Holding periods: Inverse estimation of money velocity

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Abstract

Classic formulations of money velocity assume stationary conditions, yet monetary indicators are most critical during crises and policy changes. To address this gap, we introduce an equivalent definition that generalizes to non-stationary conditions—the inverse average holding period of money. This quantity can be measured directly from transaction records. When applied to Sarafu, a digital community currency in Kenya, this reveals striking heterogeneity in system tightness during the COVID-19 pandemic: velocity varied seven-fold across localities. Subsequently, an intervention that removed 27% of supply produced no response in one area and reactivation of dormant balances in another. The approach suits any digital payment system, enabling timely monitoring of money velocity during unstable conditions and across fragmented currency systems.

Keywords: Velocity of money, Temporal network, Community Currency, Nonstationary, Transaction data

JEL Codes: E41, E42, C63, L14

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1 Introduction

The ability of central banks to conduct monetary policy during crises depends on timely, accurate measurement. Modern payment infrastructure is largely digital, and "naturally occurring data" in the form of digital transaction records offers the potential to re-engineer national economic indicators (Ehrlich et al. 2019). For example, measures of consumer spending and aggregate consumption have been successfully constructed from records of retail transactions and used for timely, disaggregated analyses (Aladangady et al. 2022; Buda et al. 2022). Modernizing monetary indicators has proven to be a greater challenge. Money velocity, for instance, remains anchored to definitions developed before digital payments existed (Friedman 1970). Classic formulations also assume stationary conditions, making existing measures unsuitable for disaggregation and unreliable during crises, interventions, or policy changes. To overcome this limitation, we introduce an equivalent definition of money velocity that readily generalizes to non-stationary conditions and can be measured directly from the transaction records produced by modern digital payment systems.

Holding periods of money measure how long funds sat in an account before being spent. These values can be extracted from transaction records (Mattsson and Takes 2021), and averages of their inverses have been used to disaggregate money velocity, as defined in Fisher's equation of exchange, within systems where stationarity holds or is assumed to hold (Wang, Ding, and Zhang 2003; Campajola, D'Errico, and Tessone 2023; Collibus, Campajola, and Tessone 2025). However, this is a strong assumption requiring the total balance of a system, and that of each disaggregated unit, to be stable. We show that computing the average holding period, first, and then taking the inverse of this quantity, also recovers the money velocity under stationary conditions. The inverse average holding period generalizes to non-stationary conditions, making it a new, equivalent, definition of money velocity suitable also for systems experiencing expansion, contraction, and interventions. Moreover, it becomes straightforward to exclude irrelevant transactions to obtain the equivalent of more modern measures, such as the transfer velocity, as estimated from empirical transactions aggregates of digital payment systems (Mbiti and Weil 2013; Mbiti and Weil 2015).

We study the circulation of Sarafu, a digital community currency in Kenya, during a period of economic disruption related to the COVID-19 pandemic. This provides an ideal test case where stationarity fails: community currencies see more use in periods of disruption or illiquidity (Stodder 2009; Zeller 2020; Fleischman, Dini, and Littera 2020) and Sarafu experienced documented interventions over this period (Ussher et al. 2021; Mattsson, Criscione, and Ruddick 2022). We compare the inverse average holding period to the conventionally measured transfer velocity, using complete transaction records for 2020-2021 (Ruddick 2021)

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to produce the estimates. Our estimate is more than double the conventional estimate, a substantial discrepancy that confirms the failure of the stationary assumption.

Note that community currencies are much simpler than official currencies. There is no financial system, and thus no interest rate governing monetary conditions within the Sarafu system. Instead, our measure of velocity serves as an indicator of the availability of Sarafu: the total transfer volume and issued balance of Sarafu would indicate demand and supply, respectively, under stationary conditions, so their ratio, the velocity, indicates system tightness. Our generalized definition of velocity allows us to study the conditions within the Sarafu system in response to real economic stressors and a major currency intervention.

We consider a period of sharply rising demand for Sarafu, as the pandemic brought severe economic disruption to marginalized, food-insecure communities in Kenya (FEWS NET 2020b). Indeed, the system attracted many new participants early in the pandemic. This also makes conventional indicators especially unreliable, in that new Sarafu credits were issued primarily to new accounts. The inverse average holding period reveals that different communities using Sarafu experienced widely differing monetary conditions at the same point in time. Early in the pandemic, Kinango Kwale, a poor rural area of Kenya, saw velocity rise briefly as the locally established Sarafu system expanded to meet local needs. Mukuru, an informal settlement of Nairobi where Sarafu was just being introduced, saw an extended period of frantic circulation with a velocity more than seven times higher than elsewhere.

Uneven monetary tightness complicated currency management during the crisis, especially in that the Sarafu system was highly centralized at the time. As the crisis subsided, the Sarafu system faced the converse challenge—velocity slowed. In October 2020, as a response to loosening monetary conditions more drastic than those available for official currencies, an ad-hoc currency operation was used to remove 27% of issued Sarafu almost instantaneously. This intervention was publicized ahead of time and targeted inactive accounts, yet it introduces a near-discontinuity in conventional indicators. Our indicators show no discernible change in one area, Mukuru Nairobi, where demand for Sarafu had been falling. In Kinango Kwale, where demand had been rising, likely due to seasonal food insecurity, we see long-held Sarafu re-entering circulation. Indeed, the second swell of transfer volumes in this area was led by a sharp rise in the effective balance rather than the velocity. Observing heterogeneous dynamics during unstable conditions, when conventional measures become unreliable, demonstrate the value of our method for monitoring currency systems during shocks and interventions.

