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Abstract

We explore the potential of different behavioral drivers for people to use cash when presented with digital payment alternatives in retail transactions. Behavioral finance traits in our study include the otherwise neglected emotional drivers. We conducted an online survey targeting university educated adults in sub-Saharan African countries, a continent characterized by lower levels of banking penetration, intensive use of cash, and increased popularity of mobile money accounts to reduce financial exclusion. We obtain robust evidence that the affect heuristic is the only relevant behavioral trait determining the use of cash and of payments with credit cards, while there is no evidence of behavioral drivers influencing the overall decision to use of electronic payments. However, in specific payment contexts cognitive traits, such as mental accounting, fungibility bias, and habit, do mediate in determining the choice of payment method. We found robust evidence that a higher value of our personal income proxy is associated with a reduction in the intention to use electronic payments. All results are robust to alternative econometric specifications: multinomial logistic, ordered logistic, and logit regressions. Our research provides a clear policy message, namely for authorities to promote a variety of payment alternatives, including cash, and ensure they are available in retail transactions.

Keywords: FinTech, Cash, Digital Payments, Behavioral Finance (Affect Heuristic), Africa (Ghana, Kenya, Nigeria, South Africa).

JEL Classification: E4, E5, G1, G2, L8, O0

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1. Introduction

The purpose of this article is to explore behavioral factors influencing consumers' choice to use cash when presented with digital alternatives. Accurately forecasting the declining use of cash as a payment method is of interest to academics and practitioners alike, on topics such as projecting cash measures by central banks (Biondi, 2018; IMF, 2019; Rösl and Seitz, 2022), and the pros and cons of a cashless society (Bátiz-Lazo *et al.*, 2014; Humbani and Wiese, 2018). Added to this context is an ongoing process by central banks to implement central bank digital currencies (CBDC) (e.g., Bank of Canada *et al.*, 2021). However, questions remain as to how CBDCs might coexist with other payment forms, cash included (such as Panetta, 2021a, for the Eurozone; and Narula *et al.*, 2023 for a cross-country comparison on the barriers to deploying CBDC in emerging markets).

Extant research shows some factors that determine consumer demand for cash, including consumers' preferences, service fees, payment innovation diffusion and easy access (e.g., Au and Kaufmann, 2008; Simatele and Mbedzi, 2021). But the crucial factor in driving cash out of circulation is consumers' willingness to change their payment habits (Bátiz-Lazo *et al.*, 2021; Rouse *et al.*, 2023). Recent studies have focused on the impact of different behavioral profiles on the use of new means of payment, built on the extant literature around behavioral finance, mostly oriented to the analysis of cognitive factors such as mental accounting and salience (Huebner *et al.*, 2020) and loss aversion and habit (Duxbury *et al.*, 2022). However, these studies often overlook the emotional and social factors of behavioral decision making (Kahneman and Frederick, 2002; Shiller, 2000). We test hypotheses to include different behavioral traits for a sample of adults with university education in different Sub-Saharan African countries. We focus on the "middle" of the income pyramid as most studies on inclusion and digital payments in Africa focus on lower (i.e., the "base" of the) income pyramid (Beck *et al.*, 2015; Demirgüç-Kunt and Klapper, 2012; Okello *et al.*, 2018; Ondiege, 2015). We obtain statistically significant evidence that the affect heuristic is the only relevant behavioral trait determining the use of cash and of payments with credit cards. There is no statistically significant evidence to ascertain whether cognitive traits (such as mental accounting, fungibility bias, and habit), mediate in the overall payment preference decisions. Still, there is evidence to suggest they can be important in determining payment method. We find no statistically significant evidence of behavioral drivers determining the use of electronic payments, but a higher value of our income proxy associates with a reduction in the intention to use electronic payments.

After the introduction, the structure of the article is as follows. Section 2 provides the conceptual framework of our research and poses a set of hypotheses. Section 3 describes

the sample selection performed for our study in selected African countries. Section 4 provides a closer look at payment dynamics in those African countries. Section 5 provides descriptive statistics of payment methods used by the sample of respondents in our study. Section 6 provides the empirical analysis and a discussion on the main behavioral drivers of intentions to use cash and cashless payment alternatives. Finally, Section 7 outlines a set of conclusions and policy recommendations.

2. Consumers' intentions to use cash

2.1 Determinants of consumer demand for cash

This paper aims to explore the influence of various behavioural factors on the choice of payment methods in Africa. By incorporating emotional drivers into our analysis, we aim to offer new insights into the behavioural dynamics at play in the region's increasing use of electronic payment retail systems. This motivation emerges from the increasing interest around the empirical validation of behavioral finance ideas (Peón *et al.*, 2017), alongside the increasing interest in African electronic payment retail systems.[1] As will be shown below, our intent is to incorporate emotional drivers.

An array of factors has been shown to determine consumer preferences for cash in retail transactions. These include consumers' payment preferences, easy access, and acceptance (ECB, 2020), service fees and buyers' economic incentives (Camera *et al.*, 2016), consumer demographics and income (Stavins, 2017), and payment innovation diffusion (Chen *et al.*, 2017). Bartzsch and Seitz (2016) identify five reasons to hold cash: transaction, store of wealth, availability of alternative means of payment, the size of the shadow economy, and demand by non-residents. Furthermore, Kemper and Deufel (2018) show that the situation in which a customer places an e-commerce order has significant influence on his/her payment decision (e.g., product familiarity, sales promotion, etc.) and van der Cruijsen and Knoben (2021) show that the social environment – that is, the diffusion and transmission of norms through social channels – can foster the adoption of electronic payments.

To better inform such forecasts, recent empirical research has considered the impact of different cognitive feedback profiles on the use of new means of payment, based on the framework of behavioral finance. The main contributions to this debate consider how choice context (i.e., "nudging" and mental accounting) impacts consumer decisions (see van Hove, 2016). More recently, Ceravolo *et al.* (2019) provide experimental neural evidence

[1] A search in Scopus provides near 1,000 articles, only in years 2020 to 2022, under the keywords 'payment method', 'means of payment', or 'mobile payment'.

that the higher salience of cash makes it a strong self-regulating tool for on-the-spot payments, while Huebner *et al.* (2020) show that mental accounting provides some explanations as to how increasing the salience of credit card transactions reduces consumer spending. Zhao and Bacao (2021) explore how users' technological perceptions conjointly with mental accounting influence mobile payment adoption. Duxbury *et al.* (2022) examine behavioral drivers of payment intentions, including the perceptions of the fungibility of money, loss aversion, and the propensity to habitual behavior. Habit is indeed a frequent moderator, with positive evidence provided, among others, by van der Horst and Mattjitsen (2013) and van der Cruijsen *et al.* (2015).

These are all cognitive factors. However, a common criticism of behavioral finance is that researchers had frequently neglected emotional and social factors (Kahneman and Frederick, 2002; Shiller, 2000). There is now increasing literature available on the impact of social norms over the payment instrument choice (Patil *et al.*, 2020; Singh and Sinha, 2020; van der Cruijsen and van der Horst, 2019), while on emotions we only found contributions by Kahn *et al.* (2015) and Kahn and Rivers (2019).

2.2 Behavioral drivers

The perception of risk and its potential biases have been extensively dealt with within the behavioral finance literature, since most financial decisions involve some degree of risk aversion. In contrast, in our research, we focus on a list of factors which are likely to shape individuals' intentions to choose amongst different means of payment and develop related hypotheses. This includes affect, as the main emotional driver to be tested in the study. In addition, we consider the extant to include hypotheses around mental accounting (including perceptions on fungibility), loss aversion, and habit as control factors. The relationships we established were as follows:

Affect. As noted above, the focus of our study is to measure the impact of the emotional driver on the choice of payment method. Following Finucane *et al.* (2000), we consider that people rely on affect – the specific quality of goodness or badness – when judging risks and benefits of specific hazards. To the best of our knowledge, the impact of affect heuristics on payment behavior has not been tested before. Here we suggest using the conceptual framework of risk-as-feelings (Skagerlung *et al.*, 2020; Slovic, 1987), which would indicate that if using cards and electronic payments is perceived as riskier under the affect heuristic, we would observe a higher tendency to use cash. Hence, we pose the following hypothesis:

H1a: *The higher the affect, the higher the intention to use cash.*

H1b: *The higher the affect, the lower the intention to use alternatives to cash.*

Mental accounting. As mentioned, the affect heuristic was moderated by other well documented behavioral variables. First, mental accounting (Kahneman and Tversky, 1984; Thaler, 1985) refers to the implicit methods individuals use to code and evaluate transactions, investments, and other financial activities. Statman (1999) claims that people label money as "some is college education money, some is retirement money, some is vacation money". Mental accounting is a proven determinant in the allocation of personal wealth (e.g., Antonides *et al.*, 2011). Hernandez *et al.* (2017) show that cash, together with debit card payments, is helpful for monitoring household finances. Due to higher salience and levels of recall, cash might be expected to facilitate sticking to a budget compared to non-cash payments. Consequently, we set the following hypothesis:

H2a: *The higher the mental accounting, the higher the intention to pay in cash.*

