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Tracking price dynamics during a pandemic in Kenya and Uganda*

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Abstract

As the Covid-19 pandemic unfolded across the globe, the economic impact has been characterised by a combination of supply and demand shocks with an *a priori* unclear effect on price dynamics. Using real-time primary price data covering a wide range of geographic areas, we track the impact of the pandemic on prices in Kenya and Uganda during the initial shutdown period and the subsequent re-opening phase. We find evidence that price levels for essential food items were higher during the initial phase of the pandemic. The impact was short-lived and moderate in Kenya, but continued for an extended period in Uganda where government restrictions were tighter and in place for a more prolonged period of time. We further combine the price data with information on changes in visiting patterns of smartphone users at localities like workplaces, grocery stores and other retail locations. The results suggest that mobility patterns continue to have an impact on price dynamics beyond the initial shutdown phase. We estimate that a 10 percentage point reduction in activities at workplace locations leads to a 0.3% and 1.4% increase in food prices in Kenya and Uganda respectively. This result is stable across a variety of empirical specifications, although we cannot rule out that the effect is zero in Kenya.

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1 Introduction

As the Covid-19 pandemic unfolded across the globe, its economic impact has been characterised by a combination of supply and demand shocks with an *a priori* unclear, but likely sector- and context-specific, effect on price dynamics. Food price dynamics have been a central concern for policy makers throughout the pandemic due to their importance for food security and the high expenditure share on food especially for low-income households. Across the globe the food component of Consumer Price Index (CPI) has been rising faster than CPI itself throughout 2020 and early 2021.[1]

Our study focuses on documenting and understanding retail price dynamics of essential food items. Complementary, timely data collection through non-traditional channels can be a vital tool to track prices in a fast-changing and uncertain environment. Over the course of several months we collected high-frequency, geo-coded retail price data across Kenya and Uganda. Our data collection succeeded in its primary goal of generating high-frequency data with a wide geographic coverage. The trend of prices in the price survey closely mirrors movement in national prices by statistical agencies in both countries. We use this data to study price dynamics during the initial lockdown period in the first half of 2020, and the subsequent re-opening phase in the second half of 2020 and early 2021. The pandemic fundamentally altered mobility and consumption patterns even above and beyond immediate government-imposed restrictions. Our report therefore specifically looks at the links between price dynamics and mobility patterns. To measure changes in mobility we draw on publicly available data on changes in visiting patterns of smartphone users at locations like workplaces, grocery stores and other retail stores.[2] For each day the indices capture the percentage change in activity relative to the median activity level on the same weekdays during a 5-week baseline period in January and February 2020.
The ongoing crisis entails both substantial demand side and supply side shocks, which simultaneously impact prices in different ways (Jaravel and O'Connell, 2020; Baqaee and Farhi, 2021). The fall in production and supply chain disruptions may lead to supply shortages (Baldwin and Tomiura, 2020) and thus result in an increase in product prices. A second potential source of market price disruptions lies in the demand side. The sharp fall in incomes may lead to a negative demand shock with deflationary pressure (Jaravel and O'Connell, 2020; Baqaee and Farhi, 2021).[3] Due to the complex nature and interaction of these shocks, the ultimate outcome

[1] https://ilostat.ilo.org/covid-19-is-driving-up-food-prices-all-over-the-world/

[2] The Google Covid-19 Mobility Reports can be downloaded here: https://www.google.com/covid19/mobility/

[3] As the spread of coronavirus unfolded, global panic led to consumers stockpiling essential commodities especially staple food products (O'Connell et al., 2020) and medicine. However, at least for the UK, O'Connell et al. (2020) find this effect to be rather short lived and concentrated among high income households.

on prices is unclear and is thought to vary highly across sectors (Jaravel and O'Connell, 2020).

The ability to compare dynamics in two neighbouring economies with similar household consumption patterns, but variation in the stringency of the initial shutdown policies provides us with an interesting case study. We find evidence that prices were higher during the initial weeks of shutdown orders to contain the spread of Covid-19 in Kenya and Uganda. Due to the long-lived and more stringent nature of the lockdown, the impact seems to have been more pronounced in Uganda. In Kenya, we find that prices remained relatively low for an extended period after the end of the lockdown. While we cannot rule out a partial role of seasonality, this finding is likely driven by the sustained reduction in household incomes due to the pandemic and the associated economic shock (Pape et al., 2020; Kansiime et al., 2021). Further we find that the price trend in Greater Nairobi and Mombasa, which had seen additional travel restrictions early on in the pandemic, does not follow a different trajectory than the rest of the country. In Uganda, prices remained high until July 2020 in the 40 border districts that had prolonged lockdown measures imposed. However, the same pattern is also observed for the Greater Kampala region.

In contrast to the more short-lived impact of the lockdown measures, we further show that changes in mobility patterns continue to drive price dynamics beyond the initial lockdown phase. Interestingly, our findings suggest that retail prices increase as the level of activity at workplaces, grocery and retail stores declines. We estimate that a 10 percentage point reduction in activities at workplace locations corresponds to a 0.3% and 1.4% increase in food prices in Kenya and Uganda respectively. The effect is more pronounced if we look at activity at grocery stores and other retail locations. However, we mainly focus on workplace activity (which highly correlates with the other indices) in our analysis as the index for this measure is available for a more consistent sample of administrative units over time. The results are stable across a number of alternative specifications, although we cannot rule out that the effect is indeed zero in Kenya. In Uganda, we find that prices for imported products follow a different pattern, where prices rise with an increase in mobility. In addition, the impact of the local level of activity increases with distance to the product origin for branded items in Uganda.

In line with findings in other contexts (Aum et al., 2020; Goolsbee and Syverson, 2021), the results suggest that lockdown measures are not the only driver of economic outcomes during the pandemic. Changes in consumption and mobility patterns can equally impact price dynamics. This can occur due to changes in behaviour to avoid infection, but importantly can also be driven by the sustained adverse impact of the pandemic on income-generating activities. Furthermore, post-lockdown mobility patterns might drive business decisions to re-open and thereby contribute to sustained supply side effects.

By March 2020, most countries in East Africa had reported the first cases of coronavirus patients and had swiftly implemented measures to contain the spread of SARS-CoV-2.[4] Zoning of potential epicentres and eventual closing down of markets, public gatherings, and cross-zonal travel were characteristic local containment measures. Even though there was a deliberate effort to ensure local and international trade remained unaffected, these measures bore a range of consequences. Product flows were affected and workers were forced to either lose jobs or cut down on hours of trade owing to nightfall curfews and zoning.

The stringency of the containment measures ranged from almost complete lockdown in Uganda to night-time curfew and city-specific travel-restrictions in Kenya. Despite differential policy measures, both Kenya and Uganda were substantially affected by disruptions to global supply chains and the emerging global economic crisis (coupled with a second locust outbreak in the Horn of Africa). Many households, especially those employed in the large informal sector faced substantial income losses (Pape et al., 2020; Kansiime et al., 2021).

We relied on a quick-response online survey to track product prices and availability of selected essential consumer products across Kenya and Uganda. This allowed us to generate real-time data during the evolving pandemic. We recruited volunteers, mainly university students and staff/network members of NGOs. They recorded prices through an online form - either when or after visiting a shop in-person or getting deliveries. We also collected additional information on product brands, neighbourhood and shop characteristics. This allowed us to develop a more nuanced understanding of the nature and magnitude of price effects.

1.1 Related literature:

This study adds to the literate in three important ways: First, we contribute to the literature tackling questions of food security during the pandemic. The majority of papers in this literature focuses on households on the one side (Abay et al., 2020; Kansiime et al., 2021; Mahmud and Riley, 2021; Egger et al., 2021) and wholesale markets on the other side (Ruan et al., 2020; Lowe et al., 2020). By studying retail price dynamics, we zoom in on the link between the two. One of the studies closest related to ours (Mahajan and Tomar, 2021), uses data from India's

[4]See for example https://www.theigc.org/blog/rwandas-response-to-covid-19-and-future-challenges/.

largest online retailer for whom they are able to observe the entire supply chain, including both wholesale and retail prices as well as product origins for all items (which we are only able to trace for branded items). They estimate a 10% fall in the availability of vegetables, fruits and edible oils and only a minimal impact on prices. Their findings point to supply chain disruptions as the main drivers of the decline in product availability. A key limitation of their study is that online retailers largely target India's middle-class, which has been less affected by income losses. While we observe fewer details on the nature of supply chains, our approach of using quick response online surveys filled out by a varied network of volunteers allows us to trace price dynamics relevant for a broader set of income groups. Another closely related study by Narayanan and Saha (2020) compiles a large data set containing retail and wholesale prices using administrative data from India. Like us they focus on fast moving food commodities. They find a substantial surge in prices right after the announcement of the national lockdown in India with no sign of prices reverting back to pre-lockdown levels a month later. Our study builds on theirs by (i) adding a context with much less stringent lockdown measures, and (ii) tracking price dynamics throughout a re-opening phase. Our findings are in line with Amare et al. (2020), who also detect increased levels of food insecurity, falling household incomes, increased food prices during times of lockdown restrictions in Nigeria.

Second, we contribute to a fast growing literature assessing the impact of shutdown policies as a containment measure and contrasts it with shifts in individual behaviour to avoid contraction of the virus (Aum et al., 2020; Goolsbee and Syverson, 2021)[5]. Looking at price dynamics during both the lockdown and re-opening phase, our setting does not allow us to cleanly distinguish between the two. However, in our context the drop in household incomes due to the pandemic - driven by a complex interplay of factors such as global trade disruptions, local shutdowns, and changes in the nature of social and economic activities (Nechifor et al., 2021) - might be the key driver of our findings. Highlighting the relevance of this channel, Kansiime et al. (2021) show that 2/3 of the households in their sample experienced a loss in income during the pandemic in Kenya and Uganda. Shupler et al. (2020) report that households in urban informal settlements are even more likely to have experiences a loss in income (95%) and struggle with food-insecurity (88%).

Lastly, the project serves as a proof of concept showing that it is possible to collect high-quality, high-frequency price data at scale through a crowd-sourcing approach. Statistical bureau's like the U.S. Bureau of Labour Statistics reported challenges in collecting vital food price data during

[5]For updated findings, see https://bfi.uchicago.edu/insight/research-update-drivers-of-economic-decline/.

the pandemic.[6] Their challenges have been most pronounced for prices where consumption and buying patterns shifted dramatically with the pandemic. Response rates for food prices fell by 15-30% between June 2019 and June 2020. Complementary data collection through non-traditional channels can thus be a vital tool to track prices in a fast changing and uncertain environment (Jaravel and O'Connell, 2020). Jaravel and O'Connell (2020), for example, make the case for using household level scanner data to track price dynamics in times of crisis. They and O'Connell et al. (2020) use millions of transactions for fast moving consumer goods from the Kantar FMCG Purchase Panel to track prices and household consumption behaviour during the first lockdown in the UK.[7] In the absence of such alternative data sources, crowd-sourcing can be an effective data collection tool. Crowd-sourcing as a means of data collection has traditionally been popular in the humanitarian sector, e.g. to map humanitarian needs after natural disasters (Butler, 2013). While it is by no means a perfect substitute for traditional data collection methods, the advent of the pandemic presented limited options to engage in a contact data collection approach. Similar studies using novel approaches include that of Kansiime et al. (2021) who broadcast an online survey through WhatsApp, Facebook, Telegram and Twitter in Kenya and Uganda to study the implications of the coronavirus pandemic on household income and food security. In our case, the efficacy of the crowd-sourcing approach had the advantage that while respondents went out to make general purchases of otherwise planned expenditure or ordered online, we got a chance to receive feedback on the prices they paid for their merchandise. With the support of over 250 respondents across Kenya and Uganda, we collected a comprehensive panel for essential consumer products, mainly food items, over the course of several months. A key limitation of our approach lies in the challenge of collecting data in particularly remote regions that are less populated (Figure 16) and have limited internet connectivity. With an increasing levels of smart phone penetration worldwide, crowd-sourcing approaches, however, become an option for complementary data collection for policy makers and academics.

[6] https://www.bls.gov/opub/mlr/2020/article/the-impact-of-the-covid-19-pandemic-on-food-price-indexes-and-data-collection.htm

[7] Transaction-level financial data have become a very popular tool during the pandemic to track expenditure patterns of households (see for example Baker et al. (2020) for the US, Carvalho et al. (2020) for Spain and Andersen et al. (2020) for Denmark). Such data allows for detailed documentation of the impact of the crisis both across space, sectors and demographics. Unfortunately, bank transaction data, as opposed to scanner data, usually does not contain information on prices and similar data sets, e.g. from mobile money accounts, are at the moment not available for the purpose of research in Kenya or Uganda.

2 Covid-19 Pandemic in Kenya and Uganda

In mid-March Uganda and Kenya both limited international travel from countries with ongoing Covid-19 epidemics. On 13th March 2020, the first Covid-19 case was recorded in Kenya with Uganda following a week later on 21st March 2020. Throughout March and April national and local governments in both countries swiftly introduced a series of containment measures.

Government Covid-19 control measures in Uganda kicked off with various restrictions comprising the closures of services oriented businesses, a national lockdown and curfew as well as travel restrictions (except for goods and cargo). From end-May onward, a gradual easing of the lockdown for non-border districts took place and merchandising shops and markets were allowed to operate under strict Standard Operating Procedures (SOPs). Travel restrictions remained in place for 40 border districts until early August and for a subset of nine districts until late September. Although most markets and shops were generally allowed to operate from June, some agents opted to suspend their operations either due to failure to implement the SOPs or labour mobility related to travel restrictions. Until early August, Uganda registered only very few Covid-19 cases. The first, smaller wave hit its peak in late September, while the peak of the second wave was registered in mid-December 2020 (Roser et al., 2020).[8]

Throughout March 2020, the Government of Kenya gradually rolled out a number of containment measures starting with limits to public gatherings, followed by school closures, restaurant and hotel shutdowns, and lastly a night-time curfew. In early April, passenger travel in and out of the coastal counties Kilifi, Kwale, and Mombasa as well as the Greater Nairobi areas and the border county Mandera were restricted. Cargo transport remained unaffected by this measure. In early June the travel restrictions were lifted for Kilifi in Kwale, and Mombasa, Mandera and Nairobi followed in early July. The vast majority of the measures were lifted by September 2020. The nighttime curfew and school closures, however, remained in place. In January 2021, renewed restrictions on public gatherings were imposed.

Thus far Kenya has experienced two relatively moderate waves of Covid-19 with peaks in the number of confirmed Covid-19 cases in early August and mid-November respectively. Kenya is currently experiencing the third wave of Covid-19 cases.

For a more in-depth discussion of the evolution of the pandemic and related policy measures in

[8] https://ourworldindata.org/coronavirus/country/kenya?country=KEN~UGA Data retrieved 28th March 2021.

Kenya and Uganda see among others Kansiime et al. (2021).

2.1 Market closures

As part of this project we collected detailed information on market closures in Kenya, which we map in Figure 8.[9] Several county governments closed down markets in mid-March, many of which, however, re-opened in early or mid-April. Unfortunately, we were not able to track the timing of market re-opening as closely as closures. In many cases the re-opening went hand-in-hand with the introduction of new sanitation and hand-washing facilities. In some cases markets were re-routed to more spacious locations. Of the counties with official closure and re-opening announcements, only Siaya County in Western Kenya and Kwale County on the coast closed markets for a prolonged period. However, both re-opened by August. Responding to localised outbreaks a small number of counties like Machakos, Kiambu and Bomet, temporarily shut markets in later months. However, given that our data coverage is weakest during the time markets were closed, we observe little geographic variation in shutdowns in later months, and re-opening dates are unknown in most cases, we are unable to speak to the impact of market closures in our analysis.

3 Data collection

3.1 Price survey

To generate real-time data during the evolving pandemic, we relied on a quick-response online survey to track product prices and availability of selected essential consumer products across Kenya and Uganda. We recruited volunteers, mainly university students and staff/network members of NGOs. They recorded prices through an online form - either when or after visiting a shop in-person or getting deliveries.

In the short run, our goal was to provide policy makers in Kenya and Uganda with reliable real-time data to inform decision making. In a dynamically evolving situation like the Covid-19 crisis, real-time price data can help decision-makers in planning, implementing, and assessing the effectiveness of relevant policies. Cash transfer programmes, for example, targeted at vulnerable households only translate into increased food security if the markets for essential consumer goods are relatively stable (Gerard et al., 2020; Gadenne et al., 2021). We therefore worked towards providing an easily scale-able data collection tool and source of information for policy makers and researchers that goes beyond the standard methodology of tracking inflation. Our

[9] The Ugandan government adopted a national policy with only few deviations.

approach emphasized on tracking prices on a frequent basis rather than monthly and focused on a large variety of geographic areas rather than mainly major urban centres.