This work contributes directly to the emerging literature on constructing macroeconomic indicators from naturally occurring data (Ehrlich et al. 2019). Experimental data series have been produced from the transaction records of commercial banks, card payment processors, automated clearing systems, and real-time gross settlement systems (Buda et al. 2022; Al-

adangady et al. 2022; Hötte and Naddeo 2024; Silva, Amancio, and Tabak 2022). Modernizing monetary indicators is increasingly urgent with the rising importance of digital financial services, cryptocurrencies, and central bank digital currencies. We show that comprehensive transaction records from a stand-alone currency system can generate meaningful monetary indicators with the timeliness and granularity needed for policy-making. Furthermore, each payment system within a larger, fragmented, currency system is likely to operate under non-stationary conditions. Our methodology allows for sound empirical measurement of the money velocity within a payment system (Mbiti and Weil 2013) from its own transaction records. Empirical estimates for different components of a monetary aggregate can then be combined (Cramer 1986; Mbiti and Weil 2015) and so it becomes feasible to measure money velocity directly from the digital records of modern payment infrastructures.

Our work also relates to other strands of literature. Measuring money velocity has long been of interest to monetary economists, and we extend the classic transactions-based formulation (Friedman 1970; Leontief and Brody 1993) to non-stationary conditions. Timeseries of money velocity have been found to be stochastic and to show inconsistent behavior across different dynamical regimes (Serletis 1995; Ardakani 2023), but the stationarity assumption embedded in conventional measurement had not been articulated. Even so, heterogeneity has long been recognized across sectors (Leontief and Brody 1993; Brody 2000), between payment systems (Cramer 1986; Mbiti and Weil 2015), and, more recently, among individual accounts (Mbiti and Weil 2013; Campajola, D'Errico, and Tessone 2023). There is growing evidence that many macroeconomic measures, such as inflation and unemployment, as well as important macroeconomic channels in monetary policy, affect individuals, groups, and locales differently (Argente and Lee 2021; Gornemann, Kuester, and Nakajima 2021; Bartscher et al. 2021). We add to this literature in that we use new data and empirical techniques to identify and analyze heterogeneity in a measure of monetary tightness. Finally, our analysis of Sarafu contributes to the empirical literature on complementary currencies during crises (Stodder 2009; Zeller 2020). As alternative digital currencies proliferate (ElBahrawy et al. 2017; Guo, Härdle, and Tao 2024) we provide a new tool for empirical study of this evolving landscape.

The remainder of this paper develops these contributions in detail. Section 2 introduces the average holding period of money and defines its relation to money velocity. In Section 3 we detail our methodology for measuring this value from transaction data as recorded by real-world payment systems. Section 4 describes the Sarafu system, our applied case. We present novel empirical analyses of this system in Section 5. Section 6 concludes.

2 Average holding period of money

The rate at which money changes hands is an important macroeconomic indicator and plays a key role in determining inflation (Benati 2020; Benati 2023). However, conventional measures of money velocity reflect classic formulations as the term that balances a "quantity equation" constructed from aggregate accounting identities (Friedman 1970). Fisher and, later, Leontief, favored a quantity equation constructed from the sum total of transactions in an economy (Fisher 1911; Leontief and Brody 1993) though transactions aggregates were difficult to measure (Cramer 1986). Today, payment infrastructure is largely digital and producing data from transaction records is highly compelling (Ehrlich et al. 2019).

The *transfer velocity of money* is the ratio between the total transaction volume facilitated by a payment system and the average total balance held by users of that system (Mbiti and Weil 2013). Within a fragmented currency system, this empirical quantity gives the contribution of one payment system to the aggregate transactions velocity of money (Mbiti and Weil 2015). Eqn. 1 describes the empirical aggregate ratio. The total transfer volume or the total flow of money, F_T, in a time window, $t_0 < t < t_1$, is related to the amount of money in circulation, M, and its (aggregate) transfer velocity, V. We include the length of time $\Delta t = t_1 - t_0$ in our formulation, explicitly, so that both F_T and M are amounts denoted in units of currency. The scale of V can be defined such that $\Delta t = 1$.

$$F_T = M \cdot \Delta t \cdot V \tag{1}$$

Money velocity can also be defined using the concept of a "holding period." Denoted τ, holding periods are the durations between when accounts receive and re-transact particular units of money. Wang, Ding, and Zhang (2003, Eqn. 4) define $P(\tau)$ as the probability density for a given unit of money being used in a transaction after an interval of τ. With respect to the units of money, $P(\tau)$ can be considered a waiting time distribution. Integrating over this distribution is to consider the waiting time of each unit of money, at a snapshot in time, allowing an expression for the transfer velocity (Wang, Ding, and Zhang 2003, Eqn. 8):

$$V = \int_0^\infty P(\tau) \cdot \frac{1}{\tau} \cdot d\tau \text{ where } 1 = \int_0^\infty P(\tau) d\tau \tag{2}$$

The definitions in Eqns. 1 and 2 both assume stationary conditions. Mbiti and Weil (2013) do so implicitly, taking M to be the time-average of $M(t)$. Recent work employing an analogous approximation in the context of production, rather than spending, make the assumption explicit (Antràs and Tubdenov 2025). Wang, Ding, and Zhang (2003) consider a stochastic transaction process in its stationary state, where $P(\tau)$ is explicitly independent of

t. Here we introduce $P(\tau, t)$ as the non-stationary generalization of $P(\tau)$. While a waiting time distribution that changes in time is conceptually difficult to relate to observables of a real system, it proves useful in derivations. Eqn. 3 formulates a generalized version of the expression for F_T without assuming stationary conditions, that is, where both M and $P(\tau)$ are functions also of t (cf. Wang, Ding, and Zhang 2003, Eqn. 7). Eqn. 4 uses differential form to express the transfer volume generated by the share of money transacted after a period of exactly τ (cf. Wang, Ding, and Zhang 2003, Eqn. 6).

$$F_T = \int_{t_0}^{t_1} \int_0^\infty M(t)P(\tau, t) \cdot \frac{1}{\tau} \cdot \partial\tau\partial t \tag{3}$$

$$F_T(\tau) = \int_{t_0}^{t_1} M(t)P(\tau, t) \cdot \frac{1}{\tau} \cdot \mathrm{d}t \tag{4}$$

