Cover Page

Name: Michael Olabisi

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Date of Ph.D.: May 2015

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Current Research:
To address the development challenges of low-income countries today, we must pay attention to the working of markets and trade. I have worked on papers that show how the development goal of reducing poverty is hampered by second-degree price discrimination - as the poorest do not buy in bulk or are unable to do so. I have ongoing work on how gender affects the prices that traders get or pay for food grains in West Africa, based on a three-year study of grain markets in West Africa. My collaborators and I expect other papers on how mobile phone technology affects the workings of markets from that study. One product of the study is a working paper (recently submitted to the Journal of Development Economics), on methods to undertake productive field experiments.

Summer Institute Sessions of Interest:

Development Economics

Public Economics

Urban Economics

Methods Lectures

Michael Adetayo OLABISI

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Michigan State University
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Academic Positions

Michigan State University,
Depart of Community Sustainability (from August 2020)
Depart of Agricultural, Food and Resource Economics
Assistant Professor, August 2017 –

Pepperdine University,
Assistant Professor of Economics, August 2015 – July 2017

Education

University of Michigan, Ann Arbor: Ph.D. (2015).
Business Economics

Cornell University, Ithaca: M. Eng. (2004)
Chemical Engineering

Obafemi Awolowo University, Ile-Ife, Nigeria: B.Sc. (1999)
Chemical Engineering

Papers and Publications

(† - with MSU Graduate Student, * - with non-MSU graduate student, ** - with undegrad)

Peer-Reviewed Publications (16)

Olabisi, M., Richardson, R., and Adelaja, A., (2022) **Closing Africa's Renewable Energy Financing Gap**
Africa Year in Review (Published Jan 2023)

Olabisi, M., Richardson, R., and Adelaja, A., (2022) **The Next Global Crisis: Africa's Renewable Energy Financing Gap**
Climate and Development (Published online Sep 2022)

Olabisi, M., and Richardson, R., (2022) **Why the Poor Pay Higher Energy Prices: Evidence from Tanzania**
World Development Perspectives 26 (June): 100414

Mora, J. and Olabisi, M. (2022) **Economic Development and Export Diversification: The Role of Trade Costs**
International Economics (Published online Nov 2022)

Ashworth, J., and Olabisi, M. (2022) **Distance and Mismatch in Graduate School Selection**
Education Economics (Published online Feb 2022)

* Olabisi, M., Obekpa, H.O. and Liverpool-Tasie, L.S.O. (2021) **Is Growing Your Own Food Necessary for Dietary Diversity? Evidence from Nigeria**
Food Policy 104 (Oct): 102144

Olabisi, M., Tschirley, D., Nyange, D. and Awokuse, T. (2021) **Does Trade Protectionism Promote Domestic Food Security? Evidence from Tanzanian Edible Oil Imports**
Global Food Security 28 (3) 100470

Mora, J. and Olabisi, M. (2021) **Export Growth Drivers and Econ. Development**
Empirical Economics (Published online Jan 2022)

Olabisi, M. and Sawyer, W C. (2021) **The Demand for Imports and Exports in Africa: A Survey**
Journal of African Trade 7 (1-2) 45–59

Olabisi, M. (2020) **Trade Shocks and Youth Jobs**
IZA Labour Policy 10 (1) 2020011

Olabisi, M. (2020) **Input-Output Linkages and Sectoral Volatility**
Economica 87 (347): 713–746

Mora, J. and Olabisi, M. (2020) **Economic Development and the Margins of Trade: Are the Least Developed Countries Different?**
Economic Inquiry 59 (2): 600-621

Olabisi, M, Blanco, L., Mora, J. and Prieger, J. (2020) **Export Survival in Africa and Latin America: Diversification, Synergies and Competition**
Southern Economic Journal 87 (1): 245-273

Olabisi, M., Tschirley, D., Nyange, D. and Awokuse, T. (2019) **Energy Demand Substitution from Biomass to Imported Kerosene: Evidence from Tanzania**
Energy Policy 130 (7): 243–252

Olabisi, M. (2019) **Bridging the Enforcement Gap in International Trade: Participation in the New York Convention on Arbitration**
Journal of International Business Policy 2 (1): 86–109

Olabisi, M. (2017) **The Impact of Exporting and FDI on Product Innovation: Evidence from Chinese Manufacturers**
Contemporary Economic Policy 35 (4): 735–750

Olabisi, M. and Stein, H (2015) **Sovereign Bond Issues: Do African Countries Pay More to Borrow?**

Journal of African Trade 2 (1-2): 87–109

Submitted Journal Articles (2)

Olabisi, M., Liu, J., Maredia, M., Ajeigbe, H.A., Ajibade, T.B. (2022) **In-Group Competition for Incentives**
(Submitted to *Journal of Development Economics*)

** Olabisi, M. and Nicolaysen, M. (2022) **Discrimination in Retail**
(Submitted to *Journal of Consumer Affairs*)

Articles in Preparation (7)

Economic Development and Export Growth: The Role of Trade Costs
(with Mora, J.)

Gender Participation Rates in Food Value Chains: Evidence from Nigeria
(with Maredia, M., Ajeigbe, H.A., and Ajibade, T.B.)

Market Linkages in the West African Food Value Chain
(with Maredia, M., Ajeigbe, H.A., and Ajibade, T.B.)

Why Bulk Discounts for Food Elude the Poor: Evidence from Tanzania
(Previously submitted to the *Journal of Development Economics*, with Persaud, A.)

Sovereign Bond Issues: Why African Countries Still Pay More to Borrow
(with Stein, H.)

Trade and Global Economic Shocks: A Network Perspective

Market Linkages and Price Volatility: Evidence from Nigerian Grain Markets

Published Working Papers Not Peer-Reviewed (3)

Olabisi, M. (2019) **Export Diversification: Evidence from Sino-African Trade**
(SSRN Working Paper)

Olabisi, M., Tschirley, D., Nyange, D. and Awokuse, T. (2018) **The Challenge of Substituting Sunflower Oil for Imported Palm Oil: Evidence from Tanzania**
(FSP Working Paper)

Olabisi, M. (2016) **Demand Volatility and Export Entry**
(FREIT Working Paper)

Service

Committee Service for Department(s)

2022-23 - CSUS Diversity. Equity and Inclusion Committee (Committee Chair)

2023 - AFRE MS - Theses Selection Awards Committee

2022 - CSUS Award Review Committee

2021-22 - CSUS Undergraduate Advisory Council Committee

2019-21 - AFRE Graduate Placement Committee

2018 - AFRE Graduate Dissertation Award Committee

Other Service

Reviewer for Energy Policy Journal

Reviewer for Agricultural Economics Journal

Reviewer for Population and Environment Journal

NSF SBE Advisory Board

Carnegie Africa Diaspora Fellowship Program - Review and Conf. Committee Service

Mentoring and Student Advising

2021– Doctoral Student - Liu Jiawen

2022– Masters Student - Asma Sampa

2022– Undergraduate Research Mentor for William Carvalho and Shubham Aggarwal

2020-22 Honors College Undergraduate Research Mentor for Maren Nicolaysen

2019-20 Honors College Undergraduate Research Mentor for Allan Kiambuthi

2020-22 Doctoral Dissertation Committee for Jun-Tae Park (Graduated 2022)

2019-21 Doctoral Dissertation Committee for Jeognhwan Choi (Graduated 2021)

2018-20 Doctoral Student Supervision for Rahul Dhar

2018-19 Doctoral Student Supervision for Ahmed Salim Nuhu

2018-20 Research Instructor and Mentor to NAPP Doctoral Visitors to MSU: Obekpa, Hephzibah; Sule, Balarabba; Onyinye Choko and Olumba, Charles

External Grants, Fellowships, Awards and Research Visits

2021: **Feed the Future: Legume Systems Innovation Lab**
Early Career Researcher Award.

2021: **Feed the Future: Legume Systems Innovation Lab**
Lead Principal Investigator on research grant to study value chain linkages between markets in West Africa, Phases I & II (with Maredia, M. and Crawford, E.).
(˜$775,000)

2020: **National Science Foundation**
Principal Investigator on, Trade and Global Economic Shocks: A Network Perspective.
(˜$75,000)

2019: **Feed the Future: Legume Systems Innovation Lab**
Lead Principal Investigator on research grant to study value chain linkages between markets in West Africa, Commissioned Activity, (with Maredia, M.).
(˜$104,000)

2018, 2016: **Carnegie African Diaspora Fellowship**
Full travel grant for a research visit. Selected for an international research/teaching collaboration with peers from the University of Ibadan, Nigeria. Mentored graduate students and taught a research methods workshop during the 2016 visit.

2016, 2015: **AEA-NSF Travel Grants**
Received funds to travel, and participate in the National Science Foundation Summer Pipeline Conference in Albuquerque NM (July 2015), the AEA Annual meetings in San Francisco CA (January 2016) and the WEAI Conference in Portland OR (July 2016). Mentored prospective economics graduate students from under-represented backgrounds and presented research papers at the Summer Pipeline meetings.

2013: **Advanced Graduate Workshop on Globalization and Development**
Full travel, board and conference tuition grant. Selected from a global pool of applicants for a two-week workshop in Bangalore, India, organized by Columbia University's Initiative for Policy Dialogue. Presented preliminary work on export failure –the extensive margin of trade.

2010: **National Science Foundation, East Asia and Pacific Summer Institutes (OISE-1014618)**
Selected in US-wide competition for East Asia research visitor program. Attached to the National University of Singapore from June to August 2010. Worked on product innovation impacts of FDI and export participation. (See Publications section).
(Expenses + ˜$5,000)

Internal Grants and Awards

2018: **TPP Research Grant**
Two-year grant awarded for pilot research projects to study linkages in food value chains, by the Tanzania Partnership Program (TPP) at Michigan State University.
(˜$30,000)

2016: **Rothschild Applied Research Fellowship**
One-year fellowship and cash grant awarded to an outstanding researcher at Pepperdine

University's Graziadio School of Business and Management.
(˜$5,000)

2016: **Cross-School Collaborative Research Award**
Received funds to support research projects that cross boundaries within Pepperdine University. Joint research project with James Prieger and Luisa Blanco of the School of Public Policy, selected from university-wide search. (See Works in Progress section.)
(˜$16,000)

Conferences and Other Presentations

† - Invited Presentations, Seminars and Panels

2023: † **California State University, Chico California**. Mar 27-28, Invited Seminar, based on work on market linkages.

2023: **Global Convening for the Legume Systems Innovation Research Lab, Livingstone Zambia**. Feb 20-24, Led a team that presented work on market linkages.

2023: **American Economic Association Conference, New Orleans**. Jan 07-08, Presented papers on economic development and trade costs.

2022: **Canadian Economic Association Conference, Ottawa Canada**. Jun 02-05, Presented paper on economic development and trade costs.

2022: † **University of Michigan Ross Alumni Speaker Series**. Apr 1. Presentation on Climate Issues in Academia and Beyond.

2022: † **United Nations Conference, Johannesburg South Africa (Online Presentation)**. Mar 1. Presented paper on Challenges of Financing Sustainable Energy Transition for African countries.

2021: † **University of Richmond, Richmond VA**. Dec 4. Seminar on joint work with Alexander Persaud on Prices and Poverty.

2021: † **Bayero University Kano Center for Dryland Agriculture, Kano Nigeria**. Nov 2021. International Presentation - about work on Linkages and Price Volatility in Food Markets.

2021: † **University of Minnesota, Minneapolis MN**. Nov 4 Trade and Development Seminar Series. Presented work on Linkages and Price Volatility in Food Markets.

2021: **Carnegie Africa Diaspora Fellows Conference, Washington DC**. Oct 05-08, Conference Steering Committee Member.

2021: **Western Economic Association International Conference, Hawaii HI**. Jun 26-29. Presented paper on trade costs and trade margins.

2021: **Bureau for Research and Economic Analysis of Development (BREAD) Conference at NYU**. May 6-8. Presented joint work with Alexander Persaud on Prices and Poverty.

2021: † **UCLA Africa Studies Center, Los Angeles CA**. April 30. Presented paper on Financing Sustainable Energy Transition for African countries.

2020: **Centre for the Study of African Economies (CSAE) China's Economic Engagement with the African Continent Conference, Oxford UK**. Accepted paper on Sino-African Trade.

