The Effect of Covid-19 Lockdown on Community Currency Trade

A Synthetic Control Analysis

Rebecca Mqamelo

May 2020

Abstract

This paper studies how Kenya's government-instituted lockdown aimed at preventing the spread of Covid-19 affected trade within the Sarafu Community Currency Network in Nairobi. Using synthetic control methods, I show that community currency users who were exposed to the lockdown display a notable increase in trade. This is despite most people having experienced a decrease in income due to the economic effects of the pandemic. The evidence therefore suggests that community currencies have higher utility when there is a greater scarcity of national currency. The contribution of this paper is to add quantitative and empirical evidence to the growing weight of research that supports community currencies as an effective counter-cyclical buffer against economic shocks.

Department of Social Sciences (Economics and Society)

Minerva Schools at KGI

[3,162 words]

Contents

1 Introduction

A complementary or community currency (CC) is defined as a complementary medium of exchange to a national currency that draws on the strength of community networks in order to stimulate local economic activity with some social or environmental objective in mind (Utting, 2013). While models vary, a standard CC consists of physical vouchers or digital tokens which are issued and honoured by members of a network and can only be spent on goods and services provided by other members in the network (Bendell et al., 2015). The last decade has seen CCs receive fresh attention for their potential to mitigate the problems associated with high inflation, currency volatility and external risk (Castilla-Rubio et al., 2016; Ruddick, 2019). In addition, a number of use cases highlight CCs as a viable and more effective successor to the unconditional cash transfer model.

One of the strongest arguments in favour of CCs is that by operating parallel to national currencies, they act as a countercyclical buffer when money is scarce, such as during economic shocks (Sahakian, 2014; Sobiecki, 2018; Ruddick, 2019). An economic shock is broadly defined as a sudden and unexpected threat or opportunity caused by an unpredictable change in exogenous factors that cannot be explained by economics (Briguglio et al., 2009). Across the world, government-enforced lockdowns in response to the Covid-19 pandemic are an economic shock of devastating proportions. The response has been varied, and in lower-income communities, the day-to-day impact has been especially severe. This is because disruptors on any scale – from a bad harvest season to the effects of the Covid-19 pandemic – usually hit the economically marginalized the hardest. It is becoming increasingly clear that development models interested in lifting people out of poverty must therefore start prioritizing socio-economic resilience at a *network* level.

Given that the Covid-19 pandemic is a global and evolving phenomenon, there is still relatively little known about the most effective methods to stimulate local economies during a time like this, much less those that operate informally. According to Kiiru (2010), remittances have traditionally been used to deal with household economic shocks in low-income Kenyan communities. These shocks range from the death of a breadwinner to natural disasters. Shocks related to global events and currency volatility, however, are much harder to deal with because everyone suffers. For example, during the Covid-19 pandemic, even remittances have run dry for many. There is already evidence that during severe economic downturn or after high-spending periods such as the December festive season, people are more likely to spend their CC tokens as they try to save what little national currency they have (Ruddick, 2019). Given the unique economic impact of Covid-19, one would expect trade volumes to spike, because more business owners are likely to accept payments partially in CC tokens in order to maintain profits. What is unclear, however, is how to quantify the impact of an economic shock like Covid-19 lockdown on CC trade. This paper will analyze CC daily trade volumes for pre- and post-lockdown periods in Nairobi, comparing the effect of lockdown to a synthetic control.

In addressing this problem, I propose a synthetic control analysis of the Sarafu Network[1], a CC program founded by Grassroots Economics in 2010. The network spans over 50 communities across Kenya, who trade daily via USSD codes to send and receive blockchain-based tokens. What makes this network unique is that all trades are traceable on a publicly accessible blockchain, enabling an unprecedented level of real-time impact evaluation. Kenya's national lockdown was instituted on 25 March 2020, therefore the study will explore differences in Nairobi trade volumes before and after the implementation date.

The rest of this paper is organized as follows: Section 2 introduces the data and provides detailed information on how the data was prepared for the study; Section 3 discusses the methodological framework for the synthetic control; Section 4 presents the results combined with empirical findings; Section 5 explores limitations of the analysis, and finally, Section 6 offers concluding remarks.

[1] Note: *Sarafu* means "currency" in Swahili

2 Data

The data for this study is publicly available on the Grassroots Economics website. There are 85,176 observations for trades placed on the Sarafu Network between 25 January 2020 and 14 April 2020 with information on the timestamp, blockchain hash of the sender and receiver, gender, community token name, purpose of the trade and trade amount. At first glance, there is a noticeable difference between the trend in trade volumes before and after the lockdown (25 March 2020). Fig. 1 and 2 show trade analytics for the entire CC network, spanning over 50 communities.