Notably, $F_T(\tau)$ is in principle observable for real digital payment systems. This would be the distribution of holding periods completed over $t_0 < t < t_1$, that is, the periods for which funds were held ahead of the transactions in this time window. Eqn. 4 then lets us define the average period of time that money was held prior to being spent during the time window $t_0 < t < t_1$. This is the average holding period, denoted as $\bar{\tau}_T$ in Eqn. 5:

$$\bar{\tau}_T = \frac{1}{F_T} \int_0^\infty F_T(\tau) \cdot \tau \cdot \mathrm{d}\tau \tag{5}$$

We can now show that the inverse average holding period is equivalent to the transfer velocity under stationary conditions. Incorporating Eqn. 4 into Eqn. 5 produces Eqn. 6. When $M(t)$ and $P(\tau, t)$ are independent of t, the double integral simplifies to $M \cdot \Delta t$. Rearranging the simplified expression gives us Eqn. 7. Note the parallel to Eqn. 1, with $\bar{\tau}_T^{-1}$ in place of V.

$$\bar{\tau}_T = \frac{1}{F_T} \int_0^\infty \int_{t_0}^{t_1} M(t)P(\tau, t)\partial t\partial\tau \tag{6}$$

$$F_T = M \cdot \Delta t \cdot \bar{\tau}_T^{-1} \tag{7}$$

While the inverse average holding period $\bar{\tau}_T^{-1}$ is equivalent to the transfer velocity V under stationary conditions, it is defined without assuming stationary conditions and so it serves as a more general definition that extends to non-stationary conditions. Eqn. 8 gives the new, generalized definition of the transfer velocity, which we denote using V_T because it is defined over the time window $t_0 < t < t_1$ in the same sense as is the total transfer volume F_T.

$$V_T = \bar{\tau}_T^{-1} \tag{8}$$

The generalized transfer velocity V_T also does not rest on estimates of M. This means we can define the *effective balance* of the system over $t_0 < t < t_1$ as the fixed balance that satisfies the aggregate relationship in Eqn. 7 between V_T and the total transfer volume F_T. The effective balance M_T is defined in Eqn. 9, drawing from Eqn. 6.

$$M_T = \frac{1}{\Delta t} \int_0^\infty \int_{t_0}^{t_1} M(t) P(\tau, t) \partial t \partial \tau = \frac{1}{\Delta t} \cdot F_T \cdot \bar{\tau}_T \tag{9}$$

3 Methodology

The transfer velocity is the rate at which money changes hands within a specific payment system, and digital transaction records allow direct empirical measurement. Section 3.1 describes the conventional approach to measuring the transfer velocity from digital transaction records. Our methodology for direct empirical measurement of the generalized transfer velocity, that is, of the inverse average holding period, is introduced in Section 3.2.

3.1 Measuring the transfer velocity

An empirical estimate for the transfer velocity V can be computed using Eqn. 1. The total flow of money F_T is a measurable quantity and the total balance M that is issued within the system can be estimated. In practice, one considers the time-average balance over the time window $t_0 < t < t_1$ (Mbiti and Weil 2013). Eqn. 10 formulates an expression for the transfer velocity V using the empirical time-average of $M(t)$. Times t_0 and t_1 can be selected so that $\Delta t = t_1 - t_0 = 1$ in the time unit also used for reporting V.

$$V = F_T / (M_{\text{avg}} \cdot \Delta t) \text{ where } M_{\text{avg}} = \int_{T_0}^{T_1} M(t) \mathrm{d}t / \Delta t \tag{10}$$

Empirical values for F_T and $M(t)$ can be measured from the transaction records of a payment system. The total flow F_T is the sum of transaction sizes for user-initiated transfers that occur in the time window $t_0 < t < t_1$. The total balance $M(t)$ is the sum of the amounts of money held in that moment by all user-facing accounts; this needs to be measured at regular intervals or inferred from records of issuance and dissolution. Note that balances held by provider-facing accounts are generally not included in the total (Mbiti and Weil 2013).

3.2 Measuring the generalized transfer velocity

The generalized transfer velocity V_T is simply the inverse of the average holding period of money $\bar{\tau}_T$, and $\bar{\tau}_T$ can be computed using Eqn. 5. The distribution of completed holding

periods $F_T(\tau)$ over the time window $t_0 < t < t_1$ is possible to obtain from transaction records. Specifically, a computational technique called "trajectory extraction" gives empirical holding periods from transaction data (Mattsson and Takes 2021). Transactions out of an account are allocated funds from prior transactions into that account. An outgoing transaction at time t completes one or more holding periods τ that become observed in that moment. The holding periods that end in transfer transactions occurring in the time window $t_0 < t < t_1$ are collected into an empirical distribution; this is $F_T(\tau)$. This distribution can be constructed for the full system, and for any subset of accounts. Eqn. 5 is evaluated as a weighted average.

Trajectory extraction is a data transformation based in the theory of walk processes on networks, respecting the conservation of funds by design (Mattsson and Takes 2021). We represent the perfect fungibility of funds by selecting the "well-mixed" heuristic in applying the allocation algorithm. This ensures we consider all possible pairs of transactions, assigning an amount to every time-respecting pair under proportional allocation. This is computationally intensive and simpler heuristics are available for use with larger datasets, being known to produce precise estimates in practice (Collibus, Campajola, and Tessone 2025).

4   Data

The Sarafu system is a set of digital community currencies in Kenya operated by Grassroots Economics Foundation, a Kenyan nonprofit organization, whose efforts are concentrated in specific areas and aimed at supporting marginalized, food insecure communities. In 2020-21, the system comprised a single currency (Sarafu) under centralized management.[1] Payments in Sarafu credits were made via a mobile phone interface. One unit of Sarafu credits was roughly equivalent in value to a Kenyan shilling but the system itself is wholly separate from the national currency. The explicit involvement of community-based institutions, especially savings and lending groups, is an innovative aspect of the Sarafu system. Here we describe the records available for this stand-alone currency system, as well as the most relevant background for interpreting our novel monetary indicators across geographic areas and over time.