2019: **Midwest Macro Meetings Fall 2019, East Lansing MI**. Accepted paper on linkages and sectoral volatility.

2019: † **Pepperdine University, Malibu CA**. Fall 2019 PEP Talk Seminar Series. Presented work on Linkages and Volatility

2019: **Western Economic Association International Conference, San Francisco CA**. Presented paper on linkages and sectoral volatility.

2019: **American Economics Association Conference, Atlanta GA**. Presented joint work with Jared Ashworth.

2018: **Agricultural and Applied Economics Association Conference, Washington DC**. Presented paper on international trade margins

2017: **Southern Economic Association Conference, Tampa FL**. Presented multiple papers

2017: **Western Economic Association Conference, San Diego CA**. Presented multiple papers

2016: **Southern Economic Association Conference, Washington DC**. Presented Paper: Determinants of Export Survival and Failure: Evidence from Firm-Level Export Transactions.

2016: **European Trade Study Group Conference, Helsinki, Finland**. Presented Paper: Demand Volatility and Export Entry.

2016: **American Econ. Association Summer Mentoring Pipeline Conference, East Lansing MI**. Presented Paper: Sectoral Volatility and Input-Output Linkages.

2016: **Western Economic Association International (WEAI) Conference, Portland OR**. Presented Paper: The Impact of Exporting and FDI on Product Innovation: Evidence from Chinese Manufacturers.

2015: **American Economic Association Summer Mentoring Pipeline Conference, Albuquerque NM**. Presented Paper: Demand Volatility and Export Entry.

2015: **Trans-Atlantic Doctoral Conference at the London School of Economics, London UK**. Presented Paper: Demand Volatility and Export Entry.

2012: **American Public Policy and Management Fall Research Conference, Washington DC**. Presented: Trade and the Convention on Foreign Arbitral Awards.

2011: **European University Institute Global Governance Program Conference, Florence, Italy**. Presented Preliminary Paper: Participation in the New York Convention on Arbitration.

2010: **National Science Foundation/NRF East Asia Pacific Summer Institute Research Presentation, Singapore**. Presented Preliminary Paper: FDI Flows, Exporting and Product Innovation.

Teaching

Michigan State University, Sustainable Development (CSUS 824: 2022)

Michigan State University, Public Policy for the Agrifood System (AFRE 300: 2018-20, 2022)

Michigan State University, Undergraduate Research Seminar (UGS 200H: 2018-20)

Michigan State University, Agribusiness Strategic Management (FIM 439: 2018-20)

Pepperdine University, Macroeconomics (ECNM 592: 2015-17)

Pepperdine University, Economic Concepts (ECNM 592: 2015-17)

Pepperdine University, Managerial Economics (ECNM 602: 2015-17)

Other Experience and Service

2015–2017 **Associate Board Member, Non-Profit**, Shelter Partnership (Los Angeles)

2008–2009 **Board Member, Non-Profit**, North Minneapolis Meals on Wheels

2005–2008 **Advisory Services Senior Associate**, KPMG

2001–2003 **Advisory Services Senior Associate**, PricewaterhouseCoopers

Languages

Chinese: Beginner

French: Intermediate

Yoruba: Native

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Little Cash, Little Carry: Liquidity Constraints and Missing Out on Bulk Discounts in Tanzania*

Michael Olabisi†

Alexander Persaud‡

March 18, 2023

Abstract

Why do some households forego bulk discounts on food purchases? Using high-frequency data on households' item-level purchases from Tanzania, we show that liquidity constraints keep the poor from using bulk discounts consistently. Poorer households capture bulk discounts less frequently as they buy smaller quantities on average per transaction. Households that rely primarily on monthly wage income change the pattern of food purchases – with larger purchases and more bulk discounts around the 'flush' days of the month. The intensity of the swings in spending within the month is moderated by wealth, as predicted in our conceptual framework, when consumers are liquidity-constrained. Thus, households at the first quartile of wealth lose an additional 5% of their spending on food relative to households at the third quartile, from not using bulk discounts.

JEL classification: O12, D12

Keywords: Bulk Discounts; Poverty; Tanzania

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1 Introduction

When poor households cannot access and use bulk discounts in food markets like wealthy households in many developing countries, it effectively creates a poverty price penalty. *Why* some households fail to use bulk discounts—or use them consistently—when such discounts are theoretically available remains an open question, in part because data on prices and purchases at the household level are scarce. We are concerned about this question because food consistently comprises a large share of poor households' budgets in developing economies.[1]

We focus on short-term liquidity constraints as an answer to the question. Buying in bulk implies differences in the smoothness of day-to-day spending for the poor, which fits earlier papers on liquidity-constraints and spending over the course of the month (Evans and Moore, 2011, 2012; Stephens, 2003). Our rationale follows the conclusions of earlier papers that show consumption is limited by liquidity constraints (e.g., Hayashi, 1985; Zeldes, 1989; Chetty et al., 2020). Different endowments of wealth and varying patterns of periodic income flows that create 'lean' and 'flush' times affect households' ability to use bulk discounts. Using novel data from the expenditure diaries of almost 10,000 households in Tanzania, we exploit the variation in household income flow patterns to show that liquidity constraints bind.

First, we show that bulk discounts exist, are non-trivial, are persistent across time, and affect most food items. This first finding fits a broad array of papers that show economically significant bulk discounts in the United States (Orhun and Palazzolo, 2019), the United Kingdom (Beatty, 2010; Griffith et al., 2009), Israel (Eizenberg et al., 2021), Mexico (Attanasio and Pastorino, 2020) and Colombia (Attanasio and Frayne, 2006). Bulk discounts are non-trivial because buying in small quantities is widespread in Tanzania and other developing economies. 53% of households recorded food purchases on more than 25 days of their

[1]The literature provides robust arguments and evidence for Engel curves that show declines in food budget shares with increasing household income (Engel, 1895; Blundell, 1988; Banks et al., 1997; Aitchison and Brown, 1954; Working, 1943).

one-month observation period in the data. The average rice-buying household, for example, made about eight purchases of this leading staple in a month, although it is non-perishable. It is usually purchased in quantities no larger than a three-day ration for households. Buying in small quantities means that households could lose notable shares of the household budget to the higher unit values (prices) that come with missing out on bulk discounts.

Second, we lay out a basic framework of household spending behavior in the presence of liquidity constraints. Liquidity constraints can arise from a lack of wealth, low or infrequent income, or both, and they prevent poor households from making bulk purchases, even of storable goods. The framework gives several testable hypotheses on how bulk discounts change the prices and quantities obtained by different households for the same product.

Third, we show that liquidity constraints are an underlying cause for why households fail to take advantage of bulk discounts. We use data on whether households depend largely on a monthly wage to show a sharp distinction between the 'flush' days of the month when households use bulk discounts more, and the 'lean' days of lower quantities and higher per-unit values. In the flush days, households experience roughly 2% lower prices across the board compared to their lean period. Households with less frequent income also show a higher tendency to make major purchases when flush – a sign of liquidity constraints and limited ability to smooth spending. Our approach focuses on identifying price differences, even if our estimates are biased downwards by differences in quality between households. Our approach also avoids concerns about potential poverty-related differences in time preferences (c.f., Tanaka et al., 2010; Ubfal, 2016), or uncertainty about income.[2]

Fourth, we show that poorer households lose a larger share of their household budgets to missed bulk discounts. Bulk discount losses eat up more than 20% of the food budget for the average household in our data. Increasing a household's wealth index by 1 (about the

[2]Just as others have noted, we expect prices to increase with quality, and that wealthier households will spend more for higher-quality food (McKelvey, 2011; Deaton, 1988).

interquartile range), decreases the estimated bulk discount losses by 1% on average. This estimate is robust to controls for the perishable goods' share of total spending, and the household's own-production share. When controls for rural-urban status are included, the estimate drops - as much of the losses are explained by the quantity index that measures how large typical purchases are for households, and the neighborhood clusters where households live – which may determine their access to bulk purchases.The welfare implications are non-trivial. Hypothetically, households below the median wealth level lose 5% more of their food budget by failing to use bulk discounts when compared with the relatively well-off in our data.

Our main contribution is evidence that *liquidity constraints* explain the non-use of bulk-discounts for food by the poor. It follows on others that show households cannot easily save or borrow to finance large purchases for consumption in developing economies (Brune and Kerwin, 2019; Kraay and McKenzie, 2014; Carter and Lybbert, 2012; Banerjee and Newman, 1994). The work complements the 'poverty penalty' literature, where the question of whether the poor pay more remains an unsettled debate. On the one hand, there is strong evidence of a "CostCo effect," where the rich access even more price-savings over a broad range of consumer goods through bulk discounts (Orhun and Palazzolo, 2019; Chung and Myers, 1999), but the poor, at least in high-income countries, are more active users of coupons, sale events and other price-savings tools (Griffith et al., 2009; Beatty, 2010). Richer data from Tanzania, a country where the average person subsisted on less than $2/day, promises insights more relevant to policy and practice in developing economies.

Our work extends and complements Dillon et al. (2020), which also looks at prices paid by households in Tanzania. Their study covered non-food and non-perishable food items, while we focus on food items (including perishable ones). We use a richer and more detailed data set, compared to their work. Ours covered more households (9,700 vs. 1,493), over a longer diary period (one month vs 14 days), for a broader range of products (199 vs 73) from

a wider set of local districts (117 vs seven). They test for and find evidence for other factors that keep households from bulk discounts: social pressure to share large purchases, inability to coordinate large purchases within households, and storage costs. They do not test for liquidity constraints in the same way that we do, nor do they find it. We find as they do, that households could get bulk discounts by foregoing consumption for a few days on a set of selected items, namely, tea, sugar, salt, and cigarettes. We view the differences in our findings as largely complementary except for our finding on liquidity constraints. However, we find that gifts and sharing with other households form a very small part of overall transactions. Our work does not necessarily contradict the findings in papers that suggest a rotten-kin hypothesis for purchasing behavior (e.g., Jakiela and Ozier, 2016; Goldberg, 2017).

Earlier papers that explore prices and poverty or liquidity constraints in developing economies include arguments for bulk discounts and a poverty penalty in Colombia (Attanasio and Pastorino, 2020; Attanasio and Frayne, 2006), Rwanda (Muller, 2002) and India (Rao, 2000). Rao (2000) has been criticized on the grounds that unit values do not necessarily represent prices, and that the existence of bulk discounts does not dictate their use by the rich (Beatty, 2010).[3]

The rest of the paper is organized as follows: Section 2 presents the data and motivates the empirical work by showing the existence of bulk discounts. Next, we lay out a framework for testing the role of liquidity constraints in the usage of bulk discounts. Section 4 follows with the main empirical approaches and results. Section 5 concludes.

[3]A paper using household-level data from Papua New Guinea is one of the rare exceptions that use detailed household-level data from a low-income country (Gibson and Kim, 2011).

2 Data and Descriptive Analysis

2.1 Data

We use the Tanzania Household Budget Survey (HBS) data, covering the day-to-day spending of just over 9,700 households in 692 categories of products and services, taken over the twelve months from October 2011 to September 2012. Households were selected for the survey from 400 geographic clusters in 117 districts, covering 21 of Tanzania's 31 regions (states) in a stratified, nationally representative random sample. A National Bureau of Statistics (NBS) enumerator followed each household for one month to record all purchase transactions. The survey captures quantities and values on 1.89 million household-level individual transactions.[4]

Food items represent 67% of the data with 1.2 million transactions, of which 963,000 are purchases from market sources. 199 unique product (COICOP) codes between 111011 and 213107 identify food items, while non-food items are captured by 493 unique COICOP codes between 221100 and 1271105. Several COICOP codes are supplemented with product descriptions to identify the product brand or other meaningful detail and do give some traction on quality. For example, we identify palm oil as transactions with the 115406 COICOP code and item descriptions exclusive to palm oil, i.e., *Mafuta ya Mawese*, the Swahili expression for palm oil, and *Mafuta ya Korie*, a brand that is exclusively palm oil. *Mafuta ya Mawese* and *Mafuta ya Korie* are treated as different items in our analyses.