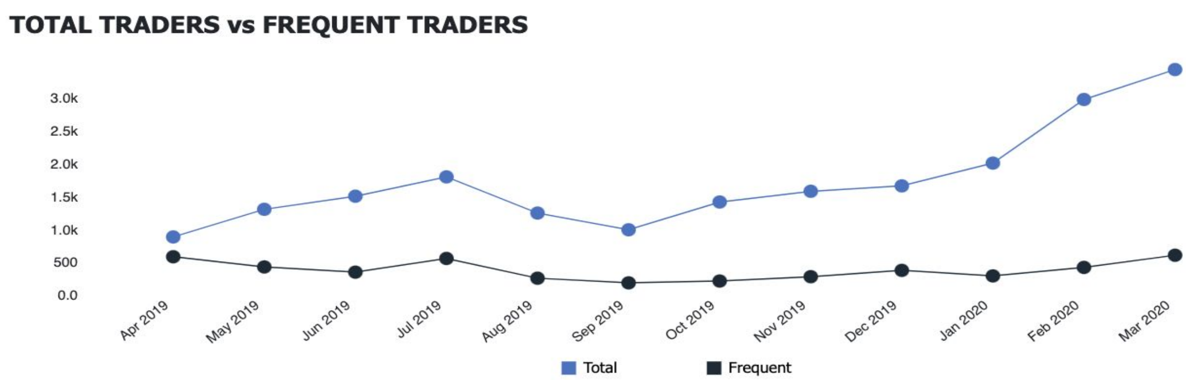

Fig 1. Increase in traders on the Sarafu Network during March 2020. Source: Grassroots Economics (2020)

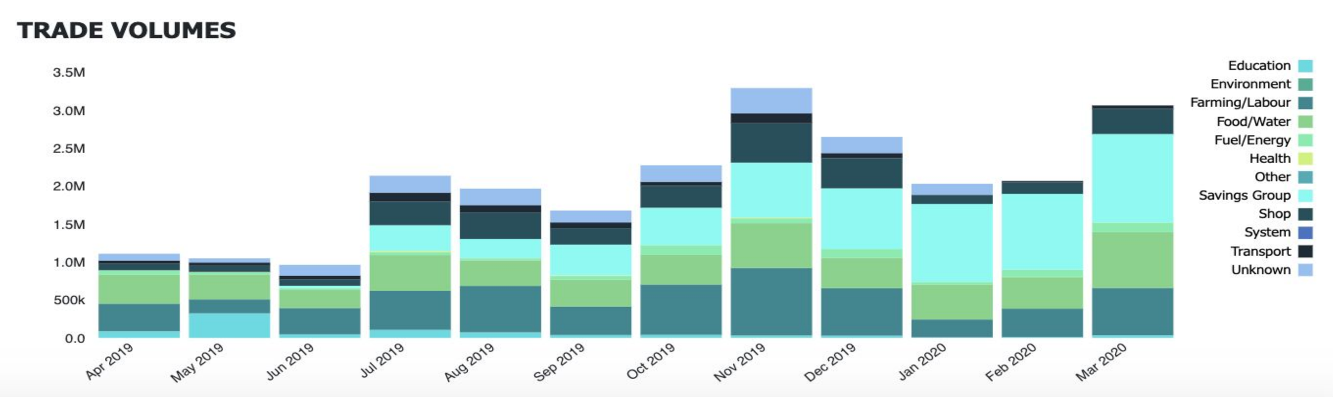

Fig 2. Increase in trade on the Sarafu Network during March 2020. Source: Grassroots Economics (2020)

The main challenge for this study was modifying the data into a panel dataset in order to control time-invariant confounders between daily observations grouped by location. Data preprocessing included dropping transactions for reclamation of tokens between users and the system; categorically encoding the location and purpose of each transaction; and combing through the often misspelt variations of the names of locations. The dataset was reduced to 81 daily observations for 43 locations around Kenya, with variables for daily trade volume, gender ratio (the proportion of females to males in daily trading activity), number of daily trades, number of new users, and the main purpose of the trade such as paying for food, education or transport.