H2b: *The higher the mental accounting, the lower the intention to use alternatives to cash.*

Fungibility. People violate the economic principle of fungibility when they engage in mental accounting in the perception of potential outcomes and cost-benefit evaluation, the decision to allocate money among different accounts, or the frequency with which these accounts are evaluated (Thaler, 1999). Hence, we seek to measure perceptions on fungibility of money, and observe whether respondents treat money as perfectly fungible and avoid the mental accounting bias. Following Cesarini *et al.* (2012), individuals who perceive money as non-fungible have a higher propensity to use cash. This is also consistent with hypothesis H2, so we define the following hypothesis:

H3a: *The higher the fungibility bias, the higher the intention to pay in cash.*

H3b: *The higher the fungibility bias, the lower the intention to use alternatives to cash.*

Loss aversion. Within the framework of prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), individuals evaluate outcomes by means of a value function with three key features: reference dependence (the carriers of value are gains and losses defined relative to a reference point), loss aversion (the function is steeper for losses than for gains) and diminishing sensitivity (the marginal value of both gains and losses decreases with size). Loss aversion can occur in both riskless and risky choice. In riskless choice, in the context of payment methods, there is a long-standing literature examining the "pain of paying" associated with cash (e.g., Thomas *et al.*, 2011; Kamleitner and Erki, 2013). People show a higher willingness to pay (WTP) on cards than with cash (e.g., Prelec and Simester, 2001; Runnemark *et al.*, 2015) because of a reduced pain of payment by card due to card payment being less salient than paying by cash and the decoupling of purchase and payment implied (e.g., Raghubir and Srivastava, 2008). Recent research has focused on comparing

the WTP of cards versus mobile payment (Boden *et al.*, 2020) and of gift cards versus cash (Helion and Gilovich, 2014). Thus, people tend to experience a negative reaction when paying by cash (as they are "giving up cash"), not experienced, or only to a lesser extent, when paying via other payment methods. Hence, we pose the following hypothesis:

H4a: *The lower the loss aversion, the higher the intention to use cash.*

H4b: *The lower the loss aversion, the lower the intention to use alternatives to cash.*

Habit. Habitual behavior is the act of automatically conducting oneself to repeat past action with little or no regard for current goals (Wood and Neal, 2009). It is a useful construct in understanding the mechanisms promoting repetition of behavior, in the forms of routine and automaticity (Ersche *et al.*, 2017). Routines are familiar actions that involve regularity, usually performed daily following a sequence of patterns that are executed voluntarily to reduce cognitive load, and make life more orderly (Clark, 2000; Gallimore and Lopez, 2002). Automaticity, instead, is not necessarily sequential in nature nor does it involve any kind of deliberation: these are actions initiated by environmental cues with no deliberate intention and may even continue without the involvement of conscious control (Bargh, 1994; Saling and Phillips, 2007).

In the context of payment method choice, van der Cruijsen and van der Horst (2016) find that payment habits are an integral determinant of payment decisions. However, there is little evidence on whether habit favors the use of cash or of alternatives to cash more highly. Thus, Duxbury *et al.* (2022) find that respondents with higher automaticity scores tend to use cash, while the relationship between routine and payment intention seems to be non-linear (higher use of cash on both the low end and high end of the routine scale). Hence, we pose the following hypothesis for habitual behavior:

H5a: *The higher the tendency for trait habitual behavior, the higher the intention to use cash.*

H5b: *The higher the tendency for trait habitual behavior, the lower the intention to use alternatives to cash.*

The five hypotheses above mentioned were then tested across a sample of individuals in Africa.

3. Sample selection to explore digital alternatives to cash in Africa

The dataset emerged by identifying participants of an international on-line MBA course, posting invitations to postgraduate students and in social media (namely, Facebook groups, LinkedIn, and personal invitations to and through personal acquaintances of the research

team). The search for participants targeted individuals with continued residence in Africa during the previous five years to the launch of the research instrument. This purposeful sampling introduced a desired bias, namely English speaking, university educated, digitally included, at least middle-income participants.

The above resulted in a sample of 2,009 unique email addresses.[2] An initial test of the research instrument was performed in February 2022 among 18 close acquaintances, who were invited to take part in the pilot testing of the bespoke, English-only, online survey questionnaire (distributed with the help of JISC Online Services). To validate survey constructs, individual interviews were conducted with seven of the individuals who took part in the pilot test and who gave their consent to be approached by the research team. A second adjustment to the research instrument took place in April 2022, through the random selection of 130 email addresses within the database. This second test returned 13 (10%) usable responses.

These contributors enabled an iterative process to fine tune the survey instrument. The final version of the questionnaire had three sections. A first set of questions aimed to profile respondents around socio-demographic factors and financial literacy. A second set of questions compared the use of cash with alternative payment methods in different contexts. A third part considered a set of short tests targeted to measure behavioral biases.

The questionnaire was then distributed amongst the remaining 1,862 addresses and responses collected between May and June 2022. As mentioned, there was no intent to seek a representative sample of the African population but a first exploration of the behavior of a particular socio-economic group that has somewhat been neglected. There were 252 usable returns (13.5% of the sample). Table 1 summarizes the distribution of usable returns per country of residence in the five years prior to the survey.

Table 1. Number of respondents per country of residence in the sample

Country	N	%	Country	N	%
Nigeria	91	36.1%	Eswatini	3	1.2%
Ghana	24	9.5%	Mozambique	3	1.2%
South Africa	17	6.7%	Cameroon	2	0.8%
Uganda	11	4.4%	Egypt	2	0.8%
Zambia	10	4.0%	Gambia	2	0.8%
Kenya	9	3.6%	Rwanda	2	0.8%

[2] In order to ensure ethic innocuousness according to the regulations and principles of the authors' university ethics and governance compliance, participants were informed of the purpose of the study and granted full anonymity concerning personal data, professional affiliation or similar personal information other than for statistical purposes. No reward, (monetary or otherwise) was offered to participants. Permission was given by participants in all cases. In line with regulations regarding the storage of personal information, original survey responses were deleted once statistical analysis was concluded. Personal notes from researchers were the only record of interviews during feedback of the pilot tests.

Zimbabwe	9	3.6%	Senegal	2	0.8%
Botswana	7	2.8%	Other (Africa)	7	2.8%
Malawi	7	2.8%	Other (non Africa)	40	15.9%
Sierra Leone	4	1.6%			

Table 1 shows usable responses from 24 African countries – including 22 of the 34 sub-Saharan African countries plus Egypt and Morocco.[3] However, only five countries – Nigeria, Ghana, South Africa, Uganda, and Zambia – exceed 10 observations (153 returns or 61% of the sample), with Nigerian respondents accounting for more than one third of the sample (36%). Respondents from another 17 sub-Saharan countries plus participants from Egypt and Morocco, contributed between nine and one usable returns per country (accruing 59 usable responses or 23.2% of the sample). A further 40 usable responses (15.9% of the sample) emerged from respondents of African origin who had not been resident in Africa for the last five years.

In summary, the survey was distributed amongst a small number of participants. Results should therefore be taken as indicative of potential trends rather than fully representative of individual behavior across residents in Africa. Given that the sample is somewhat tilted to a small number of countries, the payments situation in these countries is reviewed next to provide some further context.

4. The context of retail payments in selected African countries

Responses from our survey tilt to a small group of countries that present a particular profile in terms of e-payments and economic data. South Africa, for instance, is the largest and most mature financial services market in the continent, and the country with the highest per capita income (Botta *et al.*, 2022). Together with Nigeria – the most populated African country – they show the greatest development in the area (Botta *et al.*, 2022). South Africa, Nigeria, and Kenya, along with Morocco and Egypt, employ approximately half of Africa's software developers, according to estimates by IFC (2020). Table 2 shows that South Africa, Ghana, and Nigeria in anglophone West Africa, and Kenya in East Africa have a strong penetration rate of digital payments within their populations. Other African countries with a potential for strong growth in the retail financial services market at the time of writing included Cameroon, Ivory Coast, Egypt, Morocco, Senegal, Tanzania, and Uganda (Flötotto *et al.*, 2022). It is also significant that three of the countries with the highest share of

[3] The other African countries not disclosed in Table 1 are Djibouti, Eritrea, Mauritius, Morocco, Namibia, South Sudan, and Sudan.

responses in our sample, Nigeria, Kenya, and South Africa, were among the top ten worldwide in terms of volume of cryptocurrency trade in recent years (Chainalysis, 2020).

Table 2. Digital market penetration rate (users) by segment (in percent), 2020.

	Digital Commerce	Digital Payments	Digital Remittances	Mobile POS Payments
South Africa	37.0	37.2	0.26	9.5
Nigeria	31.4	31.4	0.01	2.1
Kenya	29.0	29.0	0.03	10.3
Ghana	21.3	21.3	0.02	12.6
Total Africa	24.0	24.0	0.03	6.2
Worldwide	46.8	46.9	0.13	17.9

Note: The Digital Payments market segment is led by consumer transactions and includes payments for products and services which are made over the Internet as well as mobile payments at POS via smartphone applications and cross-border money transfers made over the internet (digital remittances). The following are not included: B2B payments and payment transactions at POS where mobile card readers (terminals) are used.