We launched the pilot phase of the data collection in late March 2020 in Kenya. With the support of students from two other public universities and support from an NGO, we were able to substantially scale up the data collection in Kenya in late May. We were further able to pilot the data collection in Uganda and subsequently scale it up in August. Thanks to support from the Uganda Economic Association, the data collection received an additional boost in October. Embedding the survey into day-to-day activities of respondents helped us to overcome concerns about initiating or prolonging human interactions that would not occur otherwise. The key advantage of mainly relying on university students as volunteers is that many own a smartphone, and in both Kenya and Uganda were scattered across the country as universities had halted on-campus activities and many returned to their families. University students and NGO staff members are highly educated thus alleviating interpretation fears with regards to our online tool as well as ensuring high data quality. Kenya's outstanding mobile network coverage also allowed volunteers located in remote parts of the country to participate. In Uganda, we expected some gaps in rural coverage and therefore partnered with an ongoing phone-based survey (Mahmud and Riley, 2021) to complement our data in rural areas. Through the phone survey we collected four rounds of data in two western districts of Uganda, Kagadi and Kyenjojo.[10]

Over the survey period our network of about 250 volunteers collected over 26,700 and 12,600 geo-coded price quotes in Kenya and Uganda respectively.[11] Figure 9 shows the daily number of collected price quotes. The online survey listed 40 pre-selected products that are purchased by households on a frequent basis, are available nationwide in both countries, and either carry substantial weight in the official consumer price index or have easily identifiable product origins. Through the last criterion we ensured that for a sufficiently large subset of products their product origin can be easily identified. While restricting the survey to a smaller selection of items could help to focus volunteers and control geographic coverage of specific items, our pilot data showed that responses naturally often covered the same 10-15 items.[12] For the purpose of this report we restrict the sample for Kenya to 17 popular items and to 11 items in Uganda for which we report

[10] The last wave of the data collection is still ongoing as off April 2021. We thus do not rely on data from the phone survey in this report. Thus far the patterns from the phone survey closely align with ones in the online survey.

[11] Throughout the data collection period, we published regularly updated real-time price information on this dashboard https://www.kenyacovidtracker.org/prices.html.

[12] At the same time volunteers appreciated the flexibility and asked for an even wider range of products to be covered in the survey.

key summary statistics in Tables 1 and 2. Rice has been the most popular item in both contexts.

Table 1: Kenya - summary statistics

Item	Quantity	N	N/month	Avg.price	Sd price	#brands	#counties
Rice	1 kg	2,072	156	123	44	11	39
Bread (white)	400 g	2,061	153	49	6	15	38
Sugar	1 kg	1,556	109	112	14	8	37
Eggs	one	1,556	163	13	3	1	42
Wheat flour	2 kg	1,338	96	128	15	13	39
Maize flour (sifted)	2 kg	1,323	98	121	18	17	39
Milk (fresh, packaged)	500 ml	1,246	88	51	9	14	39
Bread (brown)	400 g	1,104	82	49	7	11	40
Tomatoes	one	1,070	111	7	3	1	38
Banana (ripe)	one	967	100	8	4	1	39
Cooking oil	1 litre	777	52	170	39	10	40
Onions (bulbs)	1 kg	770	80	66	34	1	33
Cabbage	one	672	73	46	30	1	38
Avocado	one	657	73	19	10	1	35
Mango	one	628	72	18	10	1	35
Soda/Soft drink	300 ml	576	64	30	8	1	37
Salt	1 kg	352	21	39	15	5	32

Prices are denoted in Kenyan shilling.

Table 2: Uganda - summary statistics

Item	Quantity	N	N/month	Avg.price	Sd price	#brands	#districts
Rice	1 kg	1,224	264	3,740	1,751	9	58
Bread (loaf)	400 g	838	134	4,543	719	5	49
Beans (dry)	1 kg	771	132	3,587	761	2	48
Sugar	1 kg	761	190	3,357	520	7	51
Eggs	one	526	81	413	99	1	42
Avocado	one	425	70	649	323	1	41
Groundnuts	1 kg	348	45	5,700	1,190	1	37
Maize flour (sifted)	2 kg	333	76	2,020	567	11	37
Tomatoes	one	318	54	248	171	1	37
Banana (ripe)	one	192	44	337	277	1	39
Salt	1 kg	182	45	2,128	1,040	6	37

Prices are denoted in Ugandan shilling.

To track the quality of the data, we closely monitored our survey and periodically reached out to individual respondents whenever we found implausible entries. In cases of obvious typos and misunderstandings of the survey, corrections were made. Finally, we standardised prices for each item to the quantities and measurements reported in the summary tables. For fruits and vegetables volunteers mostly found it easier to record the prices for an individual item instead of a standardised unit of measurement. Acknowledging the caveat that mango, avocado, cabbage, and tomato sizes might vary substantially, we opted for sticking with this preferred measurement.

3.2 Product origins

For a subset of branded items where the product origin can be easily pinned down, we further collected information on factory locations through a phone survey and online research. We aimed to validate each product origin by at least two sources, e.g. the producers annual report and a phone conversation with a sales manager.

3.3 Government response measures

We further collected detailed information on policy response measures by the Government of Kenya and the Government of Uganda considering both national and local branches of government. Our main source of information are public announcements in government gazettes. The information was complemented by news reports.

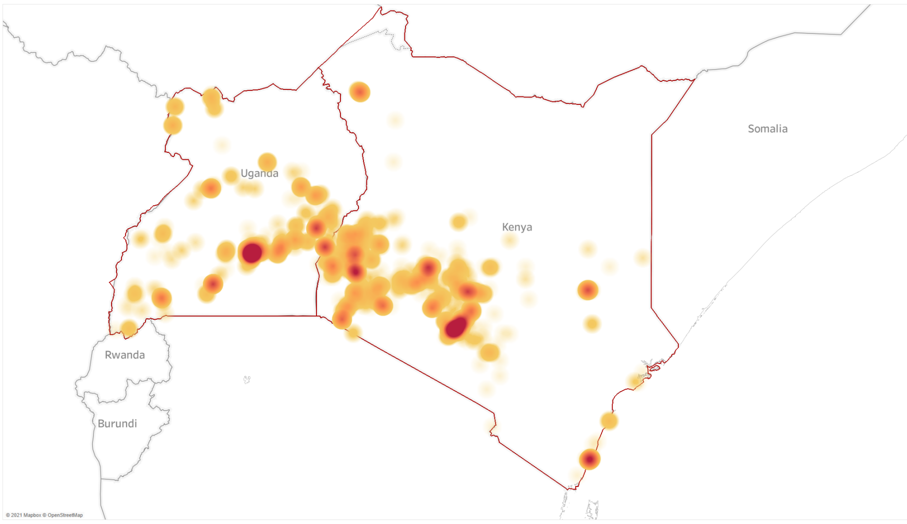
4 Data description

4.1 Mapping price quotes

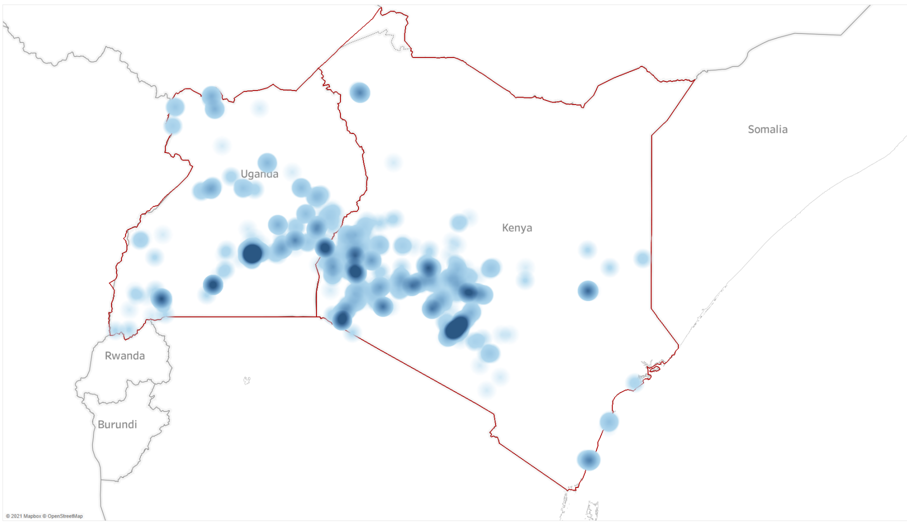
Our data collection succeed in its primary goal to achieve a wide geographic scope and generate high-frequency output. The number of collected price quotes further highly correlates with population density. In Figure 1 we map the geography of the overall number of responses for rice, sugar and eggs. Darker areas indicate a higher density of price quotes. For the two most popular items rice and bread, we collect at least one response in 39 out of Kenya's 47 counties during the course of data collection period (see Table 1). The maps further highlight a consistent geographic pattern across items and also across time (see Figure 15). Across Kenya and Uganda the sample is skewed towards urban areas. In Uganda, we only cover the most populous districts (see Figure 16) and 50% of the price quotes used in the following analysis have been recorded in the Greater Kampala region. For more details on the geographic coverage of the data and correlations with indicators such as population density, mobile phone coverage and internet access, see Appendix section 8.2.

Figure 1: Geographic dispersion of price quotes for popular items

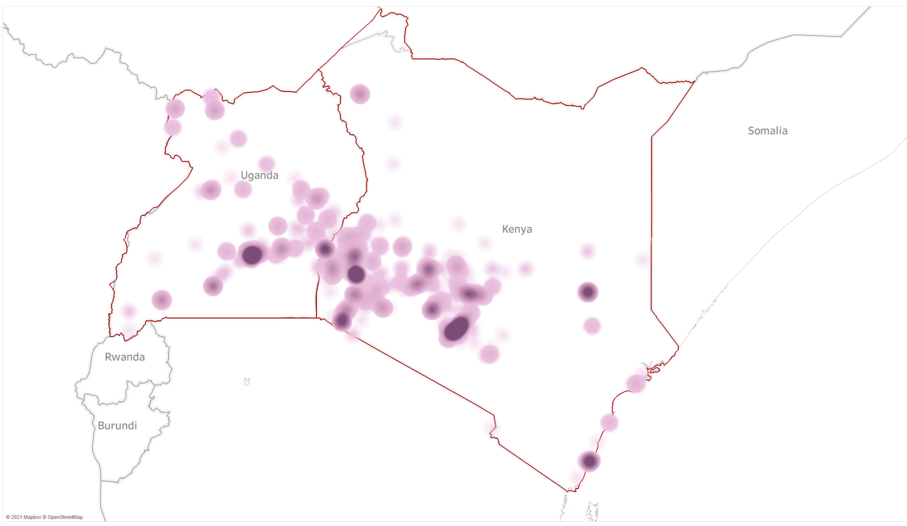
Rice



Sugar



Eggs



The above maps plot the geographic dispersion of the collected price quotes for rice, sugar and eggs (from top to bottom). Darker colours indicate a greater density of price quotes. Lighter colours indicate fewer price quotes.

While our sample of respondents is not representative of the wider population, their shopping locations overlap more closely with the wider population. General shops and kibandas - the most ubiquitous forms of retail in both Kenya and Uganda - are well-represented and are the most frequently observed retail locality for all items (see last columns of Tables 1 and 2). However, our respondents are more likely to shop at supermarkets and less likely to record price information from open air markets. This is important to keep in mind given prices for the same item and brand tend to be higher at supermarkets (see Figure 18).

4.2 Benchmarking

We further benchmark the data against available alternative sources. In Kenya we are able to compare them to monthly national average prices published by both the Kenya National Bureau of Statistics (KNBS)[13] and the Famine Early Warning Systems Network (FEWS).[14] in Figure 10 and 11. Unfortunately, the KNBS varies the selection of items for which the item-level national average price is reported in their monthly price bulletin. For the FEWS we are only able to obtain prices for cooking oil, maize flour, bread and milk. Other key limitation of this benchmarking exercise is that (i) the detailed brand for which KNBS and FEWS collect prices are unknown and we hence compare the prices to the simple average across all observed brands in our sample, and (ii) FEWS and KNBS' data collection are limited to Nairobi in the case of the former, and mainly urban centres[15] in the case of the latter. We therefore additionally report the comparison with the average prices for Nairobi in Figure 12. The observed trend provides evidence that our price averages for maize flour, cooking oil, pasteurised milk and bread for Nairobi did not differ systematically from those reported by FEWS and KNBS. We had to scale tomato and mango prices to a kilogram to make them comparable to KNBS prices - the overall price trend, however, looks the same if only one fruit is considered as the standard unit. As for sugar, wheat flour and tomatoes, the trends look generally similar even after overlaying the 2019 KNBS national averages.

In Uganda, we benchmark the average price of each of the 11 commodities from the price survey against the average price for the same commodity compiled by the Uganda Bureau of Statistics (UBoS) in the same period (see Figure 14). UBoS prices are collected from ten centers across the country. Albeit we are unable to compare prices at the beginning of the lockdown period, both UBOS and survey prices depict a declining trend with the easing of COVID-19 mitigation measures. Some of the discrepancies between UBoS prices and the price survey are likely driven

[13] We extracted the data from monthly inflation reports for the years 2019, 2020 and the first two months of 2021. See February 2021 as an example: https://www.knbs.or.ke/?wpdmpro=cpi-february-2021

[14] https://fews.net/fews-data/337

[15] https://www.knbs.or.ke/?p=5171

by the bias towards more price quotes from Greater Kampala (see 1), where prices generally tend to be higher than in the rest of the country.[16] Similar to Kenya, we overlaid historical data for 2019 from UboS, highlighting the seasonality of some products and the generally lower price levels in the second half of the year.

The price of beans gradually declines from June, only to rise up slightly around September/October, before resuming the fall. Survey prices of maize flour, sugar, and tomatoes move consistently with UBoS compiled prices, indicating high prices in June and a gradual fall thereafter. Similarly, bread and avocado prices in both sources depict a falling trend and a gentle rise around September/October. Egg prices from both the survey and UBoS pick up following improved demand due to a recovery led by partial easing of the containment measures where the main consumers mainly hotels and restaurants were allowed to operate as outside caterers and as "take outs". The initial spike in rice prices in the survey data is mainly driven by the Kampala bias early on in the data collection. Higher priced, imported rice brands are more prevalent in Greater Kampala.

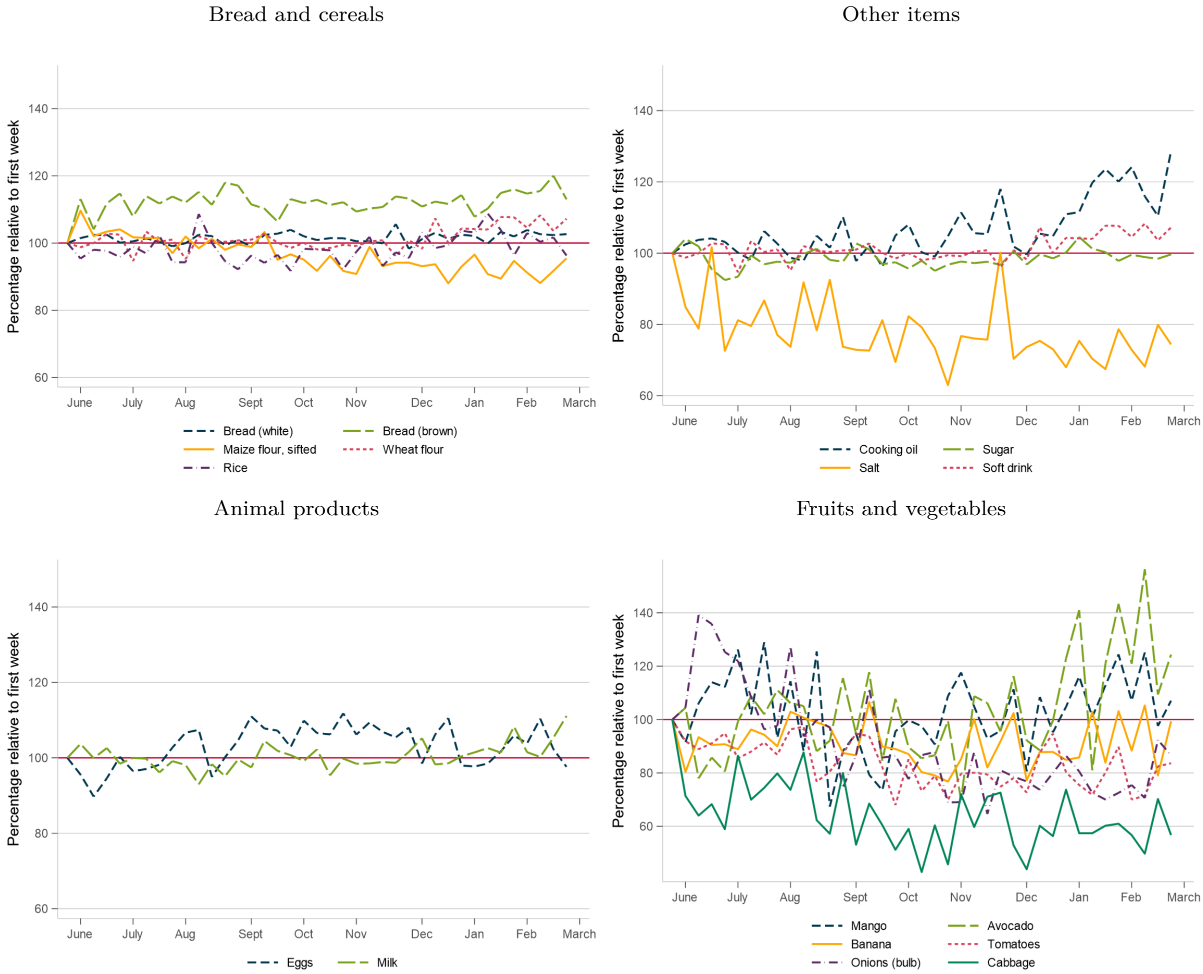
4.3 Price fluctuations across product groups

To get a first insight into price fluctuations observed in the collected price data, we normalise prices to the first week of our full-scale data collection - i.e. the last week of May and first week of August in Kenya and Uganda respectively. We plot the relative changes in prices in Figure 2 and 3. In both Kenya and Uganda prices for bread, cereals, sugar and animal products have been remarkably stable throughout the data collection period. Fruits and vegetables on the other hand are more seasonal and prices tend to fluctuate. Note that the unit price for items like salt is relatively low and small deviations therefore look more extreme in relative terms. Comparing our findings for Kenya and Uganda to global patterns, the FAO's global Food Price Index documents a steep rise in sugar and vegetable oil prices since the start of the pandemic.[17] While we also document a recent increase in prices for cooking oil in Kenya, sugar prices have been stable throughout the pandemic. This could be partly driven by a substantial share of domestic sugar production. 38% of all sugar prices recorded are for a domestically produced brand of sugar, another 31% captures prices for non-branded - likely also domestically produced - sugar.