We focus on food purchases from commercial sources as identified in the HBS data. Commercial sources—including shops, markets, and street vendors—comprise the majority of transactions and transaction value (See transaction counts, and description of the source

[4]More about the HBS survey can be found on the website of Tanzania's National Bureau of Statistics: `http://www.nbs.go.tz/nbstz/index.php/english/statistics-by-subject/household-budget-survey-hbs`. The same data featured in related publications (Olabisi and Richardson, 2022; Olabisi et al., 2021, 2019, e.g.).

types in Table A1). It is also reasonable to expect that the meaningful savings from bulk discounts, if any, are limited to these arms-length exchanges. Non-commercial sources include own-production, gifts and exchanges with other households. Gifts and exchanges with other households constitute only about 5% of the value of food. We do not expect such a small share of spending to determine bulk discount use, but we do conduct robustness checks later in the paper to verify that gifts and exchanges do not affect our main results.

In addition to transaction data on expenditures at the household level, the HBS collected socio-demographic variables, indicators of asset ownership, and the rural or urban location of households. Notably, the survey included data on the main sources of income for adults in each household: monthly wage income, wage income that was not monthly, and non-wage income. By combining all the incomes from all adults in each household, we are able to classify households as wage income monthly only, monthly wage income combined with some other income, wage income only but not monthly, or in combination with non-wage income and only non-wage income. Households that reported no data on this variable were coded as non-wage income.

We follow Dillon et al. (2020) and Sahn and Stifel (2003) in using household assets to construct a wealth index for households. For each household, enumerators described the building quality, for example, the floor and roof material. In a separate table, enumerators documented whether households possessed assets in one or more of 18 categories, ranging from cheap items like watches, cooking pots and mosquito nets to valuable items like air conditioners. We apply principal component analysis to define the wealth index as the first principal component of building quality and valuable household assets. Tables A2 and A3 show statistics on these underlying variables. The wealth index has a positive correlation with the total observed spending ($\rho = 0.3$).

In cleaning the data, we exclude transactions with missing quantities or values and non-commercial transactions (see Table A1). Items purchased for uses other than household

consumption, e.g. purchases for re-sale, were excluded, as were transactions for which the quantity unit of record did not match the majority of transactions for a given product. For example, sunflower oil is typically measured in liters and milliliters, so we exclude the two transactions for sunflower oil recorded in kilograms out of 19,564 total sunflower oil transactions.

2.2 Descriptives

A few items make up most of the spending on food. Table 1 summarizes this pattern for the 9,700 households with purchases in the data. For convenience, the table is limited to the 20 items with the largest share of recorded purchases. These top 20 items account for 76% of total food spending. The last columns provide the (cumulative) share of spending on the items, as ranked in column 1. Rice and maize flour are the leading staples, representing a combined 30% of food spending, and purchased by 79% and 67% of households, respectively. Other staples include sugar, tomatoes, onions, and dried sardines. These are purchased by 65%, 86%, 81%, and 69% of households, in that order. Put together, these four account for 14% of food spending. Some high-value items like palm oil (purchased by 56% of all households) and beef (42%) also account for large shares of overall spending. These two combined are 10% of spending, even if they were not purchased by many households.

Small quantities and frequent purchases are common for food items. (Figure A1 shows households buying food almost every day). Column 4 of Table 1 shows the average number of purchases per household-month for the top 20 items, conditional on households purchasing the item at least once. Most households make multiple purchases of the same item within the same week. For example, nearly 80% of households purchased rice; these rice-buying households averaged two purchases of rice per week. Maize flour and tomatoes have the highest purchase frequencies, with more than 11 transactions per month for the average buying household. The frequencies indicate that the average household buys in quantities

meant to last a few days, even for shelf-stable items like maize flour, rice, and cooking oil.

Perishable items make up a large share of food spending. Column 1 of Table 1 marks each item with an asterisk (*) if the item if perishable, and a dagger symbol (†) if semi-perishable.[5] The four non-perishable items in the top 20 represent only about 36% of food spending by households, such that semi-perishable items like onions and cooking oil, as well as perishable items like tomatoes, dominate the food budgets of households. We expect and find high purchase frequencies for perishables, liquidity notwithstanding, as the Table shows.

Probing the data beyond the summary in Table 1 confirms the pattern of small purchases, leading to the question of whether poorer households use small purchases more than their wealthier counterparts. By constructing a daily ration for each item, based on household size and the number of households that consumed the item, we estimated that the modal purchase quantity for rice was 3-days' worth, consistent with the purchase frequencies in Table 1. Maize flour is purchased in even smaller rations – more than 2500 households, the plurality, purchased maize flour in quantities just enough to match *one* day's average consumption. Fewer than 20% of the purchase transactions for maize flour represent a week or more of consumption for the purchasing household.

2.3 Testing for the Existence of Bulk Discounts

We show linear regressions of the unit values of narrowly defined items on purchased quantities, with controls that address concerns about measurement error. The results suggest that unit values decline as quantities increase.

We follow Dillon et al. (2020) and Gibson and Kim (2018) by testing for the existence of

[5]Food items that will go bad without refrigeration in one week are defined as perishable. Semi-perishable goods are goods that do not need refrigeration but spoil easily when stored improperly. In particular, we designate edible oils as semi-perishable. Table A3 shows that only about 15% of households own refrigerators.

bulk discounts with the following specification:

$$\log(p_{hit}) = \alpha_0 + \alpha_m + \alpha_c + \beta_p log(q_{hit}) + \varepsilon_{hit} \tag{1}$$

Price p for transaction t by household h buying item i is taken to to include α intercepts for location and month, as well as a β_p parameter of interest that corresponds to the test of bulk discounts. q_{hit} is the quantity of item i purchased in transaction t. The unit values $p_{hit} = v_{hit}/q_{hit}$ and quantities q_{hit} are in logs. The estimates are run separately for each item, given differences in perishability and other factors that may decide bulk discounts. Prior work in developing economies lead us to expect negative β estimates as evidence for bulk discounts (e.g., Attanasio and Pastorino, 2020; Attanasio and Frayne, 2006).

The regression estimates in Table 2 show statistically significant bulk discounts for all top-20 food items. All the items have downward-sloping price schedules, from staples purchased by most households like tomatoes and cooking oil, to the rare treats like sliced bread. Bulk discounts affect processed ready-to-eat items like brown sugar, just as they affect dry goods and uncooked items like rice. We find bulk discounts for items that may have the additional cost of splitting standard packages (e.g., cooking oil), as well as for items with no splitting costs (e.g., onions), just as we find bulk discounts for items that are usually bought in standard sizes (e.g., maize flour) and items that are not (e.g., tomatoes and onions). Nevertheless, a small fraction of what we call bulk discounts could be "fractional purchase penalties," as sellers add the cost of dividing packaged goods into the small quantities purchased by poor households.[6]

However, the magnitudes of bulk discounts vary notably from item to item. The items in the table are arranged by perishability, with the rank from Table 1 preserved in the first column. The coefficients in Table 2 range from -0.09 to -0.03 for non-perishable items. As

[6]We are thankful to Xavier Gine for highlighting the point on standard sizes and packaged items during the BREAD conference.

expected, perishable and semi-perishable items show the largest coefficients in absolute value, i.e., the effect of bulk discounts is more pronounced for items with high storage costs.

As a preview of the next point in the paper, Figure 1 shows a strong clear pattern of poorer households making more purchase transactions in small quantities that miss out on bulk discounts. The bulk discount threshold is defined as the focal quantity (see Table 5) with the lowest median price for a district – these focal quantities are usually small rations that amount to a week or less of household consumption, but are large enough that they attract discounts compared to other commonly purchased quantities. Transactions below this bulk discount threshold fall into the category of purchases with bulk discount losses. The poorest quartile have more than 35% of transactions in this category, while the top quartile have less than 23%. Despite the difference, it appears that almost everyone–97% of households–buys in small quantities for at least some items. Furthermore, most purchases appear to be at or above the relatively small quantities in Table 5 that yield bulk discounts. For even the poorest quartile of households, 62% of transactions are at or above the threshold. The data shows that 99.8% of households made at least one purchase at or above the bulk discount threshold.

At the same time, the share of spending on quantities that fall below the bulk discount threshold is small, with the declining pattern only obvious for the top 6 deciles. Spending on small quantities is roughly near 16.3% for all deciles below median wealth. The lower percentages of the share of spending versus the share of transactions below the bulk discount threshold imply that more of the transactions made in small quantities are for low-value items that account for smaller shares of household spending.

Beyond showing that bulk discounts are pervasive, we formally show that poorer households drive the pattern of small-quantity purchases captured in Table 1. We use the following

specification:

$$\log(\overline{q}_{hit}) = \alpha_0 + \alpha_m + \alpha_c + \beta_q Wealth_h + \varepsilon^q_{hit} \tag{2}$$

where $Wealth_h$ is a household's wealth level and $log(\overline{q}_{hit})$ is the log of average purchase quantity per transaction of good i. The results in Table 3 indicate that wealthier households make larger purchases, on average (with positive β_qs across the board). The results are statistically significant for almost all items in the Table. The three exceptions, cooking bananas, sliced bread, and spinach, are perishable items that are difficult to store in the tropics, even with a refrigerator.

Though the β_q coefficients vary across products, Table 3 supports the expectation that wealthier households purchase in larger quantities. The result supports the concern about a poverty-price penalty in Section 1 —for a poverty price penalty to exist, bulk discounts must exist as shown in Table 2, and poorer households must use them less, by buying in smaller quantities (as shown in Table 3).

3 Conceptual framework

Given that bulk discounts do exist in Tanzania, we lay out the motivating framework of a household making food purchase decisions over a short reference period. We do not adopt an Euler equation approach due to the short reference time frame and the small scale of purchases. Instead, we show that households' purchases must maximize utility with a short-term budget constraint and the presence of bulk discounts. The intuitive interpretation of the reference period here is a month.

Bulk discounts may exist for multiple reasons. Sellers may choose to offer discounts on perishable and semi-perishable goods to turn over inventory faster. Sellers may pass on the

lower per-unit costs of packaging larger items to the consumer, and they may also pass on the costs of splitting a larger package into smaller quantities. Bulk discounts are also expected to reflect price discrimination. Purchasing small quantities may indicate that a consumer is liquidity-constrained and demands a good more inelastically, which in turn causes sellers to raise prices for small quantities. Demand for a product, which is observable, drives price differences. Unlike Hendel and Nevo (2013), preference heterogeneity among consumers is a sufficient but not necessary driver of per-unit price heterogeneity in our model. We also differ from much of the literature on second-degree price discrimination in that we do not solve for the seller-side to explain the pricing strategy but rather focus on household purchasing dynamics.

An extension of the existence of bulk discounts is that buyers' use of bulk discounts leads to the lowest per-unit prices in a reference period. Rather than waiting for sales events as in Hendel and Nevo (2013), households can preemptively lower their per-unit prices by purchasing larger quantities. This assumption formalizes our expectations that prices are a function of the quantity purchased.

Households in our framework must purchase food to meet subsistence requirements. Table 1 supports this claim. The simple fact that households must buy food to eat is sufficient to support the presumption of a positive level of consumption in every period for each household. For example, well-known staple dishes explain why most households buy items like tomatoes, onions and maize flour. This need to buy food must then be matched against the stored wealth and income flows of households.

A brief sketch of the household problem shows the role of liquidity constraints in a household's expenditure choices. A household h consumes a vector of goods $\mathbf{q}_t$ at time t, where there are J total goods, i.e., $\mathbf{q}_t = [q_{1t}, q_{2t}, \ldots, q_{Jt}]$. Each household has specific preferences that are captured in a term θ_h. The consumer's problem is to choose purchases to maximize utility $U_{ht}(\mathbf{q}; \theta_h)$ based on consumption $\mathbf{q_t}$, purchases $\mathbf{x_t}$, and expiration $\mathbf{e_t}$ of

the J goods over a reference period R, subject to the availability of income or liquidity:

$$\max \sum_{t=1}^{R} \beta_h^t \mathbb{E}[U_{ht}(\mathbf{q}; \theta_h)] \tag{3}$$

subject to

$$\mathbf{q_t} \leq \mathbf{x_t} + \sum_{\tau=1}^{t-1} (\mathbf{x}_\tau - \mathbf{q}_\tau - \mathbf{e}_\tau) \qquad \text{(Constraint 1)}$$

and

$$\sum_{t=1}^{R} \mathbf{p_t}(\mathbf{x_t})\mathbf{x_t} \leq \sum_{t=1}^{R} y_t \qquad \text{(Constraint 2)}$$

where β_h is the discount factor and y_t is the household income at time t. Constraint 1 is the identity that shows households may only consume from what is purchased or what was stored (and not expired) from earlier purchases. We effectively exclude external borrowing via Constraint 2, because as noted above, it is difficult to borrow to finance consumption in many developing countries. Households buy food items from income. In doing so, they trade off cash in the future and storage costs now for a potentially lower per-unit price for a good i. The optimization problem equalizes the marginal utility of saving with the marginal utility of a purchased item.