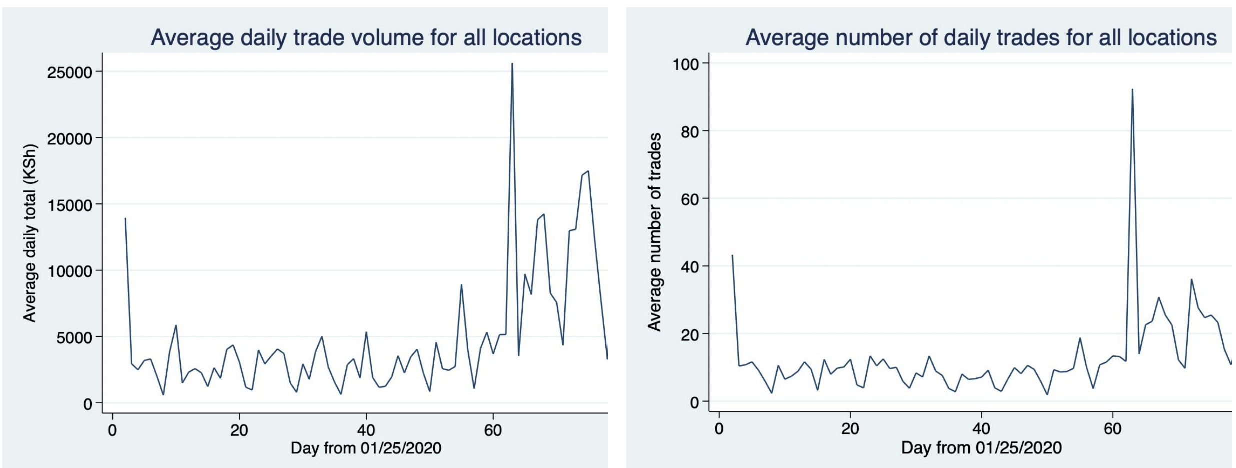

Fig. 3 Average daily trade volume and average number of daily trades on the Sarafu Network.

Fig. 3 shows a clear trend in the increase in trade volume around the time of Covid-19 lockdown. The large standard deviations in Table 1, however, indicate there is great variation in the data, supporting the use of a unit-weighted synthetic control.[2]

[2] Note: Summary statistics for daily trade volume by location can be found in Appendix A.

Table 1. Summary statistics for daily trade volume		
Variable	Mean	Standard deviation
Daily total (KSh)	6072.41	76330.61
Gender ratio (buyers)	0.82	2.02
Gender ratio (sellers)	1.04	2.67
Number of daily trades	14.85	134.72
Number of new users per day	0.89=	7.82
Main trade purpose	7.83	3.12

Table 1: Summary statistics reported for all locations (3,483 observations)

One limitation of the data is that there were very few explanatory variables to capture demographic-related factors such as age or education. This posed a serious challenge for establishing comparability between treatment and control units because transaction data alone potentially omits dozens of confounding variables. A labour-intensive solution to this problem was to find "data about the data" as a proxy for unavailable information. For each daily observation for each location, it was possible to extract the ratio of females to males in people who made and received purchases; the most popular trade category for that day, the number of trades placed, and the number of new users who joined the network. This kind of information gives us some idea about the gender balance of business ownership in an area, its main economic sector, and the general amount of economic activity that occurs there. Table 2 shows the final list of variables used in the model.

Table 2. Dependent and independent variables	
Dependent variable	Independent variables
Daily trade volume (> week 11)	Daily trade volume (weeks 1-11)
	Trade purpose (weeks 1-11)
	Buyer gender ratio (weeks 1-11)
	Seller gender ratio (weeks 1-11)
	Number of trades (weeks 1-11)
	Number of new users (weeks 1-11)

Table 2: Variables used in the synthetic control model, with each independent variable fixed at weekly periods

3 Method

To evaluate the effect of Covid-19 lockdown on trade volume in Nairobi, the central question is how trade volume would have evolved in Nairobi after 25 March 2020 in the absence of the lockdown. The synthetic control method developed by Abadie et al. (2010, 2015) and Abadie and Gardeazabal (2003) provides a systematic way to estimate this counterfactual. This method is based on the belief that when there are a number of aggregate units being analyzed (such as cities, states of countries, etc.), a combination of these comparison units (the "synthetic control") does a better job of reproducing characteristics of a treated unit than using a single comparison unit alone (Cunningham, 2018). An ideal synthetic control nearly perfectly satisfies the parallel trends assumption. While Difference-in-Differences methods allow for some variation in the pre-treatment trends of treated and control units, the synthetic control ought to produce an exact pre-treatment replica because it is the closest construction of a realistic counterfactual.