[16] By including item-level fixed-effects in all specifications below, we control for the potentially higher average price levels picked up by the survey.

[17] http://www.fao.org/worldfoodsituation/foodpricesindex/en

Figure 2: Kenya: Weekly variations in food prices by product group



This graph compares weekly price fluctuations over time for different product groups in Kenya. Prices are normalised to the last week of May 2020, the first week of the scaled up data collection.

Figure 3: Uganda: Weekly variations in food prices by product group

This graph compares weekly price fluctuations over time for different product groups in Uganda. Prices are normalised to the first week of August 2020, the first week of the scaled up data collection.

5 The evolution of price dynamics during the Covid-19 pandemic in Kenya and Uganda

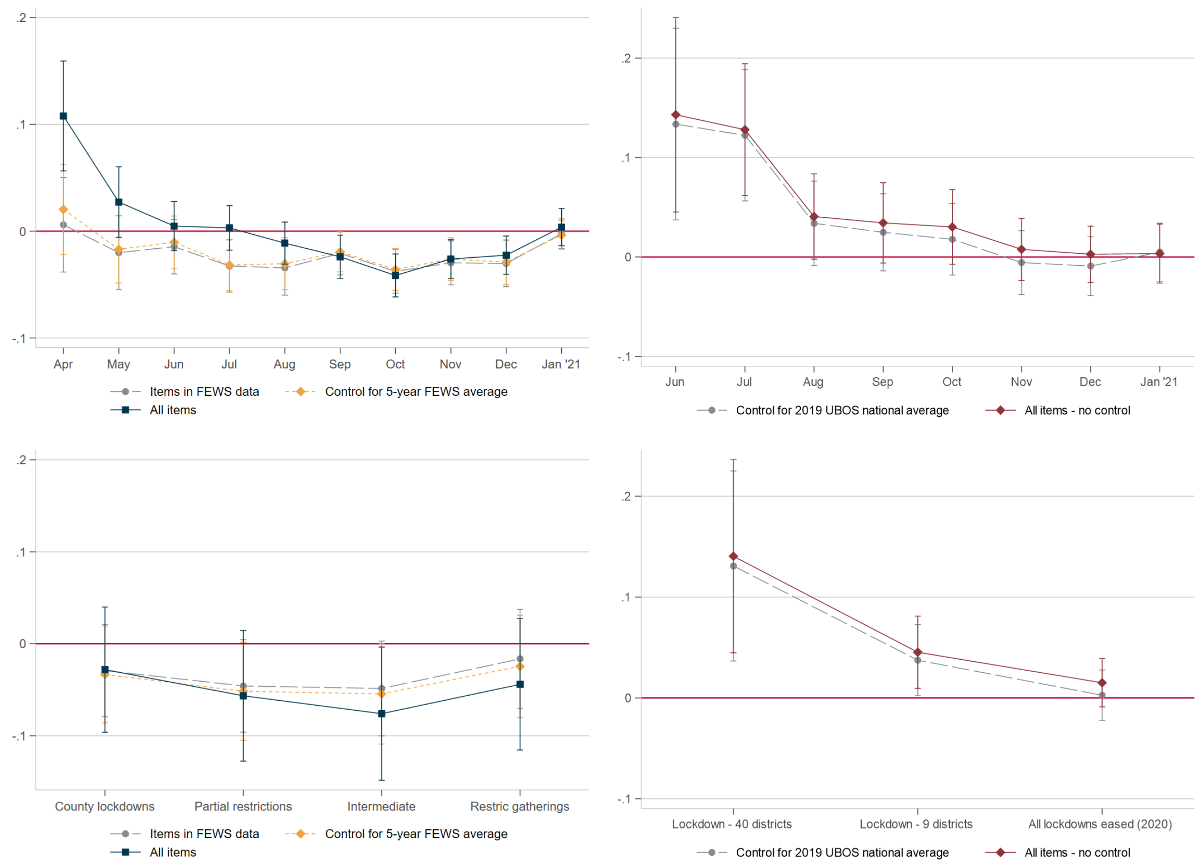
To study the impact of the Covid-19 shock on prices for essential consumer products, we firstly employ an event study approach. Given the lack of baseline data prior to the first lockdown phase, we use prices in the final weeks of our data collection in February and March 2021 as the comparison group. Figure 4 shows that prices have indeed been higher during the initial shutdown in Kenya in April and May 2020 when passenger travel in and out of specific counties were restricted and several market places still closed down. The estimates for Uganda suggest a prolonged impact of the Covid-19 shock on retail prices that continues into June and July, the two months in the immediate aftermath of the national lockdown. The results indicate that the initial effects have been of a similar magnitude - with the caveat that we do not observe prices in April and May in Uganda. As an alternative specification to using monthly indicator dummies in our event study design, we divide our study period into different phases based on containment policies.[18] This alternative approach, however, yields little additional insight (see Figure 4).

A key limitation of our analysis is that our data does not allow us to control for seasonality. To partly address this issue, in an alternative specification, we control for historical 5-year monthly average prices relying on the sub-sample of four items for which FEWS publishes monthly item-level price data for Nairobi. The estimated price effect in April and May now becomes indistinguishable from zero. However, we cannot rule out that this is driven by sample selection as the price effect is zero even in April for the sub-sample for which FEWS prices are available. In Uganda, the results are unchanged if we control for the national average price in the same month in 2019 reported by UBoS. UBOS prices are available for all items in our sample.

[18] Following a similar approach in Lowe et al. (2020) for India.

Figure 4: Price dynamics for April 2020 - mid-March 2021

Kenya Uganda

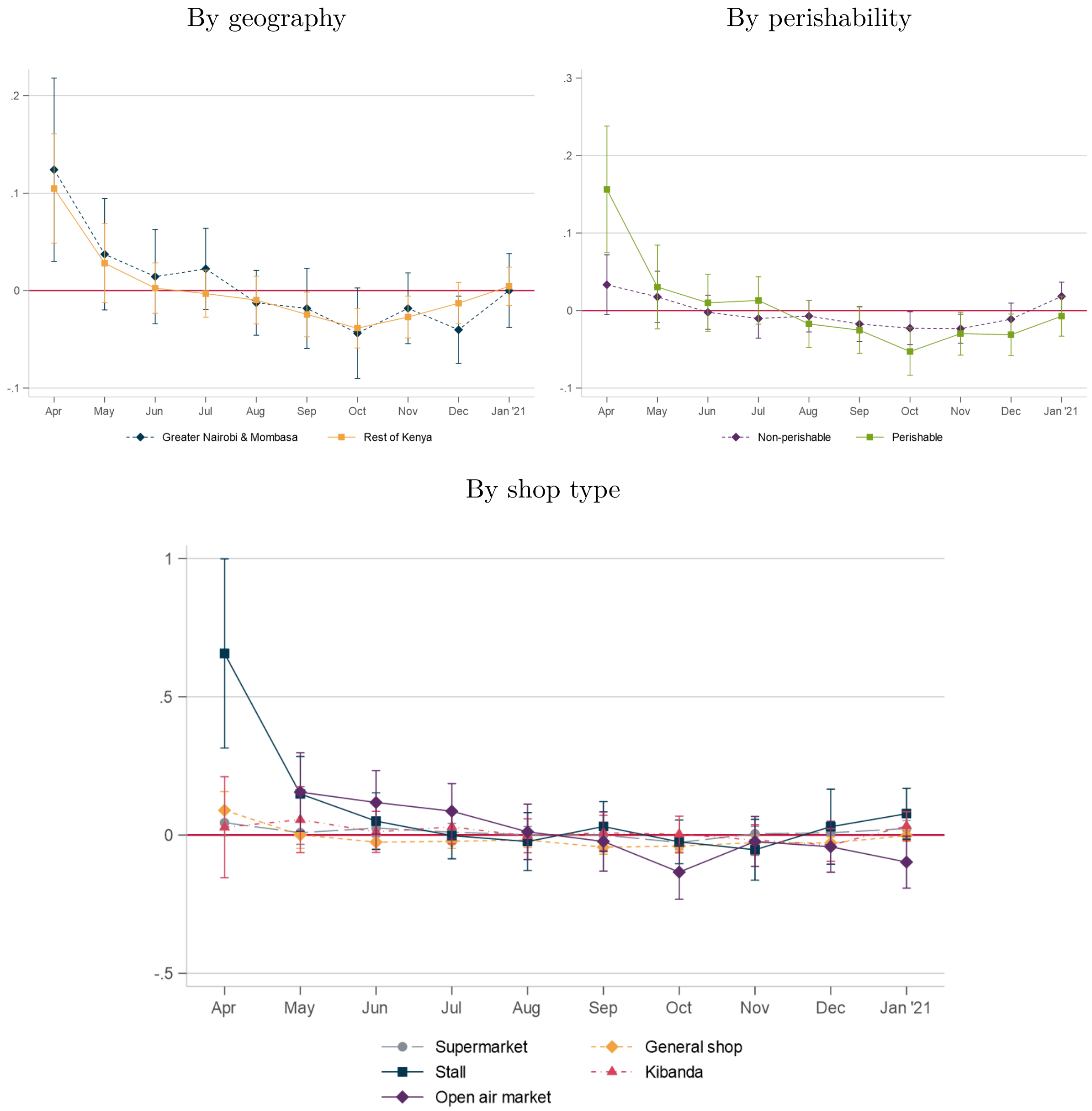


In the above graphs we regress the log price on a series of monthly time dummies. We further include item, brand and county/district fixed effects. Prices are winsorised at the 1% level. Standard errors are clustered at the item-district/county level. The error bars show the 95% confidence intervals. For Kenya, the data covers the time period between the last week of March 2020 until the first week of March 2021. For Uganda, the data covers the time period between the last week of May 2020 until the second week of March 2021. We further show the results for an alternative specification where we control for historical price trends. In Uganda control for the national average price in the same month in 2019 (grey plot), which is available for all items included in our sample. For Kenya, we show two alternative specifications. First, we restrict the sample to the four items for which historic FEWS data are available (grey plot). Second, we control for the 5-year average price in the corresponding month (orange plot). In the bottom graphs we divide the sample into phases with which government restrictions were lifted. We define the phases as follows: **Kenya:** The first phase (not shown in the plot) spans the period 27th March to 5th April and was marked by the first wave of Covid-19 response measures, most importantly market closures and restaurant closures. The second phase runs from 6th April to 6th July and marks the time when travel restrictions in and out of Nairobi and Mombasa (plus a few other counties) were in place. The third phase from 7th July until 29th September captures the period when major restrictions on the hospitality sector, domestic and international travel were sequentially lifted. During the intermediate phase only few restrictions, like the nighttime curfew, remained in place. In the final phase, starting 3rd January 2021, public gatherings and events were again prohibited. **Uganda:** The first phase spans the period 26th May to 29th June 2020 and was marked by the easing of Covid-19 response measures across Uganda. However, during this phase 40 border districts remained in lockdown. The second phase runs from 30th June to 23rd September and marks the time when only 9 border districts still had lockdowns imposed. The third phase runs from the date those final lockdown measures were lifted until the end of 2020, i.e. three months after the last lockdown. The final phase (not shown in the plot) combines all data points for 2021. The final split allows us to show the trend for some of the post-lockdown phase.

As a next step we investigate whether the results are driven by a specific product category, geography or shop type. Travel restrictions in and out of the metropolitan areas of Greater Nairobi and Mombasa did not have a differential impact on price dynamics compared to the rest of Kenya (see top-left graph of Figure 5). This suggests that the travel restrictions aimed at restricting passenger travel have been successful in its goal to keep disruptions to the transportation of cargo to a minimum. In Uganda, we find evidence that the price level in the 40 border districts which remained in lockdown throughout June 2020 while the rest of the country was opening up, remained higher even for July.[19] Despite the lockdown restrictions being lifted, prices in the metropolitan area of Greater Kampala also remained higher than in the rest of Uganda for the month of July. This could be driven by supply chain disruptions for imported varieties, e.g. of rice, that are more widely consumed in Kampala or supply chain disruptions for fresh items cultivated in rural areas of Uganda. In both Kenya and Uganda, we can observe similar patterns for both perishable and non-perishable items. While the price spike in Kenya can be observed across a range of different retail outlets; supermarkets, general shops, and stalls, the effect is most pronounced for stalls and prices in this retail category remain higher in May. Only prices for kibanda's remain unchanged throughout. In Uganda the pattern is less clear, but prices in stalls seem to be more variable.

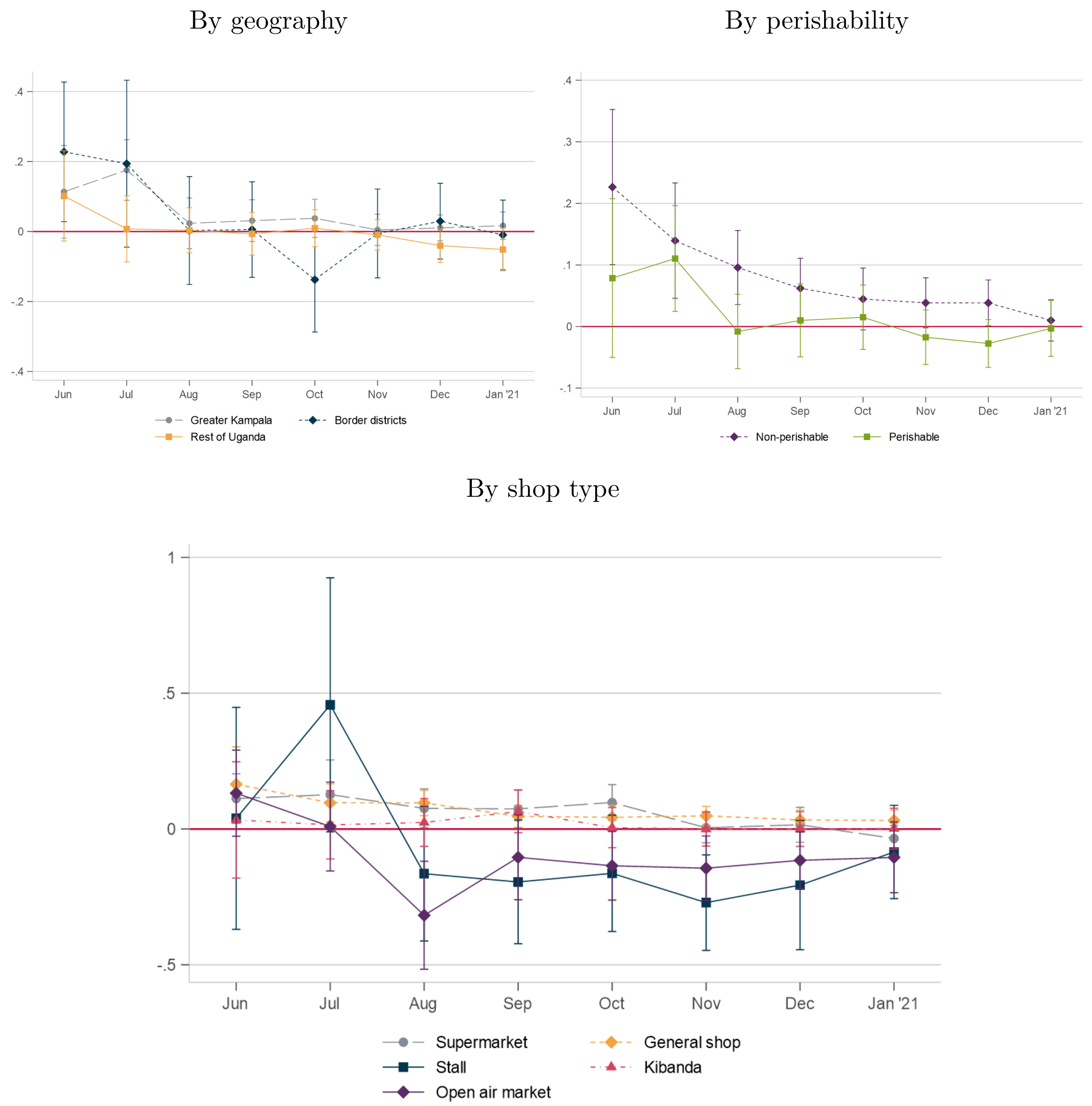
[19] Unfortunately, the collected data for the nine border districts that had restrictions in place until late September is sparse and we are therefore unable to separate them out for the purpose of this exercise.

