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Worth Your Weight: Experimental Evidence on the Benefits of Obesity in Low-Income Countries†

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I study the economic value of obesity—a status symbol in poor countries associated with raised health risks. Randomizing decision-makers in Kampala, Uganda to view weight-manipulated portraits, I find that obesity is perceived as a reliable signal of wealth but not of beauty or health. Thus, leveraging a real-stakes experiment involving professional loan officers, I show that being obese facilitates access to credit. The large obesity premium, comparable to raising borrower self-reported earnings by over 60 percent, is driven by asymmetric information and drops significantly when providing more financial information. Notably, obesity benefits and wealth-signaling value are commonly overestimated, suggesting market distortions. (*JEL* D82, G21, G51, I12, O16, Z13)

Status concerns are often seen as futile and potentially wasteful (Veblen 1899; Frank 1985; Hopkins and Kornienko 2004; Bursztyn et al. 2017). Where credible financial information is unavailable or costly, however, like in developing countries, models of statistical discrimination predict that the noisy information that visible signs of status provide may be used in economic transactions (Akerlof 1976). In theory, this prediction implies real status benefits in poor countries, which, in turn, may be relevant to interpret phenomena like large conspicuous consumption expenditures among the poor (Banerjee and Duflo 2008). Empirically, nonetheless, little

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work has investigated the benefits of status, particularly in market settings (Bursztyn and Jensen 2017).

This paper provides novel experimental evidence on the economic benefits of status in a low-income country, focusing on obesity. Being fat is a common status symbol in poor countries.[1] Even though behavior is just one of the many determinants of body size, which include genetics and early life experiences, in most poor countries today, similar to the West in the past, rich people are more likely to be obese, and fatness is associated with prosperity.[2]

My empirical strategy leverages two complementary experiments (a beliefs experiment and a credit experiment) set in Kampala, Uganda and involving the general population and professional loan officers. Randomizing decision-makers to see weight-manipulated portraits, I test for an obesity wealth-signaling value and the associated economic benefits in the context of credit.[3] Credit markets, in addition to being economically relevant, provide a textbook setting to test for the role of information—loan officers in poor countries face both moral hazard and adverse selection (Karlan and Zinman 2009)—allowing me to identify the asymmetric information channel.

While other status symbols, like cars or watches, could be used to investigate status benefits, focusing on obesity allows for a cleaner test because there is no collateral value that may confound the analysis. Moreover, studying the socioeconomic benefits of obesity is relevant for health policy. Public health institutions have long raised concerns over rising obesity rates in poor nations (Prentice 2006; Popkin, Corvalan, and Grummer-Strawn 2020; Shekar and Popkin 2020).[4] Understanding the perception of obese individuals in poor countries can inform policies to prevent malnutrition.[5]

In the first experiment, the beliefs experiment, I ask 511 Kampala residents to rate randomly selected weight-manipulated portraits along several characteristics, including wealth. I find that the obese portraits are rated as being wealthier than their normal-weight counterpart (0.69 standard deviations, $p = 0.00$). To the contrary, I find obesity has no effect on perceived beauty, health, life expectancy, self-control, ability, or trustworthiness. Thus, Kampala residents perceive obesity as a signal of wealth but not of other traits commonly assumed to be associated with obesity. The obesity wealth signal is strong: obese individuals are perceived as being as wealthy as normal-weight people who own a car. The signal is also relevant since being obese provides information on top of other common signs of status: when portraits

[1] In this paper, I utilize the term "fat" in alignment with the body positivity movement's aim to destigmatize and reclaim the word.

[2] Qualitative studies showing evidence of positive perception of fat bodies include among others, and in addition to Uganda, the following countries: Belize, Jamaica, Mauritania, Niger, Nigeria, Kenya, Senegal, and South Africa.

[3] I build 30 pairs of weight-manipulated portraits of Kampala residents and assign respondents to view the thinner or fatter version of each original portrait. Given how portraits are manipulated, the average treatment effect captures the causal effect of obesity relative to normal weight.

[4] While the medical literature debates the existence of health risks of being overweight, obesity, defined by the World Health Organization (WHO) as a body mass index (BMI) greater than or equal to 30, is associated with a higher risk of developing noncommunicable diseases and mortality. Obesity health risk is consistent across studies and countries (Di Angelantonio et al. 2016).