Source: Statista (2021): FinTech Report 2021. Digital Payments. Statista Digital Market Outlook, segment report. Available at https://www.statista.com/outlook/dmo/fintech/digital-payments/worldwide?currency=USD

As suggested by Table 2, South Africa and Nigeria had a penetration close to or higher than that of Kenya and Ghana in the digital commerce and digital payment segments. Only Ghana fell below the African mean. Digital remittances in South Africa were much higher than the African and worldwide averages, largely due to the importance of its migrant communities. Likewise, in the mobile POS payment segment, the penetration rate in the sample countries exceeded the continental average. This was not the case for Nigeria. Nonetheless, in this country, a strong acceleration in mobile-money transactions seems to have taken place after 2020.

Table 3 below provides statistics on banking penetration in the countries making up the largest share of respondents in our sample. This data attests how most African countries were subject to low levels of banking penetration (branches and ATMs), intensive use of cash, and difficult access to credit (Chironga *et al.*, 2018).

Table 3. Banking markets and users in selected countries, 2016

	Banking penetration (% of GDP, 2016) and nominal GDP per capita, 2016	Asset CAGR* 2012-16	Share of unbanked population 2021 (%)	ATMs per 100,000 adults 2021 (%)	Internet users 2021 (%)
South Africa	Relatively mature	< 8%	31	65.3	56
Nigeria	Sleeping giants	8% - 13%	60	16.9	70
Kenya	Transition markets	8% - 13%	44	7.7	83
Ghana	Transition markets	> 13%	42	-	-

* Compound Annual Growth Rate

Sources: IMF, McKinsey & Co. (Chironga *et al.*, 2018); Global Finance (2021, from MerchantMachine.co.uk).

Data in Table 3 suggests that South Africa was a country with "relative banking maturity" as it was the African country with the highest level of banked population. Ghana and Kenya could be characterized as "transition banking markets", with fast growth as compared to the rest of the continent in terms of growth and profitability. Table 3 also shows Nigeria in its role as the "sleeping giant", as it recorded one of the highest levels of unbanked population in the world – after Morocco, Vietnam, Egypt, Philippines and Mexico (Global Finance, 2021).

According to official data, electronic payments in Africa have significantly increased since the early 2000s. Online commerce grew approximately 40% between 2020 and 2021 in South Africa (SARB, 2020). In Nigeria mobile-money transactions doubled in volume for that same period (CBN, 2020). In Ghana, the total volume of transactions via mobile money increased by 43.2% between 2012 and 2018 (BG 2018, 2020), through three mobile money operators, while in Kenya, retail/low-value payment systems in the years prior to 2019 intensified thanks to new products (payment cards and mobile money transfers) and technological advances (CBK, 2021). This trend accelerated after the establishment of infrastructures such as Kenya Electronic Payment and Settlement System, KEPSS (real-time gross settlement), which had direct implications for the security and reliability of retail payments (CBK, 2018).

The surveys and reports on National Payment Strategies for the 2022-2025 period of certain central banks (BG, 2018; CBK, 2021; CBN, 2020; SARB, 2020) expected electronic payment methods to significantly increase across sub-Saharan Africa in the 10 years to 2030. Improvements in real-time infrastructures will positively affect account-based transactions, even though this could be affected by the persistent low penetration of bank accounts. Cards and e-wallets (especially the latter, due to their capacity to integrate different payment methods, including mobile money) were very promising in a deeply fragmented scenario, such as that of payment methods in Africa. Nigeria, for instance, addressed financial exclusion through an attempt at a "Cashless Policy" in June 2012. It was hoped that this policy would curb the demand for banknotes and coins whilst encouraging the use of electronic banking (Ezuwore-Obodoekwe *et al.*, 2014). However, currency in circulation more than doubled between 2015 and 2022 and Nigeria remained a largely cash-based economy where up to 60% of trade takes place through the informal economy. Apparently, high levels of internet fraud and financial illiteracy hampered the implementation of the cashless policy (Okoye and Ezejiofor, 2013). These preferences were in contrast with records of ambiguous preference for cash in Western countries and the persistence of traditional payment options, such as plastic cards (Panetta, 2021b).

The data in this section provide some context on electronic payments and banking infrastructure within the highest response countries in our sample. Data suggest large use of mobile money and electronic payments but also high levels of cash in the hands of consumers within selected countries. This context thus provides an interesting milieu to explore behavioral traits behind the use of cash versus digital payments.

5. Descriptive statistics of cash and e-payments usage in African countries

5.1 Demographic profile, the use of cash and its alternatives

This section discusses the individual profile of respondents and their use of cash. The use of descriptive statistics to ascertain behavioral tests is discussed in a different subsection.

To ascertain individual profiles, the first part of the survey explored aspects of the use of cash while controlling for socio-demographic factors (Wakamori and Welte, 2017) and financial literacy factors (Fujiki, 2020; Li *et al.*, 2020). Table 4 summarizes results for socio-demographic factors.

Table 4. Socio-demographic factors in survey sample, 2022.

Variable	Values	N	%
Gender	Male	132	52.4%
	Female	118	46.8%
	N/A	2	0.8%
Age	under 30	23	9.1%
	30 – 39	118	46.8%
	40 – 49	85	33.7%
	over 49	26	10.3%
Ethnicity	Black/African/Caribbean	222	88.1%
	Asian	8	3.2%
	White	6	2.4%
	Mixed/multiple ethnic	8	3.2%
	Other / prefer not to say	8	3.2%
Education	No qualification	0	0.0%
	Elementary	0	0.0%
	Secondary	0	0.0%
	Graduate	109	43.3%
	Postgraduate	137	54.4%
	PhD	6	2.4%
Property	Owner	114	45.2%
	Rented	103	40.9%
	with family	27	10.7%
	Other	8	3.2%

Variable	Values	N	%
Employment	Employed (full-time)	196	77.8%
	Employed (part-time)	22	8.7%
	Self employed	12	4.8%
	Unemployed	8	3.2%
	Other	14	5.6%
	N/A	0	0.0%
Expenditures:	$0-$50	4	1.6%
Food (month)	$51-$100	32	12.7%
	$101-$200	75	29.8%
	Over $200	134	53.2%
	N/A	7	2.8%
Expenditures:	$0-$50	58	23.0%
Leisure (month)	$51-$100	83	32.9%
	$101-$200	52	20.6%
	Over $200	41	16.3%
	N/A	18	7.1%
Dependents	0	30	11.9%
	1	25	9.9%
	2	65	25.8%
	+3	127	50.4%
	N/A	5	2.0%

Table 4 suggests the sample was roughly equally split between male (52% of the sample) and female respondents (47%). The largest age group was the 30- to 39-year-old (47%).

The sample overwhelmingly came from a Black/African/Caribbean ethnicity (88%). As a result, there was no attempt to include controls for different ethnicity during econometric analysis.

Respondents clearly displayed traits of higher education in business profile as they were employed (78%), educated participants (all respondents had at least graduate education or equivalent), with the largest group having two or more dependents (76%) and roughly split between house-owners (45%) and renters (41%).

Two measures were used as proxies of personal income – namely, expenditures in food and in leisure. These proxies enabled a workaround for the well-known bias of underestimating personal income in self-reporting surveys (Greene and Stavins, 2018). Subsistence expenditure tends to be inelastic while there is greater discretion in household budget allocation for leisure. Results suggested most respondents came from a middle-income bracket as they reported a subsistence expenditure of 200 US dollars or more per month (53%), which was well above the poverty line, while only a minority spent an equal amount of 200 US dollars or more per month on leisure (16%). Respondents were assumed to have been financially included but, admittedly, we did not test specifically for barriers to financial inclusion, exclusion, under banked or similar.

Table 5 summarizes the responses for payment method preferences. Participants were offered four alternatives: cash, debit card, credit card, and a broad category for electronic payments (mobile app, text message payments, etc.). The ordering of these payment methods supported the econometric strategy by enabling multinomial logistic, ordered logistic, and logistic regressions. The ordering took place in three steps. First, we asked participants to rank payment methods from highest to lowest overall preference (see panel A in Table 5). Second, participants ranked their preferred payment method for purchases of less than $1, between $1 and $5, and more than $5 per transaction (panel B in Table 5). Third, participants ranked payment alternatives in five different contexts: bar/café, hairdresser, petrol station, restaurant, and supermarket (panel C in Table 5).