Figure 5: Kenya - Price dynamics for April 2020 - February 2021



In the above graphs we regress the log price on a series of monthly time dummies. We further include item, brand and county/district fixed effects. Prices are winsorised at the 1% level. Standard errors are clustered at the item-county level. The error bars show the 95% confidence intervals. In the first graph we distinguish between the Rest of Kenya and Greater Nairobi and Mombasa, which have seen travel restrictions imposed between 6th April and 7th July 2020. The second graph presents a disagregation by item type. In the third graph we distinguish by shop type. The pattern does not change if we further pool the coastal counties of Kilifi and Kwale with Greater Nairobi and Mombasa. The two counties saw travel restrictions imposed between 6th April and 6th June 2020. We define Greater Nairobi as the counties Nairobi and Kiambu.

Figure 6: Uganda - Price dynamics for June 2020 - mid-March 2021



In the above graphs we regress the log price on a series of monthly time dummies. We further include item, brand and county/district fixed effects. Prices are winsorised at the 1% level. Standard errors are clustered at the item-district level. The error bars show the 95% confidence intervals. In the first graph we distinguish between Greater Kampala, the border districts which were under prolonged lockdowns, and the rest of Uganda. The second graph distinguishes between perishables and non-perishable items. In the third graph we distinguish by shop type. We define Greater Kampala as the districts of Kampala, Wakiso, Mukono, Mpigi, Buikwe, and Luwero.

6 Linking mobility patterns and price dynamics

The pandemic has altered economic and social interactions through temporary or permanent business closures, changes in consumption due to income losses, but also reduced levels of commuting. Many of these changes persisted beyond the initial lockdown phase (see for example

Mahmud and Riley (2020); Pape et al. (2020); Egger et al. (2021)). We therefore further look at the impact of changes in mobility patterns on price dynamics. This will help us to get a better understanding of price dynamics not only during, but most importantly also after the lockdown period. We find that prices are lower as activity at workplaces, grocery, and retail-related localities increases.

To measure the change in mobility patterns and activity levels at specific localities, we rely on daily indices capturing movements trends from Google's Community Mobility Reports [20] The published measures capture the change in activity levels at different types of localities relative to a 5-week baseline period between 3rd January and 6th February 2020 at the county (Kenya) or district (Uganda) level. For each day the indices capture the percentage change in activity relative to the median activity level on the same weekdays during the baseline period. The measures therefore already account for differential mobility patterns on weekends relative to working days.

Figure 7: Variation in activity levels across different categories of locations

The graphs compare the variation in activity levels across time for three different Google mobility indices. The daily index is reported at the county level in Kenya and at the district level in Uganda. Each dot represents a county-day (district-day) observation.

Figure 7, shows the evolution of changes in activity levels for both Kenya and Uganda between March 2020 and March 2021. The first insight is that, unsurprisingly, the most drastic change for both countries is picked up in April when imposed government-restrictions were at their height. While the drop off is rather sudden - in particular in Uganda - the recovery is more gradual and stretches several months. Workplace-related activities, and to some extent also activities at grocery and pharmacy-related localities, recover sooner than those linked to retail

[20] https://www.google.com/covid19/mobility/ Google compiles the underlying data from the location history of Google users (Aktay et al., 2020).

and recreation. Given our focus on retail prices of essential consumer products, our two preferred indices to capture changes in mobility patterns are the index for Grocery and Pharmacy and the index for Retail and Recreation-related localities. Unfortunately, the geographic coverage of the two indices is not as comprehensive and not as stable over time as it is for the workplace index (see Figure 19 and Figure 20). We therefore instead use the workplace index as our default measure for changes in mobility. The downside of using the workplace index is that (i) if mobility patterns mainly capture the demand side effect of the economic shock, workplace mobility might not be as relevant, (ii) during certain periods of the year it moves counter-cyclical to retail activities, e.g. during the holiday season in December and early January. We discuss the geographic coverage of the mobility index and changes in mobility patterns over time in more detail in the appendix (see Section 8.5).[21]

Table 3: Price dynamics and mobility

	Kenya	Uganda
Mobility	-0.032	-0.147***
	(0.029)	(0.054)
No. observations	16627	3986
R2 adj.	0.927	0.928
R2 adj. within	0.000	0.003
Item FE	Yes	Yes
Brand FE	Yes	Yes
Shop type FE	No	No
Month FE	Yes	Yes
Admin FE	No	No

In the above table we regress the log price on the Google mobility index (workplace) while controlling for item, brand, and month fixed effects. Standard errors are clustered at the item-district/county level. Prices are winsorised at the 1% level. The Google mobility index captures the level of activity at a specified category of locations relative to a baseline period in January and February 2020. *; **; and *** denote significance at the 10; 5; and 1 percent levels respectively.

Using changes in mobility patterns to study price dynamics during the lockdown and re-opening period, we find that retail prices decline as activity levels increase relative to the baseline period (see Table 3). In Uganda, a 10 percentage point difference in the change in mobility leads to a 1.4% decline in prices. In Kenya the estimated effect size is much smaller: prices respond only with a 0.3% decline. In addition, for our preferred specification, we can't reject the null hypothesis that the coefficient is indeed zero at the 10% level. In the main specification, we include month fixed effects, alongside item, and brand fixed effects. We therefore rely on vari-

[21] In Table 8 and 9 we report additional summary statistics for the sub-sample of price quotes that we are able to map to the workplace mobility index. In Uganda we can map 63% of the price quotes and 68% in Kenya. Both the average price and standard deviation are very similar to the full sample.

ation in changes of mobility patterns across space and within the same month.[22] To test for the robustness of our results, we run a number of alternative specifications. In column 1 of Table 4 and 5 we only include item and brand fixed effects and thereby rely on both spatial variation as well as on the time dimension in the data to estimate the coefficient of interest. The effect size increases in both context, with the coefficient for Uganda being larger by a sizeable magnitude. Next we control for administrative unit fixed effects to control for the role of location specific characteristics such as a historic difference in price levels due to local market characteristics (column 3). The coefficient remains fairly stable for Kenya if we include county fixed effects, i.e. we only rely on the variation in mobility across time. In Uganda, including district fixed effects leads to a lower, but still negative coefficient (see column 3). If we instead rely on variation in activity levels within the same months and across counties (by including month fixed effects in column 2), we can no longer reject the null hypothesis that the coefficient is indeed different from zero in Kenya. It, however, remains stable in Uganda meaning that regardless of whether we rely on variation in prices and mobility across time or space, we obtain almost identical results. Given the variation in prices across shop types, we further include shop type fixed effects in column 4 of Table 4 and 5. In Kenya the coefficient becomes more clearly indistinguishable from zero, while the coefficient in Uganda is still negative and sizeable, but less precisely estimated. Including shop type fixed effects of course does not account for a potential bias that originates in selection. For example, supermarkets are less common in largely rural counties/districts, but these are also areas where mobility was impacted to a lesser extent than in more urbanised counties/districts. The same might hold true across time, in the sense that smaller retail outlets might have been more likely to close down when activity levels were at a minimum. This could be an interesting area for future research.

In column 5, we then restrict the sample of included price quotes to dates after the data collection was scaled up (June in Kenya and August in Uganda). This specification allows us to (i) test for the sensitivity of the results to a period with less robust data quality, and (ii) shows that the results are not solely driven by dynamics during the initial shutdown periods. The coefficient results are largely unchanged relative to the main specification. In column 6, we do not winsorise prices at the 1% level, which also does not alter our headline findings.

Finally, we swap out the measure for activity at workplaces for the grocery and pharmacy index (column 6) and the retail and recreation index (column 7) for the restricted sample of administrative units for which the two measures are available. For Grocery and Phamcy the coefficient in Uganda becomes indistinguishable from zero, while in Kenya the absolute effect size increases.

[22] Results are largely unchanged if we include week or day fixed effects. Results are available on request.

In contrast the results relying on the retail and recreation index are even more pronounced than for the workplace mobility index. A 10 percentage point decline in mobility is associated with a 1.5% increase in prices in Kenya and a 2.1% increase in Uganda. In Uganda we can rule out that this is largely driven by sample selection. If we re-run the main specification for the sample where the grocery index or the retail index is available respectively, the coefficient is largely unchanged, but becomes less tightly estimated. In Kenya, the coefficient for workplace mobility is more precisely estimated for the sub-sample for which the retail index is available, while the one for grocery is similar to the baseline results. The results indicate that in particular the retail price index seems to pick up different relevant variations in prices that are not associated with workplace mobility patterns, in particular during the holiday season.

Prices for imported products might have experienced additional shocks due to disruption in global supply chains. The pandemic came with tight border restrictions, mainly for air travel, but border controls for cargo crossing between Kenya and Uganda, as well as with Tanzania - another important origin for imported varieties, became tighter.

In Kenya we observe only few prices for imported products (mainly specific rice brands) and are therefore unable to explore this dimension. In Uganda, a considerable subset of products are imports, mainly from India, Pakistan, Kenya, and Tanzania.[23] We find that price dynamics for imported products run in the opposite direction compared to domestically produced products. Here we find a strong positive association between mobility and prices: A 10% increase in mobility leads to a 8.5% increase in prices for imported products. This effect could be both driven by supply shortages due to additional obstacles for cross-border shipments, but also a fall in demand for typically higher priced imported products. It is further not implausible to assume that the two effects reinforce each other.

6.1 Price dynamics and the length of supply chains

To investigate the role of supply chains - in particular their length - we compute the distance to the product origin. Our approach follows Atkin and Donaldson (2015) and is limited to branded products in our sample. We are able to pin down the product origin for 9 out of 17 products in Kenya and for 5 out of 11 products in Uganda.[24] We are, however, unable to match each price quote to a brand for which we know the origin given a large number of locally produced, non-branded alternatives, e.g. in the case of rice and sugar, and the large variety of brands for some the items like maize flour (see Table 8 for details on number of price quotes we are able to

[23] We assume that all non-branded items are domestically sourced.

[24] For now we use greater circle distance as our distance measure.

Table 4: Kenya - price dynamics and mobility

	Basic	Month FE	Admin FE	Shop type FE	Post scale up	Non-winsorised	Grocery	Retail	Distance to origin
Workplaces	-0.053**	-0.032	-0.051**	-0.024	-0.030	-0.026			-0.008
	(0.027)	(0.029)	(0.023)	(0.029)	(0.029)	(0.030)			(0.014)
Grocery and pharmacy							-0.089*		
							(0.048)		
Retail and recreation								-0.168***	
								(0.049)	
Distance to product origin									0.003
									(0.003)
No. observations	16627	16627	16627	16310	15786	16627	9440	11154	7453
R2 adj.	0.927	0.927	0.930	0.928	0.928	0.917	0.931	0.931	0.916
R2 adj. within	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.005	0.000
Item FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shop type FE	No	No	No	Yes	No	No	No	No	No
Month FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No
Admin FE	No	No	Yes	No	No	No	No	No	Yes

In the above table we regress the log price on the Google mobility index (workplace) while controlling for item, and brand fixed effects. Standard errors are clustered at the item-county level. The Google mobility index captures the level of activity at a specified category of locations relative to a baseline period in January and February 2020. *; **; and *** denote significance at the 10; 5; and 1 percent levels respectively.

Table 5: Uganda - price dynamics and mobility

	Basic	Month FE	Admin FE	Shop type FE	Post scale up	Non-winsorised	Grocery	Retail	Imports	Distance to origin
Workplaces	-0.209***	-0.147***	-0.131*	-0.117**	-0.152***	-0.147***			-0.164***	-0.063
	(0.063)	(0.054)	(0.072)	(0.051)	(0.051)	(0.054)			(0.053)	(0.064)
Grocery and pharmacy							-0.005			
							(0.063)			
Retail and recreation								-0.239*		
								(0.120)		
Mobility*Import									0.617**	
									(0.279)	
Distance to product origin										0.016
										(0.012)
No. observations	3986	3986	3986	3927	3695	3986	2548	2895	3986	1142
R2 adj.	0.927	0.928	0.928	0.929	0.931	0.923	0.923	0.924	0.928	0.679
R2 adj. within	0.008	0.003	0.003	0.002	0.003	0.003	-0.000	0.002	0.005	0.002
Item FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shop type FE	No	No	No	Yes	No	No	Yes	No	No	No
Month FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No
Admin FE	No	No	Yes	No	No	No	No	No	No	Yes

In the above table we regress the log price on the Google mobility index (workplace) while controlling for item, brand, shop type and month fixed effects. Standard errors are clustered at the item-district level. The Google mobility index captures the level of activity at a specified category of locations relative to a baseline period in January and February 2020. *; **; and *** denote significance at the 10; 5; and 1 percent levels respectively.

match to origin information).[25]

The estimated correlation between changes in mobility and retail prices becomes indistinguishable from zero if we control for distance to product origin. In the rightmost column of Table 4 and 5 we include distance to the product origin as an additional control variable in our specification with county and district fixed effects.[26] However, we cannot rule out that this is partly driven by sample selection: The baseline results for the sub-sample for which we are able to identify product origins is zero even without controlling for distance to the origin (see column

[25]In cases where multiple origins are identified, the origin closest to the destination is considered the relevant one.

[26]We obtain similar results if we use the main specification. We, however, prefer this specification as not including admin unit fixed effects results in the distance measure picking up a lot of product destination-specific variation.

2 of Table 6 and Table 7)[27]. This suggests that the observed mobility patterns largely affect prices for non-branded items. To assess the stability of this result, we further report alternative specifications where we (i) interact mobility with distance, (ii) exclude localities where origin and destination coincide, (iii) we control for mobility at the product origin. Lastly, we look at the impact of mobility on price gaps between product origin and destination.

Interacting mobility and distance, excluding the origin, and controlling for mobility at the origin does not change the null result in Kenya.[28] However, in Uganda the negative impact of mobility on distance is more pronounced for localities that are further away from the product origin. In addition, mobility at the origin itself also has a strong negative effect on prices.[29] A potential explanation for this result could be that a reduced level of activity at workplaces picks up disruptions to production and reduced work hours, which then result in supply shortages.

Interestingly, in both Kenya and Uganda, distance to the origin is negatively associated with the price level at the product destination once we exclude prices in the district/county of origin from the sample. This result indicates that within administrative units the local level of demand and/or the shape of the demand curve play a key role for the pricing of branded items across space.

Finally, we look at the impact on the gap between product origin and destination. In line with the literature (Atkin and Donaldson, 2015), we define the origin price as the retail price at the product origin.[30] While it remains the best proxy given the data we have available, uniform pricing models (DellaVigna and Gentzkow, 2019) that are likely particularly prevalent for branded items are just one reason for why the price gap between origin and destination prices might not be the most relevant metric of interest here. Most product origins are concentrated in the metropolitan areas of Greater Nairobi and Greater Kampala (this bias is particularly pronounced in Uganda), where the price level tends to be higher than in other parts of the country due to likely less elastic and higher levels of demand. This concern is backed by the previous finding that prices further away from the origin seem to be lower in both Kenya and Uganda. However, in both contexts we do find that within a county/district the price gap itself increases with distance to the origin. In both contexts, changes in the level of activity at the origin do not seem to impact the co-movement of prices. In Uganda, however, the price gap widens as the level of activity increases at the destination, which points towards a strengthened demand at the destination driving the result.