[5] According to the WHO, the definition of malnutrition includes undernutrition, inadequate vitamins or minerals, being overweight, obesity, and resulting diet-related noncommunicable diseases. Within the United Nations Decade of Action on Nutrition (2016–2025) targets—a commitment for global action to address malnutrition—"social norms" is a key action topic.

are accompanied by place of residence or asset ownership, the effect of obesity on wealth ratings is not significantly reduced (-0.19 standard deviations, $p = 0.13$).

In the second experiment, the credit experiment, I work with 238 professional loan officers employed at 146 licensed Kampala financial institutions. I ask the loan officers to review hypothetical profiles during work hours and select borrowers they would like to meet to discuss a loan application.[6] The profiles are built by randomizing information collected from interviewing 187 prospective borrowers living in Kampala. To vary the body size dimension, each borrower profile is assigned to a weight-manipulated portrait, randomly displayed in its obese or nonobese version (portraits are standard personal identifiers in Uganda). In total, there are 30 profile pairs, and loan officers make 6,645 profile evaluations.

While I inform them that the profiles they evaluate are not real, loan officers know that, at the end of the study, they will be referred to real prospective borrowers, and these referrals will be based on their choices in the experiment. Loan officers value good referrals—they either face a performance pay or are self-employed—and thus have incentives to select good borrowers. This incentive structure follows closely the Incentivized Resume Rating (IRR) recently developed by Kessler, Low, and Sullivan (2019).[7]

I find that loan officers screen borrowers based on body mass and that being obese leads to credit market benefits. When a profile includes a borrower portrait in the obese version, loan officers rate the borrower as more creditworthy (0.18 standard deviations, $p = 0.00$), more financially able (0.15 standard deviations, $p = 0.00$), and more likely to be approved (0.2 standard deviations, $p = 0.00$). Better credit ratings translate into easier access to credit: loan officers are more likely to request the referral of obese borrowers, which, given the incentive structure, is a real choice outcome (3 percentage points, $p = 0.05$). The obesity premium is large, equivalent to the effect of a 60 percent increase in borrower self-reported income in the experiment.

I next examine what drives the credit experiment results. To identify the mechanism, I design the experiment to cross-randomize borrower body size with the degree of asymmetric information in which loan officers make their decisions. Along the information dimension, I randomly assign each profile to display self-reported financial information (occupation, collateral, and earnings) or not.[8] I find that the

[6] The institutions are about 30 percent of all licensed financial institutions in Greater Kampala that deal with the general public and offer a set of standard collateralized loans.

[7] The IRR, developed to test for discrimination in hiring in the United States, allows me to elicit loan officers' preferences in an incentive-compatible manner even if, because loan applications in Kampala are dealt in person, I cannot run a correspondence study as in Bertrand and Mullainathan (2004). My design differs from Kessler, Low, and Sullivan (2019) on several aspects. First, this is the first application (a) to credit markets, (b) in a developing country, and (c) testing for body mass discrimination. Second, I include a real choice outcome, and third, I test for the mechanism driving discrimination.

[8] Most existing studies on bias in lending exploit OLS estimates or quasi-random variation in loan officer assignment (notably, Dobbie et al. 2021) to identify the effect of borrowers' characteristics on credit, and they use outcome-based tests of bias. A recent exception is Giné and Mazer (2022), who show in an in-person audit study that less financially literate clients receive less information about financial products in Ghana, Mexico, and Peru. My approach is closer to the labor market discrimination literature, but I refine the standard paradigm to test for statistical discrimination. Correspondence studies normally cross-randomize the relevant trait with profile quality in a 2×2 design (Bertrand and Duflo 2017), while I randomize both the profile quality and the overall amount of financial information provided (2×3 design). This is a cleaner test of statistical discrimination, which does not require me to assume substitution between signals.

obesity premium is decreasing in the amount of available borrower financial information: when loan officers know about borrower self-reported profits, collateral, and occupation, the obesity premium drops by a range of 50 percent to 70 percent.[9]