Table 5. Ranking of preferred payment alternative in sample

Panel A **Method**	**1st**		**2nd**		**3rd**		**least**	
Cash	47	19%	67	27%	92	37%	46	18%
Debit card	100	40%	83	33%	50	20%	19	8%
Credit card	22	9%	24	10%	56	22%	150	60%
Electronic	83	33%	78	31%	54	21%	37	15%
Total	**252**		**252**		**252**		**252**	

Panel B **Method**	**under $1**	**$1 to $5**	**over $5 US**	correlation

Cash	155	62%	109	43%	44	17%	
Debit card	55	22%	88	35%	121	48%	-1.00
Credit card	10	4%	7	3%	16	6%	-0.73
Electronic	32	13%	48	19%	71	28%	-1.00
Total	**252**		**252**		**252**		

Panel C											
Method	**hairdresser**		**bar/café**		**petrol station**		**restaurant**		**supermarket**		correlation
Cash	170	67%	79	31%	66	26%	56	22%	35	14%	
Debit card	37	15%	128	51%	133	53%	148	59%	168	67%	-1.00
Credit card	7	3%	14	6%	27	11%	23	9%	28	11%	-0.90
Electronic	38	15%	31	12%	26	10%	25	10%	21	8%	0.96
Total	**252**		**252**		**252**		**252**		**252**		

Across Table 5 debit cards consistently appear as the most preferred payment alternative, closely followed by electronic payment alternatives. Panel A of Table 5 shows debit card was the most preferred payment method for 40% of the sample. Cash was the second (27% of the preferences) or third (37%) preferred alternative and showed a negative linear relation (Pearson's linear correlation coefficient of -0.68) with the preference for credit card payments, which was the least preferred alternative overall (60%). Panel B of Table 5 shows that payments with cash were mostly preferred for small amounts (62% and 43%) followed by debit card payments (22% and 35%). Debit cards and electronic alternatives were preferred for larger payments (48% and 28% respectively). Panel C of Table 5 shows that when preferences were ordered by context only debit card (correlation coefficient of -1.00) and credit card (correlation -0.90) change inversely to cash, while electronic payment seems to be used in a similar pattern to cash (correlation 0.96). Cash is king when considering a hairdresser (67% of the preferences), and lower for payments at a bar/café (31%), in petrol stations (26%), restaurants (22%) and the lowest value was observed for shopping at the supermarket (14%). Debit card was clearly the preferred alternative for payments at a bar/café (51%), petrol stations (53%), restaurants (59%) and at the supermarket (67%).

Preferences for payment alternatives in our sample observed similar patterns to those previously observed in the literature. For instance, propensity to pay in cash is inversely proportional to the amount of payment (Harasim, 2016). Other studies also highlight similar preferences to ours for using cash mainly in day-to-day purchases, at cafes, vending machines, and urban transport; debit cards are frequently used in petrol stations and retail outlets, and credit cards used in hotels (Deutsche Bundesbank, 2017; Sveriges Riksbank, 2020). Still, the intention to use e-payments by respondents in our sample was clearly higher than the share of digital payment channels in Africa – only 5% to 7% on average of

all payment transactions in Africa, despite the record growth in e-payments after Covid (Botta *et al.*, 2022).

Table 6 brings together preferences for alternative payment methods with the distribution of geographical and socioeconomic factors. The column under "Chi²" reports Pearson's $\chi 2$ results for the hypothesis that the rows and columns in a two-way table are independent. Consequently, the preferences by gender, age, and employment status would be quite similar across groups, while the preferences by country would be very different. For instance, respondents from Nigeria and South Africa prefer debit card tenfold compared to cash, whereas in countries such as Ghana or Uganda there was a similar, or even higher, preference for cash. It is also noticeable that eight out of nine respondents in Kenya prefer to use electronic payments (perhaps associated with the great success of mobile payments in that country as approximately 30% of Kenya's GDP is spent through mobile phones[4]).

Table 6. Distribution of potential contributing qualitative factors for the different preferred means of payment (number of observations and proportion (%)).

	Alternative payment method										
	Cash		Debit card		Credit card		Electronic		Total		Chi² (p-value)
Variable	Count	Ratio(%)	Count	Ratio(%)	Count	Ratio(%)	Count	Ratio(%)	Count	Ratio(%)	
Gender											Chi² (3)
Male	24	9.6	49	19.6	8	3.2	51	20.4	132	52.8	5.326
Female	22	8.8	50	20.0	14	5.6	32	12.8	118	47.2	0.15
Total	46	18.4	99	39.6	22	8.8	83	33.2	250	100.0	
Age											Chi² (9)
under 30	5	2.0	6	2.4	4	1.6	8	3.2	23	9.1	7.549
30 – 39	25	9.9	45	17.9	8	3.2	40	15.9	118	46.8	0.58
40 – 49	11	4.4	40	15.9	8	3.2	26	10.3	85	33.7	
over 49	6	2.4	9	3.6	2	0.8	9	3.6	26	10.3	
Total	47	18.7	100	39.7	22	8.7	83	32.9	252	100.0	
Employment											Chi² (12)
Employed (full)	34	13.5	75	29.8	18	7.1	69	27.4	196	77.8	4.722
Employed (part)	5	2.0	8	3.2	2	0.8	7	2.8	22	8.7	0.97
Self employed	3	1.2	6	2.4	1	0.4	2	0.8	12	4.8	
Unemployed	2	0.8	4	1.6	0	0.0	2	0.8	8	3.2	
Other	3	1.2	7	2.8	1	0.4	3	1.2	14	5.6	
Total	47	18.6	100	39.7	22	8.7	83	32.9	252	100.0	
Country											Chi² (27)
Nigeria	4	1.6	45	17.9	5	2.0	37	14.7	91	36.1	69.205
Ghana	9	3.6	6	2.4	2	0.8	7	2.8	24	9.5	0.00
South Africa	1	0.4	10	4.0	0	0.0	6	2.4	17	6.7	
Uganda	3	1.2	3	1.2	0	0.0	5	2.0	11	4.4	
Zambia	2	0.8	4	1.6	1	0.4	3	1.2	10	4.0	
Kenya	0	0.0	1	0.4	0	0.0	8	3.2	9	3.6	

[4] Mims, Christopher, "31% of Kenya's GDP is spent through mobile phones", *Quarz*, February 27, 2023, http://qz.com/57504/31-pf-keyna-is-spent-through-mobile-phones, Accessed July 14, 2023.

Zimbabwe	3	1.2	4	1.6	0	0.0	2	0.8	9	3.6
Botswana	2	0.8	2	0.8	0	0.0	3	1.2	7	2.8
Malawi	1	0.4	2	0.8	1	0.4	3	1.2	7	2.8
Other	22	8.7	23	9.1	13	5.2	9	3.6	67	26.6
Total	47	18.7	100	39.7	22	8.7	83	32.9	252	100.0

5.2 Behavioral tests

The survey included a series of tests to determine the profile of each respondent based on five behavioral traits – namely, mental accounting, fungibility perception, loss aversion, the tendency to form habits, and the affect heuristic. In what follows we summarize the tests implemented. The list of questions is provided in the Appendix.

Mental accounting. Following Antonides *et al.* (2011), we measure mental accounting by means of a set of four questions intended to measure the respondent's tendency to budget money in separate accounts. The responses follow a 5-step Likert scale, from totally disagree (implying low propensity to form mental accounts) to totally agree (implying high propensity). Each individual measure of mental accounting is then estimated as the average score of the four questions. The response was not tallied as part of the result if an individual chose "do not know" as an answer.

Table 7. Descriptive statistics of the variables in the research.

Variable	description	n	mean	std.dev.	min	p25	median	p75	max
preferred	1=cash, 2=debit, 3=credit, 4=electr	252	2.56	1.13	1.00	2.00	2.00	4.00	4.00
leastpref	1=cash, 2=debit, 3=credit, 4=electr	252	2.71	0.93	1.00	2.00	3.00	3.00	4.00
cash	preference ranking 1=least 4=most	252	2.46	1.00	1.00	2.00	2.00	3.00	4.00
debit	preference ranking 1=least 4=most	252	3.05	0.95	1.00	2.00	3.00	4.00	4.00
credit	preference ranking 1=least 4=most	252	1.67	0.97	1.00	1.00	1.00	2.00	4.00
electronic	preference ranking 1=least 4=most	252	2.82	1.05	1.00	2.00	3.00	4.00	4.00
gender	0=male, 1=female	250	0.47	0.50	0.00	0.00	0.00	1.00	1.00
age	discrete variable defined in Table 5	252	2.45	0.80	1.00	2.00	2.00	3.00	4.00
employ	discrete variable defined in Table 5	252	1.50	1.10	1.00	1.00	1.00	1.00	5.00
income	log of monthly food and leisure expenditure	247	5.67	0.55	3.91	5.42	5.78	6.11	6.40
capita	income divided by (1+dependents)	244	4.60	0.66	2.93	4.32	4.61	5.01	6.11
mental	average 4 questions on 1-5 Likert scale	248	3.46	1.02	1.00	2.75	3.75	4.25	5.00
fungib	0=nobias, 1=fungibility bias	199	0.23	0.42	0.00	0.00	0.00	0.00	1.00
LAavg	average ratio gains/losses	192	3.74	5.63	0.00	1.00	1.63	2.75	20.00
LAmed	median ratio gains/losses	192	3.78	5.90	0.00	1.00	1.50	2.00	20.00
habit	average 5 questions on 1-5 Likert scale	252	2.97	0.83	1.00	2.40	3.00	3.60	5.00
affect	minus correlation coefficient of risk-benefit ratings	242	0.40	0.45	-0.94	0.26	0.54	0.71	0.96

Table 7 includes two variables that were constructed from survey responses, namely overall income proxy (*income*) and personal income proxy (*capita*). The first variable resulted from

the logarithm of the sum of monthly expenditure on food plus monthly expenditure on leisure. The second variable used the same information, taking the number of dependents into account.