[27] Column 1 of Table 6 and Table 7 corresponds to the last column in Table 4 and Table 5.

[28] This remains unchanged if all three specifications are combined into one.

[29] The result again remains unchanged if we combine the interaction term and mobility at the origin in one specification. Neither does excluding the district of origin.

[30] In our specific case we winsorise origin prices at the 1% level and use the weekly average price.

In a nutshell, the attempt to throw the role of supply chains into the mix of factors explaining price dynamics lead to rather inconclusive results in Kenya. In Uganda, activity levels at the product origin play a key role, and prices at the destination fall more strongly the larger the distance between origin and destination. In the future, we hope to refine this analysis by measuring actual road distance, and including more products in Kenya.

Table 6: Kenya - mobility and the length of supply chains

	Basic	Check selection	Interaction	Exclude origin	Mobility at origin	Price gap
Mobility	-0.0075	-0.0071	-0.0262	-0.0063	-0.0133	0.0195
	(0.0138)	(0.0138)	(0.0385)	(0.0180)	(0.0216)	(0.0197)
Distance to product origin	0.0034		0.0039	-0.0095*	-0.0095*	0.0058**
	(0.0030)		(0.0030)	(0.0050)	(0.0050)	(0.0028)
Mobility*Distance			0.0042			
			(0.0097)			
Mobility at product origin					0.0178	-0.0236
					(0.0328)	(0.0293)
No. observations	7453	7453	7453	6186	6186	6300
R2 adj.	0.9163	0.9163	0.9163	0.9139	0.9139	0.1704
R2 adj. within	0.0003	-0.0001	0.0002	0.0011	0.0010	0.0011
Item FE	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Shop type FE	No	No	No	No	Yes	No
Month FE	No	No	No	No	No	No
Admin FE	Yes	Yes	Yes	Yes	Yes	Yes

In the above table we regress the log price on the Google mobility index (workplace) while controlling for item, brand and month fixed effects. Standard errors are clustered at the item-county level. The Google mobility index captures the level of activity relative to a baseline period in January and February 2020. The first column captures the baseline specification controlling for distance to product origin (last column in Figure 4). To check whether this result is potentially driven by the selection of products for which we observe the product origin, in column 2 we run the baseline specification without controlling for distance to origin. In column 3 we exclude prices where the origin and destination county coincide. To test for additional dynamics, we we add the interaction term of distance and mobility in column 4 and the mobility at the product origin in column 5. In the final column instead of looking at the price at the product destination, we look at the price gap between origin and destination (for cases where an origin price is available in a given week). *; **; and *** denote significance at the 10; 5; and 1 percent levels respectively.

6.2 Robustness: The role of data collection

By relying on a crowd-sourcing approach, a key concern is that mobility also drives the number and type of observed price quotes. We will underestimate the effect of mobility on prices, if we observe fewer prices during times when people are more inclined to stay at home and at the same time prices are indeed higher during these times. On the contrary, if more price quotes are recorded during times of a more pronounced reduction in activity, we expect to observe relatively more higher prices quotes and thus potentially overestimate the impact of mobility on prices. This concern might be valid given that we collected more price quotes right after the start of the scale up in Kenya (May/June 2020) and Uganda (August/September 2020) and

Table 7: Uganda - mobility and the length of supply chains

	Basic	Check selection	Interaction	Exclude origin	Mobility at origin	Price gap
Mobility	-0.0632	-0.0661	0.1458	-0.0363	0.1498	0.1880*
	(0.0640)	(0.0647)	(0.1333)	(0.0708)	(0.0958)	(0.1051)
Distance to product origin	0.0158		0.0080	-0.0312	0.0156	0.0312*
	(0.0120)		(0.0127)	(0.0214)	(0.0119)	(0.0169)
Mobility*Distance			-0.0617*			
			(0.0321)			
Mobility at product origin					-0.4322***	-0.1468
					(0.1572)	(0.1352)
No. observations	1142	1142	1142	879	1142	597
R2 adj.	0.6792	0.6786	0.6798	0.7162	0.6837	0.1281
R2 adj. within	0.0024	0.0005	0.0043	0.0055	0.0164	0.0067
Item FE	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Shop type FE	No	No	No	No	No	No
Month FE	No	No	No	No	No	No
Admin FE	Yes	Yes	Yes	Yes	Yes	Yes

In the above table we regress the log price on the Google mobility index (workplace) while controlling for item, brand and month fixed effects. Standard errors are clustered at the item-county level. The Google mobility index captures the level of activity relative to a baseline period in January and February 2020. The first column captures the baseline specification controlling for distance to product origin (last column in Figure 5). To check whether this result is potentially driven by the selection of products for which we observe the product origin, in column 2 we run the baseline specification without controlling for distance to origin. In column 3 we exclude prices where the origin and destination county coincide. To test for additional dynamics, we we add the interaction term of distance and mobility in column 4 and the mobility at the product origin in column 5. In the final column instead of looking at the price at the product destination, we look at the price gap between origin and destination (for cases where an origin price is available in a given week). *; **; and *** denote significance at the 10; 5; and 1 percent levels respectively.

slightly fewer in subsequent months due to attrition. In addition, volunteers might have had more time available to fill out the survey during times of the reduced activity. In additions the observed data collection could be driven by product availability. While we collected information on product availability through the price survey, the data from this module is rather sparse and barely detects any availability issues.

To test for the endogeneity of our data collection, we check whether the probability to observe a price quote is correlated with our measure of the change in activity levels. To do so, we first construct an indicator variable capturing whether or not a price quote has been observed for a given item on a given day in a given county/district. The variable takes a value of 1 if we do not observe at least one price quote in a specific item-day-location cell. We then regress the dummy variable on the mobility index controlling for item fixed effects (see Table 10). We find that changes in mobility are indeed correlated with the availability of price quotes. We collected fewer price quotes for days and locations where mobility has reduced less drastically relative to January and February 2020.[31] In the first few weeks of the data collection, the number of price quotes we observed was skewed towards Greater Kampala and Greater Nairobi. Both metropolitan areas

[31] A 10 percentage point decline in mobility leads to a 1 (1.1) percentage point reduction in the probability of observing a price quote in a specific item-day-location cell in Kenya (Uganda).

saw a more drastic decline in mobility than the rest of Kenya and Uganda (see Figure 20 and 19). As expected, we therefore see this effect to be more pronounced in the later periods where we observe the vast majority of the price quotes in locations outside the metropolitan areas. Due to structural differences between locations, e.g. because of differential price levels or differences in localities for which the mobility index picks up activities, we control for administrative unit fixed effects (counties/districts) in Table 12. By including location-related fixed effects we solely rely on variation across time to estimate the relationship of interest. Interestingly, the results now suggest a negative relationship between the change in mobility patterns and the probability of a missing observation (except for the restricted sample in Kenya). This suggests that relying on variation across potentially introduces a bias towards observing lower prices more often. As these effects might be driven by the roll-out of our data collection, we finally run the same regression with month fixed effects instead of location fixed effects. Here (Table 11) we rely on the variation in mobility changes within each month and also across localities. The suggested link between changes in mobility and the probability to not observe a price quote is again positive - this time slightly smaller in Kenya, but larger in Uganda. The standard errors suggest that the issue is indeed more prevalent in our data collection in Uganda.
The above results highlight that the likelihood of observing a price quote is indeed correlated with changes in mobility patterns. However, the direction of the bias depends on the type of variation used to estimate the relationship. Given our headline results linking price dynamics and mobility patterns remain unaffected by the type of variation used to estimate the relationship, makes us less concerned about this type of bias being the main driver of the results. In future work we hope to further investigate composition effects that not only takes into account whether or not we observe a price quote, but also looks at the share of price quotes from each type of shop and neighbourhood. This will help us to better understand whether mobility might have not only affected the types of price quotes we observe over time.

7 Conclusion

Given their importance for food security, food price dynamics have been a major concern for policy makers as the Covid-19 pandemic unfolded across the globe. Using a rapid response online survey we collected geo-coded, high-frequency retail price data in Kenya and Uganda during the initial shutdown period starting in April 2020 and the subsequent re-opening phase up until early 2021. In line with findings from other contexts, our estimates suggest that price levels for essential food items were higher during the initial phase of the pandemic. The impact was rather short-lived in Kenya, but continued for an extended period in Uganda where government restrictions were tighter and stayed in place for a more prolonged period of time. It is important to highlight that while price levels eventually fell back, even only temporarily higher prices likely had a substantial impact on food security Kansiime et al. (2021).

We further combine the price data with information on changes in visiting patterns of smartphone users at localities like workplaces, grocery stores and other retail locations. Our findings show that mobility patterns continued to have an impact on price dynamics beyond the initial shutdown phase. We estimate that a 10 percentage point reduction in mobility is associated with a 0.3% and 1.4% increase in food prices in Kenya and Uganda respectively. Although the result of a negative relationship between prices and mobility is stable across a number of empirical specifications, we cannot rule out that the effect is indeed zero in Kenya. The analysis provides insight into the economic impact of the Covid-19 shock in Kenya and Uganda, as well as into the general nexus between price dynamics and mobility patterns.

Like prices, activity levels at workplaces, grocery stores and retail locations simultaneously pick up supply and demand side dynamics. One potential interpretation of the findings points towards fewer retail businesses in operation on the supply side, which might have lead to higher prices during times of decreased mobility. Findings in other studies looking at business closures, in particular smaller, household-run businesses that dominate the retail sector, seem to support this interpretation. While only 4% of the Kenyan household-run enterprises surveyed by (Pape et al., 2020) report to have closed down permanently by June 2020, 40% of these operate in the retail and wholesale sector. Mahmud and Riley (2020) find that even by September 2020, 43% of all household-run businesses in Uganda remained closed. In addition, in order to stay in business, retailers faced with weaker consumer demand might have been forced to increase their margins on the reduced volume of items sold in order to stay afloat. Therefore, these supply effects could stem from (i) a reduction in working hours, (ii) business closures in the wholesale and retail sector, and/or (iii) retailers increasing their margins on sold items to be able to stay in business. An alternative explanation is that demand for food items has been stronger during the initial phase of the lockdown period as households prioritised food consumption over the consumption of durable goods. As the economic impact of the pandemic persisted, stockpiling might have declined and consumption levels reduced. While our analysis does not yield any further insights into the mechanisms, findings in the literature that point towards prolonged business closures and improved levels of food security (still at an alleviated level) over time (Mahmud and Riley, 2021; Pape et al., 2020) hint at the first interpretation.

Complementary evidence suggests that this effect is less likely to be primarily driven by supply

chain disruptions. The estimated relationship is stable if we restrict our sample to the post-lockdown period when supply chain disruptions due to travel restrictions were less acute.
In Uganda, the negative impact of local workplace activity on prices increases with distance to the product origin. An important caveat to the last result is that we are only able to track the product origin of branded products, a subset of products for which we do not observe a significant link between mobility and prices in our baseline specification.

The ongoing pandemic has fundamentally altered economic and social interactions across the globe and shifted market interactions in ways that reflect people's mobility patterns and the level of activity at workplaces and retail localities. We show that these dynamics matter for retail prices - even beyond periods with major government restrictions to passenger travel, market closures, and restrictions for the service sector. We benchmark prices from the survey against other sources like FEWs and KNBS in Kenya and UBoS in Uganda and find that the trend of price fluctuations from the different sources is generally similar during the survey period. The data collection serves as a proof of concept showing that it is possible to collect high-quality, high-frequency price data at scale through a crowd-sourcing approach. Such data can be used as a supplementary source of information for inflation. The methodology can be useful to policy makers and researchers to acquire real time price data and serve as a more frequent alternate source for national prices as well. A limitation of our approach lies in the challenge of collecting data in particularly remote regions that have limited internet connectivity. This can be addressed in future data collection endeavors through more targeted recruiting of volunteers in relevant areas. In addition, more crude measures (e.g. number of fruits) instead of standardized measures (e.g. kilogram) have to be used for items like fruits and vegetables. This is an important aspect to keep in mind for the interpretation of the data. Nevertheless, the study report shows that the trends in the data on fruits and vegetables prices closely align with those collected through traditional channels by the Uganda Bureau of Statistics and the Kenya Bureau of Statistics.

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Kibet Gideon, Violet Kabuga, Antony Ngumbi, and Augastine Esrom.

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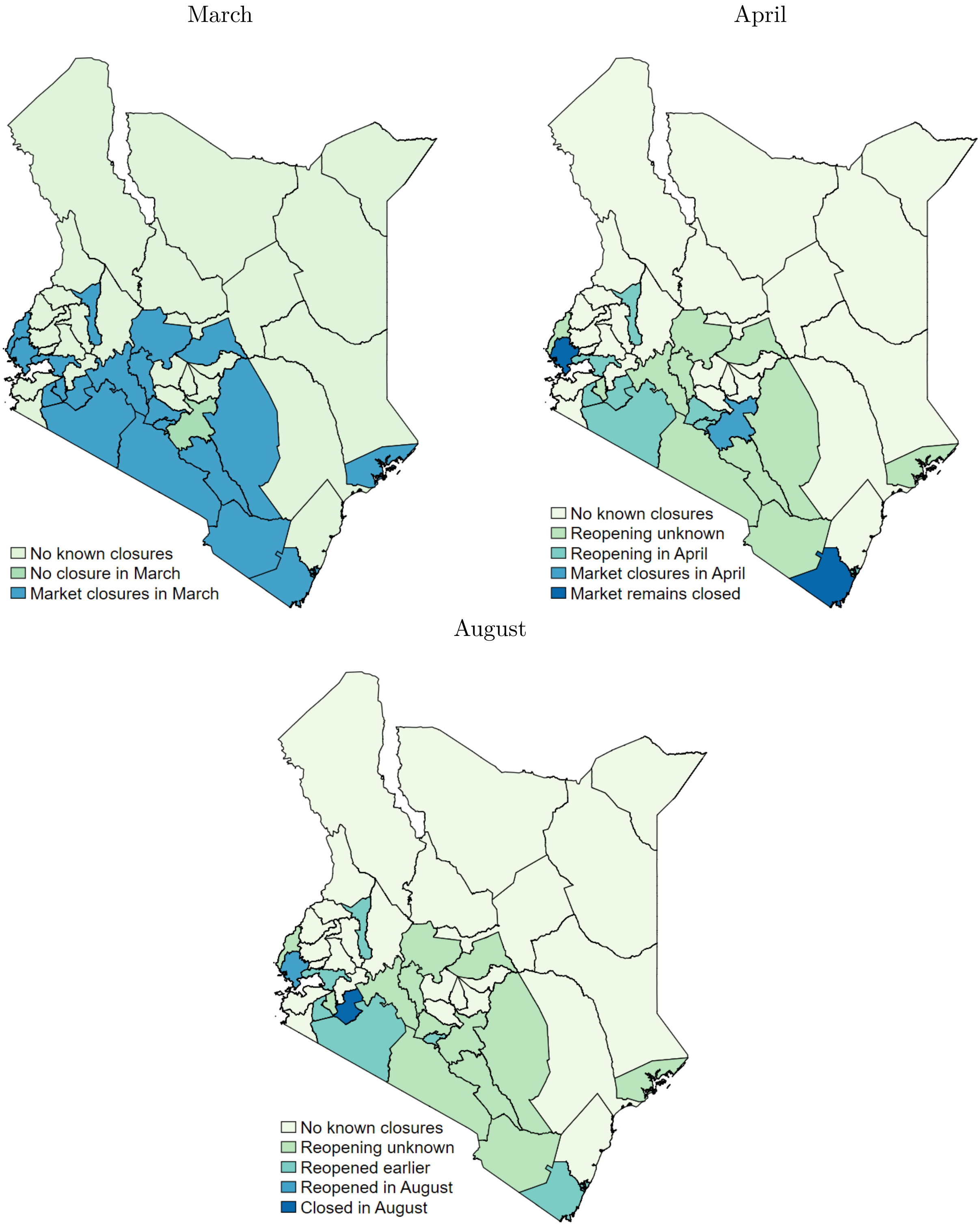
Appendix

8.1 Market closure maps

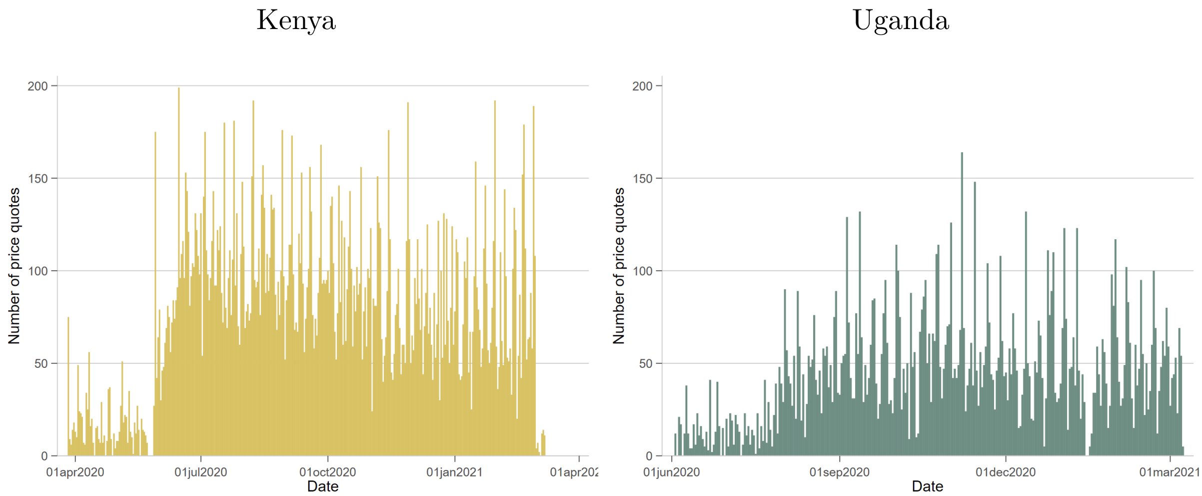
Figure 8: Map of 2020 market closures and reopening dates in Kenya



The maps highlights counties with officially announced market closures and re-opening dates in response to Covid-19. Announcements were usually made by the County Government.