Moreover, I find that the residual effect of obesity, conditional on providing financial information, does not appear to be explained by taste (e.g., homophily or a beauty premium as in Mobius and Rosenblat [2006]). This is consistent with the beliefs experiment, where obese portraits are not perceived differently along any outcome except wealth. Thus, the residual premium is likely explained by unresolved asymmetric information due to the financial information provided being unverified or incomplete. Indeed, loan officers perceive borrower information as "not very reliable" and rate obese borrowers' information as significantly more reliable.[10] In sum, asymmetric information drives obesity benefits in credit markets, and loan officers' behavior appears consistent with statistical discrimination.[11]

Evidence supports the claim that obesity matters in real life, outside the experimental setting. First, the general population in Kampala and, most notably, about 90 percent of loan officers in the credit experiment explicitly state that an obese person is more likely to be considered for a loan relative to a normal-weight one (answers to an open-ended question). Second, the credit experiment information environments are realistic. In Kampala, loan officers choose whether or not to meet with a borrower based on their first impression—the borrower has to be present on the office's premises—and minimal information about the requested loan; during the first meeting, borrowers normally share financial information, which loan officers cannot verify on the spot. The experimental results suggest that the obesity premium is likely strongest at the earlier stages of the screening process but also show that obesity still matters at later stages, as body size is still a factor even conditional on self-reported financial information. Consistent with this interpretation, BMI and access to credit are positively correlated in nationally representative survey data.[12]

Given the awareness of obesity benefits and wealth-signaling value, in Section III of the paper, I test for beliefs accuracy. I first replicate the credit experiment with Kampala residents, asking respondents to guess loan officers' evaluations.[13] I find that people overestimate the obesity premium by more than two times. I then test for misperception of the obesity wealth-signaling value by eliciting Kampala residents' beliefs on the earnings of obese and normal-weight people in the city ($N = 124$).[14]

[9] Agents may mechanically pay less attention to baseline information when more information is available. Inattention, however, appears inconsistent with the data. The interaction coefficient between more information and baseline traits is not systematically negative, as shown in online Appendix Table G2. For example, more information available leads officers to value the requested loan amount *more*.

[10] The beliefs experiment also suggests that the obesity premium is unlikely to be a trust premium as in Duarte, Siegel, and Young (2012), where trustworthy-looking borrowers have easier access to credit. Obese borrowers are more likely to be rich and in turn are more likely to own the claimed collateral, making the self-reported financial information indeed more credible.

[11] Previous literature finds that physical characteristics (beauty in Ravina et al. 2019 and, less so, not being overweight in Pope and Sydnor [2011]) matter for credit. On top of contextual and methodological differences—these papers focus on an online US peer-to-peer lending market and use observational data—the mechanism is different, as discrimination appears to be the result of bias. Several reasons may explain the difference, including that in rich countries technology may reduce the need to infer from appearance.

[12] The analysis exploits the Uganda National Panel Survey, 2019–2020 (Uganda Bureau of Statistics 2021).

[13] These are incentivized beliefs of the same Kampala residents interviewed in the beliefs experiment.

[14] Due to COVID-19, these are partly the same respondents of the beliefs experiment and partly a new sample recruited via WhatsApp.

I find that people overestimate the average income difference between obese and normal-weight people by two to three times.[15] Finally, although the credit experiment is not designed to test for beliefs accuracy, large heterogeneity in the estimated obesity premium across loan officers suggests that their beliefs may also be inaccurate.

This paper makes three main contributions. First, it provides novel experimental evidence on the economic value of status in a low-information setting. Most of the literature on social signaling does not investigate benefits (DellaVigna et al. 2016; Perez-Truglia and Cruces 2017; Karing 2018), and any experimental evidence on the tangible rewards generated by social signals that do exist is limited to social interactions (Nelissen and Meijers 2011; Bursztyn, Fujiwara, and Pallais 2017). Closely related to this paper is Bursztyn et al. (2017), which provides experimental evidence of demand for status in Indonesia. The demand for status seen in the authors' study would be in line with sizable economic benefits from signs of status that I identify in this paper.[16]

Second, the results add to the literature on the consequences of asymmetric information for financial transactions in poor countries by showing that agents screen based on visible but imperfect signals when hard information is unavailable or costly. Together with Cole, Kanz, and Klapper (2015) and Fisman, Paravisini, and Vig (2017), this study is one of few experimental studies looking at the supply side of lending in poor countries. Different from other studies testing for the effect of information on credit market outcomes (e.g., Giné, Goldberg, and Yang 2012), this paper focuses on loan officers' discriminatory behavior.