The descriptive statistics provided in Table 7 show a strong tendency on the part of most participants to form mental accounts. Thus, 50% of them show an average answer of 3.75 or more in a scale of 5, implying that they agreed or totally agreed that they tend to budget money in separate accounts. The statistics also show two tests where a large portion of participants failed to give complete answers: fungibility and loss aversion.

Fungibility. Respondents who do not treat money as fungible would conform to mental accounting. Here we asked respondents a set of two binary yes-or-no questions where providing a different answer would be evidence of treating money as non-fungible. Each individual measure of fungibility is then obtained as "the individual treats money as fungible" (coded 0) if the respondent provides consistent answers, and "the individual treats money as non-fungible" (coded 1 for mental accounting) if they are inconsistent. If they answer any question "do not know", no measure is obtained.

In spite of following Duxbury *et al.* (2020) and Kahneman and Tversky (1984) in the design of this test, the descriptive statistics showed that more than 25% of the respondents failed to answer both questions. From those who completed the test, the evidence of mental accounting in this instance was low: only 23% of the respondents would exhibit that bias. Moreover, when the Pearson correlation is measured against the previous measure of mental accounting, the relation was statistically insignificant (r=0.057, p=0.42). All this might suggested a low reliability of our fungibility indicator for our research, since there is extensive evidence both of a violation of fungibility by many subjects and of the link of this behavior to mental accounting (Abeler and Marklein, 2017; Hastings and Shapiro, 2018; Vana *et al.*, 2018).

Loss aversion. The elicitation method for loss aversion consisted of three questions on the acceptability of 50% probability lotteries with small amounts of money ($5, $10, and $20). This enabled estimation of loss aversion under the assumption that the other parameters in prospect theory – the curvature of the value function for gains and losses, and the distortion of probabilities for gains and losses – are equal to one (Rabin, 2000). Given the reduced number of questions posed, we estimated two alternative measures of loss aversion (Peón *et al.*, 2016), as either a mean or median across prospects (denoted LA_{avg} and LA_{med}, respectively). We used the median estimation as the measure by default. An individual measure was not provided in two instances: if the respondent provided any "do not know"

answer, and if an obviously inconsistent pattern of responses was provided (such as accepting a lower gain than in a previous response when facing a higher potential loss).

This test also revealed some complications. Several respondents left some or all questions unanswered. We excluded these, resulting in 50 missing responses from the overall sample. Besides, a few respondents exhibited way too large levels of loss aversion. To moderate this effect and exclude extreme values, we limited these responses to a maximum loss aversion value of 20 in each question. Even after the exclusion and moderating values, the average loss aversion in our sample was above 3.0 – higher than the typical results in the literature, which range from 1.5 to 3.0 (see Peón, 2015). Nonetheless, 75% of the sample exhibited median ratios below 2.0.

Habit. We trace the respondent's tendency to form habits by means of a set of five questions on routines and automaticity (retrieved from Ersche *et al.*, 2017). The responses followed a 5-step Likert scale, from totally disagree (implying low propensity to follow habits) to totally agree (implying high propensity). An individual measure of habitual behavior was obtained as the average measure of the five questions. No "do not know" answers were returned by any respondent, so all individual estimates were obtained.

According to data in Table 7, the participants in our survey exhibited a moderate tendency to behave according specific habits, with median and average responses of 3.0 in a 5-step Likert scale, and 50% of the responses in between 2.4 and 3.6. It is worth noting the null correlation of habit and mental accounting in our sample (r=0.103, p=0.10).

Affect. The key heuristic in our analysis was measured following Skagerlung *et al.* (2020). That research sourced a set of 15 questions on four domains about low to high-risk activities, such as taking a nap or skydiving, for which the respondent had to provide two answers per question: the perceived benefit of the activity, and the perceived risk. The individual measure of affect heuristic resulted from the correlation coefficient between the risk and benefit ratings. Since the more negative the correlation the higher the use of the affect heuristic, we changed the sign to make the indicator increase with affect. If the respondent provided the same estimations for risk and benefit in 14 or more of the 15 questions, the individual estimation of affect was discarded on the suspicion that they did not understand the test.

The respondents in our sample showed quite a strong tendency to conform with the emotion-driven affect heuristic. Thus, the sample average was +0.54 (for a measure ranging from -1.0 to +1.0) and more than 75% of the respondents showed positive values.

6. Drivers of intentions to use cash and cashless payments

We first explored the drivers of payment method' preferences. Having payment methods ranked from most preferred to least preferred allowed estimation of alternative model specifications. Table 8 provides the results of multinomial logistic regression with the preferred payment method as dependent variable. Three major adjustments were made. First, the correlation analysis identified a high linear relationship between the overall income proxy (*income*) and personal income proxy (*capita*) (rho 0.746, sig 0.000). As a result, all subsequent econometric estimations excluded the overall income proxy (*income*).

Secondly, there were no statistically significant differences in results when considering estimates for each of the age cohorts separately. Consequently, all econometric estimations below regrouped the age category in two – namely, cohorts over 29 years old versus the youngest cohort.

Thirdly, the loss of observations within results for the tests of fungibility and loss aversion resulted in two sets of econometric estimations: one, the base result, excluded fungibility and loss aversion from the analysis while using the complete sample (this is shown in the left-hand side of Table 8 and labelled Model 1). Second, an alternative estimation was performed for a subsample of participants, namely those who responded to the complete set of behavioral tests that included results for fungibility and loss aversion as potential drivers of payment choice (shown in the right-hand side of Table 8 and labelled Model 2). Statistically significant results appear in bold in Table 8 and Table 9 to ease identification.

Among the behavioral drivers, neither fungibility nor loss aversion exhibited statistically significant results (Model 2 in Table 8) – leading us to focus on the estimates for the larger sample (base case or Model 1 in Table 8). Results in Table 8 also suggest some evidence of mental accounting associated with reduced use of debit card and electronic payments relative to cash (in line with hypothesis H2b), but the results were not robust for the complete sample.

The main result was, thus, the impact of the affect heuristic on payment preference: the emotional driver associated with a reduction in the average probability of using cash by 0.12. This result somewhat contradicts hypothesis H1a, suggesting that the reduced use of cash emerged not from perceived risk ("risk as feelings"), but from some other emotional driver. Finally, there was no evidence of habit heuristic leading to any preferred payment method.

The control variables suggested a lower preference of women and of the self-employed to use electronic payments (reduced average probabilities of 0.12 and 0.23, respectively), and a lower preference of the unemployed to use credit card. Perhaps, the most surprising result was an increase in the personal income proxy (*capita*) associated with a lower use of electronic payment methods. Controlling for countries also allowed us to identify a lower-than-average preference for cash in Nigeria and South Africa (a probability of 0.25 lower than average). The same countries show a lower preference for credit card – offset by a clear preference for debit card.

Table 8. Preferred means of payment (cash base outcome)

MODEL 1 – Excluding fungibility and loss aversion (Full sample)

Estimated coefficients

	Cash		Debit card		Credit card		Electronic	
Variables	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Gender			0.33	0.50	0.51	0.35	-0.34	0.46
Age (over 29)			0.54	0.49	-1.03	0.23	-0.39	0.60
Employed (part-time)			-0.23	0.76	-0.78	0.53	-0.20	0.77
Self employed			-0.15	0.86	-0.10	0.94	**-1.46**	**0.10**
Unemployed			-0.07	0.95	**-15.57**	**0.00**	-0.80	0.52
Other employment status			-1.57	0.19	-0.95	0.52	**-2.55**	**0.03**
capita			0.34	0.36	-0.28	0.56	-0.40	0.29
Nigeria			**3.12**	**0.00**	**1.77**	**0.06**	**3.26**	**0.00**
Ghana			-0.49	0.49	-0.80	0.40	-0.57	0.38
South Africa			**2.61**	**0.01**	**-13.90**	**0.00**	**2.86**	**0.01**
Uganda			-0.62	0.53	**-15.83**	**0.00**	0.50	0.59
Zambia			0.52	0.56	0.02	0.99	0.26	0.81
mental			-0.08	0.72	-0.22	0.50	-0.19	0.41
fungib								
LAmed								
habit			-0.14	0.56	-0.06	0.89	0.09	0.72
affect			**1.15**	**0.02**	0.35	0.57	**1.04**	**0.04**
Intercept			-1.74	0.47	2.14	0.45	2.40	0.28

Model statistics

VCE robust			
N. observ.	229	Ps.R2	0.139
Wald chi^2	2,823	p-value	0.000

MODEL 2 – Including fungibility and loss aversion (Fewer observations)