4.1   Sarafu Community Inclusion Currency 2020-2021

Grassroots Economics has made a portion of the 2020-2021 system's administrative records available for research; the published dataset includes records of all Sarafu transactions

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[1]Earlier iterations of the Sarafu system favored decentralized currency management practices, as do subsequent systems in place since April 2022 and July 2023. The highly centralized system studied here was run on a PostgreSQL database; this was a temporary stop-gap technology that remained in place longer than intended as Grassroots Economics adjusted priorities during the COVID-19 pandemic.

conducted from 25 January 2020 to 15 June 2021 plus limited information about the account holders. There were about 400,000 transfers among what grew to be approximately 55,000 accounts, totaling around 300 million Sarafu. The data is accessible via the UK Data Service (Ruddick 2021) and is thoroughly documented (Mattsson, Criscione, and Ruddick 2022).

The transactions dataset is comprehensive. The creation and removal of Sarafu took place via DISBURSEMENT and RECLAMATION transactions, respectively. Most DISBURSEMENT transactions are to newly created accounts. User activity is recorded in the data as STANDARD transactions, predominantly. There are also a small number of AGENT_OUT transactions indicating purchases, of sorts, that facilitated donations to savings and lending groups; there were limited instances of this. Our precise delineation of "transfers" is detailed in Appendix I.

The anonymized account dataset includes several contextual attributes that describe the characteristics of account holders. The "area name" and "business type" are user-generated entries generalized into broader categories by staff at Grassroots Economics. They reflect the home locality of the user and the product category of the goods or services they provide to the community. Mattsson, Criscione, and Ruddick (2022) provide precise descriptions of these data fields and Ussher et al. (2021) provide further detail on the values.

4.2   Information on shocks and interventions

The 2020-21 Sarafu dataset covers the first year of the COVID-19 pandemic, an observation window that includes documented pilot projects, interventions, and currency operations (Ussher et al. 2021; Mattsson, Criscione, and Ruddick 2022). Figure 1 shows timeseries of Sarafu transfer volumes (left) and the total system balance (right). Transfer volumes surged in response to economic disruption related to the COVID-19 pandemic, especially in Nairobi and in Kinango Kwale. Kinango is an administrative division in rural Kwale county where Grassroots Economics has had a presence for many years (Cauvet 2018). Nairobi is the capital city of Kenya, where Sarafu was introduced to informal settlements of the Mukuru slum during the observation period (Mattsson, Criscione, and Ruddick 2022). The total issued balance of the Sarafu system grew substantially in the first half of the observation period, as newly created accounts were issued new Sarafu. Near-discontinuities occur where specific currency operations added or removed an appreciable fraction of the total balance.

The use of community currencies during crises has attracted growing interest. Counter-cyclical transfer volumes are consistent with the prevailing understanding of complementary currencies in times of crisis (Stodder 2009; Zeller 2020; Fleischman, Dini, and Littera 2020). The Sarafu system was already established in several areas of Kenya, with existing local circulation and considerable involvement from community-based institutions (Cauvet 2018).
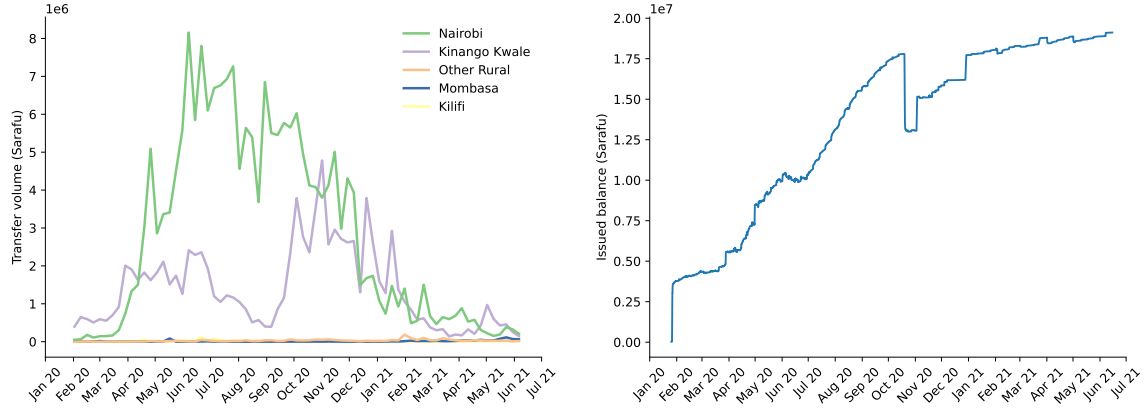
Figure 1: Weekly transfer volumes per geographic area (left) and total issued balance (right) of Sarafu.

Over the observation period, circulation within the Sarafu system remained geographically localized (Mattsson, Criscione, and Takes 2023) and the accounts held by community-based groups, of which there are some hundreds, continued to play an important role (Ba, Zignani, and Gaito 2023). Such groups also became part of an improvised pandemic-response effort. For a time, donations from international organizations were routed to active community groups via Sarafu (Mattsson, Criscione, and Ruddick 2022, *Donations to chamas*). This reflects the practitioner perspective, where digital community currencies were seen as an experimental modality for delivering humanitarian aid. Verjee (2021) describes a project of the Kenyan Red Cross conducted in collaboration with Grassroots Economics Foundation: promotion, education, and training programs began in Mukuru, Nairobi in April 2020. While long-planned as a pilot project, the campaign soon incorporated a response to the emerging COVID-19 pandemic (Mattsson, Criscione, and Ruddick 2022, *Targeted introductions & Specific interventions*). Ussher et al. (2021) articulate the argument for why digital community currencies might compare favorably to cash assistance in the context of humanitarian aid.