8.2 Appendix material: data collection and sample description

Figure 9: Daily number of collected price quotes

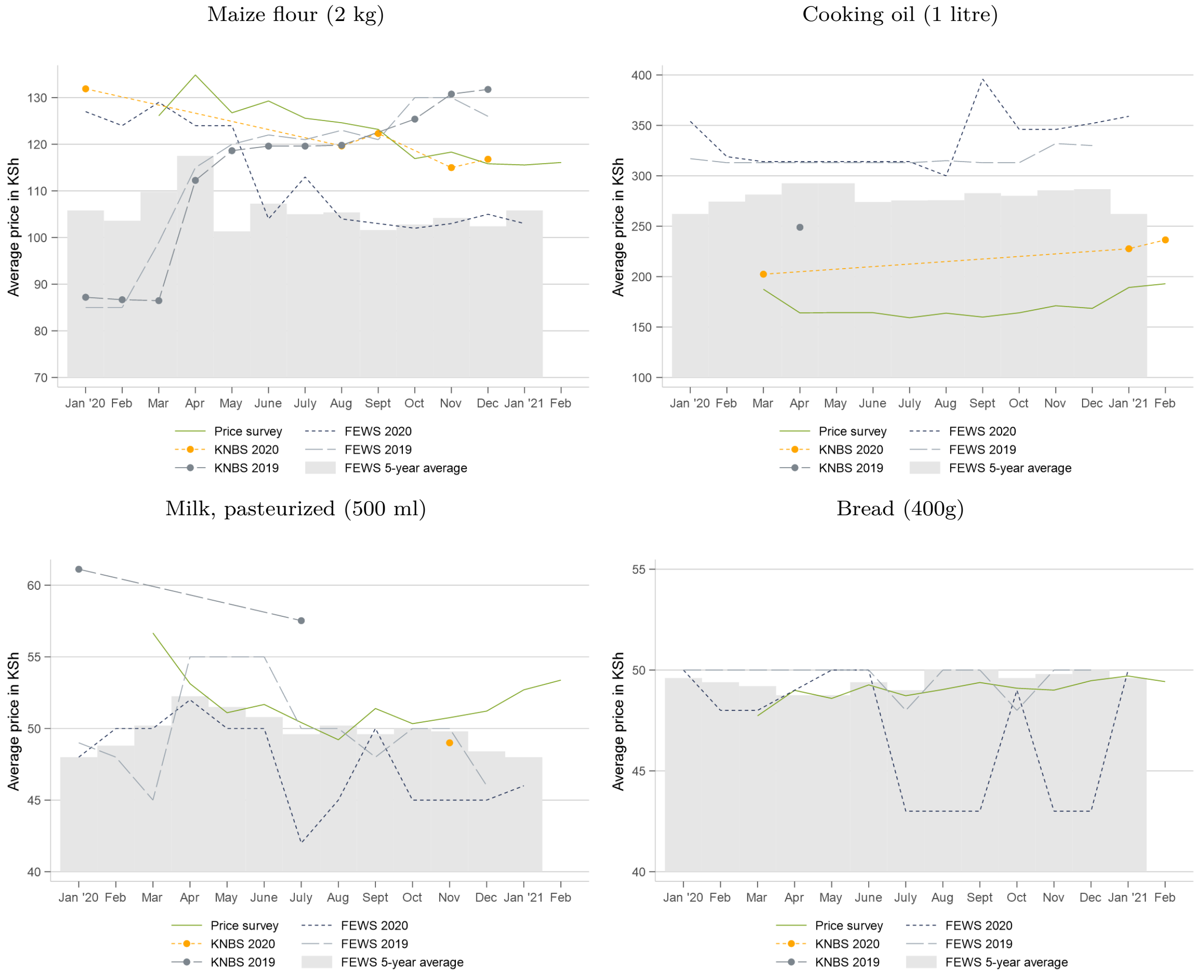


The above histogram plots the daily number of collected price quotes. The regular spikes correspond to weekends - in particular Saturdays.

Figure 10: Comparison of national average prices with KNBS

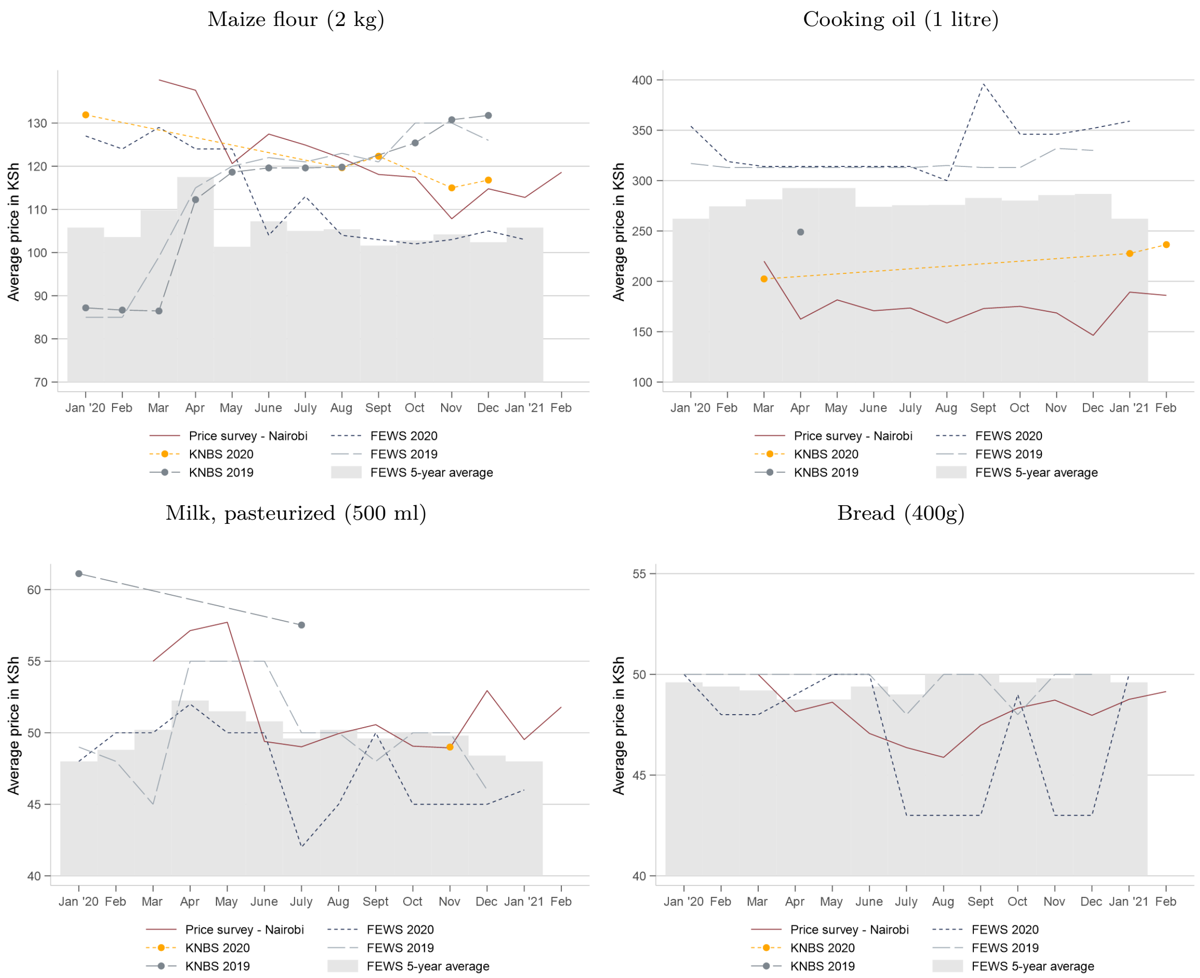
This graph compares the average prices in Nairobi from the price survey to average prices reported by the Kenya National Bureau of Statistics. Note that KNBS only publishes item-level national average prices for a selected number of items each month. In addition, the specific items reported vary from month to month. For the price survey we report the unweighted national average prices. The vast majority of respondents reported prices per piece for mangoes, cabbage and tomatoes. We therefore standardise all prices accordingly. However, as KNBS report kilo prices only, we re-scale the price for mango and tomatoes for the purpose of this graph. KNBS reports prices for onion bulbs and leeks as one item. In the price survey we specifically collected prices for bulbs.

Figure 11: Comparison of national average prices with FEWS and KNBS



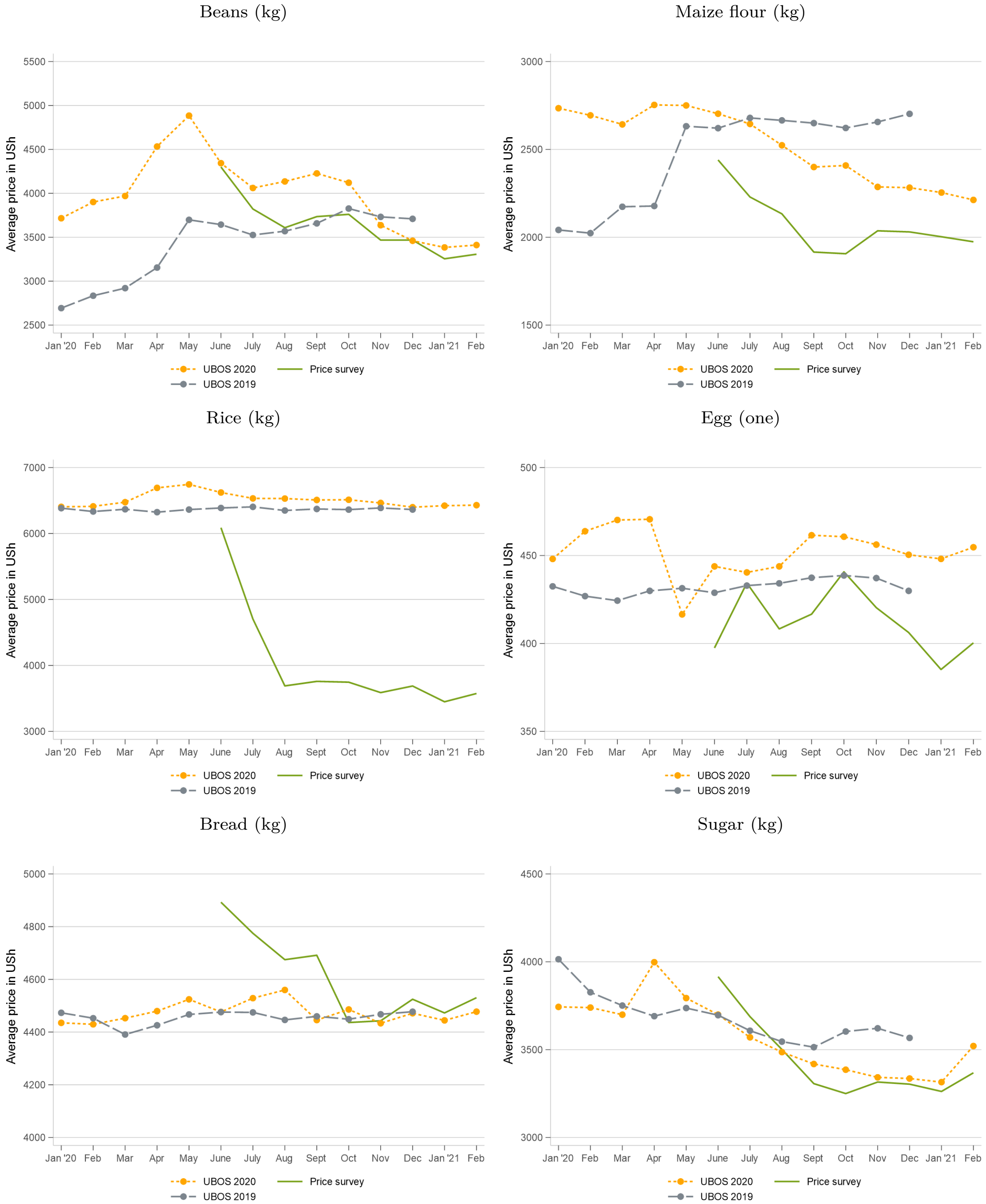
This graph compares the average prices from the price survey to average prices reported by the Kenya National Bureau of Statistics and the Famine Early Warning Systems Network (FEWS). Here we restrict the sample to items for which FEWS reports monthly prices for Nairobi (disregarding gasoline and diesel). Note that KNBS only publishes item-level national average prices for a selected number of items each month. In addition, the specific items reported vary from month to month. For the price survey we report the unweighted national average price.

Figure 12: Comparison of Nairobi average prices with FEWS and KNBS



This graph compares the average prices in Nairobi from the price survey to average prices reported by the Kenya National Bureau of Statistics and the Famine Early Warning Systems Network (FEWS). Here we restrict the sample to items for which FEWS reports monthly prices for Nairobi (disregarding gasoline and diesel). Note that KNBS only publishes item-level national average prices for a selected number of items each month. In addition, the specific items reported vary from month to month. For the price survey we report the unweighted average price for Nairobi.

Figure 13: Comparison of national average prices with UBoS I



The graphs compare national average prices from the price survey prices collected by the Uganda National Bureau of Statistics (UBoS). UBoS prices are collected from 10 centers across the country namely Arua, Fortportal, Masaka, Mbarara, Kampala lower, middle higher income, Jinja, Mbale, and Gulu. In the UBoS data, prices for salt are reported per 500g while avocado, tomatoes and bananas are reported per kg. For proper comparison with the price survey, we standardised all UBoS prices by rescalling to price per/kg and price/piece respectively. Bread was also standardized to 1 kg as it was reported in various forms. Nonetheless, the trend of banana prices was not so comparable as UBoS prices comprised of more and various types of ripe bananas compared to the price survey.

Figure 14: Comparison of national average prices with UBoS II

The graphs compare national average prices from the price survey prices collected by the Uganda National Bureau of Statistics (UBoS). UBoS prices are collected from 10 centers across the country namely Arua, Fortportal, Masaka, Mbarara, Kampala lower, middle higher income, Jinja, Mbale, and Gulu. In the UBoS data, prices for salt are reported per 500g while avocado, tomatoes and bananas are reported per kg. For proper comparison with the price survey, we standardised all UBoS prices by rescalling to price per/kg and price/piece respectively. Bread was also standardized to 1 kg as it was reported in various forms. Nonetheless, the trend of banana prices was not so comparable as UBoS prices comprised of more and various types of ripe bananas compared to the price survey.