Constraint 2 in Equation 3 gives the no-debt condition for the entire reference period. Unlike Hendel and Nevo (2013), who explicitly examine items that do not comprise much of a household's budget and assume away liquidity and wealth issues, the household problem here includes liquidity constraints. Optimal purchase quantities may take up a large part of a household's available liquidity on many days of the month. To account for both the fact that households may have other sources of liquidity on a day-to-day basis outside of current income and the large share of the budget of some items purchased, we extend the liquidity

constraint for households in Constraint 2 as follows:

$$\sum_{t=1}^{s} \mathbf{p_t}(\mathbf{x_t})\mathbf{x_t} \leq \sum_{t=1}^{s} y_t + y_0, \quad \forall s \leq R \qquad \text{(Constraint 3)}$$

Constraint 3 is the no-debt condition for each day s within the reference period. The distribution of income terms y_t and the level of outside wealth or other resources, y_0, now jointly determine purchase patterns for liquidity-constrained households. We do not modify the reference-period no-debt condition to allow borrowing from y_0 past R, i.e., any intra-household borrowing must be repaid within R periods.

We expect the action to be on the extensive margin: the participation constraint in (self) borrowing. We expect a greater share of poor households to have $y_0 = 0$, due to a lack of loanable funds (i.e., a supply-side issue), lack of collateral, or prohibitively high interest rates. On the intensive margin for a positive y_0, the level of y_0 affects the timing of purchases and whether liquidity constraints bind. Households with large wealth, namely $y_0 \geq \sum_{t=1}^{R} y_t$, give a corner case where Constraint 3 is immaterial because households borrow from themselves by reducing y_0 and then repay it later.

Households with $0 < y_0 < \sum_{t=1}^{R} y_t$ form the more interesting case. Like households with $y_0 = 0$, such households may make suboptimal choices because of Constraint 3; as $y_0 \to 0$, the distribution of y_t terms takes more and more precedence. As income is not necessarily received in equal daily installments, households potentially face two spending regimes: flush days, when it has (or just received) a boost to liquidity; and the lean days when the liquidity from income and other sources is depleted. Because households must always consume food, a household must plan ahead for the lean period by storing food or saving. Saving money for this circumstance, other than for perishable goods, is weakly worse, given the existence of bulk discounts.

Based on our framework, we generate several propositions that allow us to test the roles

of income—the *flush* and *lean* regimes—and wealth.

Proposition 1: Households pay lower per-unit prices in the flush than in the lean regime.

Corollary 1: A household with only one payday, i.e., a single t with $y_t > 0$, pays lower per-unit prices in the flush period than a household with a similar overall income but different payment frequency, all else equal.

Liquidity constraints bind less in the flush regime by definition. For this reason, a household may increase its expenditures on goods that offer bulk discounts at higher quantities. The corollary is true for households such as salaried workers: in the lean regime, the household optimizes expenditures to cover just up to the next flush regime, even if it could cover a longer period. This lowers quantities purchased in the lean regime. The combined effects accentuate the wedge in per-unit prices between the two liquidity regimes.

Proposition 2: Households with higher wealth face less of a liquidity constraint in purchasing.

This follows directly from Constraint 3. On the extensive margin, any household that can draw on outside funds beyond its income stream can better afford the high expenditures required to receive bulk discounts. On the intensive margin, as the initial endowment increases, the short-term liquidity constraint may not bind at all for any period.

Proposition 3: Liquidity-constrained households have the most to gain with bulk expenditures of non-perishable goods.

Liquidity-constrained households may purchase small, expensive bundles because of subsistence requirements, which in turn lowers their ability to save in the short run (i.e., for a period less than R). Even households with a known income stream may not be able to reduce the time between the lean and flush regimes. As such, having perishables as a large share of spending, by straining the level of liquidity for households, may contribute to missing out on bulk discount for non-perishables.

4 Bulk discount losses and liquidity constraints

4.1 Do Liquidity Constraints Matter?

Supported by evidence that bulk discounts are prevalent in Tanzania's food markets, we now test the propositions of the conceptual framework from Section 3. This section begins with Proposition 1 and its corollary. We then calculate bulk discount losses to address Proposition 3. Both analyses address the role of wealth (Proposition 2).

4.1.1 Per-unit Prices Fall in the Flush Days

According to Proposition 1, households pay lower per-unit prices in the flush regime shortly after payday than in the lean regime. We do not directly observe a household's income stream, therefore we define the flush days using the patterns of expenditure. Specifically, we define the flush regime as the top seven days of observed spending for each household. The definition implies the equivalence of top spending days (empirically) and flush days (in the model). This approach to defining spending regimes takes advantage of our access to daily spending patterns at the household-level. Furthermore, we avoid making assumptions about the specific day each household in our data received a wage or other income. We do not use a consecutive-day pattern for the flush period to accommodate differences for each household in market days, days of the month observed by enumerators, and specific pattern of income frequency. For example, households that typically make bulk purchases on the weekends, and have have a Monday pay-day would spend differently than in a month with a Friday pay-day. In the same way, households with weekly earnings, are not likely to have flush days of the month that run consecutively.

We calculate a price index for each household by taking the average price for each product within each district and standardizing it to 100. The price, relative to the neighborhood average for each item, is the basis for the household-level price index, much like other papers

that create household-level price indexes (e.g., Cravino et al., 2020; Kaplan and Schulhofer-Wohl, 2017). Each transaction contributes to the household-level price index in proportion to the value of the purchase. Thus, we calculate two price index observations per household, one for each regime (flush and lean). Our main test is a regression of the household-level price indexes on categorical variables for the flush/lean season, and for the income type that describes each household:

$$PriceIndex_{hr} = \beta_0 + \beta_1 Flush_{hr} + \gamma_1 IncomeType_h + \gamma_2 IncomeType_h \cdot Flush_{hr} + \epsilon_{hr} \quad (4)$$

where h denotes households and r captures either the flush or lean regime. $Flush$ is a binary variable equal to 1 in the flush regime. Standard errors are clustered by the geographic cluster.[7] The β_1 measures the impact on the price index when a household is in the flush regime, and each γ terms show effects by different income types.

The evidence supports Proposition 1. Column 1 of Table 4 incorporates household-level fixed effects and shows that households pay almost 20% *lower* prices in the flush season on average. The result is significant at the 1% level of statistical significance. We remove the fixed effects in column 2 in order to examine the role of wage or salary timing. As predicted by Corollary 1, the biggest flush-season price reductions are observed for the households with monthly wage incomes. In column 2, households with only a monthly wage see a statistically significant drop in the price index of about 2.5% overall, and the difference is still significant when accounting for the flush period. Households that combine a monthly wage with another income source see a statistically significant drop of over 12% overall compared with the baseline of households that report no wage income, although this effect disappears during the flush period. Households with only monthly wage income should exhibit a larger spike

[7] Clusters are geographic units within districts.

in their expenditure in the flush season.[8]

In columns 3 to 6, we split households by wealth and include all products in order to address Proposition 2. The flush regime dummy variable is significant at the 1% level in all columns. The coefficient on flush is much larger for below-median-wealth households (over 30%) than above-median ones (about 11%), which is consistent with wealth relaxing liquidity constraints throughout the month and not just during the flush regime. The effects are largely similar across columns, with households receiving wages paying lower prices in the lean period but not differing during the flush period. The coefficient on "monthly wage income only" for below median households in column 6 is negative, as expected, but no longer statistically significant. This likely comes from a difference in composition in households above and below the median wealth level: there are more than 1,300 households that receive monthly wages only above the median compared with fewer than 130 below the median.

Our results here rest on a flush period of seven days. Robustness checks using five days and ten days for the flush period instead give substantively the same results as seen in Tables A4 and A5. ith

4.2 Poverty and Bulk Discount Losses

We have shown that bulk discounts exist (Table 2), that wealthier households purchase in larger quantities and therefore use bulk discounts more (Table 3), and that liquidity constraints—proxied by wealth and income type—affect the use of bulk discounts (Table 4). We now combine all three of these together to measure the losses from purchasing smaller quantities at high unit values.

[8]In regressions that restrict to non-perishable goods (not reported in the table), we see the effect of the flush season dummy diminish. Both kinds of monthly-wage households experience a drop in price by 2% (significant at the 1% level in both cases), but the flush regime dummy is attenuated towards zero and no longer statistically significant. The larger purchases in this category for wage earners with lumpier income are evidence for Proposition 1.

4.2.1 Defining Bulk Discount Losses and Thresholds

Table 5 highlights the steps to deriving bulk discount losses. First, for each item-district-month triad, we identify the focal quantities, following the pattern in prior work (Dillon et al., 2020). Focal quantities account for the greatest share of observed purchases for each item, and therefore give the most reliable indication of prices and how they change with quantity. Using focal quantities helps to avoid measurement error in defining optimal purchase quantities, and bulk discount losses. In particular, the approach avoids bias from irregular or rarely-used size categories that may not be available to all households. Second, for these focal quantities, we flag as optimal the smallest quantity with the lowest observed median price.

For example, for rice in the first row of Table 5, the most commonly purchased quantities are 0.5, 0.75, 1, 1.5 and 2 kgs. The second row of the rice segment is consistent with the finding of bulk discounts in Table 2, as median unit values decrease with increasing quantities. In this case, the median unit value for rice purchased at 1 kg was 1900TZS/kg. Purchasing 2 kg of the same item drops the price to 1800TZS/kg. Since this is the largest quantity of the five most prevalent sizes, the optimal quantity is 2 kg for rice (tagged with an asterisk).

Table 5 shows that the five focal quantities accounted for over 90% of rice purchase transactions and almost 69% of the purchase value. Similarly, high shares for focal quantities also apply to other staple items, since most items are sold with standard measures, and households usually buy discrete multiples of those standard quantity measures for most food items. The focal quantities in Table 5 are arranged in increasing order both to highlight the existence of bulk discounts, since the prices or unit values generally decrease as quantities increase, and to clearly identify the optimal quantities where the pattern of declining prices appear to flatten out in the data. Table A8 gives the threshold quantity and median price for all top 20 items.

Bulk discount losses are defined as spending that could have been avoided if households

made each purchase transaction at the unit price for the focal quantity. Formally, for a purchase of item i in transaction t, by household h residing in district d:

$$loss_{hit}^{bd} = q_{hit} \cdot (p_{hit} - p_{dit}^{*}) \tag{5}$$

p_{hit} is the observed unit value for transaction t, defined as the ratio of the expenditure e_{hit} and quantity q_{hit}. The reference price p_{dit}^{*} is the lowest median price for the focal quantities observed for a district. The district level serves for this purpose because districts are large enough to ensure that we observe multiple purchases for most item-quantity combinations, and small enough to have comparable prices across neighborhoods. That said, prices are expected to be more correlated within urban districts than rural districts.

We estimate bulk discount losses as a share of household food expenditure, which serves as our measure of the welfare impact of the observed 'Costco Effect' or the poverty price penalty. Although we have established that bulk discounts exist and that wealthier households buy larger quantities on average, this measure makes the economic significance of bulk discounts clear. The bulk discount losses *bdl* over the month or any other time horizon, can be calculated by summing up over time, and all products purchased by the household:

$$bdl_h = \frac{\sum_t \sum_i loss_{hit}^{bd}}{\sum_t \sum_i q_{hit} * p_{hit}}$$

4.2.2 Poorer Households Have Greater Bulk Discount Losses

The base specification for explaining bulk discount losses takes the form:

$$bdl_h = \beta_0 + \beta_1 \ln(Wealth_h) + \Gamma_1 IncomeType_h + \varepsilon_h \tag{6}$$

where bdl_h is the share of household food spending lost to non-use of bulk discounts,

as defined above. $Wealth_h$ is the household wealth index, which helps to test our main hypothesis that poorer households suffer greater bulk discount losses. As above, we check for differing bulk discounts by income type. In later specifications, we control for geographic location and household-specific characteristics.