	Cash		Debit card		Credit card		Electronic	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Gender			0.15	0.78	1.60	0.19	-0.74	0.20
Age (over 29)			-0.90	0.34	**15.66**	**0.00**	**-1.56**	**0.09**
Employed (part-time)			0.95	0.35	**-15.33**	**0.00**	0.11	0.92
Self employed			-0.06	0.96	**-16.77**	**0.00**	-1.53	0.15
Unemployed			0.35	0.77	**-16.49**	**0.00**	0.23	0.85
Other employment status			-2.77	0.14	-2.34	0.12	**-4.12**	**0.03**
capita			0.49	0.24	-1.47	0.32	-0.07	0.87
Nigeria			**3.43**	**0.00**	**-15.31**	**0.00**	**3.64**	**0.00**
Ghana			-0.61	0.52	**-17.42**	**0.00**	-0.44	0.53
South Africa			**18.32**	**0.00**	1.30	0.52	**18.68**	**0.00**
Uganda			-0.33	0.76	**-17.56**	**0.00**	0.50	0.60
Zambia			-0.23	0.84	0.64	0.67	0.09	0.95
mental			**-0.55**	**0.05**	1.01	0.16	**-0.52**	**0.08**
fungib			-0.19	0.79	-1.93	0.41	0.34	0.61
LAmed			-0.02	0.70	0.01	0.89	-0.03	0.65
habit			-0.11	0.74	0.35	0.58	0.21	0.58
affect			**1.24**	**0.07**	-0.53	0.65	0.79	0.25
Intercept			0.24	0.93	**-15.18**	**0.05**	2.88	0.28

VCE robust			
N. observ.	147	Ps.R2	0.218
Wald chi^2	2,525	p-value	0.000

Marginal effects

	Cash		Debit card		Credit card		Electronic	
Variables	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value
Gender	-0.01	0.83	0.09	0.14	0.04	0.25	**-0.12**	**0.05**
Age (over 29)	0.01	0.93	**0.19**	**0.10**	-0.08	0.13	-0.12	0.25
Employed (part-time)	0.04	0.67	0.00	0.97	-0.04	0.49	0.01	0.96
Self employed	0.07	0.54	0.13	0.35	0.03	0.80	**-0.23**	**0.02**
Unemployed	0.07	0.61	0.14	0.38	**-0.09**	**0.00**	-0.12	0.45
Other employment status	0.26	0.15	-0.04	0.78	-0.23	0.84	**-0.24**	**0.01**
capita	0.01	0.90	**0.13**	**0.01**	-0.02	0.45	**-0.12**	**0.02**
Nigeria	**-0.26**	**0.00**	**0.16**	**0.02**	**-0.07**	**0.10**	**0.18**	**0.01**
Ghana	0.12	0.34	-0.03	0.77	-0.05	0.54	-0.04	0.63
South Africa	**-0.25**	**0.00**	0.16	0.26	**-0.13**	**0.00**	0.22	0.12
Uganda	0.05	0.78	-0.12	0.36	**-0.13**	**0.00**	0.21	0.22
Zambia	-0.06	0.66	0.09	0.57	-0.03	0.82	0.00	1.00
mental	0.02	0.48	0.01	0.70	-0.01	0.66	-0.02	0.51
fungib								
LAmed								
habit	0.00	0.86	-0.04	0.28	0.00	0.93	0.04	0.32
affect	**-0.12**	**0.02**	0.10	0.13	-0.03	0.36	0.05	0.45

	Cash		Debit card		Credit card		Electronic	
	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value
	0.01	0.88	0.12	0.12	**0.06**	**0.09**	**-0.19**	**0.02**
	-0.10	0.49	-0.10	0.46	**0.55**	**0.01**	**-0.35**	**0.01**
	-0.04	0.71	0.20	0.19	**-0.06**	**0.00**	-0.11	0.46
	0.12	0.40	0.19	0.37	**-0.06**	**0.00**	**-0.25**	**0.08**
	-0.01	0.95	0.05	0.79	**-0.06**	**0.00**	0.01	0.95
	0.45	**0.01**	-0.07	0.64	**-0.04**	**0.10**	**-0.33**	**0.00**
	0.00	1.00	**0.12**	**0.03**	-0.05	0.21	-0.06	0.26
	-0.28	**0.00**	**0.17**	**0.07**	**-0.12**	**0.00**	**0.24**	**0.01**
	0.17	0.25	-0.05	0.74	**-0.12**	**0.00**	0.00	0.97
	-0.32	**0.00**	0.15	0.36	**-0.12**	**0.00**	**0.28**	**0.08**
	0.03	0.85	-0.08	0.59	**-0.12**	**0.00**	0.16	0.33
	-0.01	0.94	-0.06	0.67	0.05	0.67	0.02	0.92
	0.05	0.18	-0.05	0.23	**0.04**	**0.07**	-0.04	0.33
	0.02	0.81	-0.07	0.49	-0.07	0.33	0.11	0.22
	0.00	0.70	0.00	0.86	0.00	0.77	0.00	0.74
	-0.01	0.77	-0.05	0.27	-0.01	0.59	0.05	0.33
	-0.11	0.15	**0.14**	**0.10**	-0.04	0.39	0.00	1.00

Table 9. Least preferred means of payment (cash base)

MODEL 1 – Excluding fungibility and loss aversion (Full sample)

Estimated coefficients

	Cash		Debit card		Credit card		Electronic	
Variables	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Gender			-0.31	0.66	0.17	0.68	0.22	0.67
Age (over 29)			-0.79	0.50	-0.60	0.42	-0.49	0.62
Employed (part-time)			-0.66	0.52	-0.31	0.66	0.21	0.79
Self employed			**16.41**	**0.00**	**15.10**	**0.00**	**15.42**	**0.00**
Unemployed			**-15.26**	**0.00**	-0.63	0.46	-0.10	0.93
Other employment status			**-13.54**	**0.00**	0.47	0.61	0.59	0.62
Capita			-0.04	0.93	0.34	0.26	0.65	0.11
Nigeria			-0.48	0.56	-0.41	0.36	**-1.93**	**0.00**
Ghana			1.58	0.16	0.65	0.47	-1.05	0.45
South Africa			**-15.25**	**0.00**	**-1.94**	**0.01**	**-1.54**	**0.09**
Uganda			1.56	0.27	0.56	0.65	**-14.67**	**0.00**
Zambia			0.91	0.58	0.54	0.67	0.33	0.81
mental			0.15	0.63	0.13	0.55	0.22	0.45
fungib								
LAmed								
habit			-0.27	0.49	0.00	0.99	-0.22	0.49
affect			0.20	0.79	0.40	0.31	-0.35	0.53
Intercept			0.36	0.90	-0.17	0.93	-2.14	0.42

Model statistics

VCE robust			
N. observ.	229	Ps.R2	0.117
Wald chi^2	5,387	p-value	0.000

MODEL 2 – Including fungibility and loss aversion (Fewer observations)

	Cash		Debit card		Credit card		Electronic	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Gender			0.26	0.80	0.77	0.15	0.59	0.41
Age (over 29)			**15.70**	**0.00**	-0.08	0.92	0.71	0.58
Employed (part-time)			**-14.54**	**0.00**	0.76	0.41	0.70	0.52
Self employed			**19.09**	**0.00**	**16.84**	**0.00**	**18.65**	**0.00**
Unemployed			**-16.85**	**0.00**	-0.85	0.45	-0.34	0.83
Other employment status			**-13.46**	**0.00**	0.90	0.42	**-14.12**	**0.00**
Capita			-0.53	0.38	0.01	0.98	0.31	0.54
Nigeria			-0.34	0.72	-0.45	0.42	**-2.18**	**0.03**
Ghana			2.35	0.15	0.98	0.44	-0.24	0.89
South Africa			**-16.28**	**0.00**	**-2.00**	**0.04**	**-2.08**	**0.06**
Uganda			-0.16	0.92	0.26	0.85	**-16.52**	**0.00**
Zambia			**17.12**	**0.00**	**16.06**	**0.00**	**15.96**	**0.00**
mental			0.48	0.30	0.13	0.67	0.25	0.55
fungib			-1.05	0.49	-0.51	0.41	-0.58	0.43
LAmed			0.03	0.69	-0.03	0.39	-0.06	0.35
habit			0.13	0.78	0.14	0.66	-0.28	0.48
affect			0.30	0.76	**1.04**	**0.06**	-0.45	0.58
Intercept			**-16.60**	**0.00**	0.01	1.00	-1.63	0.66

VCE robust			
N. observ.	147	Ps.R2	0.184
Wald chi^2	-	p-value	-

Marginal effects

	Cash		Debit card		Credit card		Electronic	
Variables	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value
Gender	-0.02	0.72	-0.03	0.43	0.33	0.62	0.01	0.76
Age (over 29)	0.08	0.43	-0.02	0.76	-0.06	0.61	0.00	1.00
Employed (part-time)	0.03	0.74	-0.03	0.52	-0.06	0.60	0.06	0.49
Self employed	**-0.18**	**0.00**	0.16	0.15	-0.03	0.83	0.05	0.71
Unemployed	0.10	0.51	**-0.07**	**0.00**	-0.07	0.65	0.05	0.70
Other employment status	-0.05	0.62	**-0.07**	**0.00**	0.09	0.44	0.03	0.74
Capita	-0.05	0.20	-0.02	0.31	0.03	0.59	0.05	0.20
Nigeria	0.09	0.12	0.00	0.93	0.08	0.27	**-0.17**	**0.00**
Ghana	-0.05	0.52	0.11	0.20	0.12	0.28	**-0.18**	**0.01**
South Africa	**0.33**	**0.02**	**-0.06**	**0.03**	**-0.24**	**0.07**	-0.03	0.77
Uganda	-0.03	0.74	0.12	0.22	0.15	0.26	**-0.24**	**0.00**
Zambia	-0.05	0.62	0.03	0.74	0.04	0.80	-0.03	0.84
mental	-0.02	0.48	0.00	0.90	0.00	0.93	0.01	0.60
fungib								
LAmed								
habit	0.01	0.77	-0.02	0.49	0.03	0.46	-0.02	0.48
affect	-0.03	0.50	0.00	0.94	0.11	0.13	-0.07	0.17