Finally, within the health economics literature on obesity, this paper provides the first experimental evidence of the socioeconomic benefits of obesity in poor countries. Most of the obesity literature focuses on investigating the causes and costs in high-income countries (Cutler, Glaeser, and Shapiro 2003; Cawley and Meyerhoefer 2012). In the development context, Rosenzweig and Zhang (2019) study the effects of education on healthy behaviors, including obesity, using twin data from rural China. As obesity benefits imply rewards from extra calories, the results add to the puzzle of calorie underinvestment among the poor (Subramanian and Deaton 1996; Schofield 2014; Atkin 2016).

I. Beliefs Experiment: Obesity as a Signal of Wealth

In Uganda, as common in low- and lower-middle-income countries, obesity and measures of wealth and earnings are positively correlated (Figure 1). Thus, I first design the beliefs experiment to test (i) whether in Kampala obesity is perceived as a salient signal of wealth, against other traits, and (ii) to what extent obesity is a relevant signal when compared to other common status indicators.[17]

[15] I build the benchmark out of the self-reported incomes of respondents in the beliefs experiment.

[16] Low self-esteem may also be a determinant of conspicuous consumption (Bursztyn et al. 2017).

[17] The beliefs experiment was implemented in November 2019 in partnership with IGREC Uganda and preregistered on the AEA registry (Macchi 2019b). The data are deposited with the AEA Data and Code Repository at ICPSR (Macchi 2023).