In principle, households that purchased all items in quantities high enough to obtain the lowest prices available for focal quantities will have zero bulk discount losses. Houses that buy in small quantities, and that pay the higher unit values associated with the small quantities will have bulk discount losses taking a larger share of the budget.

From Column 1 of Table 6, each unit increase in the wealth index of a household is associated reducing bulk discount losses by 1%. Given that the interquartile range of the wealth index is about 2.2, the average household at the first quartile of the wealth distribution loses an additional 1% ($e^{(0.34*0.01)}$ share of household spending) to the higher prices at small quantities compared to the median household. The baseline share lost by the average households (estimated here as 20%) is high enough to suggest additional control variables.

Starting in column 2, we include geographic (cluster-level) fixed effects to improve the fit of the model. The magnitudes on coefficients are similar to column 1, though statistical significance drops for wealth. Columns 3 and 4 add the log of the quantity index; in effect, we are checking if bulk discount losses operate through a channel *other than* higher quantities. Unsurprisingly, quantity is negative and statistically significant in both columns. The final column adds additional controls for own-production share, perishable share, and household size, none of which is large in magnitude or economically significant.

Overall, Table 6 provides evidence that poor households lose a greater share of their food budgets to bulk discount losses. However, wealth per se is not the driver of greater bulk discount losses. Instead, wealth mediates the quantities purchased, which then lead to losses. Income type does not seem to matter much, though there is the caveat that higher-wealth households are also typically higher-income. Own production is partly a proxy for

poverty—in the data, the poorest quartile of households produce more than 30% of their own food while the top quartile produced less than 2%—but its impact is muted because of the inclusion of the quantity index.

4.3 Bulk Discount Losses as Internal Rates of Return Proxies

Bulk discount losses should be higher for households with higher internal costs of borrowing. By implication, the bulk discount losses of a household can be used to infer its internal rate of return (IRR), as long as households are rational. We define the IRR as the rate of borrowing that equalizes the net present value of a household's current daily expenditure, and that of a hypothetical expenditure path with only optimal purchase quantities.[9]

We use two estimates: first, a conservative estimate that, as a nod to the concern that storage costs may influence household behavior, assumes no bulk discount losses for items purchased only once in the enumeration month; second, a more liberal estimate that includes items purchased only once in the month. 11% of the recorded value of food purchases are for such items purchased only once in the data period by households. Formally, for observed daily purchase quantities x_{it} and optimal purchase quantities q_{it}, $\sum_{t=1}^{R}\sum_{i=1}^{N} px_{it}/(1+irr_h)^n = \sum_{t=1}^{R}\sum_{i=1}^{N} p^* q^*_{hit}$

Potential savings from using bulk discounts are non-trivial, even if most purchase transactions enjoy at least some bulk discounts. Approximately 70% of the value of food purchases are for items purchased at the optimal quantity or an equivalent unit price and a further 11% enjoy some bulk discount (but not the highest), showing that households use bulk discounts when they can. (We illustrate this with a Figure in the online version of the paper). For the remaining 19% of the value of food purchases, households could have spent less than half (42%) of what they actually spent in this last category, if they had been able to fully utilize

[9]We are thankful to Chris Ahlin, Hoyt Bleakley and another attendee at the BREAD conference for suggesting this additional step in our analysis.

bulk discounts.

Table A6 in the Appendix shows a regression of the estimated internal rates of return on the household wealth index. As expected, the estimates imply that poorer households have higher IRRs. Nevertheless, IRRS are very high for the majority of households, even the households that use bulk discounts more. However, few households are able to take full advantage of bulk discounts.

The relatively steep discounts and their persistence across time in the data imply that frictions exist that keep households from buying in bulk on a consistent basis. The question is whether the frictions exist for even the less-poor households in the data. As discussed in Section 2, most households miss out on bulk discounts, but the poor miss out more than most. One could infer that the average household loses about 13% of food spending to non-use of bulk discounts, but that percentage is closer to 17% for the poorest quartile of households, by our measure.

The estimated IRRs in our data are high – comparable to some of the astronomical interest rates observed in the micro-finance literature (Baquero et al., 2018; Roberts, 2013; Cull et al., 2009). The high IRR estimates underscore the impact of bulk discounts and their use or non-use on household budgets. For example, a 10% discount on an item purchased once a week amounts to more than 500% annual interest, if the same item is purchased twice a week, the interest rate goes up to more than 1000%. Furthermore, our findings could suggest inquiries into why microfinance for business does not always achieve its objectives, especially when households spend the cash inflow on food (Tarozzi et al., 2015; Collins et al., 2009). That said, related work show that microfinance can relieve the liquidity constraints that keep households from spending (Tarozzi et al., 2014).

4.4 Robustness Checks

To address concerns that the choice of seven days as the flush period could introduce bias in results, we conduct robustness checks using five- and ten-day flush periods. For example, a household with higher monthly income may spread its spending out over more days than one with a lower income. The coefficients in Table A4 and Table A5 show some attenuation when compared to Table 4, but the households still pay lower prices in the alternatively defined flush regimes.

We understand that households share food and may feel social pressure to share (e.g., Goldberg, 2017). Therefore one must consider whether social pressures to share, explain non-use of bulk discounts, at least compared to liquidity constraints. In our case, the data include records of purchases from commercial sources, as well as gifts from other households. The online appendix shows that controlling for the share of gifts and exchanges in the household budget does not significantly change the estimated impacts of bulk discount use in flush seasons on prices.

Although our results point to the existence of bulk discounts, there could be other explanations for the observed patterns of purchases and non-use of bulk discounts, in particular, behavioral explanations. For instance, Shapiro (2005) shows in a developed-world context (the United States) that food stamp recipients have short-run impatience. Because of this, consumption drops over the course of a month after receipt of food stamps. A closer example in the Tanzanian context comes from Dillon et al. (2020). They argue against liquidity constraints because eliminating purchases of selected items like salt, sugar, tea and cigarettes, enables households to take advantage of liquidity constraints in a short amount of time.

We replicate the latter paper's methodology here by calculating the median number of days that a household must go without selected items, in order to save enough to afford the optimal quantity of each of the top 20 items. Like Dillon et al. (2020), we selected four target items tea, cigarettes, salt, and sugar (both brown sugar and white sugar). To provide

enough support across quantities and prices, we use national-level data on focal quantities and prices. Then, we calculate the number of days each household requires to save enough for one good's focal quantity by foregoing its purchases of the selected products as well as that good itself.[10]

Table A7 shows the median number of days required to save, both overall and broken down by wealth quartile. The first measure excludes the good itself, while the second measure includes it. For example, households overall must forego the target items for 2.55 days to save enough for bulk discounts on rice, and households must forego the target items *and* rice itself for 1.38 days to save enough for bulk discounts on rice. Unsurprisingly, the median falls monotonically when moving from the lowest-wealth quartile to the highest-wealth quartile under both measures. Some foods, like tomatoes, round onions, and palm oil, echo Dillon et al. (2020)'s result that households need to skip purchases for a few days in order to take advantage of a bulk discount. With other products, though, we find a larger difference. The lowest-wealth households would require more than five days without such purchases to save enough to purchase of rice at the focal quantity. Beef, cooking bananas, and fish (both fresh preserved) all show similar trends.

Thus, while households can sometimes "fast" from some goods for a few days in order to enjoy a bulk discount later, this lesson does not hold across all products. Furthermore, these measures only reflect bulk discounts for a single item rather than bulk discounts across multiple goods, let alone the entire product space.

5 Discussion and Conclusion

Bulk discounts are an important feature of consumer food purchases in Tanzania and most developing economies. We identify liquidity constraints as a key mechanism that explains

[10]See the notes for Table A7 for a description of how to calculate this measure.

the non-use of bulk discounts. Households limited to a once-a-month wage income change expenditure patterns more over the month, compared to households with other patterns of income flows. When flush with income, these monthly-wage households can and do take advantage of bulk discounts. In other words, we do not observe smooth spending over the month, especially for the poorest households in this category. The data suggest real financial frictions or missing credit markets to support consumption for poor households with short-term liquidity. The pattern may also be explained by households' desires to reduce discretionary borrowing, which would be arguably rational if the borrowing costs are higher than gains from using bulk discounts. As Table 2 shows, the overall effect is that households utilize bulk discounts more in some part of the month than others. Even if households were to go through a 'fast' on some items to relieve the need for liquidity, they would still not be able to capture bulk discounts quickly or consistently across products (see Table A7 in the Appendix for more details).

The large number of product codes mitigates some of the problems in catching quality-related price differences, even if imperfectly. Households could switch to lower-quality items within a product code, as (McKenzie et al., 2011) find in Argentina, which we cannot capture.

We find evidence consistent with the hypothesis that wealth relaxes liquidity constraints. The less-poor households buy higher quantities per-transaction on average. They take advantage of bulk discounts through higher average purchase quantities, and as evidence of being less constrained, have smoother purchase patterns over the course of a typical month of spending. The findings are consistent with prior evidence that poor households have limited ability to smooth consumption over time in the face of shocks (e.g., Attanasio et al., 2013; Attanasio and Székely, 2004).

The losses to poorer households from *not* receiving lower prices through bulk discounts are non-trivial. The hypothetical gains possible with buying at price-optimal quantities, is about 10% of household spending for the average household, and increases by about 1%*IQR across

the interquartile range in our simplest specification. Wage workers see lower bulk discount losses of 1-2% as well. We observe notable differences between rural and urban areas, with households in the largest urban area ceding about 5% less of their total food spending to bulk discount losses, and rural households losing an additional 1% compared to households in Tanzania's other urban areas. As expected, households that produce more of their own food, purchase less from the market and lose a greater share of their spending to bulk discount losses. Similarly, households that spend more on perishable items also lose more of their food spending to bulk discount losses. Further research on rural-urban differences and how the markets work for the poor can help to identify even more specific mechanisms for how bulk discounts operate, and how the poor can get greater access to them.

Although our paper highlights liquidity constraints, we cannot rule out several alternative mechanisms. Social pressures, gifts, and intra-household coordination could play a role in the non-use of bulk discounts, as shown in Dillon et al. (2020). Given the absence of data on social networks, we cannot fully test the effects of social pressures, even though our limited results do not make the case for social pressures as a driver of bulk discounts use. Our robustness checks do not weaken the argument for liquidity constraints as a cause, but data limitations prevent us from examining the explanations further.

Bulk discounts and their non-use matters, given that poor households in developing economies usually spend well over half of their budgets on food. Reducing bulk discount losses on food could free up resources for non-food expenditure. The results suggest some possibilities to policymakers with an interest in poverty: encouraging group-buying, as posited by Attanasio and Frayne (2006), addressing storage issues (Burke et al., 2019), or supporting group-lending to relieve liquidity constraints (Ahlin, 2015). Beyond the possibilities, however, the results raise the real concern that markets may not always work to the advantage of the poor, and might even, with features like bulk discounts or other forms of price discrimination, penalize households with the least resources.

