1)	(2)	(3)	(4)
Area	.002***		.00192***	
	(.000398)		(.000409)	
Distance		.0895***		.0908***
		(.0156)		(.0162)
Age of neighboring market at the time			-.00566	-.00507
			(.00476)	(.00472)
Population of $\sim$			.00192*	.00249**
			(.001)	(.00102)
Road access to $\sim$			-.12	-.0939
			(.149)	(.15)
Day FEs				
Tuesday	-.249	-.152	-.277	-.175
	(.206)	(.203)	(.207)	(.204)
Wednesday	-.0324	-.00634	-.00601	.0277
	(.199)	(.201)	(.2)	(.202)
Thursday	-.393*	-.421*	-.342	-.364*
	(.217)	(.218)	(.218)	(.22)
Friday	-.595***	-.558**	-.566**	-.52**
	(.229)	(.227)	(.233)	(.232)
Saturday	-1.06***	-.936***	-1.05***	-.935***
	(.255)	(.248)	(.255)	(.25)
Sunday	-.297	-.275	-.271	-.234
	(.209)	(.209)	(.211)	(.212)
Observations	2009	2009	2009	2009

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$