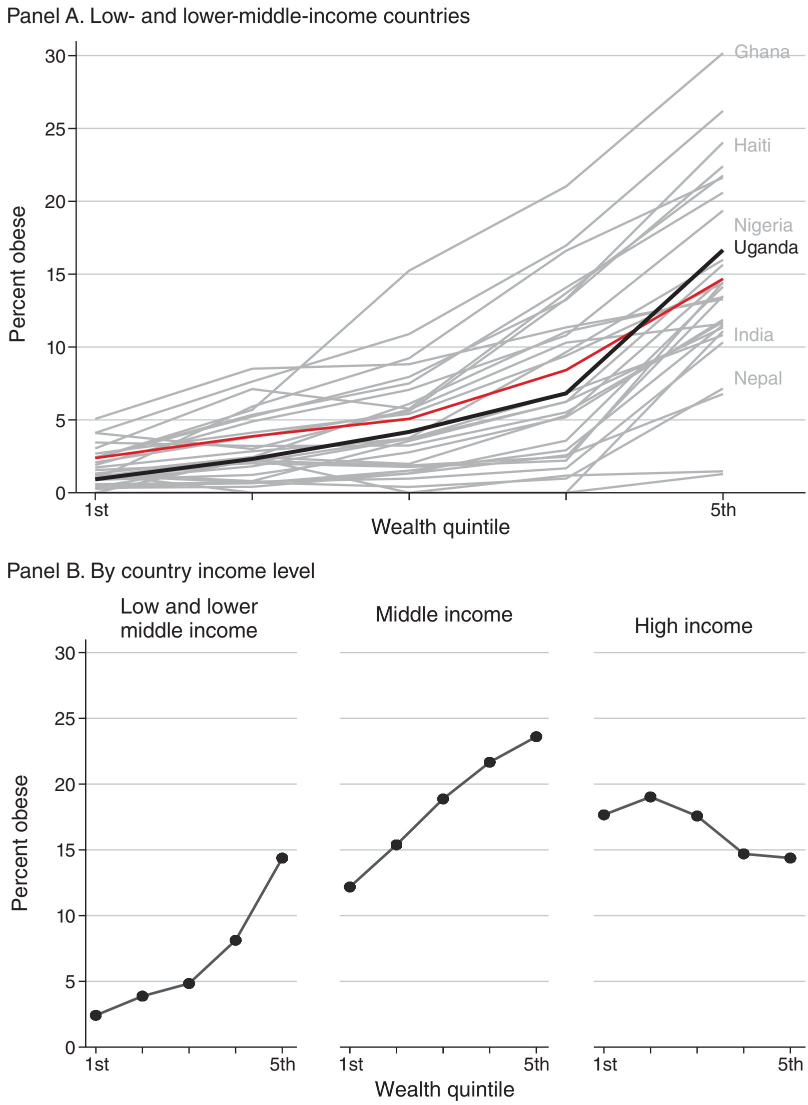

Figure 1. Obesity Prevalence by Wealth Quintile

Notes: Panel A plots the percent of obese respondents by wealth quintile, from the most recent DHS wave 2019 (2010–2016) for low- and lower-middle-income countries (ICF 2004–2017): Armenia, Bangladesh, Benin, Bolivia, Burkina Faso, Burundi, Cambodia, Cameroon, Comoros, DRC, Ethiopia, the Gambia, Ghana, Guinea, Haiti, India, Côte d'Ivoire, Kenya, Kyrgyzstan, Liberia, Lesotho, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Tajikistan, Tanzania, Timor-Leste, Togo, Uganda, Uzbekistan, Zambia, and Zimbabwe. The red line is the quintile-level average. Obesity is defined as a BMI greater than or equal to 30 (WHO definition). Panel B aggregates at the country income level and includes also data from Eurostat, Centers for Disease Control and Prevention, and the World Bank national accounts data and OECD National Accounts data files (World Bank 2017).

A. *Beliefs Experiment*

Sample Selection.—Respondents live in Kampala, Mukono, and Wakiso, the three largest districts in terms of population size of the Greater Kampala Metropolitan

Area (National Population and Housing Census 2014 [Uganda Bureau of Statistics 2016]). They are at least 18 years old and provide written consent. I stratify the sample by age, gender, and socioeconomic status.[18] Ex ante, obesity perception may depend on these three characteristics: the association between scarcity and positive perception of fat bodies is common; the anthropology literature describes obesity as a sign of fertility (Popenoe 2012); and younger people, likely more exposed to Western media, may have changed their perception of body mass (La Ferrara, Chong, and Duryea 2012).

The survey was described as part of a study, in partnership with the University of Zurich, on how appearance affects people's perception in Uganda. It lasted for about one hour. Respondents received a fixed fee in airtime as compensation for their time, plus a bonus depending on the incentivized answers' accuracy. They were also informed of their height, weight, and body mass status (underweight, normal weight, overweight, obese). Since most people in Kampala do not have access to weight scales or height boards, the anthropometric measurements were a good incentive to participate.

The final sample includes 511 Kampala residents. Table 1 summarizes the sample characteristics. Field officers walked around the districts and enrolled respondents quasi-randomly until they reached the required number by strata. Because of the stratification, the sample is 50 percent male. Respondents are heterogeneous in terms of personal income, occupation, age, and measured body mass. On average, respondents are overweight (BMI 25.66). This data point is aligned with nationally representative data for Kampala.[19]

Identifying the Causal Effect of Body Mass.—Body mass realizations are endogenous to preferences and constraints. Experimentally varying body mass, for example, by randomly assigning subjects' caloric intake, poses significant ethical concerns. In this paper, I instead identify the causal effect of body mass using weight-manipulated portraits.[20] The original portraits are of 30 Kampala residents, plus 4 White-race individuals,[21] and I manipulate each portrait's body mass using a photo-morphing software.

For each portrait, I create a thinner and fatter version and discard the original. That is, I compare within manipulated portraits instead of comparing the original portrait with a fatter, manipulated portrait as is common in previous work testing for weight discrimination (see the reviews of Bertrand and Duflo [2017] and Neumark [2018] for some examples). After discarding the originals, the weight-manipulated

[18] To proxy for socioeconomic status, I use wards of residence (smallest Ugandan census unit). I rank and stratify the wards according to a poverty index based on dwelling characteristics, access to credit, and food security. The procedure is detailed in online Appendix B1.

[19] The average BMI for respondents living in the Greater Kampala districts was 25.14 in the Uganda National Panel Survey, 2019–2020 (Uganda Bureau of Statistics 2021).

[20] Photo manipulation allows me to isolate one trait at a time but, in turn, may give rise to ethical issues related to stereotyping. Research benefits and costs should be evaluated case by case. In this setting, stereotyping risks are low because obesity is more objectively defined based on a single parameter, body size, as compared to concepts like gender or race. Moreover, alternative ways to experimentally manipulate body size appeared problematic during piloting activities. For example, using original portraits of people with different body sizes led to many confounds (e.g., ethnicity), while height and weight numbers conveyed no information since respondents were unfamiliar with the measures.