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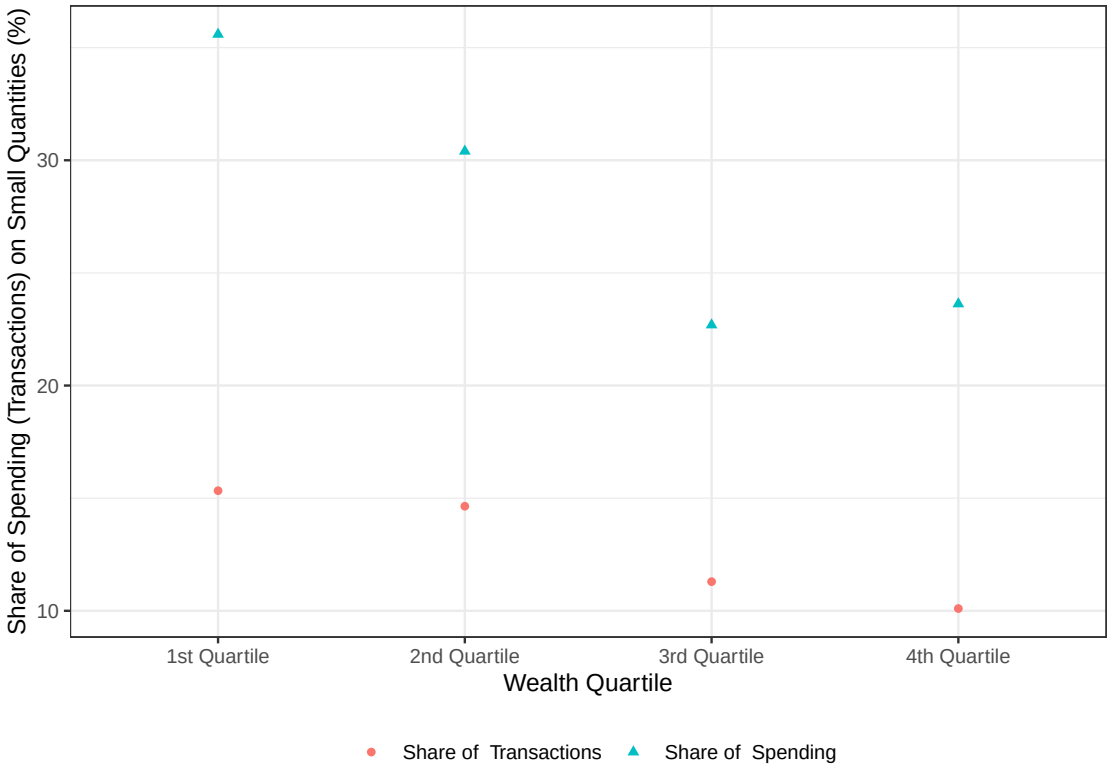
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Figures and Tables

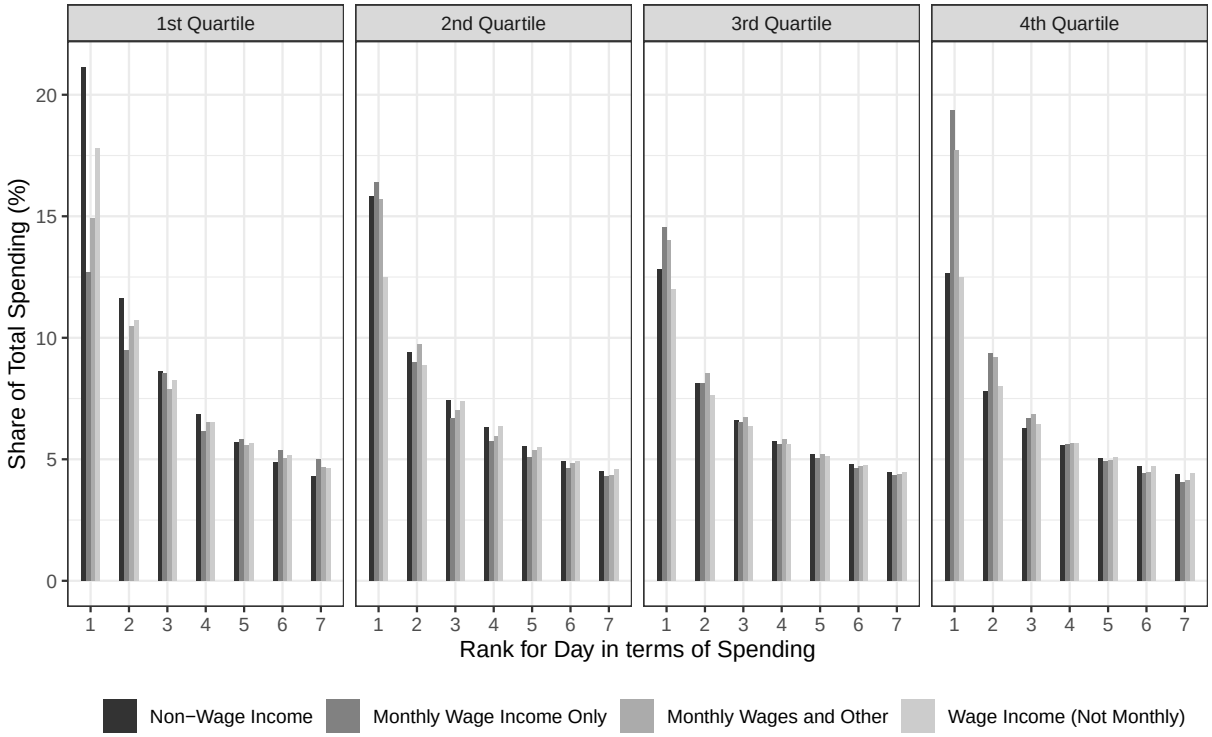
Figures

Figure 1: Wealth and Buying Below the Bulk Discount Threshold



Transactions are the unweighted number of purchases of food, irrespective of price paid. Spending incorporates the price paid. Households are split by wealth quartile. The bulk discount threshold is defined as the focal quantity (see Table 5) with the lowest median price for a district.

Figure 2: Sharpest Daily Spending Spikes by Wealth Quartile



The share in overall spending on food appears on the vertical axis, and the horizontal axis gives the rank order of days. Day 1 is the top spending day. Households are split by the type of income that they report receiving within each wealth quartile.

Tables

Table 1: Summary: Spending by Food Item

Rank	Description	Share of Households	No. of Purchases	Spending Share (%)	Cumulative Share (%)
1	Rice	78.9	7.7	17.7	17.7
2	White Maize Flour	67.2	11.2	11.6	29.3
3*	Bones-in Beef	41.7	3.6	6.0	35.3
4	Brown Sugar	64.9	7.4	5.4	40.6
5*	Round Tomatoes	86.3	11.7	4.1	44.8
6†	Korie Palm Oil	56.0	10.6	4.1	48.8
7*	Fresh Fish	35.3	3.6	3.2	52.0
8†	Maize Grain	28.7	2.2	3.0	55.0
9†	Soybeans	39.1	5.4	2.6	57.6
10†	Dried Sardines	68.7	4.3	2.6	60.2
11	Dried Beans	35.8	4.5	1.9	62.1
12†	Round Onions	81.2	10.4	1.9	63.9
13*	Cooking Bananas	31.3	2.5	1.8	65.8
14†	Cooking Oil	30.3	9.0	1.7	67.5
15*	Fried Bread (Buns)	40.1	5.1	1.6	69.2
16*	Sliced Bread	23.8	5.2	1.5	70.7
17*	Dried Fish	30.5	2.6	1.4	72.1
18†	Unhusked Coconut	26.9	6.6	1.3	73.4
19†	Sunflower Oil	18.2	10.6	1.2	74.7
20*	Fried Fish	23.4	2.9	1.2	75.9

9183 households

The spending above represents outlays to commercial outlets, and excludes the value of own-production, as well as other non-commercial categories described in Table A1. Number of purchases is conditional on purchasing. Each item in column 1 of the Table is marked with an asterisk (*) if the item is perishable, and a dagger symbol (†) if semi-perishable. 9,183 households buy at least one of these top 20 items.

Table 2: Do Bulk Discounts Exist? (with HH FEs)

	Description	β	s.e.	R^2	N
	Non-Perishable Items				
1	Rice	−0.03	0.003	0.75	58,872
2	White Maize Flour	−0.07	0.004	0.71	73,354
4	Brown Sugar	−0.04	0.01	0.63	46,800
11	Dried Beans	−0.09	0.01	0.73	15,579
	Semi-Perishable Items				
6	Korie Palm Oil	−0.26	0.02	0.78	57,327
8	Maize Grain	−0.20	0.01	0.87	6,154
9	Soybeans	−0.23	0.01	0.47	20,579
10	Dried Sardines	−0.46	0.02	0.84	28,866
12	Round Onions	−0.38	0.01	0.78	82,121
14	Cooking Oil	−0.28	0.02	0.78	26,535
19	Sunflower Oil	−0.19	0.01	0.77	18,694
	Perishable Items				
3	Bones-in Beef	−0.18	0.02	0.46	14,628
5	Round Tomatoes	−0.38	0.01	0.80	97,979
7	Fresh Fish	−0.48	0.02	0.81	12,280
13	Cooking Bananas	−0.53	0.02	0.86	7,677
15	Fried Bread (Buns)	−0.40	0.02	0.80	20,015
16	Sliced Bread	−0.49	0.02	0.63	11,975
17	Dried Fish	−0.53	0.02	0.85	7,677
18	Unhusked Coconut	−0.47	0.03	0.79	17,191
20	Fried Fish	−0.52	0.02	0.83	6,702

β is the coefficient on log(quantity). Estimates are negative for 276 of 302 products, statistically significant for 175, (including for all top 35 items – 86.5% of food spending). The dependent variable is log of unit price, and the main control variable is the log of quantity, as specified in Equation (1). Standard errors are clustered by district. The first column shows the item rank in share of household spending from Table 1.

Table 3: Average Per-Purchase Quantity vs. Wealth Index

	Description	β_q	se	R^2	N
	Non-Perishable Items				
1	Rice	6.51	1.49	0.19	7,659
2	White Maize Flour	−0.52	2.13	0.19	6,524
4	Brown Sugar	11.75	2.30	0.16	6,297
11	Dried Beans	6.54	1.83	0.13	3,476
	Semi-Perishable Items				
6	Korie Palm Oil	22.02	3.58	0.08	5,433
8	Maize Grain	−1.57	6.73	0.06	2,782
9	Soybeans	8.98	2.80	0.19	3,796
10	Dried Sardines	4.12	1.90	0.18	6,668
12	Round Onions	7.55	1.50	0.11	7,888
14	Cooking Oil	18.72	3.75	0.12	2,939
19	Sunflower Oil	18.26	4.63	0.20	1,773
	Perishable Items				
3	Bones-in Beef	−0.57	1.87	0.43	4,049
5	Round Tomatoes	1.54	1.10	0.14	8,382
7	Fresh Fish	7.11	2.47	0.29	3,430
13	Cooking Bananas	5.51	4.51	0.13	3,039
15	Fried Bread (Buns)	3.59	2.00	0.29	3,896
16	Sliced Bread	2.49	1.59	0.60	2,309
17	Dried Fish	1.66	3.08	0.23	2,956
18	Unhusked Coconut	2.21	0.99	0.45	2,613
20	Fried Fish	6.71	4.24	0.25	2,274

The dependent variable is scaled for all the rows in the table, that is, we calculated the average per-purchase quantity for each household, as well as the average for each district. We compare the ratio of the two average per-purchase-quantities (multiplied by 100) across products. Using a quantity-index, rather than average quantities makes it possible to compare coefficients across products. The table reports OLS estimates for regressions of the scaled per-purchase average quantities against the log of the household wealth index, with β as the coefficient of interest, as in Equation (2). The regressions include controls for household size, geographic-cluster fixed effects, and use household-level sample weights.

Table 4: Prices by Time of the Month

	Dependent variable: Price Index					
	All HHs		Above Median		Below Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Flush Regime Dummy	-19.82	-24.16	-11.14	-10.84	-28.35	-30.79
	(2.29)	(2.92)	(0.78)	(1.35)	(3.20)	(3.78)
Monthly Wage Income Only		-6.16		3.48		-16.67
		(3.36)		(2.30)		(9.41)
Monthly Wages and Other		-12.00		-1.08		-17.63
		(3.92)		(3.37)		(4.63)
Wage Income (Not Monthly)		-11.71		-2.94		-15.17
		(3.32)		(1.77)		(6.84)
Flush*Monthly Wage Income Only		11.64		-1.75		19.70
		(3.43)		(2.38)		(9.09)
Flush*Monthly Wages and Other		14.64		1.30		21.89
		(4.02)		(3.00)		(6.59)
Flush*Wage Income (Not Monthly)		12.80		1.72		13.44
		(3.09)		(2.15)		(4.89)
Perishable Share		0.14		0.18		0.14
		(0.04)		(0.03)		(0.07)
HH size 4–6		-0.56		-1.14		-0.44
		(1.95)		(1.09)		(4.02)
HH size 7+		1.22		0.32		0.62
		(2.75)		(1.36)		(5.11)
Observations	17,766	17,272	8,802	8,490	8,964	8,782
R^2	0.55	0.03	0.62	0.04	0.54	0.04

The dependent variable is the price index, which is calculated as a weighted average of household purchase prices divided by average local prices for items. The total purchase value for an item is its weight. Each product's average price is calculated within the geographic neighborhood cluster used for sampling and standardized to 100 within each cluster. Columns 3 to 6 split the data by the median of household wealth. Even columns include neighborhood-cluster fixed effects as the only additional controls. The flush regime is defined as the top seven days of spending, which cumulatively account for roughly 43% of all monthly spending on average. Non-wage income is the omitted wage type. 69 % of households have non-wage income, 7 % of households have non-monthly wage income, 11 % of households have monthly wages and another income source, and 13 % rely on monthly wages only. In terms of household size, just under 40% of households are three or fewer persons. These represent the baseline. Another 40% of households have between 4 and 6 people, while just under 20% of households have 7 or more people. Only items purchased in both the flush and lean periods were used to construct the data. All columns use clustered standard errors.