Locations omitted from the donor pool are Kwale, Kilifi and Mombasa, as these areas also received Covid-19 lockdown. The number of pre-treatment periods included in the model are taken weekly from day 7 (2 February 2020) through day 77 (12 April 2020) in order to minimize bias in the data. The advantage of this approach is that it allows effects of confounding unobserved characteristics to vary with time (Abadie et al., 2010). Table 3 shows the unit weights used to build the synthetic control.

Table 3. Synthetic control unit weights	
Control Unit *(Code / Name)*	Unit Weight
(0) Chidzivuni	0.024
(24) Miyani/Mnkanyeni	0.487
(25) Mkanyeni	0.134
(27) Mwangaraba	0.317
(38) Yowani	0.037

Table 3: Synthetic control unit weights

Table 4 compares the pre-treatment characteristics of Nairobi with its synthetic counterfactual, as well as with the population-weighted average of the 39 other areas in the donor pool. For simplicity, only values for day 70 and 77 are shown, however the model uses all weekly periods. It is clear that the average of areas that did not receive lockdown does not provide a suitable control group for Nairobi. Unfortunately, the synthetic control does not appear to be a perfect match either, suggesting that there are unobservable confounding variables in the data related to the number and volume of daily trades and the gender balance of business owners (the synthetic control appears to have more female sellers).

Table 4. Daily trade volume predictor means			
	Nairobi		Average of 39 control areas
Variables	Real	Synthetic	
Daily trade total(70)	47531	62099.97	7846.55
Daily trade total(77)	221239	14540.54	6987.21
Main trade activity (70)	3 (Food/Water)	3.02 (Food/Water)	7.09 (Retail)
Main trade activity (77)	3 (Food/Water)	3 (Food/Water)	7.20 (Retail)
Buyer gender ratio (70)	2.10	2.17	0.87
Buyer gender ratio (77)	1.14	2.98	0.61
Seller gender ratio (70)	1.81	4.79	1.04
Seller gender ratio (77)	1.01	2.83	1.39
Number of daily trades (70)	121	40.88	9.39
Number of daily trades (77)	289	46.8	13.05
Number of new users (70)	0	3.85	0.5
Number of new users (77)	0	2.55	0.5

Table 4: Daily trade volume predictor means

4 Results

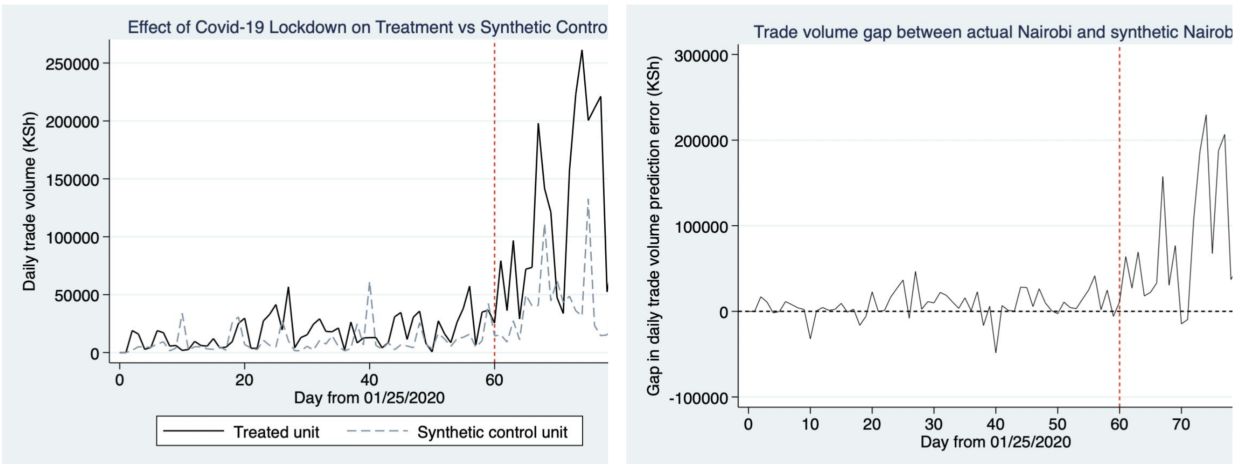

Fig. 4. Pre- and post-treatment trends for trade volume (total and gap) in Nairobi vs its synthetic control

Fig. 4 shows that there is a slight increase in daily trade volume for the synthetic control. Consequently, the gap in daily trade volume between Nairobi and the control does not show a sharp discontinuity between the pre- and post-treatment periods. According to these results, Nairobi has experienced a spike in trade volume of up to KSh200,000 (USD 1,867.94) more than its synthetic control. This is promising because it means that the alternative currency people are using to pay for goods and services is money that otherwise would not have circulated during this time. For small business owners, this additional income can be a lifeboat.