[21] White-race portraits are computer generated.

Table 1—Descriptive Statistics

Variables	Beliefs experiment		Credit experiment			
	General population		*Loan officers*		*Institutions*	
	Mean	SD	Mean	SD	Mean	SD
District: Kampala	0.63	0.48	0.78	0.41	0.80	0.40
District: Wakiso	0.33	0.47	0.19	0.40	0.18	0.39
District: Mukono	0.03	0.18	0.03	0.16	0.02	0.14
Age	37.54	13.30	31.28	7.15		
Gender: Male	1.50	0.50	0.60	0.49		
Body mass index (kg/m^2)	25.66	5.28	24.37	4.62		
Education (Years)	10.15	3.92	15.39	1.79		
Family members	3.57	3.62	3.46	2.13		
Personal income: Under USh 500k	0.76	0.43	0.32	0.47		
Personal income: USh 500k to 1 mil	0.13	0.34	0.40	0.49		
Personal income: USh 1 to 1.5 mil	0.03	0.17	0.22	0.42		
Personal income: USh 1.5 to 2 mil	0.03	0.16	0.04	0.20		
Personal income: Over USh 2 mil	0.06	0.24	0.02	0.14		
Role: Loan officer			0.63	0.48		
Role: Owner			0.14	0.35		
Role: Manager			0.09	0.29		
Performance pay or owner			0.91	0.29		
Years at institution			2.69	2.79		
Can set interest rate			0.56	0.50		
Task: Receive borrowers			0.88	0.32		
Task: Provide product information			0.95	0.21		
Task: Review personal information			0.95	0.21		
Task: Review financial information			0.91	0.29		
Task: Refer borrowers to next step			0.80	0.40		
Task: Recruit new borrowers			0.75	0.43		
Task: Approve borrowers			0.74	0.44		
Task: Collect credit			0.68	0.47		
Task: Verify financial information			0.82	0.39		
Days/week to verify information			2.32	1.45		
Borrowers met daily			8.12	8.56		
Type: Credit institutions					0.01	0.08
Type: Microfinance institutions					0.22	0.41
Type: Non-deposit-taking MFIs					0.14	0.35
Type: Licensed moneylenders					0.64	0.48
Branches					6.09	21.94
Employees per branch					6.18	6.54
Offer personal and business loans					0.90	0.31
Interest rate USh 1 mil					11.82	7.07
Interest rate USh 5 mil					11.90	7.27
Interest rate USh 7 mil					11.62	7.15
Observations	511		238		143	

Notes: All data are self-reported, except for the body mass index (BMI) information. In the general population (laypeople) sample, the BMI is measured by enumerators using a height board and a scale. In the loan officers sample, enumerators note the loan officer BMI using the Body Size Scale for African Populations, developed and validated by Cohen et al. (2015).

portrait set is composed of 34 portrait pairs, each made of the thinner and fatter version of the same portrait (online Appendix Figure G1). Half are men and half are women.

To identify the effect of obesity, I randomly assign decision-makers to view the thinner or fatter version of the original portraits. Kampala residents perceive the thinner portraits as normal weight, while fatter portraits are perceived as obese

(BMI greater than or equal to 30).[22] Thus, the average treatment effect captures the effect of obesity relative to normal weight.

Holding the manipulation constant allows for a cleaner identification of the effect of weight changes and is a more powered choice. At the same time, if some thinner portraits were perceived as underweight, it could challenge the interpretation of the results, which may be capturing the effect of "not being thin." Nevertheless, as shown in Appendix Figure A1, the experimental results are unlikely to reflect a thinness penalty. First, all fatter manipulated portraits are perceived as at least obese. Second, none of the thinner manipulated portraits is perceived as underweight, while a few are perceived as overweight.

Design.—In the beliefs experiment, respondents see and rate a sequence of four portraits randomly selected from the weight-manipulated portrait set. The design cross-randomizes obesity with the amount of status signals available in a 2×3 design (online Appendix Figure G3). Along the first dimension, each portrait is shown either in the thinner or fatter version, allowing me to capture the causal effect of obesity, conditional on respondent and portrait pair fixed effects. Along the second dimension, respondents are assigned to one of two treatment arms. In the one-signal arm, respondents face one potential wealth signal (obesity). In the multiple-signal arm, they receive a second wealth signal: either the person owns a car (rich type) or lives in a slum (poor type). In either case, respondents learn the age of the portrayed individuals.