	Cash		Debit card		Credit card		Electronic	
	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value	dy/dx	p-value
	-0.09	0.17	-0.02	0.68	0.11	0.18	0.00	0.96
	-0.14	0.17	**0.86**	**0.00**	**-0.66**	**0.00**	-0.06	0.55
	-0.08	0.39	**-0.07**	**0.00**	0.13	0.22	0.02	0.80
	-0.20	**0.00**	0.21	0.13	-0.23	0.15	0.22	0.23
	0.14	0.50	**-0.07**	**0.00**	-0.11	0.58	0.03	0.80
	-0.07	0.52	**-0.07**	**0.00**	**0.26**	**0.03**	**-0.12**	**0.00**
	0.00	0.95	-0.03	0.32	0.00	0.98	0.03	0.43
	0.10	0.20	0.01	0.73	0.05	0.59	**-0.16**	**0.00**
	-0.08	0.34	0.14	0.29	0.08	0.62	-0.13	0.13
	0.39	**0.03**	**-0.05**	**0.05**	-0.25	0.18	-0.09	0.36
	0.01	0.94	0.00	1.00	0.20	0.22	**-0.21**	**0.00**
	-0.14	**0.00**	0.09	0.51	-0.57	0.77	0.00	0.99
	-0.02	0.56	0.02	0.34	-0.01	0.84	0.01	0.71
	0.07	0.36	-0.03	0.66	-0.03	0.80	-0.01	0.83
	0.00	0.38	0.00	0.27	0.00	0.54	0.00	0.50
	-0.01	0.80	0.00	0.84	0.04	0.37	-0.04	0.22
	-0.10	0.14	-0.02	0.69	**0.23**	**0.01**	**-0.11**	**0.08**

Table 9 performs a similar analysis but using the least preferred payment method as dependent variable for the multinomial logistic regression. This approach seeks to identify potential drivers detrimental to the use of specific payment methods.

Once again, the affect heuristic shows the most relevant results among the behavioral traits. Thus, the emotional driver increased the average probability of choosing credit card as the least preferred method among the four available alternatives. The results were significative at $p<0.01$ for the reduced sample, although only at $p\approx0.1$ for the complete sample.

Other relevant results among the control variables included a preference for cash among the self-employed (implied by a negative sign of the marginal effect for cash as least preferred method) and higher preference for electronic payments (again, negative marginal effects) in Nigeria, Ghana, and Uganda.

The above results were validated using alternative methods of analysis. Having the payment alternatives ranked from most preferred to least preferred allowed estimation of the drivers of the preference for each payment method using ordered logistic regression. Moreover, a logistic estimation for each payment method compared when a particular method was ranked as the most preferred (value 1) or not (value 0). Table 10 summarizes the results obtained for the complete sample (on top) and the shortened sample to include fungibility and loss aversion (below), for the alternative econometric specifications. Individual results available upon request.

Table 10. Robustness test. Summary of statistically significant results for drivers of preferred means of payment across three estimations: multinomial logistic, ordered logistic, and logistic regression.

MODEL 1 – Excluding fungibility and loss aversion (Full sample)

	Cash				Debit card				Credit card				Electronic				No Credit card			
Variables	impact	mult	ord	log	impact	mult	ord	log	impact	mult	ord	log	impact	mult	ord	log	impact	mult	ord#	log
Gender													**neg**	**		*				
Age (over 29)					**pos**	*	*	*												
Empl. part-time																				
Self employed													**neg**	**		*				
Unemployed									neg	***										
Other status													**neg**	***	**	*				
capita					**pos**	***	***	***					**neg**	**	*	**				
Nigeria	**neg**	***	***	***	**pos**	**	**	**	**neg**	*		*	**pos**	***	***	**				
Ghana																				
South Africa	**neg**	***	***	***					**neg**	***		***					**neg**	*		*
Uganda									**neg**	***		***	pos		*					
Zambia																				
mental																				
fungib																				
LAmed																				
habit																				
affect	**neg**	**		**	pos	·			neg		*						pos	·	*	*

MODEL 2 – Including fungibility and loss aversion (Fewer observations)

	Cash				Debit card				Credit card				Electronic				No Credit card			
Variables	impact	mult	ord	log	impact	mult	ord	log	impact	mult	ord	log	impact	mult	ord	log	impact	mult	ord#	log
Gender									**pos**	*			**neg**	**		**				
Age (over 29)									**pos**	***			**neg**	***	*	*	neg	***		
Empl. part-time									**neg**	***		***								
Self employed									**neg**	***		***	neg	*						
Unemployed									**neg**	***		***								
Other status	**pos**	***		*					**neg**	*		***	neg	***			pos	**		
capita					**pos**	**		**												
Nigeria	**neg**	***	***	***	**pos**	*			**neg**	***		***	**pos**	***	***	**				
Ghana									**neg**	***		***								
South Africa	**neg**	***	***	***					**neg**	***		***	**pos**	*		*				
Uganda									**neg**	***		***								
Zambia																				
mental	pos			*					**pos**	*		*								
fungib																				
LAmed																				
habit																				
affect	neg	·		·	**pos**	*		·	neg		***						**pos**	***	***	**

As results of the ordered logistic regression for credit card as least preferred method we exhibit the same results of the ordered logistic regression for credit card as preferred method, with the signs inverted

* significant al 10%; ** significant at 5%; *** significant at 1%. · for behavioral traits only, near significance (p≈10%)

Statistically significant results are highlighted in bold. Credit card results for multinomial logistic and logistic regressions should be considered with caution, since we only had 22 observations for Model 1, even fewer for Model 2 (the ordered logistic regression, instead, used the complete sample). To better identify the drivers of credit card preferences, we added in the column to the right, the results of regressions for credit card being chosen as the least preferred method (for which we had 150 observations in Model 1 – see Table 5).

Focusing on behavioral traits there was a clear conclusion: the emotional factor (affect) was the main and only robustly significant driver, to some extent a lower preference for the use of cash, and more clearly lower preference for the use of credit card.

These results were revealing in at least two instances. First, most research has focused on "nudging" and mental accounting, and the limited empirical evidence finds some link with credit card use (Huebner *et al.*, 2020) and mobile payment adoption (Zhao and Bacao, 2021). Some authors have also identified the role of habit in reducing debit card adoption (van der Cruijsen *et al.*, 2015). Our results, however, do not reveal any significant impact of mental accounting (including fungibility bias) and habit on the overall preference for one payment option or another.

The second reason why these results are revealing comes from the absence of significant results associated with loss aversion. Loss aversion is frequently used to understand choice in a risky environment, and the credit card is the single payment method here considered that includes explicit risk (credit) as a complementary feature. However, our results suggested that loss aversion had no impact at all; in contrast, the main driver against using credit card appeared to be the affect heuristic. This suggested that the risk perception of using credit card instead of cash operates at an emotional level and, more importantly, it is in line with the traditional criticism of behavioral finance for placing more emphasis on cognitive biases than on emotional biases. The relevance of the affect heuristic on the use of credit card is, to the best of our knowledge, a novel result in the literature.

Beyond behavioral biases, Table 10 reveals robust evidence that individuals with higher personal income proxy (*capita*) preferred to use debit card rather than electronic payment. Results also suggested some preference of older cohorts and of women to use debit card rather than electronic payments. Results also suggested a distinctive payment behavior in Nigeria and South Africa, particularly a lower preference for the use of cash. All results were robust to alternative specifications of fungibility (including missing responses as evidence of the bias) and loss aversion.

No further evidence has been traced. We believe this might be a result of our sample bias: survey respondents are all highly educated and most of them of the same ethnicity. For all intents and purposes they were, therefore, a homogeneous group. This is most evident in aspects such as age and employment status. Still, such behavior would be unrepresentative of other profiles common in sub-Saharan Africa – such as low-income black population.

Finally, we explored the impact of the behavioral traits on the choice of payment method for different amounts of money and different payment contexts. We explored two payment amounts (lower than $1 and higher than $5) and five point-of-sale (POS) contexts: payments at a bar, haircut, petrol station, restaurant, and supermarket. Table 11 summarizes results of a multinomial logistic regression for the complete sample, where only the statistically significant results were displayed.

For clarity, we have highlighted in bold any significant results of behavioral biases, while only including results at 5% significance for the control variables. Again, we must be cautious with the results for credit card use (where we have also blurred coefficients lower than 0.10 for the sake of interpretation).