5 Results

We study the Sarafu system using the transaction records from 2020-2021. Section 5.1 compares the inverse average holding period of Sarafu, over the full time window available, to the conventional velocity measure, confirming that circulation of Sarafu was non-stationary. The added value of our generalized definition of velocity is that it allows us to characterize monetary conditions during the documented shocks and interventions. Starting with the first, Section 5.2 tracks the generalized velocity of Sarafu in the context of localized pandemic-related economic disruption, considering separately the communities using Sarafu in urban

Nairobi and in rural Kinango Kwale. Section 5.3 illustrates the monitoring of money velocity while a substantial currency intervention was actively taking place.

5.1 Money velocity under non-stationary conditions

Our analysis confirms that circulation within the Sarafu system was non-stationary over this period. Measured in the conventional manner, units of Sarafu changed hands on average 0.31 times per week over the full observation period. The inverse average holding period implies faster circulation. The Sarafu used in transfers had been held for 1.36 weeks, on average, corresponding to a generalized transfer velocity of 0.74 transactions per week. Sarafu circulated twice as fast as assuming stationarity would suggest, indicating that a substantial portion of the issued balance of Sarafu was sitting in accounts that did not contribute proportionately towards the total transfer volume. Circulating at 0.74 transactions per week, only 42% of the issued balance would have been needed to produce the observed volume of transfers; in this sense, 58% of the total Sarafu balance was, effectively, not in use.

This value encompasses considerable geographic heterogeneity. Table 1 summarizes the circulation of Sarafu within communities of Nairobi, Mombasa, Kilifi, Kinango Kwale, and other rural areas over the full observation period. Communities of Nairobi are an outlier with respect to the speed of circulation; most transfers used Sarafu that was within a week of receipt. This corresponds to a generalized transfer velocity between six and seven transactions per month. As a comparison to the national currency, the conventionally estimated transfer velocity for MPesa, the Kenyan mobile money system and the model for the Sarafu system's mobile interface, rose from around 2 transactions per month in 2007 to around 4 in 2010 (Mbiti and Weil 2015). However, there is extraordinarily wide variation in historical estimates of the transfer velocity across systems and the effect of non-stationarity is ambiguous. The circulation of Sarafu was slower within communities of Kinango Kwale and elsewhere: a lower value for the money velocity, one transfer every three to four weeks, is fairly consistent.

Area	Transfer volume	Holding period	Transfer velocity	Effective balance	Issued balance
	F_T, Sarafu	$\bar{\tau}_T$, weeks	V_T, per week	M_T, Sarafu	M_{avg}, Sarafu
Nairobi	200.05m	0.66	1.53	1.81m	5.42m
Kinango Kwale	98.49m	2.74	0.36	3.73m	7.34m
Other Rural	2.04m	2.25	0.44	0.06m	0.28m
Kilifi	0.96m	2.57	0.39	0.03m	0.17m
Mombasa	0.92m	3.54	0.28	0.04m	0.33m
Total	302.47m	1.36	0.74	5.94m	13.55m

Table 1: Non-stationary measures of the circulation of Sarafu, for different areas of Kenya. Reported as the issued balance in each area is the time-average of this value measured hourly.

The empirical distribution of completed holding periods spans many orders of magnitude—

some Sarafu credits were held for minutes, others for months. Figure 2 shows the probability density of observing holding periods with particular durations prior to a recorded transaction. Sarafu was sometimes spent the same day it was received, or even in a matter of minutes. It was most common for Sarafu to be held overnight and spent later in the same week, or in the following week. At times, Sarafu was held for longer periods before being spent. However, many of the longest-duration holding periods were observed prior to RECLAMATION transactions used to remove Sarafu from circulation, not transfers initiated by spenders. Notably, high variance in velocity has been found also within larger payment systems including mobile money payment systems and cryptocurrencies (Mbiti and Weil 2013; Campajola, D'Errico, and Tessone 2023; Collibus, Campajola, and Tessone 2025).
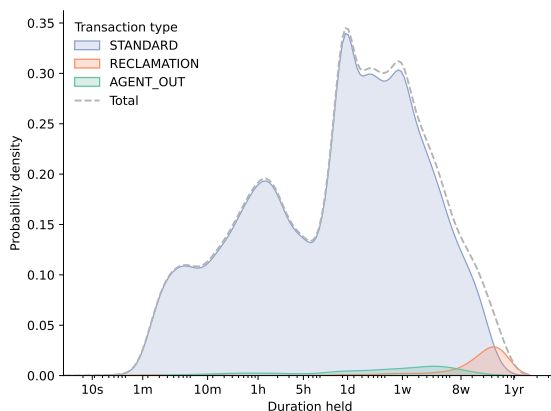
Figure 2: Distribution of completed holding periods. Durations are shown for holding periods ending with Sarafu transactions observed between 25 January 2020 and 15 June 2021, normalized by the total transaction volume. Contributing to the total distribution (dashed line) are transactions of different types. RECLAMATION transactions are not transfers.

5.2 Heterogeneity in monetary conditions

Money tends to move faster when the economy is doing well and slower when the economy is doing poorly (Leão 2005); the opposite is to be expected for community currencies, which behave counter-cyclically (Stodder and Lietaer 2016). Beginning in March 2020, widespread behavioral change and national mitigation policies contra the COVID-19 pandemic strongly affected transport, mobility, and business operations in Kenya. This resulted in substantial economic disruption, particularly in poor urban areas (FEWS NET 2020b). As noted in Section 4.2, the Sarafu system saw rapid expansion and the total issued balance grew substantially. The inverse average holding period remains a valid measure of the transfer velocity, providing a reliable indicator of monetary conditions within the system. In the

following sections we relate the experience of pandemic-related economic disruption in urban Nairobi and in rural Kinango Kwale to timeseries of our monetary indicators for Sarafu, noting that local velocities of Sarafu were strikingly different indicating uneven tightness.