Outcomes.—Respondents rate each portrait along seven characteristics presented in random order: wealth, beauty, health, longevity, self-control (ability to resist temptation), ability to get things done, and trustworthiness. Wealth is the preregistered primary outcome. The secondary outcomes were chosen based on qualities that are anecdotally and positively associated with obesity in low-income countries (health, beauty, life expectancy) and those associated with body mass stigma in high-income countries (self-control, ability). Trustworthiness is a potential determinant of credit outcomes (Duarte, Siegel, and Young 2012). Importantly, having respondents rate portraits in terms of health outcomes allows me to also test whether the body mass variation is capturing the effect of normal weight relative to underweight: if so, one would expect a negative treatment effect on health outcomes.[23]

First-order beliefs—the primary outcome of interest—cannot be incentivized. Because I elicit many characteristics, it is unlikely that respondents guess the experimental hypothesis. Yet lack of monetary incentives may still raise concerns. First, people may not take the evaluation seriously. To address this issue, I elicit an incentivized measure of beliefs as a secondary outcome: beliefs on the most frequent rating given

[22] To quantify the body mass variation, ten independent raters from Kampala evaluate the portraits' perceived body mass. I ask the raters to compare each portrait to the figurative Body Size Scale for African Populations, developed and validated in Cohen et al. (2015) (online Appendix Figure G2). Using the scale, as detailed in online Appendix A, I can convert each rating into an average perceived BMI number for each portrait. BMI is a measure of whether someone is over- or underweight, calculated by scaling their weight in kilograms by the square of their height in meters, and is therefore hard to guess. While BMI has flaws, it is the standard body mass measure used by health institutions like the WHO.

[23] All secondary outcomes were preregistered except for trustworthiness, which was added during the data collection.

by other respondents (beliefs about others' beliefs).[24] Second, and more generally, people's attention may be unnaturally drawn to body mass. To reduce the likelihood of this happening, I include a second salient and visible wealth signal: about one out of four rated portraits is of White people.[25]

B. *Main Results*

Figure 2, panel A plots the average wealth ratings by the portraits' obesity status and other wealth signals. The wealth-rating difference between the obese and nonobese portraits is positive and statistically significant across outcomes and treatment arms. Obesity appears to be a strong wealth signal. To see this, I benchmark the effect of obesity against the effect of car ownership, another common wealth signal.[26] The effect of car ownership in the multiple-signal arm is not statistically different from the obesity effect in the single arm (test p-value $= 0.4397$).

To quantify the value of obesity as a wealth signal, and to test whether obesity affects the perception of other characteristics, I estimate the following regression model:

$$(1)\quad Y_{ij}^{k} = \beta_0 + \beta_1 Obese_{ij} + \beta_2 MultiSignals_j + \beta_3 Obese_{ij} \times MultiSignals_j + \alpha_i + \gamma_j + u_{ij},$$

where Y_{ij}^{k} is the rating with respect to outcome k of portrait i by respondent j. $Obese_{ij}$ is a dummy variable for portrait i being displayed to respondent j in the obese version. $MultiSignals_j$ is a dummy variable for whether respondent j was assigned to the multiple-signal arm. α_i are portrait pair fixed effects, and γ_j are respondent fixed effects. Standard errors are clustered at the respondent level. The coefficient of interest is β_1, which captures the effect of obesity on ratings, controlling for portrait-specific characteristics and respondent rating leniency thanks to the fixed effects.

Figure 2, panel B visualizes the main results by comparing the effect of obesity on wealth ratings to the effects of obesity on the other ratings. Table 2, panel A reports the corresponding regression analysis. The same portrait in its obese version is rated 0.7 standard deviations ($p = 0.000$) wealthier as compared to its nonobese counterpart. In contrast, obese portraits are not perceived as more beautiful, healthier, or more likely to live a long life.[27] Obesity is also not associated with trust, the

[24] The portraits are introduced with the following: "Imagine you just met this person for the first time in Kampala …" The wording for first-order beliefs is "How would you rate this person's $outcome? Please, provide your answer on a scale from 1 (not at all $outcome) to 4 (very $outcome)." For beliefs about others' beliefs, the wording is "How did other respondents rate this person's $outcome? Please provide your best guess of the most frequent answer on a scale from 1 (not at all $outcome) to 4 (very $outcome)." Second-order beliefs are incentivized using pilot data.