However, the fact that the synthetic control also increases may be attributed to the fact that although other areas did not receive lockdown, Covid-19 has still had a widespread effect on the entire nation, causing a simultaneous increase in volume in all communities. The overall effect of Covid-19 in Kenya may distort the distinction between areas that receive lockdown and those that do not. It is therefore impossible to isolate a perfect treatment assignment because in some way or another, everyone is economically affected. For example, the Kenyan Shilling has depreciated in value relative to the US dollar, government-funded employment opportunities are more scarce as more money goes towards healthcare, and schools are closed so teachers may be receiving salary cuts.

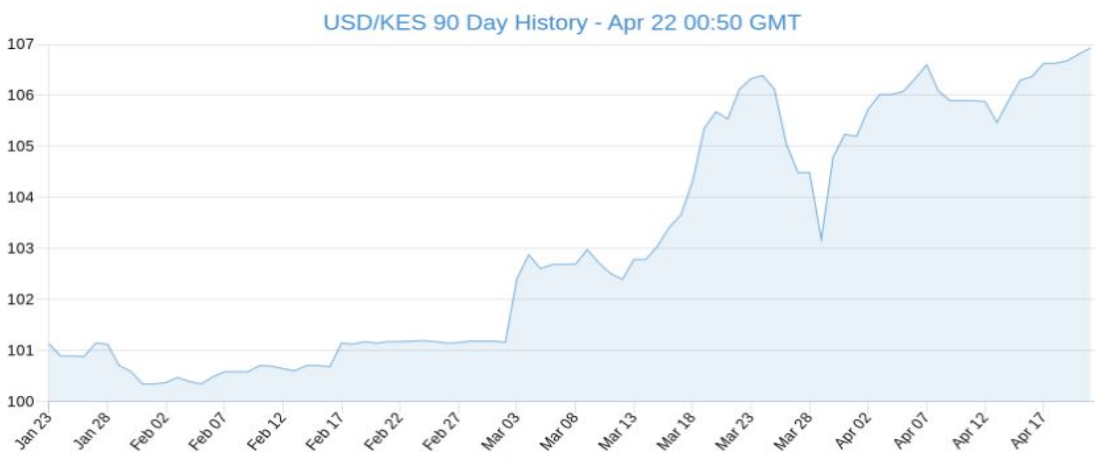

Fig. 5 USD to KSh exchange rate from 01/23/2020 to 04/17/2020 Source: Exchange Rates UK (2020)

Unit weights in the synthetic control model are selected according to the distribution of ratios of post-to-pre treatment root mean squared prediction errors (RMSPE).

$$RMSPE = ((\frac{1}{T-T_0})\sum_{t=T_0+t}^{T}(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt})^2)^{\frac{1}{2}}$$

This formula compares the treatment to counterfactual state for each time period (Cunningham, 2018). By iterating through this process for each unit for both pre- and post-treatment periods, each location has its own placebo treatment and counterfactual. The ratio of the post-to-pre treatment RMSPEs is then sorted in descending order, with higher values indicating the treatment effect is more extreme relative to the other placebos. Since Nairobi only ranks 6^{th}, its ratio in the distribution $= \frac{RANK}{TOTAL} = \frac{6}{40} = 0.15$. This tells us that ultimately, these results are not statistically significant. However, their economic significance arguably still stands. The general increase in trade volume and new traders across all locations (seen in Fig. 3) is most likely a response to the nation-wide effect of Covid-19. This trend supports the hypothesis that community currencies are a useful tool for buffering economic shocks.