5.2.1 Income shock in Urban Nairobi

The velocity of Sarafu in urban Nairobi, as measured by the inverse average holding period, tracks real economic stressors. Figure 3 (left) shows the weekly transfer volume by accounts registered in Nairobi, with periods of more severe restrictions noted in darker shades of grey. The COVID-19 pandemic impacted urban areas of Kenya directly and prompted a series of official mitigation policies: remote-work directives and nationwide school closures were announced on 15 March 2020; targeted restrictions took effect over the following week and a stringent nationwide curfew was imposed on 27 March; limitations on free movement into and out of Kenya's major cities began on 6 April and remained in effect until 7 July; the nationwide curfew was progressively relaxed on 7 June and on 29 September; bars were allowed to re-open on 29 September; schools were reopened for three grade-levels on 12 October 2020, and fully reopened on 4 January 2021[2]. In acting early, Kenya delayed and mitigated a potentially devastating initial wave of infection—the COVID-19 pandemic first peaked in Kenya in early August (Kimita et al. 2022). However, the economic impact was substantial and the Kenyan economy shrank in 2020 amid otherwise robust growth.
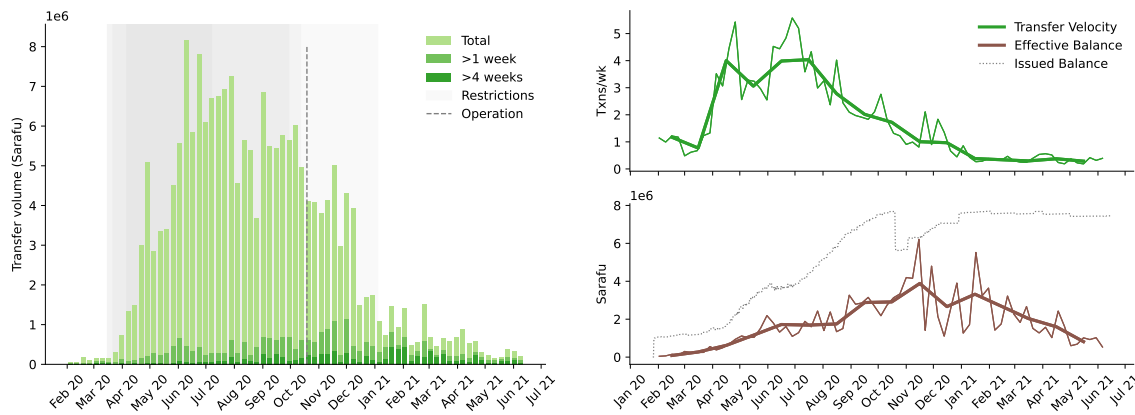

Figure 3: The volume of transfers made each week by users registered in Nairobi (left) and our novel monetary indicators, weekly and monthly (right). The share of transfer volumes plotted in darker green are attributable to funds held for at least one or four weeks immediately prior to being transferred. Shaded in grey are periods with more restrictive COVID-19 pandemic mitigation policies. The grey vertical line gives the timing of a currency operation that removed a substantial share of Sarafu from the system, noticeable also in the issued balance.

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[2]Data from www.health.go.ke/press-releases

The urban poor experienced especially severe economic disruption. Reduced movement and limitations on business operations led to widespread losses in employment and income-generating opportunities for poor urban households. At the same time, mobility restrictions and delays in cross-border trade raised prices for consumer goods including staple foods (FEWS NET 2020b). In phone surveys conducted on 14 April 2020 in informal settlements of Nairobi, 81% of respondents reported complete or partial loss of income (36% and 45%, respectively). 87% of respondents reported increased household expenditures, especially on food (*Kenya* 2020; Pinchoff et al. 2021). By June, informal settlements of Nairobi were noted as an *Area of Concern* in the Food Security Outlook for Kenya published by the Famine Early Warning Systems Network (FEWS NET 2020b). Food insecurity persisted through August for many poor urban households and lingered into December for some households, even as the wider Kenyan economy had begun to recover (FEWS NET 2020c; FEWS NET 2020a).

Transfer volumes rose by several orders of magnitude during the April 2020 targeted introduction of Sarafu in Mukuru, Nairobi and declined towards the end of 2020, as the economic recovery reached even the poorest urban households. This pattern of use aligns with the prevailing understanding of community currencies in periods of economic disruption (Stodder 2009; Zeller 2020). Figure 3 (right) decompose this timeseries into the velocity and balance of Sarafu, by week and by month.

The velocity was much higher here than elsewhere, and strongly counter-cyclical. The velocity rose from below one to above three transactions per week in April 2020 and remained exceptionally high into July 2020. Indeed, we can see from Figure 3 (left) that most of the transfer volume in April 2020, and over the subsequent months, is attributable to funds held for less than a week before being re-transacted. The frenzied circulation of Sarafu in Nairobi began to slow around the time the most restrictive COVID-19 pandemic mitigation policies were lifted, in July 2020. However, transfer volumes remained elevated through November 2020 becoming reflected instead in the continued growth of the effective balance. The transfer velocity of Sarafu, for the smaller share of Sarafu still in use, eventually settled at around one transfer every three to four weeks. Note that this value is remarkably similar to those seen, on average, in communities using Sarafu elsewhere in Kenya (see Table 1).