8.2.1 Geographic coverage of the price survey data

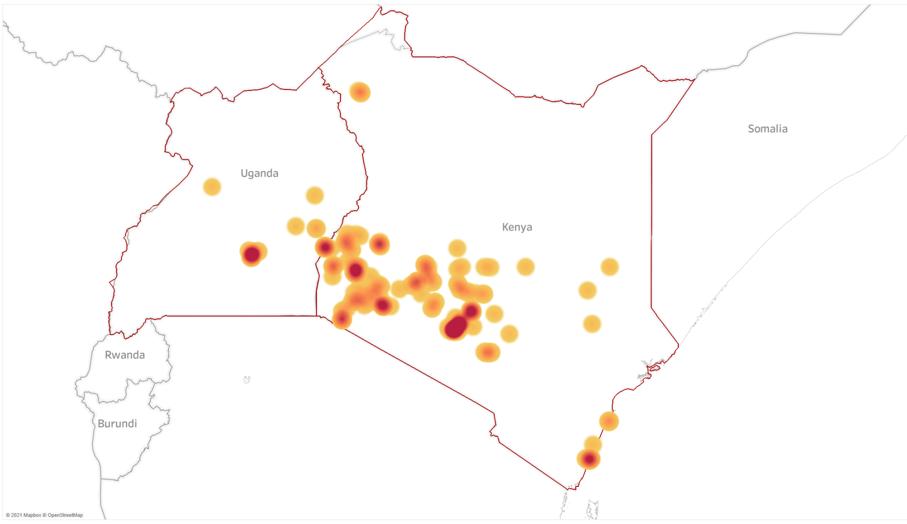
The number of collected price quotes highly correlates with population density. In Figure 16 we plot population size for each district (Uganda) and county (Kenya) against the number of price quotes collected (both on a log scale). Each marker represents a district/county and their size is proportional to their population. Clearly, larger administrative units increasingly reported a higher number of price quotes.

Darker spots on the maps in Figure 1 and 15 can be easily mapped back to major towns in Kenya and Uganda. Admittedly so, most of our respondents were more likely to report prices paid in urban areas. This was partly due to the sample of our respondents, majority being university students and NGO workers as well as due geographic variation in internet coverage particularly in Uganda.

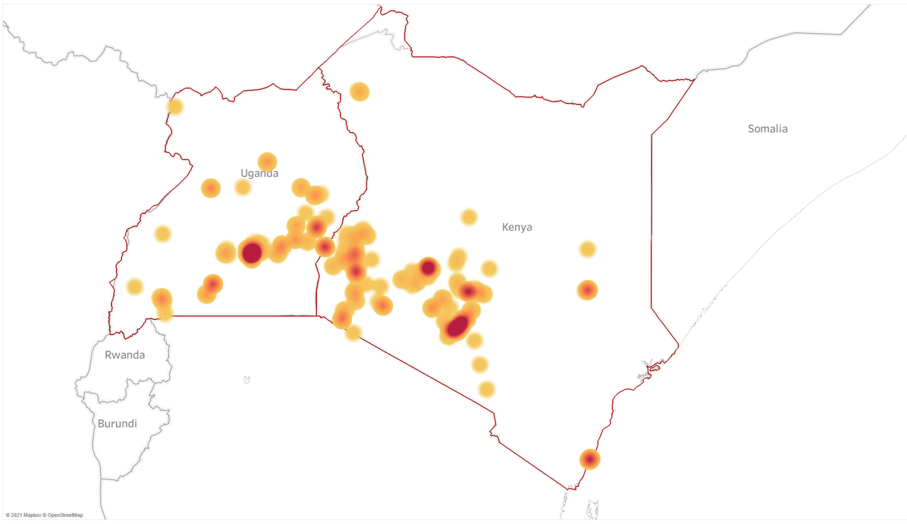
Using additional information from Kenya's latest census (*Economic Survey*, 2019), we further link the number of collected price quotes to population density, mobile phone and internet access. In Figure 17, we show the correlation of population density and the number of price quotes per square kilometre, as well as the correlation of the number of price quotes per million people and mobile phone and internet penetration in Kenya. Each marker again represents a county. The graph on the left panel takes in consideration the number of reported price quotes per square kilometre while in the right panel, the percentage of population with access to internet/mobile phone is considered. We note that the fitted line is noticeably steeper than a 45° line implying a disproportionate higher concentration of price quotes in densely populated counties.

Figure 15: Geographic dispersion of price quotes for rice over time

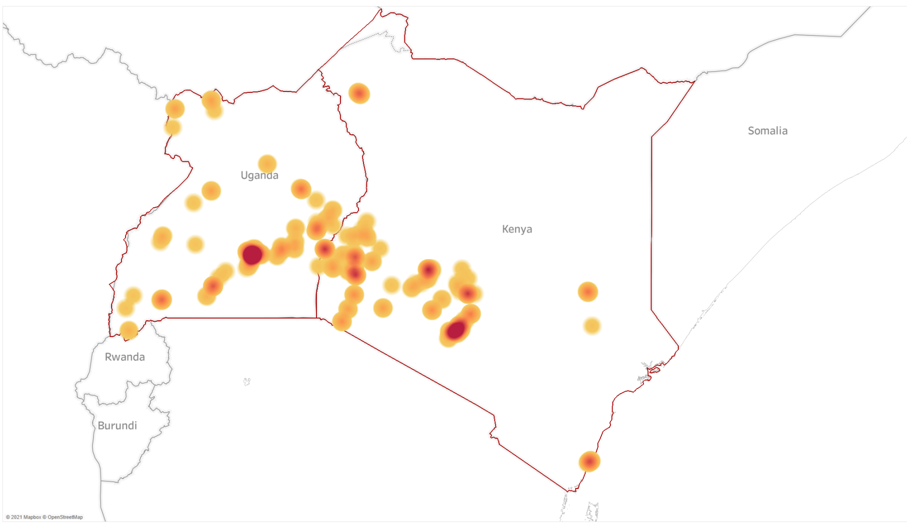
June



October

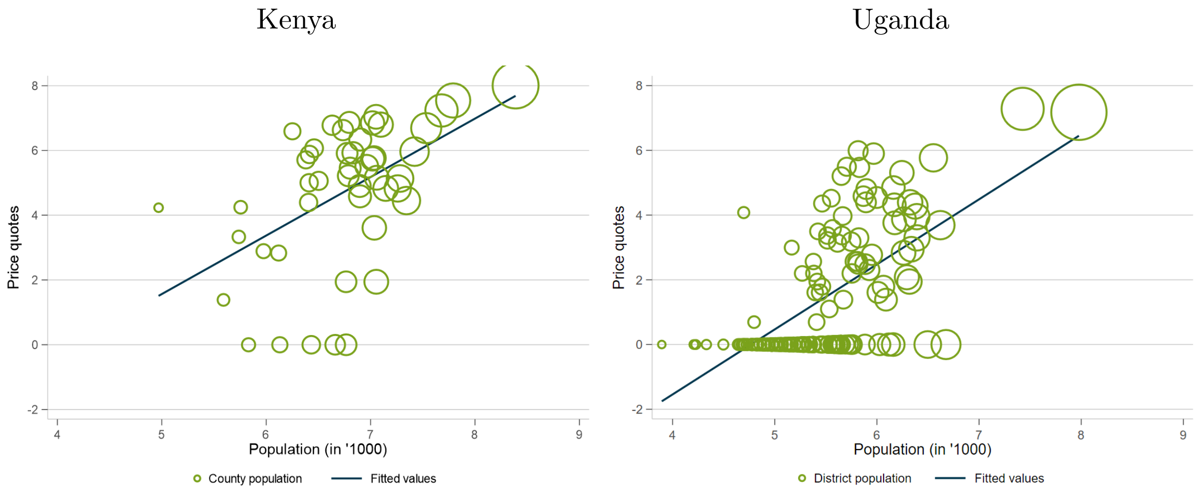


February



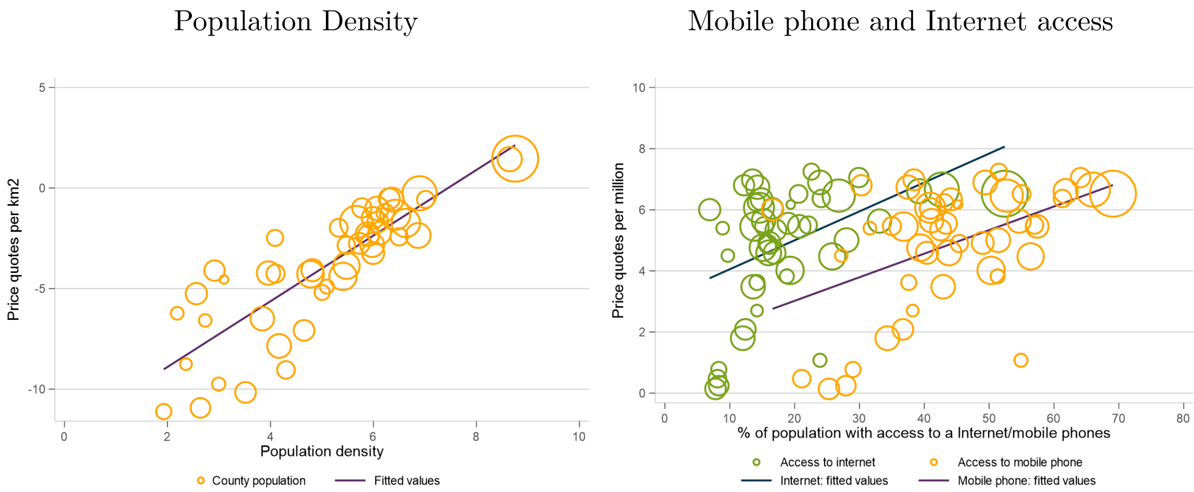
The above maps plot the geographic dispersion of the collected rice prices for the months June 2020, October 2020, and February 2021. Darker colours indicate a greater density of price quotes. Lighter colours indicate fewer price quotes.

Figure 16: Population and the number of collected price quotes across space



The above graphs plot log population on the x-axis and the log number of price quotes collected in each county (Kenya) and district (Uganda) on the y-axis. Each marker represents one of Kenya's 47 counties or Uganda's 135 districts. The size of each marker is proportional to the county's/district's population. The population data for Kenya are sourced from the 2019 Population and Housing Census (KNBS, 2019). For Uganda the data are sourced from the Uganda Bureau of Statistics (UBOS, 2020). Population figures for 2020 are projections.

Figure 17: Population density, Internet access and the number of collected price quotes across space

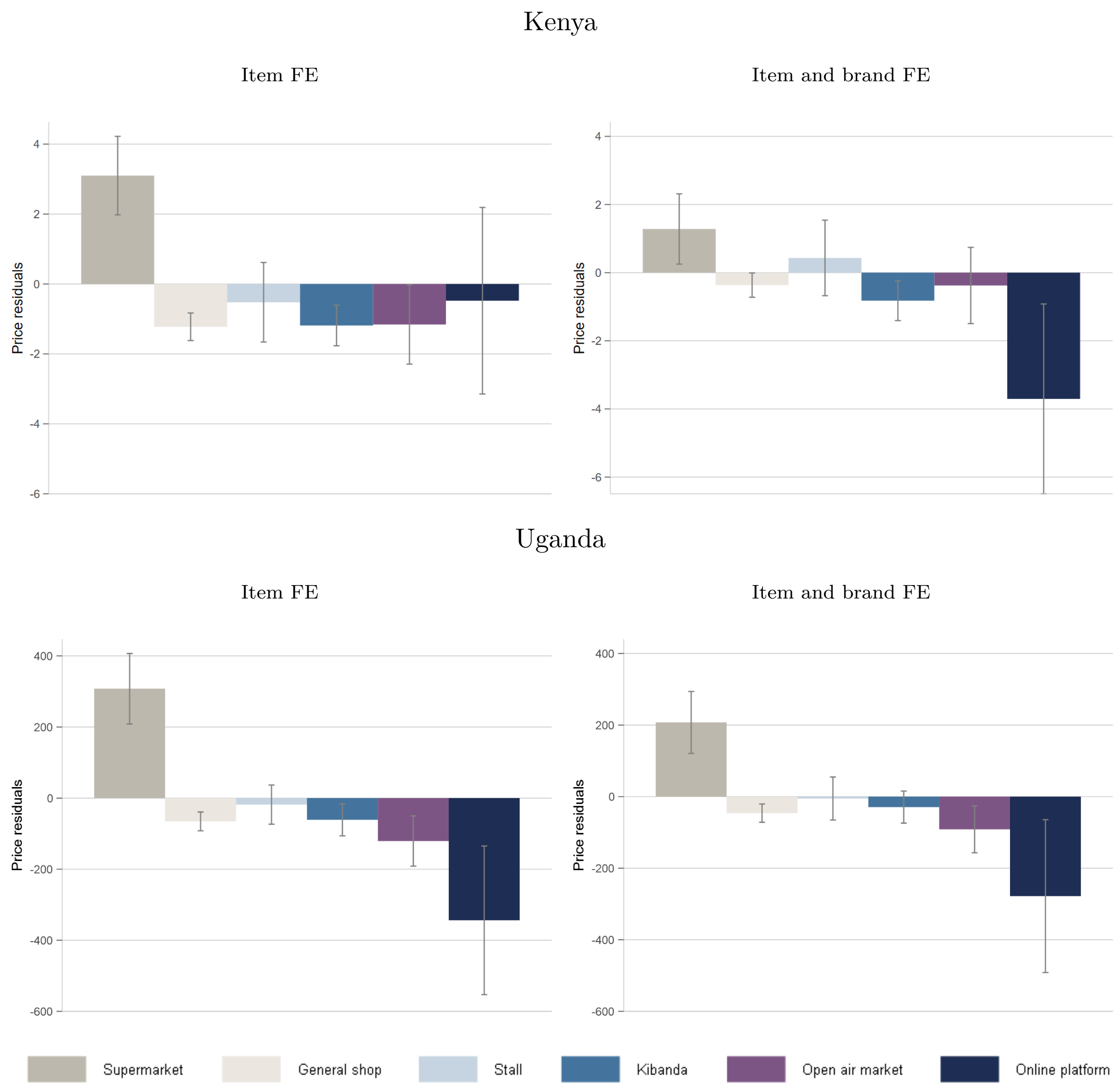


The above graphs plot the log number of price quotes (per km^2 or million people) collected in each Kenyan county on the y-axis. In the left graph we plot it against population density and in the right graph against the percentage of the population with access to a mobile phone and Internet respectively. Each marker represents one of Kenya's 47 counties. The size of each marker is proportional to the county's population.The slope of the fitted line is slightly steeper than a 45° line, suggesting a dis-proportionally higher concentration of price quotes in densely populated counties. The population data and information on Internet access and mobile phone access are sourced from the 2019 Population and Housing Census (KNBS, 2019).

8.3 Price dynamics across retail categories

As noted, our sample of respondents might be dis-proportionally likely to shop at supermarkets and less likely to shop at open air markets. We also take note that different items would more likely be sold in certain shop types. For instance, fruits and vegetables are more likely to be found in a *kibanda* as opposed to a general shop. In addition, some item brands and varieties thereof are likely to be found in certain types of shops. Here we show by what extent prices varied with shop type. Figure 18 shows the variation in prices across different types of shops, controlling for item fixed effects in the left column and item as well as brand fixed effects in the right column. The residual variation in prices across shop types is drastically reduced once we control for brand fixed effects.

Figure 18: Variation in prices by shop type



The above graphs show the variation retail prices by shop type. In the left column we control for item fixed effects only. In the right column we add brand fixed effects. The grey error bars show the 95% confidence intervals.

8.4 Additional summary statistics from the price data

Table 8: Kenya - detailed summary statistics

Item	Quantity	N	N/month	Avg. price	Sd price	#brands	#counties	#counties/month	N mobility	Avg.price mobility	Sd price mobility	#counties mobility	N origin	Avg. distance to origin	Shop type
Rice	2,072	1 kg	156	123	44	11	39	23	1,841	124	44	34	985	168	General shop
Bread (white)	2,061	400 g	153	49	6	15	38	22	1,823	49	6	33	1,713	175	General shop
Sugar	1,556	1 kg	109	112	14	8	37	19	1,367	112	14	33	578	188	General shop
Eggs	1,556	one	163	13	3	1	42	28	1,352	13	3	36			General shop
Wheat flour	1,338	2 kg	96	128	15	13	39	19	1,166	128	15	34	1,192	352	General shop
Maize flour (sifted)	1,323	2 kg	98	121	18	17	39	19	1,182	120	17	34	1,066	175	General shop
Milk (fresh, packaged)	1,246	500 ml	88	51	9	14	39	19	1,135	51	9	33	1,010	167	General shop
Bread (brown)	1,104	400 g	82	49	7	11	40	18	1,001	49	7	36	878	133	General shop
Tomatoes	1,070	one	111	7	3	1	38	23	961	6	3	32			Kibanda
Banana (ripe)	967	one	100	8	4	1	39	24	850	8	4	33			Kibanda
Cooking oil	777	1 litre	52	170	39	10	40	16	687	170	39	34	562	373	General shop
Onions (bulbs)	770	1 kg	80	66	34	1	33	21	684	66	34	30			Kibanda
Cabbage	672	one	73	46	30	1	38	22	586	45	29	31			Open air market
Avocado	657	one	73	19	10	1	35	21	580	20	10	31			Kibanda
Mango	628	one	72	18	10	1	35	20	576	18	10	31			Kibanda
Soda/Soft drink	576	300 ml	64	30	8	1	37	21	506	30	8	33			General shop
Salt	352	1 kg	21	39	15	5	32	10	315	39	15	29	345	515	General shop

Prices are denoted in Kenyan Shilling.