Table 11. Factors driving the preference of payment method by transaction value and transaction context (multinomial logistic regression).

Marginal effects (dy/dx)														
Variables	**less $1**		**more $5**		**bar**		**haircut**		**petrol**		**restaurant**		**supermkt**	
Cash														
Gender							-0.13	**			-0.14	***		
capita											-0.08	**		
Nigeria	-0.15	**	-0.16	***	-0.25	***			-0.18	***			-0.10	**
Ghana					0.34	***								
South Africa					-0.21	**			-0.33	***	-0.21	***	-0.15	***
Uganda					0.44	***					0.37	**		
affect							**-0.11**	*			**-0.13**	**		
Debit card														
Gender											0.14	**		
Nigeria	0.21	***			0.35	***			0.34	***	0.24	***	0.25	***
Ghana					-0.29	***	-0.12	***			-0.30	***		
South Africa					0.30	**			0.48	***				
Uganda	-0.14	***	-0.44	***	-0.29	***	-0.12	***	-0.24	**			-0.34	**
Zambia							-0.12	***						
mental									**-0.07**	**				
habit			**-0.07**	*			**-0.06**	**						
affect									**0.16**	**	**0.11**	*	**0.13**	*
Credit card														
Gender			0.08	**										
Age (over 29)					-0.10	**								
Nigeria			-0.07	**							-0.09	**	-0.09	**
Ghana	-0.07	**	-0.10	***			-0.02	**	-0.16	***				
South Africa	-0.07	**			-0.10	***	0.22	***						
Uganda	-0.07	**	-0.10	***	-0.10	***	-0.02	**			-0.14	***		

Zambia	-0.07	**	-0.10	***	-0.10	***	-0.02	**			-0.14	***	
mental			**-0.02**	**	**-0.03**	**							
habit			**0.05**	***	**0.05**	*							
affect			**0.05**	**			**0.08**	*					
Electronic													
age (over 29)									0.16	***			0.11	***
Nigeria									-0.08	**			
Uganda			0.41	***							-0.14	***	
Zambia											-0.14	***	-0.11	***
mental									**0.04**	*			
Model statistics													
VCE robust													
N. observ.	229		229		229		229		229		229		229	
Wald chi^2	3,937		3,899		1,967		5,345		8,541		4,940			
p-value	0.000		0.000		0.000		0.000		0.000		0.000			
Ps.R2	0.131		0.153		0.201		0.205		0.178		0.171		0.148	

Note: * significant at 10%; ** significant at 5%; *** significant at 1%.

The results by purchase amount and transaction context were particularly revealing. In this instance we observed statistically significant evidence of mental accounting and habit driving payment choice for different purchase amount and transaction context, mostly around the use of debit and credit cards.

Respondents also exhibited a marked habit to prefer credit card rather than debit card for payments greater than $5, and mental accounting helped to explain why electronic payments were preferred to debit cards in petrol stations.

Still, affect heuristic helps to explain most of the results associated with lower use of cash (for haircuts and in restaurants), and in favor of using the debit card in most payment contexts. Both results rejected hypothesis H1 (the higher affect, the higher intention to use cash), suggesting that the affect heuristic does not operate through a perceived higher risk profile of payment methods alternative to cash, as we hypothesize. Instead, there seems to be an emotional response against the use of cash for respondents who rely on the affect heuristic to make decisions. Finally, it is worth mentioning that in an undisclosed result, we obtain significative evidence that a higher fungibility bias increased use of cash (in favor of hypothesis H2 – the higher mental accounting, the higher use of cash) and reduced the use of credit in payments of less than 1$.

We believe that behavioral traits (habit and mental accounting in particular) have not been revealed before as significant in the context of payment methods because previous studies did not mediate in the overall preference for one payment method or another, but rather

explored the contexts around which people preferred to use each of the options available. Our results suggested that individuals do not have a preferred payment method: they choose the one that best suited their needs according to the context or situation.

These results suggested that monetary authorities would have two options available. One is to be aware of where and when people prefer to use a given payment method, and intervene if they want to change that behavior (for instance, if it is considered costly from a societal point of view). In this regard, it is worth mentioning that the results in Table 11 offer a transversal lecture for electronic payments: they are barely affected by any behavioral traits. The other option available to authorities, which is better aligned with the aims made explicit by the main central banks in their proposal to launch CBDCs in the future (Bank of Canada *et al.*, 2021), is to ensure that a wide variety of payment alternatives is available for people to use, including cash, and let them choose.

7. Conclusions

This article delved into the potential behavioral drivers that influence individual decisions to use cash or alternatives to cash in retail transactions. The survey sample was tilted towards English speaking, university educated, digitally included, at least middle-income adults in Africa. This provided an interesting context to study the use of cash and its alternatives for reasons such as the lower levels of banking penetration and recent trends towards electronic payments across African countries.

The results show that an emotional driver (affect heuristic) was the single behavioral trait that decided the overall use of one payment method or another – in particular, the decision to use cash or a credit card. Other behavioral traits did not mediate in the overall preference; still, mental accounting and habit helped to explain situations in which people prefer to use one payment method or another. Loss aversion seems not to have had any impact at all, once controlling for the emotional driver. The results were robust to different econometric specifications, subsets of data, and estimations of the behavioral drivers.

Within the extant literature, recommendation are for government policy to "invest more in nudging" (Benartzi and Beshears, 2017), that is, to use psychological behavior and habits to influence, for instance, greater use of electronic payment methods or eliminate cash transactions. However, most people in our sample declared not to have a preferred payment method. Instead, they choose according to transaction context in specific situations.

In our view, these results suggest that authorities would have two options available for policy making. First, develop an awareness of where and when people prefer to use a given payment method and intervene if desired. For instance, by reducing a high share of cash transactions that may be considered costly from a societal point of view (e.g., the ECB estimates that these costs amount 45 billion per year (Schmiedel *et al.*, 2012)). Second, ensure that a wide variety of payment alternatives is available for people to use, including cash, and let them choose – this option being aligned with the position by the main central banks and the Bank of International Settlements in their recent joint proposal to launch CBDCs in the future (Bank of Canada *et al.*, 2021). These recommendations thus support a view to manage the downsizing but not the total elimination of the cash management infrastructure.

The main limitations of the study come from the need to test different behavioral biases and demographic priors with reduced-form tests, for the sake of survey brevity. This might have led to partially reliable measures (e.g., for fungibility and loss aversion). Future research might explore some of these biases individually, allowing implementation of more complex tests.

Declaration of interest

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APPENDIX

Test for mental accounting

Now we would like to ask you about how you budget your money. Please indicate to what extent each of the following statements apply to you. Please select one option for each statement.

1. *I regularly reserve or set money aside for different expenses (such as clothing, food, transport, etc).*
2. *I never spend more than a fixed amount on food, clothing, transportation, etc.*
3. *If I spend more than usual on one thing, I will spend less on other expenses.*
4. *If I overspend on one thing in one month, I will spend less on other things in the next month.*

Test for fungibility perception

Please, select Yes or No for the following scenarios. Consider the equivalent amounts in your local currency to those in US dollar.

1. *Imagine that you have decided to attend a concert that costs $5. When you enter the venue to buy the ticket you discover that you have lost a $5 note. Will you still pay $5 to watch the play?*
2. *Now imagine that you have decided to attend a concert and that you have already bought a ticket for $5. When you enter the venue, you discover that you have lost the ticket. It is impossible to get a refund for the lost ticket. Would you buy a new ticket for $5?*

Test for loss aversion

1. *Imagine you take part in a "fair" game with a friend in which you will toss a coin. By fair we mean there is an equal chance of heads or tails on each toss. What is the minimum gain you will be willing to earn to play this game, if you could lose $5 US dollars.*
2. *You take part in a "fair" game with another friend in which you will also toss a coin. What is the minimum gain you will be willing to earn to play this game, if you could lose $10 US dollars.*
3. *You take part in a "fair" game with another friend in which you will also toss a coin. What is the minimum gain you will be willing to earn and play this game, if you could lose $20 US dollars.*

Test for habitual behavior

We would like to ask you questions about routines and habits in your life. Please indicate to what extent you agree with the statements below. Select one for each statement.

1. *I quite happily work within my comfort zone rather than challenging myself.*
2. *I tend to do things in the same order every morning (e.g., get up, go to the toilet, have a coffee…).*
3. *Whenever I go into the kitchen, I typically look in the fridge.*
4. *I normally buy the same foods from the same grocery store.*
5. *I tend to like routine.*

Test for the affect heuristic

Below you will find a list of activities. For each of them, please rate both the Risk and Benefit perceived of that activity, regardless of whether you feel they are morally or ethically appropriate:

1. Speaking to a large audience. 2. Go shopping. 3. Having an affair. 4. Horseback riding. 5. Vaccinating. 6. Take a nap. 7. Undergo surgery. 8. Play board games. 9. Read a book. 10. Skydiving. 11. Using cocaine. 12. Playing the lottery. 13. Dining out. 14. Buy shares in the stock market. 15. Take a loan.