5.2.2 Expansion in Rural Kinango Kwale

The communities using Sarafu in Kinango Kwale saw two periods of raised transfer volumes, which our measure of velocity indicates were of decidedly different characters. Figure 4 (left) shows the volume of transfers made each week by users registered in Kinango Kwale and Figure 4 (right) presents the inverse of the average holding period and the effective balance, weekly and monthly. Kinango Kwale is a poor rural area where many experience seasonal

food insecurity. Marginal agricultural enterprises provide seasonal work for laborers and own agricultural production provides seasonal support for subsistence, both subject to climate variability (FEWS NET 2020b; MoALF 2016). It is common for residents to leave for nearby urban areas in search of income-generating opportunities (Cauvet 2018).
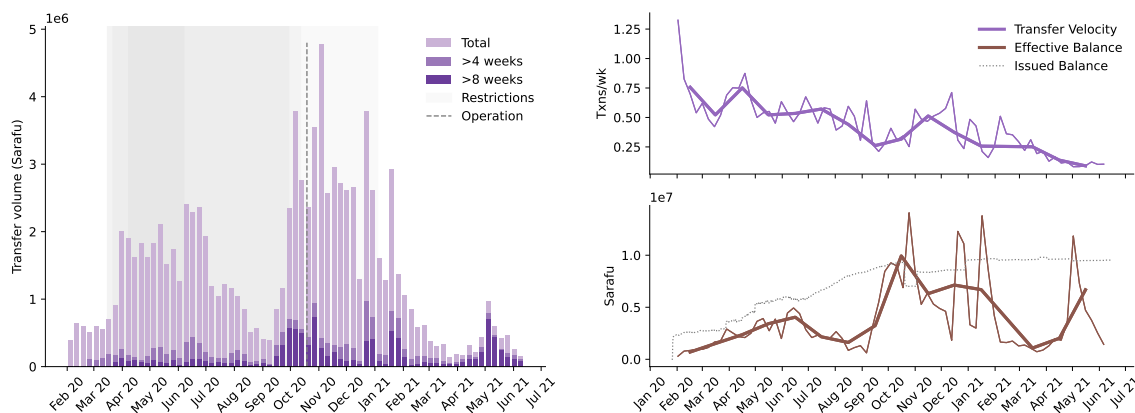

Figure 4: The volume of transfers made each week by users registered in Kinango Kwale (left) and our novel monetary indicators, weekly and monthly (right). Transfer volumes plotted in darker shades are attributable to funds held for more than four or eight weeks immediately prior to being transferred. Shaded in grey are periods with more restrictive COVID-19 pandemic mitigation policies. The grey vertical line gives the timing of a currency operation that removed a substantial share of Sarafu from the system.

Sarafu saw an increase in use in Kinango Kwale beginning in late March 2020—weekly transfer volumes tripled between February and April. We see a temporary spike in the velocity, suggesting that already-active users stepped up their use of Sarafu as nationwide restrictions entered into effect. Their impact was less severe in rural areas; rural livelihoods were indirectly affected via disruptions in the livelihoods of migrant workers in urban areas and changes in the prices of staple foods. Staff at Grassroots Economics liken the economic shock affecting Kinango Kwale to that seen during holiday periods: an influx of migrant workers returning home. In meeting the needs of additional people at higher prices, communities with existing access to the Sarafu system had the option to use the alternative currency. The velocity normalized even as high transfer volumes were sustained for several months, with the effective balance increasing. Perhaps because of existing familiarity with Sarafu in the community, large amounts of Sarafu issued to new users reached those keen on using in; this parallels the trend in active participants (Ussher et al. 2021).

Limitations on free movement were lifted for Kwale county on 7 June, though they remained in effect in Kenya's major cities until 7 July. These developments and, especially, a good harvest in July and August lessened the economic stressors affecting marginal agricultural

areas of eastern Kenya (FEWS NET 2020c). Use of Sarafu in Kinango Kwale reached a lull in September, with the transfer velocity and the effective balance falling in tandem. This is a similar pattern as that which occurred in Nairobi when economic conditions normalized, occurring some months earlier.

The second swell in transfer volume in Kinango Kwale, beginning in late September 2020, is different: we initially see a spike not in the velocity but in the effective balance, meaning that rising transfer volumes initially reflected the renewed use of older funds. Higher transfer volumes were sustained over the following months in that the money velocity subsequently rose. This resurgence likely reflects local seasonality in livelihoods and heightened food insecurity (FEWS NET 2020c; FEWS NET 2020a), consistent with community currencies seeing more use in difficult times (Stodder 2009; Zeller 2020), though in the following section we consider also an accompanying explanation, wherein communities in Kinango Kwale may have been responding logically to a specific intervention by Grassroots Economics.

5.3   Measurement during interventions

The Sarafu system happened to be highly centralized when the COVID-19 pandemic arrived in Kenya. Uneven availability of Sarafu complicated currency management during the ensuing crisis, and posed a particular challenge as the crisis subsided. Notice that the velocity was slowing, both in Nairobi and in Kinango Kwale, in August 2020, indicating a loosening of the monetary conditions within the Sarafu system, as a whole. The options available in such a situation, for a stand-alone community currency, are substantially different from those available for official currencies. Here we use the generalized transfer velocity to monitor the response to an especially drastic intervention that took place within the Sarafu system.

On 19 October 2020, Grassroots Economics initiated a large set of RECLAMATION transactions that removed Sarafu from a large set of accounts (Mattsson, Criscione, and Ruddick 2022). This operation dissolved 26.7% of all Sarafu credits over two days, visible as a near-instantaneous drop in the total issued balance in Figure 1 (right). Conventional estimates of the transfer velocity would be affected via the time-average of the total issued balance, as in Eqn. 10. The average holding period, and thus its inverse, is not necessarily affected. Completed holding periods are observed when users make transactions and their average duration is affected only to the extent the intervention impacts user activity.

The October 2020 intervention was targeted primarily at inactive accounts and, secondarily, at accounts with large balances. This currency operation accounted for 66.2% of all Sarafu removed via RECLAMATION transactions over the entire observation window. It removed predominantly long-held funds, as can be seen in Figure 2. These units of Sarafu had been

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sitting in the same account for, on average, 25.1 weeks prior to being dissolved; 89.8% had never been transferred. Mattsson, Criscione, and Ruddick (2022) report that the intention to close out inactive accounts was announced by Grassroots Economics ahead of the operation.