Table 9: Uganda - detailed summary statistics

Item	Quantity	N	N/month	Avg. price	Sd price	#brands	#districts	#districts/month	N mobility	Avg.price mobility	Sd price mobility	#districts mobility	N origin	Avg. distance to origin	Shop type
Rice	1 kg	1,224	264	3,740	1,751	9	58	5	819	3,982	1,991	14	160	65	General shop
Bread (loaf)	400 g	838	134	4,543	719	5	49	5	692	4,553	659	14	621	85	General shop
Beans (dry)	1 kg	771	132	3,587	761	2	48	5	511	3,657	770	14	0		General shop
Sugar	1 kg	761	190	3,357	520	7	51	4	480	3,376	541	13	671	143	General shop
Eggs	one	526	81	413	99	1	42	6	376	399	96	13	0		General shop
Avocado	one	425	70	649	323	1	41	5	306	711	344	15	0		General shop
Groundnuts	1 kg	348	45	5,700	1,190	1	37	5	266	5,849	1,202	14	0		General shop
Maize flour (sifted)	2 kg	333	76	2,020	567	11	37	3	225	2,084	602	11	245	86	General shop
Tomatoes	one	318	54	248	171	1	37	4	245	258	180	11	0		Open air market
Banana (ripe)	one	192	44	337	277	1	39	4	223	376	274	13	0		General shop
Salt	1 kg	182	45	2,128	1,040	6	37	2	129	2,074	1,024	11	3	102	General shop

Prices are denoted in Ugandan Shilling.

8.5 Google mobility data

We use the Google Mobility data to track changes in mobility patterns during our study period. Related studies often rely on fine-grinned high-frequency smartphone data to track changes in consumption patterns and mobility during the Covid-19 pandemic (Couture et al., 2020). However, such data are only available for a limited number of contexts. We therefore rely on more aggregated mobility data published by Google (Aktay et al., 2020). The data has, for example, been used by other researchers to provide cross-country evidence on the link between mobility and the transmission of SARS-CoV-2. Similar to other smartphone data, the data is likely bias towards picking up mobility patterns for certain demographics - typically the younger and wealthier in the context of Kenya (Gollin et al., 2020) and Uganda. Despite the skew towards higher income groups and higher educated , Gollin et al. (2020) provide detailed insight into smartphone ownership and mobility patterns in Kenya, showing that especially in urban areas smartphone data gives insights into mobility patterns of a relatively broad subset of the wider population. Nevertheless, we want to highlight that this skew is be particular relevant for the purpose of our study given those groups might also have been better positioned to work from home during the lockdown period and their mobility patterns have been affected more drastically as a result.

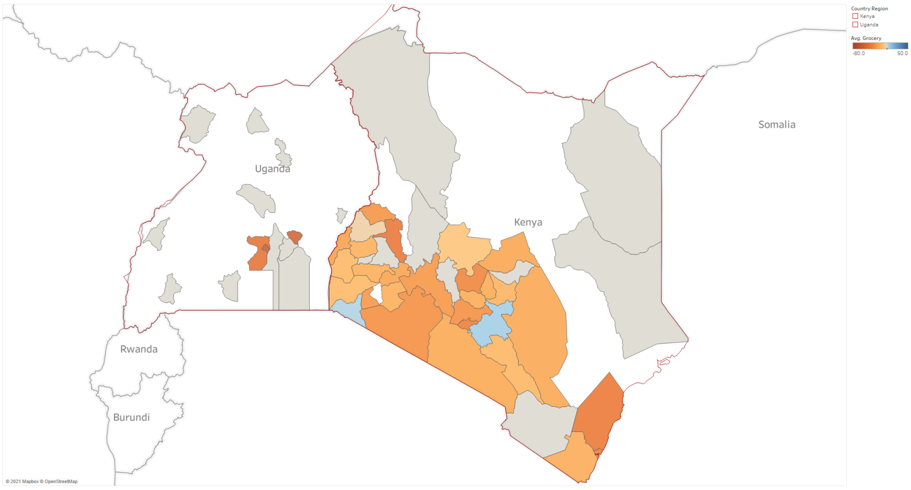
The Google mobility index documents how Android smartphone users's movement and time spent at certain locations has been affected by the pandemic relative to a baseline period in January and February 2021. Figure 19 depicts the changes in activity at grocery and pharmacy-related locations for April and November 2020. The maps are color coded such that dark red colour means a reduction in activity of up to 80% relative to the baseline. Dark blue colour means an increase in activity of up to 50% relative to the baseline. To some considerable extent, activities reduced significantly in most parts of Kenya for which Google has data on. Counties that were targeted by the lockdown measures are seen to reduce activities the most. Data coverage in Uganda is more spares and largely centred around the major urban centres, in particular Greater Kampala. Here the lockdown had the most pronounced impact (dark red region in the top map of Figure 19). In November of 2020, there was improved movement in Kenya even though the coastal region with Mombasa remained constrained.[32] One limitation is that data availability is highly correlated with internet and mobile phone coverage. Google requires a certain number of data points for it to publish an index for a specific administrative unit. For the blank regions in we do not observe any data throughout the sample period. In Kenya this mostly affects the sparsely populated counties, while large areas of Uganda are not

[32] This could be partly driven by the drastic reduction in tourist numbers on the coast.

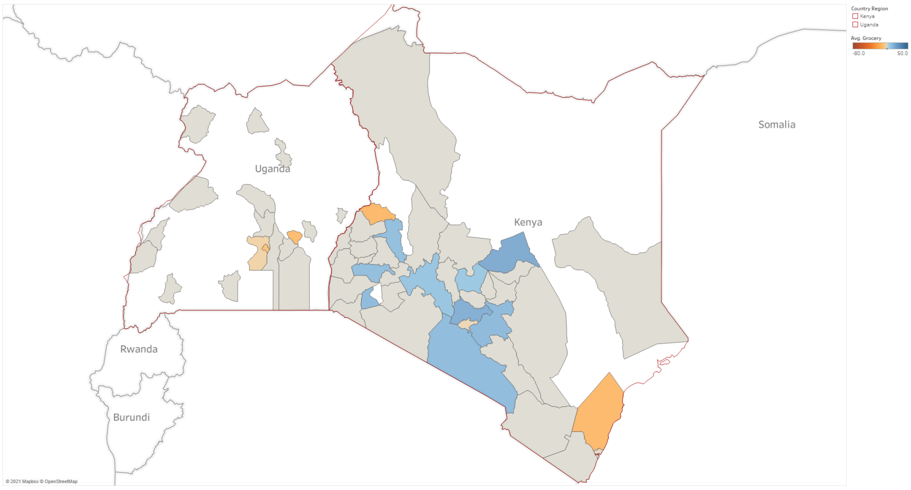
observed in the data. For the grey areas we observe data for at least one of the indices in a given month, but not the one mapped here. Figure 20 highlights the more comprehensive geographic coverage of the workplace index. Looking at the workplace index in Figure 20, we find even more convincing evidence that workplaces were significantly affected in April of 2020. This was at a time when non-essential workers were advised to work from home. By June of 2020 there was considerable improvements in mobility in some counties/districts. By February 2021 we observe fewer extreme values - darker shades of red or blue - and most values fluctuate around zero. However, the overall tendency still seems to suggest lower activity levels than in January and February 2020. In Uganda, this trend might be partly driven by the aftermath of the January 2021 election.

Figure 19: Mapping mobility: Grocery and pharmacy index

April 2020



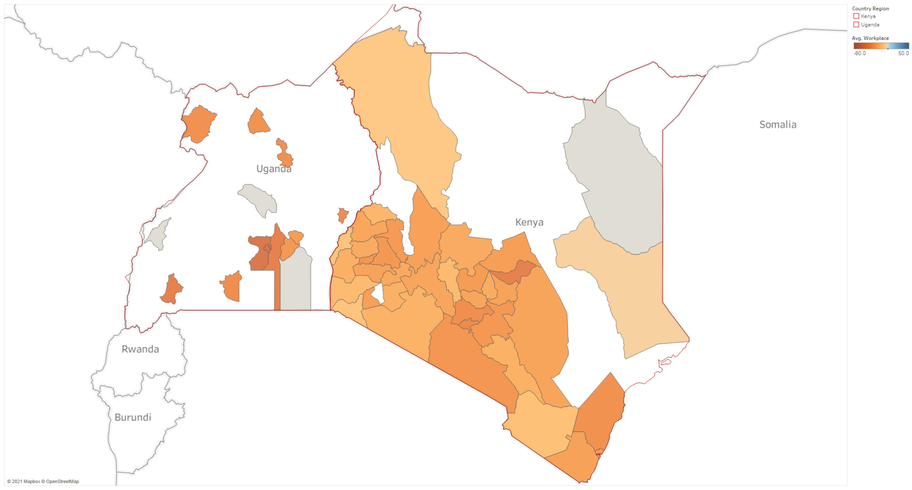
November 2020



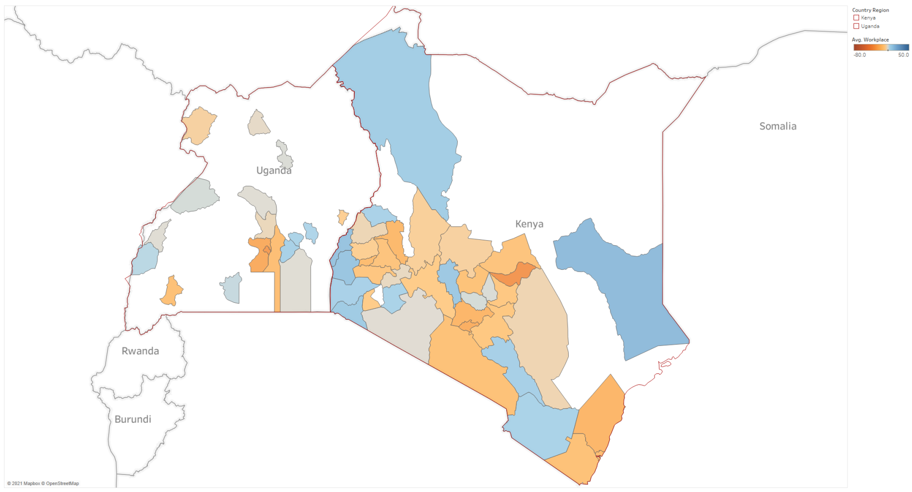
The maps shows the spatial variation in the availability of Google mobility data in Kenya and Uganda for the month of April and November 2020 as well as February 2021. Districts/counties marked in grey are administrative units for which any mobility data is available at some point, however, not in the shown period. Blank areas indicate that mobility data are missing for the time period studied. The colour scheme further indicates the percentage change in activity relative to Google's baseline in January and February 2020. Dark red means a reduction in activity up to 80% relative to the baseline, dark blue means an increase in activity of up to 50% relative to the baseline. The lighter the colour, the closer mobility is to the baseline. The Google mobility data can be downloaded here: https://www.google.com/covid19/mobility/

Figure 20: Mapping mobility: Workplace index

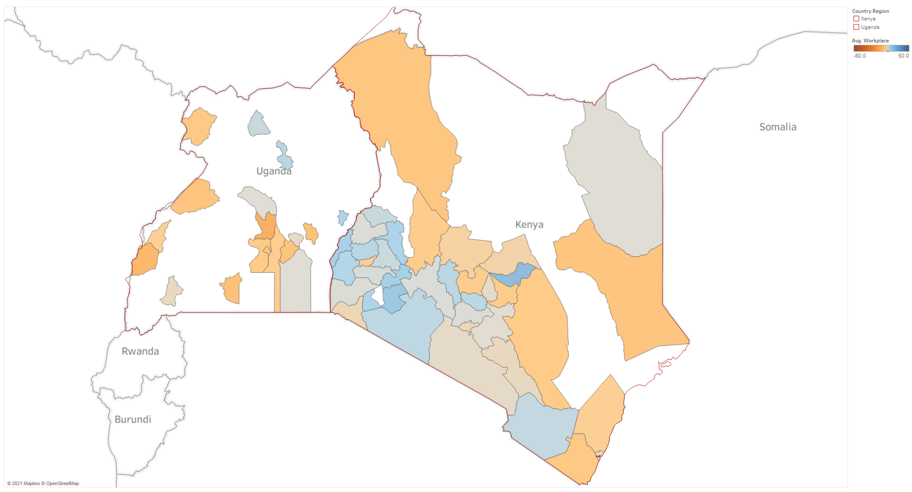
April 2020



June 2020



February 2021



The maps shows the spatial variation in the availability of Google mobility data in Kenya and Uganda for the month of April and November 2020. Districts/counties marked in grey are administrative units for which any mobility data is available at some point, however, not in the shown period. Blank areas indicate that mobility data are missing for the time period studied. The colour scheme further indicates the percentage change in activity relative to Google's baseline in January and February 2020. Dark red means a reduction in activity up to 80% relative to the baseline, dark blue means an increase in activity of up to 50% relative to the baseline. The lighter the colour, the closer mobility is to the baseline. The Google mobility data can be downloaded here: https://www.google.com/covid19/mobility/

8.6 Results on mobility and data collection patterns

Table 10: Mobility and data collection - using variation across space and time

	Kenya		Uganda	
	Full sample	Post scale up	Full sample	Post scale up
Mobility	0.055***	0.095***	0.098***	0.114***
	(0.017)	(0.021)	(0.024)	(0.031)
Constant	0.899***	0.898***	0.896***	0.898***
	(0.004)	(0.004)	(0.010)	(0.011)
No. observations	138652	127931	27879	23411
R2 adj.	0.012	0.015	0.024	0.025
R2 adj. within	0.001	0.002	0.002	0.003
Item FE	Yes	Yes	Yes	Yes

The outcome variable captures whether a price quote was recorded for a given day, item, and administrative unit for which Google mobility data were available. The variable takes a value of one if the price was quote was missing. The independent variable captures the change in activity relative to January and February 2020 in percentage points. It takes a value of zero if the observed activity is similar to the baseline period, positive values represent an increase in activity levels, negative values a decline. In Kenya observed values range from -0.7 to 0.4. In Uganda they range from -1 to 0.3. Standard errors are clustered at the item-location level (counties in Kenya, districts in Uganda). *; **; and *** denote significance at the 10; 5; and 1 percent levels respectively.

Table 11: Mobility and data collection - using variation across space

	Kenya		Uganda	
	Full sample	Post scale up	Full sample	Post scale up
Mobility	0.071***	0.072***	0.155***	0.136***
	(0.020)	(0.021)	(0.032)	(0.033)
Constant	0.900***	0.896***	0.901***	0.899***
	(0.004)	(0.004)	(0.009)	(0.010)
No. observations	138652	127931	27879	23411
R2 adj.	0.024	0.024	0.035	0.033
R2 adj. within	0.001	0.001	0.005	0.004
Item FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

The outcome variable captures whether a price quote was recorded for a given day, item, and administrative unit for which Google mobility data were available. The variable takes a value of one if the price was quote was missing. The independent variable captures the change in activity relative to January and February 2020 in percentage points. It takes a value of zero if the observed activity is similar to the baseline period, positive values represent an increase in activity levels, negative values a decline. In Kenya observed values range from -0.7 to 0.4. In Uganda they range from -1 to 0.3. Standard errors are clustered at the item-location level (counties in Kenya, districts in Uganda). *; **; and *** denote significance at the 10; 5; and 1 percent levels respectively.

Table 12: Mobility and data collection - using variation across time

	Kenya		Uganda	
	Full sample	Post scale up	Full sample	Post scale up
Mobility	-0.021*	0.080***	-0.174***	-0.104***
	(0.012)	(0.010)	(0.030)	(0.019)
Constant	0.894***	0.897***	0.874***	0.883***
	(0.002)	(0.002)	(0.006)	(0.006)
No. observations	138652	127931	27879	23411
R2 adj.	0.092	0.107	0.136	0.176
R2 adj. within	0.000	0.001	0.006	0.002
Admin FE	Yes	Yes	Yes	Yes
Item FE	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes

The outcome variable captures whether a price quote was recorded for a given day, item, and administrative unit for which Google mobility data were available. The variable takes a value of one if the price was quote was missing. The independent variable captures the change in activity relative to January and February 2020 in percentage points. It takes a value of zero if the observed activity is similar to the baseline period, positive values represent an increase in activity levels, negative values a decline. In Kenya observed values range from -0.7 to 0.4. In Uganda they range from -1 to 0.3. Standard errors are clustered at the item-location level (counties in Kenya, districts in Uganda). *; **; and *** denote significance at the 10; 5; and 1 percent levels respectively.

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