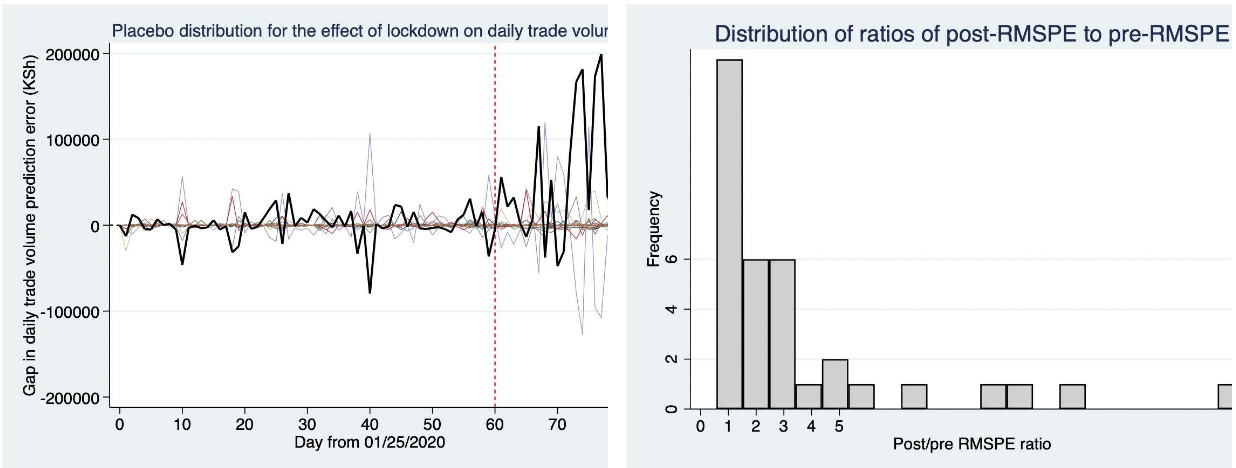

Fig. 6 Synthetic control placebos for each location pre- and post-treatment (left), based on ratios of the post-to-pre treatment RMSPE amongst control units (right). In the first graph, the bolded line shows daily volume in Nairobi, which remains considerably higher than in locations that did not receive lockdown. In the second graph, Nairobi is the furthermost bin and the preceding 5 bins are the units included in the synthetic control.

5 Limitations

While the results show some notable differences in daily trade volume between regions, it is undeniable that this dataset suffers from a lack of explanatory data. This highlights the constraints on inferring causality based on non-experimental data, where no predefined program or study has necessitated the collection of auxiliary data such as regional demographics and socio-economic conditions. Spending behaviour between regions is only comparable to a certain degree; in reality, there are a host of unobserved factors that may affect a difference in trends.

Another concern is that the treatment under consideration – curfew restrictions due to the Covid-19 pandemic – may not be universally applied to units labelled as the treatment group. While Nairobi is a bustling capital city and has seen considerable police presence to enforce the curfew, it is impossible to tell to what extent the treatment differs from the control units. It is hardly likely that police are patrolling the streets as in places like Italy, least of all in dense slum communities. Instead, the treatment in this case is best interpreted as the combination of the effects of curfew: the knowledge of there being a curfew and the fear of punishment along with closed stores and a general slowdown in economic activity.

It can best be said that this project was an exercise on finding causal effects when working with very tricky and messy data. While large, cleaned datasets exist for well-known programs, this is often not the case when working with highly specific, contextual studies. The motivation to work with this data nonetheless is that not all empirical economic phenomena can be analyzed through the neatly-packaged lens of a well-funded program. It would be a shame to not study things simply because they’re too difficult and inconvenient to analyze. The challenge to economists who are interested in non-conventional economic models is that proving they are worth studying, debating or implementing requires a skillful ability to translate what is disorganized or incomprehensible in a language that others can understand. The results may not be perfect, the statistics a little off, but the exercise itself moves the field one step closer to understanding an economic phenomenon that someone else may choose to further analyse in the future.

6 Conclusion

The Covid-19 pandemic has exposed the fragility of economies that share risk through interdependent currencies and global supply chains. At a hyper-local level, there is an urgent need to provide adequate social protection policies for communities that are vulnerable to economic shocks. More sobering, perhaps, is the reality that in many regions around the world, these “shocks” are not a once-in-a-blue-moon occurrence but a perpetual state of currency scarcity and economic stagnation. Community currencies offer a promising model to address this by providing people with an alternative when national currency is no longer available. Evidence from the increase in trade on the Sarafu Network due to Covid-19 lockdown in Nairobi suggests that these currencies can be extremely useful as a countercyclical buffer.