Our measures reveal the absence of a strong response by spenders in Nairobi to the announcement and implementation of the October 2020 currency operation. A total of 2.1 million Sarafu was removed from accounts in Nairobi, corresponding to 27% of their total issued balance. Neither the velocity nor the effective balance deviated from their trends in September/October 2020 (Figure 3, right). The transfer velocity was falling and the effective balance was rising, both gradually. The transfer volume remained large in Nairobi through September and October 2020; the share of transfers made with long-held funds remained small (Figure 3, left). We see no response from Sarafu users in Nairobi.

Similar amounts were removed from accounts in Kinango Kwale, a total of 2.2 million Sarafu corresponding to 24% of their total issued balance. We see from Figure 4 that transfer volume, our proxy for demand, and the share of transfers with older funds were increasing in late September and early October 2020 with a pronounced peak in the week following the intervention. Unfortunately, the timing of the announcement is not precisely known. The pattern is consistent with a robust response to the announcement of a future intervention targeting inactive accounts and with renewed demand for Sarafu in a period of seasonal food insecurity. In any case, older Sarafu re-entering active circulation is captured by our measures as a jump in the effective balance. Indeed, the effective balance in Kinango Kwale (9.9 million Sarafu) exceeded the issued balance in Kinango Kwale (8.4 million Sarafu) in the month of October 2020. This is remarkably different from the pattern observed in this area five or six months earlier, where transfer volumes picked up due to a jump in the transfer velocity. Measuring the inverse average holding period of Sarafu lets us distinguish these patterns.

6   Conclusion

This work has introduced a generalized definition of the transfer velocity of money that can be measured from the transaction records of a digital payment system. We have shown that the inverse average holding period of money can serve as an indicator of monetary conditions even during unstable conditions and interventions. Our methodological advance contributes to a growing literature that acknowledges heterogeneity in how groups and individuals experience the economy and seeks out novel data to enable disaggregation. For monetary indicators, transaction records open up a new frontier. Our approach can be used in the future to conduct analyses on other digital payment systems, such as those operated by mobile payment providers, commercial banks, and central banks. In dispensing with the assumption that these

real-world systems operate under stationary conditions we make it possible to consider money velocity, empirically, even when payment processing is highly fragmented or undergoing change. Finally, our generalized transfer velocity remains properly defined even when the monetary base expands or contracts suddenly. Ours is a responsive measure of money velocity that remains reliable precisely when monetary indicators are most necessary—during crises, interventions, and policy changes.

Acknowledgments

Data Availability Statement

The Sarafu CIC 2020–2021 dataset, is available via the UK Data Service (UKDS) ReShare platform (Ruddick 2021). Note that the dataset is "safeguarded", meaning that access is limited to those who have registered with the UKDS. The supplementary material includes instructions on applying for an account and downloading the data. Re-use is constrained by the UKDS End User License; re-identifying individuals is prohibited.

Supplementary Material

The code and configuration files required to reproduce our analysis are available online or via GitHub: https://github.com/carolinamattsson/transfer-velocity-of-money.

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Appendix: Implementation details

The creation and removal of Sarafu took place via DISBURSEMENT and RECLAMATION transactions, respectively. New Sarafu was systematically issued to newly created accounts. Later in the observation period, so-called demurrage charges served to remove a small fraction of existing Sarafu each month. Besides routine currency management, various administrative operations were undertaken at times. The accounts involved in currency management and administrative operations are identified in the data with a *system* label. We include in this category also the account labeled *vendor*, since it was used to facilitate pandemic aid. Values reported in our figures and tables do not include the contribution of *system* accounts.

Most user activity was recorded in the data as STANDARD transactions. These would capture various economic and financial activities such as local purchases and participation in savings and lending groups. We also consider AGENT_OUT transactions to be "transfers" in that they indicate purchases, of sorts, that facilitated donations to savings and lending groups; there were limited instances of this. Generally, the exchange of Sarafu with Kenyan Shillings was not facilitated (Mattsson, Criscione, and Ruddick 2022).

Pairwise trajectory extraction is done using `follow-the-money`, an open-source piece of software available at https://github.com/carolinamattsson/follow-the-money. The system specifications are noted in a configuration file included with the supplementary material. Briefly, the system boundary is precisely defined by the DISBURSEMENT and RECLAMATION transactions. The parameters used are noted in a script file included with the supplementary material. Tracing digital funds requires selecting an allocation heuristic, as discussed in Section 3 and in Mattsson and Takes (2021). We use the `--well-mixed` heuristic together with the `--pairwise` option to consider all possible pairs of sequential in- and out-transactions in all accounts. Fragments of received transactions with a size below the default `--size limit` 0.01 Sarafu are not tracked indefinitely; using the upper or lower bound for untracked durations gives the same estimates at the reported precision. Finally, a very small amount of Sarafu is mis-recorded in the data (Mattsson, Criscione, and Ruddick 2022). We

employ the functionality provided in `follow-the-money` to infer the existence of missing funds, and find this to be an insignificant source of noise.

The empirical distributions are produced using the held durations observed over the entire observation period (from 25 January 2020 through 15 June 2021). Weekly and monthly estimates are produced for the weeks and months that fall fully within this period, excluding the first week. Holding times that took place at *system* accounts are filtered out. The total issued balance of the Sarafu system is computed at every hour as captured by the DISBURSEMENT and RECLAMATION transactions (see Section 4). The balance of *system* accounts is subtracted from the total. Transaction volumes correspond to STANDARD and AGENT_OUT transactions (collectively referred to as *transfers* throughout this work).

The code is written in `python`, analysis was performed in `pandas`, and figures were produced using `matplotlib` and `seaborn` (Waskom 2021). Distributions are smoothed using kernel density estimation on a logarithmic scale, utilizing the `seaborn` default method for selecting the smoothing bandwidth.