Table 5: Focal and Optimal Quantities for rice, maize flour, and beef

	Product	Variable	F1	F2	F3	F4	F5	Share
1	Rice	Quantity	0.50	0.75	1	1.50	2*	
		Unit Value	2,000	2,000	1,900	1,900	1,800	
		% of Transactions	21.79	5.36	44.19	8.86	10.04	90.24
		% of Value	8.57	3.03	33.01	9.79	14.55	68.95
2	Maize Flour White	Quantity	0.25	0.50*	0.75	1	2	
		Unit Value	1,000	900	900	900	900	
		% of Transactions	8.78	32.56	7.35	33.58	6.16	88.43
		% of Value	2.44	16.38	5.40	33.17	12.02	69.40
3	Beef with Bones	Quantity	0.25	0.50*	1	1.50	2	
		Unit Value	6,000	5,000	5,000	5,000	5,000	
		% of Transactions	9.91	54.17	28.58	1.73	1.39	95.77
		% of Value	3.91	39.01	40.10	3.33	3.79	90.15

F1 to F5 represent the focal purchase points for each of the items in the first column. Each focal point shows one of the most commonly-purchased quantities for an item (arranged in order of size), and the median unit value for each quantity. (The prices were selected for the district with the largest number of transactions for each item). The declining unit values with size for the focal points highlight the bulk discounts documented in Table 2. The focal points also show each quantity's share of the total quantity and value purchased for the item. The share column at the end of the table sums all the shares across the focal quantities. We construct this table for all the top twenty items, but show only the top three to manage space. The optimal quantity, or threshold for bulk discounts, marked by an asterisk (*), is the smallest quantity that gets the lowest median price for these focal quantities.

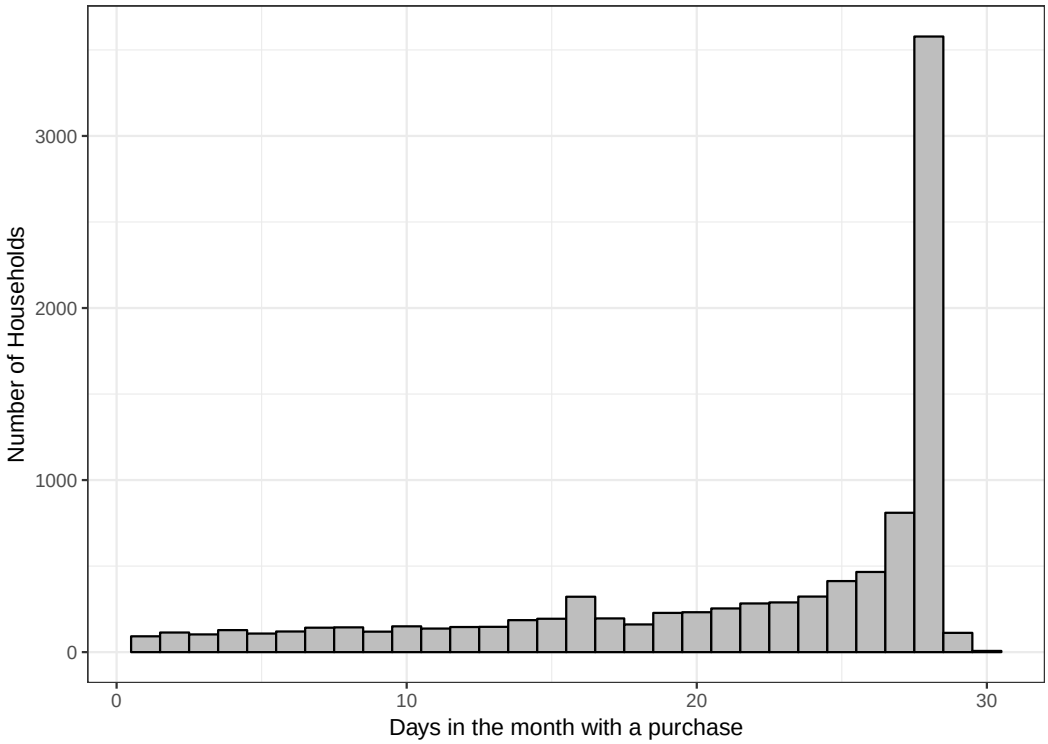
Table 6: Poverty and Bulk Discount Losses

	(1)	(2)	(3)	(4)
	Dependent variable: Lost Share of Spending			
log(Wealth index)	-0.01^{**}	-0.02^{***}	-0.01^{*}	-0.005
	(0.003)	(0.01)	(0.01)	(0.01)
Monthly Wage Income Only	0.01^{*}	0.002	0.01	0.01^{*}
	(0.01)	(0.01)	(0.01)	(0.01)
Monthly Wages and Other	-0.02^{***}	-0.01^{**}	0.001	0.01
	(0.01)	(0.004)	(0.005)	(0.005)
Wage Income (Not Monthly)	0.005	-0.002	-0.01	0.003
	(0.01)	(0.01)	(0.01)	(0.01)
log(Quantity Index)			-0.04^{***}	-0.03^{***}
			(0.004)	(0.005)
Perishable Share				0.001^{***}
				(0.0003)
Own-Production Share				0.10^{***}
				(0.02)
HH Size $4-6$				-0.003
				(0.004)
HH Size 7+				-0.01
				(0.01)
Constant	0.43^{***}			
	(0.002)			
Observations	8,973	8,973	8,973	8,973
R^2	0.01	0.23	0.26	0.27
Cluster FE	N	Y	Y	Y
Note:				*p<0.1; **p<0.05; ***p<0.01

The table highlights the impact of poverty on households' bulk discount losses. We add 3.53 to the wealth index to ensure all values are positive, before taking logs. It controls for perishable items' the share of household consumption, motivated by the results in Table 2. The control for own-production is motivated by the 18% of consumption that is produced by households (in Table A1. The own-production variable reflects share of household food from own-production. As expected, poorer households produce a greater share of their own food. The last three columns of the table use cluster-fixed effects. The omitted categories for income type and HH size are non-wage earners, and households with fewer than 4 people. All specifications use cluster-robust standard errors.

Appendices

Figure A1: Households Purchase Food (Almost) Daily

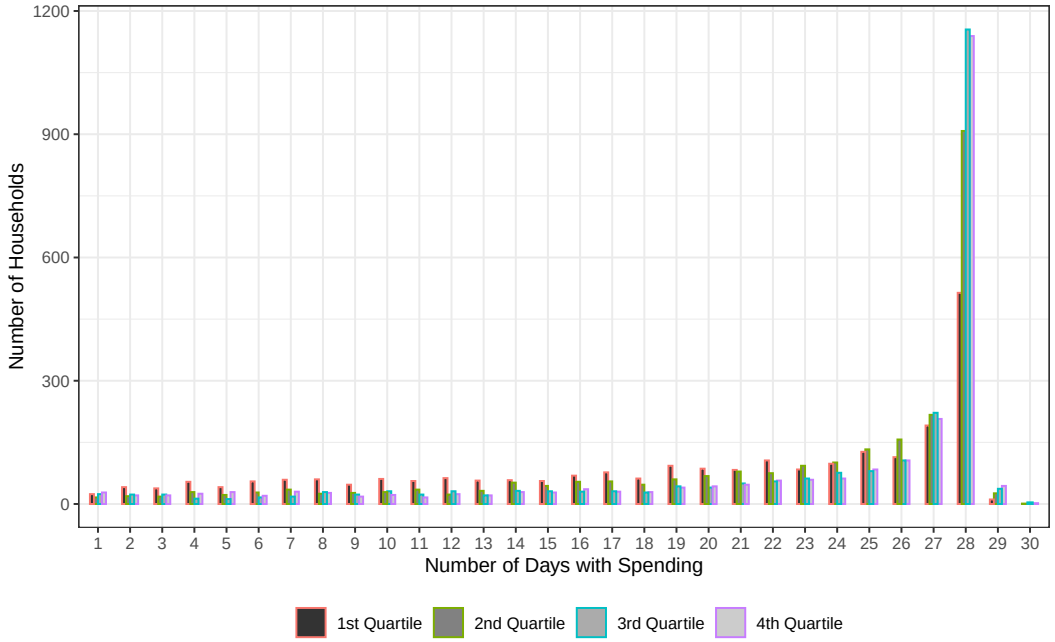


Only food transactions from commercial sources count as purchases.

Table 7

	Dependent variable	
	log(hloss)	
	OLS	
	(1)	(2)
log(3.53 + windex)	0.003	−0.03*
	(0.01)	(0.01)
typeMonthly Wage Income Only	−0.15**	−0.16**
	(0.07)	(0.07)
typeMonthly Wages and Other	−0.11***	−0.08*
	(0.04)	(0.04)
typeWage Income (Not Monthly)	0.06	0.04
	(0.04)	(0.04)
log(hqindex)		
pshare		
hhsizegHH46		
hhsizegHH7p		
ownprodshare		
log(3.53 + windex):typeMonthly Wage Income Only	0.12***	0.11**
	(0.04)	(0.05)
log(3.53 + windex):typeMonthly Wages and Other	0.07**	0.05
	(0.03)	(0.03)
log(3.53 + windex):typeWage Income (Not Monthly)	−0.02	−0.02
	(0.03)	(0.03)
Constant	−0.91***	
	(0.01)	
Observations	9,446	9,446
R^2	0.003	0.26
Adjusted R^2	0.003	0.25

Figure A2: Food Purchase Days by W. Quartile



Only food transactions from commercial sources count as purchases.

Table A1: Food Item Sources

Source	Number of Purchases	Share of Food Value
Market	454917	0.30
Shop	483594	0.37
Street vendor	23773	0.02
Supermarket	349	0.00
Duka kubwa (Department Store)	508	0.00
Other household	38492	0.03
Other	119363	0.09
Produced by household	132767	0.18
Gift from other	7846	0.01
Gift or free	10401	0.01
Aid from different organizations	598	0.00

Number of purchases shows the number of transactions reported for each source of food items, while the spending share reports the share of household spending allocated to each source. Commercial sources for food in the table are presented in *italics*. Shops resemble the delis and mini-groceries found around the United States and other high-income countries. Markets resemble the typical flea market, or open air markets with some structures for overnight storage. Street vendors hawk their wares on major roads or on neighborhood beats with a small selection of items.

Table A2: Assets by Number of Households

	Asset	Number of Households
1	Cooking pots	9,180
2	Beds	9,058
3	Mosquito net	8,863
4	Chairs	7,522
5	Tables	7,421
6	Charcoal stove	6,304
7	Lanterns	5,393
8	Iron (electric or charcoal)	3,557
9	Cupboards	3,408
10	Watch	2,479
11	Sofas	2,286
12	Firewood and coal stove	1,946
13	Fan	1,908
14	Refrigerator, freezer or fridge-freezer	1,526
15	Sewing machine	878
16	Water heater	769
17	Electric or gas stove (including microwave)	508
18	Air conditioning	327

10,186 households surveyed.