7 References

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, *105*(490), 493-505. Available through Claremont Libraries, Database: ABI/INFORM Collection

Bendell, J. Slater, M. and Ruddick, W. (2015). Reimagining Money to Broaden the Future of Development Finance. United Nations Research Institute for Social Development. Retrieved from http://www.unrisd.org/80256B3C005BCCF9/%28httpAuxPages%29/99FCA15CAF8E24F4C1257E7E00501101/$file/Bendell%20et%20al.pdf

Briguglio, L., Cordina, G., Farrugia, N. and Vella, S. (2009). Economic Vulnerability and Resilience: Concepts and Measurements. Oxford Development Studies, Volume 37. https://doi.org/10.1080/13600810903089893

Castilla-Rubio, J., Zadek, S. and Robins, N. (2016). Fintech and Sustainable Development: Assessing the Implications. United Nations Environment Programme (UNEP) Inquiry into the Design of a Sustainable Financial System. Retrieved from http://unepinquiry.org/wp-content/uploads/2016/12/Fintech_and_Sustainable_Development_Assessing_the_Implications_Summary.pdf

Cunningham, S. (2018). *Causal inference: The mixtape* (pp. 287-313). Retrieved July 1, 2018 from: Retrieved from http://scunning.com/mixtape.html

Grassroots Economics. (2020). *2020 - Current xDAI Blockchain Data*. Retrieved April 18, 2020 from https://www.grassrootseconomics.org/research

Kiiru, J. M. (2010). Remittances and Poverty in Kenya. OIDA International Journal of Sustainable Development, Vol. 1, No. 8, pp. 33-41

Republic of Kenya. (February 23, 2007). *The Kenya Gazette*. Volume CIX No. 18.

Ruddick, W. and Chirenga, C. (2019). Liquid Community Currencies. Retrieved from https://docs.wixstatic.com/ugd/ce30dd_d5c510a583604ce3991e0e3f45204afc.pdf

Sahakian, M. (2014) Complementary currencies: what opportunities for sustainable consumption in times of crisis and beyond? Sustainability: Science, Practice and Policy, 10:1, 4-13, DOI: 10.1080/15487733.2014.11908121

Stoddard, C. (n.d.) *Basic Panel Data Commands in STATA*. ECNS 562: Stata Resources. Montana State University. Retrieved April 18, 2020 from http://www.montana.edu/cstoddard/562/panelcommands.pdf

Utting, P. (April 29, 2013). Social and Solidarity Economy: A Pathway to Socially Sustainable Development? United Nations Research Institute for Social Development. Retrieved from http://www.unrisd.org/thinkpiece-utting

8 Appendix A: Data

Before conversion to panel data format:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	id	timeset	transfer_sub	transfe	source	s_comm_tkn	s_ge	s_location	s_business_t	target	t_comm_tkn	t_gender	t_location	t_business_	tx_token	weight	tx_hash	type	token_name	token_addre
2	1	13:17.7	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x245fc81fe	None	female	GE Office	Savings Group		18000	no hash foun	directed	Sarafu	0x0Fd6e8F2
3	2	13:19.1	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xC1697C13	None	male	GE Nairobi	Farming/Labour		9047.66089	no hash foun	directed	Sarafu	0x0Fd6e8F2
4	3	13:20.3	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xBAB77A2	None	male	GE Nairobi	Farming/Labour		25378.726	no hash foun	directed	Sarafu	0x0Fd6e8F2
5	4	13:21.5	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xD95954e3	None	male	G.E	Farming/Labour		4495.93258	no hash foun	directed	Sarafu	0x0Fd6e8F2
6	5	48:43.0	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x4AB73Cfa	None	male	Home	Farming/Labour		400	no hash foun	directed	Sarafu	0x0Fd6e8F2
7	14	34:16.7	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x4AfD04b9	None	male	Test	Health		400	no hash foun	directed	Sarafu	0x0Fd6e8F2
8	19	32:36.5	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xeFad5486	None	male	Gatina	Food/Water		621.689801	no hash foun	directed	Sarafu	0x0Fd6e8F2
9	20	32:38.0	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x66878365	None	male	Gatina	Shop		714.378298	no hash foun	directed	Sarafu	0x0Fd6e8F2
10	21	32:39.4	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xD239dc57	None	female	Gatina	Food/Water		268.709888	no hash foun	directed	Sarafu	0x0Fd6e8F2
11	22	32:40.8	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xD6766d64	None	female	Gatina	Shop		499.631281	no hash foun	directed	Sarafu	0x0Fd6e8F2
12	23	32:42.2	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xaA7Fd999	None	female	congo	Food/Water		694.614875	no hash foun	directed	Sarafu	0x0Fd6e8F2
13	24	32:43.5	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x7002Fde3	None	female	congo	Shop		2819.65507	no hash foun	directed	Sarafu	0x0Fd6e8F2
14	25	32:45.1	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x27175679	None	female	congo	Farming/Labour		223	no hash foun	directed	Sarafu	0x0Fd6e8F2
15	26	32:46.4	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xfDa3ab16	None	female	congo	Farming/Labour		556.678592	no hash foun	directed	Sarafu	0x0Fd6e8F2
16	27	32:47.6	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xdfe2C99A	None	female	bangladesh	Food/Water		1028	no hash foun	directed	Sarafu	0x0Fd6e8F2
17	28	32:49.0	DISBURSEMENT		0xBDB3Bc88	None		None	System	0xE2982a68	None	female	Bangla	Food/Water		1063	no hash foun	directed	Sarafu	0x0Fd6e8F2
18	29	32:50.5	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x7bA9716b	None	male	bangladesh	Farming/Labour		432	no hash foun	directed	Sarafu	0x0Fd6e8F2
19	30	32:52.3	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x33ef718d4	None	male	Kangemi	Farming/Labour		690	no hash foun	directed	Sarafu	0x0Fd6e8F2
20	31	32:53.7	DISBURSEMENT		0xBDB3Bc88	None		None	System	0x3c77Ab27	None	female	Lindi	Food/Water		514	no hash foun	directed	Sarafu	0x0Fd6e8F2