Table A3: Summary of Wealth Index Variables

Statistic	Mean	St. Dev.	Min	Max
Electric or gas stove (including microwave oven)	0.05	0.22	0	1
Refrigerator, freezer or fridge-freezer	0.15	0.36	0	1
Sofas	0.22	0.42	0	1
Iron (electric or charcoal)	0.35	0.48	0	1
Air conditioning	0.03	0.18	0	1
Good Floor Quality	0.59	0.49	0	1
Good Wall Quality	0.40	0.49	0	1
Good Roof Quality	0.80	0.40	0	1
Homeowner	0.61	0.49	0	1
Bedrooms per person	0.59	0.44	0.05	12.00

The assets selected from Table A2 are high-value, and therefore exclude beds, cupboards and watches; as well as items likely to be used for a trade, e.g., sewing machines.

Table A4: Prices by Time of the Month and Income Type - 5-Day Flush Period

	Dependent variable: Price Index					
	All HHs		Above Median		Below Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Flush (5-day)	-27.90	-26.06	-29.17	-28.15	-26.69	-25.08
	(1.05)	(1.21)	(1.00)	(1.21)	(1.33)	(1.45)
typeMonthly Wage Income Only		-4.69		-5.11		-2.80
		(1.13)		(1.02)		(3.51)
typeMonthly Wages and Other		-3.64		-4.37		-1.61
		(1.23)		(1.15)		(2.90)
typeWage Income (Not Monthly)		-0.72		-0.61		-1.71
		(1.42)		(1.29)		(2.73)
hhsizegHH46		0.94		0.58		0.96
		(0.73)		(0.89)		(1.07)
hhsizegHH7p		-0.52		-0.20		-0.98
		(1.23)		(1.49)		(1.94)
pshare		-0.05		-0.04		-0.02
		(0.02)		(0.03)		(0.04)
flush5*Monthly Wage Income Only		4.58		6.16		7.82
		(1.40)		(1.34)		(5.90)
flush5*Monthly Wages and Other		0.88		3.33		-1.59
		(1.48)		(1.67)		(2.88)
flush5*Wage Income (Not Monthly)		-1.74		-1.63		2.45
		(1.54)		(1.30)		(3.85)
Observations	17,075	16,668	8,337	8,062	8,738	8,606
R^2	0.70	0.15	0.72	0.18	0.68	0.15
Note:						p<0.1; p<0.05; p<0.01

The dependent variable is the price index, the weighted average of household purchase prices divided by average prices for all top 20 items, as in Table 4. The flush regime for this table is defined as the top five days of spending, which cumulatively account for roughly 34% of all monthly spending on average.

Table A5: Prices by Time of the Month and Income Type - 10-Day Flush Period

	Dependent variable: Price Index					
	All HHs		Above Median		Below Median	
	(1)	(2)	(3)	(4)	(5)	(6)
flush0	53.95	58.37	50.79	52.63	57.32	61.22
	(1.15)	(1.36)	(0.91)	(1.57)	(1.19)	(1.41)
typeMonthly Wage Income Only		0.46		-1.92		4.87
		(0.84)		(0.78)		(3.39)
typeMonthly Wages and Other		0.58		-1.48		1.43
		(0.93)		(0.97)		(1.62)
typeWage Income (Not Monthly)		2.97		0.52		3.86
		(1.07)		(0.92)		(2.59)
hhsizegHH46		0.20		0.57		-0.63
		(0.69)		(0.79)		(1.25)
hhsizegHH7p		-1.50		-0.24		-3.09
		(1.13)		(1.51)		(1.96)
pshare		-0.01		0.01		0.02
		(0.02)		(0.02)		(0.04)
flush0*Monthly Wage Income Only		-4.51		1.16		-6.89
		(1.89)		(2.09)		(7.07)
flush0*Monthly Wages and Other		-5.37		-0.65		-4.69
		(1.63)		(1.64)		(3.43)
flush0*Wage Income (Not Monthly)		-8.34		-3.83		-7.44
		(1.51)		(1.65)		(3.70)
Observations	15,724	15,351	7,857	7,607	7,867	7,744
R^2	0.84	0.38	0.82	0.42	0.85	0.36
Note:						p<0.1; p<0.05; p<0.01

The dependent variable is the price index, the weighted average of household purchase prices divided by average prices for all top 20 items, as in Table 4. The flush regime for this table is defined as the top ten days of spending, which cumulatively account for roughly 54% of all monthly spending on average.

Table A6: Internal Rates of Return and Wealth

	Dependent variable:			
	log(IRR)			
	(1)	(2)	(3)	(4)
Wealth Index	-0.16	-0.16	-0.16	-0.19
	(0.04)	(0.04)	(0.04)	(0.05)
Household Size		-0.01	-0.01	-0.004
		(0.01)	(0.01)	(0.01)
Gender (Male = 1)			-0.02	-0.01
			(0.05)	(0.05)
Primary level education				-0.20
				(0.14)
Secondary or higher education				-0.15
				(0.14)
Constant	8.34	8.38	8.41	8.60
	(0.06)	(0.07)	(0.10)	(0.19)
Observations	8,264	8,264	8,264	6,992
R^2	0.002	0.002	0.002	0.002
Note:				p<0.1; p<0.05; p<0.01

Table A7: Median Days to Save Enough for Bulk Discounts

	Description	All HHs	By Quartile -Exclusive Q1	Q2	Q3	Q4	All HHs	By Quartile -Inclusive Q1	Q2	Q3	Q4
1	Rice	2.55	5.42	3.29	2.18	1.46	1.38	2.86	1.87	1.24	0.83
2	Maize Flour White	0.33	0.73	0.43	0.30	0.20	0.19	0.30	0.22	0.19	0.14
3	Beef with bones	2.63	4.72	3.23	2.70	1.86	1.81	3.03	2.25	1.86	1.38
4	Brown sugar	0.71	1.32	0.97	0.64	0.41	0.53	1.02	0.71	0.50	0.34
5	Tomatoes	0.35	0.75	0.42	0.28	0.20	0.29	0.58	0.35	0.24	0.18
6	Korie Palm Oil	0.45	0.92	0.53	0.37	0.26	0.34	0.69	0.41	0.29	0.21
7	Fresh or frozen fish	3.26	5.31	3.69	3.12	2.90	2.56	3.39	2.65	2.54	2.34
8	White Maize grains	1.63	2.93	1.94	1.45	1	1.17	1.40	1.26	1.20	0.92
9	Soybeans	0.51	1.43	0.71	0.51	0.35	0.42	0.97	0.55	0.42	0.30
10	Dried sardines	0.96	2.31	1.11	0.71	0.48	0.82	1.60	0.92	0.63	0.43
11	Beans	1.27	2.55	1.43	0.90	0.62	1.00	1.78	1.10	0.77	0.55
12	Round Onions	0.16	0.37	0.19	0.12	0.08	0.14	0.32	0.18	0.11	0.08
13	Vegetable cooking oil	0.35	0.89	0.43	0.26	0.17	0.27	0.61	0.33	0.21	0.14
14	Cooking bananas	2.71	4.66	3.13	2.66	2.03	2.18	3.13	2.52	2.19	1.80
15	Fried Bread (buns)	0.56	0.97	0.77	0.52	0.37	0.49	0.84	0.64	0.44	0.33
16	Sliced bread	0.75	1.07	1.09	0.86	0.64	0.65	0.98	0.94	0.76	0.54
17	Dried or salted (shell)fish	1.66	3.50	1.94	1.13	0.93	1.33	2.46	1.55	0.97	0.83
18	Coconut (Unhusked)	0.65	1.14	0.81	0.65	0.47	0.56	0.88	0.67	0.57	0.43
19	Spinach/Lettuce	0.42	0.98	0.56	0.37	0.26	0.39	0.83	0.52	0.35	0.25
20	Sunflower oil	0.44	0.88	0.50	0.24	0.15	0.32	0.53	0.34	0.18	0.12
	Any Item	0.63	1.28	0.81	0.55	0.39	0.52	0.96	0.65	0.47	0.34
	All Items	105.86	119.60	113.52	101.36	93.63	4.34	5.96	6.38	4.03	2.10

The table shows the estimated median number of days of going without an item, as well as tea, cigarettes, salt and sugar, that allows households to save enough to get bulk discounts when buying the item. For the columns that represent wealth quartiles, Q1 is the poorest. The steps follow a similar exercise in Dillon et al. (2020). The number of days of foregoing items to enjoy bulk discounts is calculated as $d_{hi} = e_i^*/a_h$. For the first five columns, we define a_h as only average expenses for the four selected items, and for the last five columns we define a_h as in Dillon et al. (2020) to include spending for each item. The last two rows of the table represent the median number of days of delayed spending are needed to get bulk discounts for any item, and for every item.

The table suggests that for some items in typical household budgets, giving up a few items to finance bulk discounts is not an easy option. For most items however, much like in Dillon et al. (2020), not much delay is needed to start enjoying bulk discounts. We are not willing to commit to the idea that tea, sugar, and salt are non-necessities for poor households, but we present the table as an illustrative data point that is comparable to the work done with a smaller data set in Dillon et al. (2020). The results match for many comparable items that exist in Table A7 and the corresponding table in Dillon et al. (2020): Onions, Cooking oil, Dried sardines.

We construct the table to match the steps in Dillon et al. (2020). For each household, we calculated the total amount spent in the 30-odd days of data on the same four item groups flagged in their paper. We calculated the total spending on each food item at the household level. We use the optimal quantities, derived from the item-level price schedules, to identify the optimal unit values, and by extension, the spending required to buy enough of item i to enjoy bulk discounts (e^*_{min}). The number of days of foregoing items to enjoy bulk discounts is calculated as $d_{hi} = e^*_{min}/(\sum_{j \in D} \hat{e}_{hj})$. For the first five columns, we define a_h as the total spending of household h on the four selected items, and for the last five columns we define a_h as in Dillon et al. (2020) to include spending on a set that includes the item in the first column, as well as the four target items. The last two rows of the table represent the median number of days of delayed spending are needed to get bulk discounts for any item, and for every item, respectively

Our main point is that while for many items households can enjoy bulk discounts by having a brief once-and-for-all 'fast' from a few items, the principle does not hold for all items. More importantly, the table suggests – in the last row, that the median household must starve just to about the point of dying, before it can make a switch from buying sometimes in small quantities, to always buying in quantities that yield bulk discounts – about 6 days for the poorest households, and about 2 days for the less-poor. To get any bulk discounts at all, the waiting period is generally less than a day for the median household. We believe the number of days households must wait to start enjoying bulk discounts on *all* items, is the more useful measure.

Here is Table A8 showing the top 20 items, and the quantities that mark the threshold at which households start enjoying bulk discounts for the item. The last columns of the table show the average, minimum and maximum prices across geographic clusters, that correspond to the threshold quantity. The quantities are really small, not by any means the CostCo quantities on would associate with buying in bulk in a high-income economy.

Table A8: Threshold Purchase Quantities and Amounts for Bulk Discounts

rank	Description	Quantity* (in kg or L)	Prices (Tsh/kg or Tsh/L) median*	min.	max.
1	Rice	2	1,800	1,000	2,500
2	Maize Flour White	1	900	450	2,000
3	Beef with bones	0.50	5,000	600	8,200
4	Brown sugar	0.25	2,000	1,600	3,000
5	Tomatoes	0.36	833.33	277.78	3,333.33
6	Korie Palm Oil	0.12	2,400	1,200	9,520
7	Fresh chilled or frozen fish	1	5,000	600	8,000
8	White Maize grains	2	500	200	1,300
9	Soya beans	2	1,600	475	4,000
10	Dried sardines	0.30	2,000	666.67	13,333.33
11	Beans	2	1,500	500	2,251
12	Round Onions	0.08	1,250	625	12,500
13	Other cooking oil	0.12	2,400	1,600	8,000
14	Cooking bananas	3	1,000	166.67	2,166.67
15	Fried Bread (buns)	0.48	1,666.67	625	5,000
16	Sliced bread	0.80	1,250	125	12,500
17	Dried or salted fish/ shellfish	0.31	2,258.06	1,612.90	9,677.42
18	Coconut (Un husked)	0.60	1,166.67	166.67	2,666.67
19	Spinach / Lettuce	0.40	1,000	250	3,750
20	Sunflower oil	0.10	2,000	1,000	10,000

The table shows the threshold quantities that give bulk discounts (quantities we label as optimal quantities). For each geographic cluster (or neighborhood) in the data, we found the median price for the optimal quantities. The last columns of the table show the minimum and maximum of those cluster-level prices for optimal quantities.