After conversion to panel data format (data cleaning processed using Python):

	A	B	C	D	E	F	G	H
1	date	location	daily_total	gender_ratio	gender_ratio	main_purpos	n_trades	n_new_users
2	0	0	0	0	0	10	0	0
3	1	0	0	0	0	10	0	65
4	2	0	100	1	1	6	1	0
5	3	0	0	0	0	10	0	0
6	4	0	0	0	0	10	0	0
7	5	0	0	0	0	10	0	0
8	6	0	5	1	1	3	1	0
9	7	0	830	0.5	2	3	3	0
10	8	0	0	0	0	10	0	0
11	9	0	202	2	2	3	3	0
12	10	0	0	0	0	10	0	0
13	11	0	300	0.5	0.5	3	3	0
14	12	0	0	0	0	10	0	0
15	13	0	0	0	0	10	0	0
16	14	0	0	0	0	10	0	0
17	15	0	400	1	1	3	1	0
18	16	0	200	1	1	6	1	1
19	17	0	0	0	0	10	0	0
20	18	0	1000	1.33333333	0	3	7	0

Summary statistics for daily trade volume by location:

Unit	Obs	Mean	Std. Dev.	Min	Max
0 |	81	668.9259	1529.618	0	9530
1 |	81	9.876543	88.88889	0	800
2 |	81	752.5235	1125.714	0	7870
3 |	81	59.71605	193.9472	0	910
4 |	81	426.8272	997.9642	0	6000
5 |	81	118492.5	479303.1	0	4267536
6 |	81	428.7531	1043.492	0	5600
7 |	81	9.876543	62.45986	0	400
8 |	81	4.938272	44.44444	0	400
9 |	81	31.48148	110.2396	0	800
10 |	81	37.03704	109.7662	0	400
11 |	81	367.5432	840.1389	0	5360
12 |	81	28.2716	81.75864	0	400
13 |	81	11158.82	19514.09	0	164115
14 |	81	11.49383	57.55978	0	385
15 |	81	8.024691	52.11573	0	400
16 |	81	28616.05	27017.64	0	155656.1
17 |	81	24.83951	102.8605	0	634
18 |	81	2827.037	6374.393	0	48602
19 |	81	1.259259	7.806692	0	50
20 |	81	4.320988	38.88889	0	350
21 |	81	7.654321	49.04772	0	360
22 |	81	2.469136	22.22222	0	200
23 |	81	3.08642	16.48044	0	100
24 |	81	31556.18	42655.58	0	237041
25 |	81	7169.787	10441.61	0	60586
26 |	81	1211.469	2322.378	0	16970
27 |	81	2632.432	3982.638	0	26510
28 |	81	44628.11	62574.54	0	261390
29 |	81	4.938272	44.44444	0	400
30 |	81	18.08642	76.8219	0	560
31 |	81	7.037037	40.41796	0	350
32 |	81	7.962963	27.70128	0	140
33 |	81	454.9136	2031.062	0	18026
34 |	81	9.876543	56.13586	0	400
35 |	81	4.938272	43.88546	0	395
36 |	81	3.45679	15.98128	0	100
37 |	81	425.8519	1250.123	0	8780
38 |	81	4933.938	7484.367	0	38400
39 |	81	3903.642	8638.809	0	48260
40 |	81	1.234568	11.11111	0	100
41 |	81	116.0494	272.6017	0	1680
42 |	81	40.12346	113.032	0	500

9 Appendix B: Stata code

The stata .do file can be found on Github here.