[25] White-race portraits are excluded from the analysis.

[26] In Uganda in 2016, there were 40 registered motor vehicles per 1,000 inhabitants. As a comparison, in the United States there were 838 cars per 1,000 inhabitants and 716 per 1,000 in Switzerland. The experimental text does not specify a model, but field officers were trained to report average car models if prompted by respondents' clarifying questions.

[27] The same respondents appear to be aware of the health costs of obesity (mortality risk) in a survey questionnaire at the end of the beliefs experiment. I see two possible explanations for the apparent inconsistency between

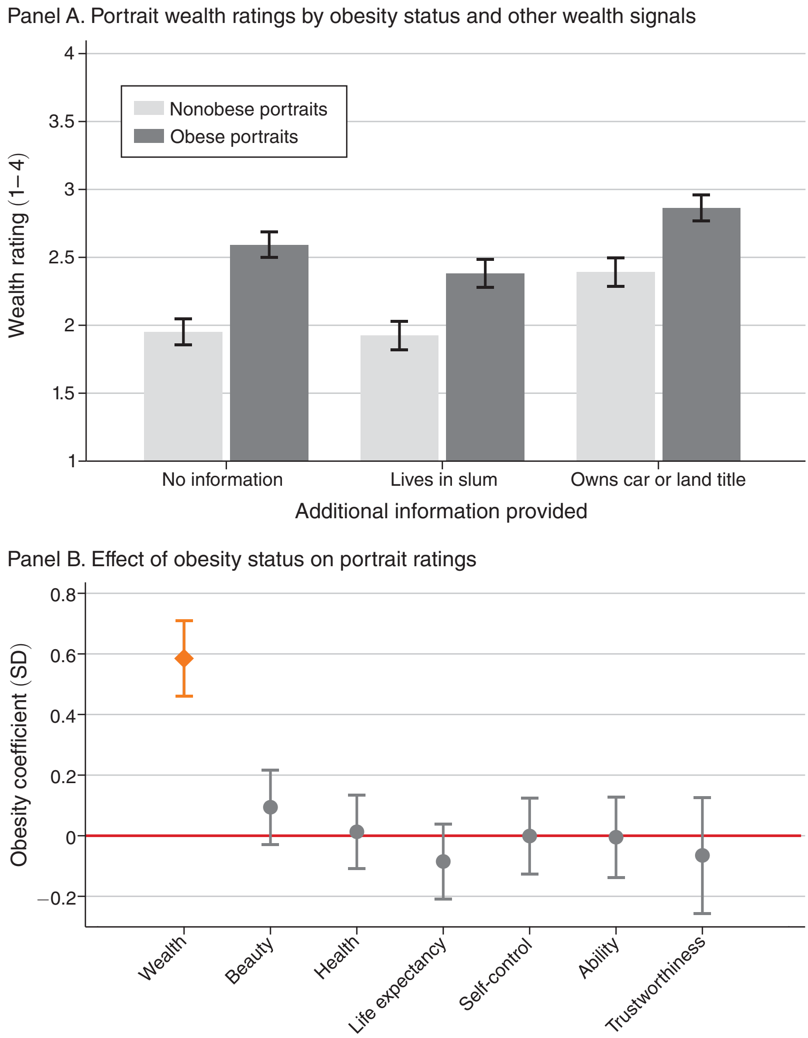

Figure 2. Beliefs Experiment Results

Notes: The figure plots the main beliefs experiment results. The bars are 95 percent confidence intervals. A total of 511 respondents rate 3 to 4 Black-race portraits each, for a total of 1,699 observations. Wealth ratings are the preregistered primary outcome. Panel A plots the raw wealth ratings data by the portrayed person's obesity status and other information. About two-thirds of the respondents receive additional wealth signals about the respondents, either asset ownership (rich type) or slum residence (poor type). Panel B plots the obesity coefficient from a regression including all the evaluations, with and without additional wealth information, standardized outcomes, portrait-pair and respondent fixed effects, and standard errors clustered at the respondent level.

ability to get things done, or self-control. These results are robust, as they are not driven by specific portraits: the large wealth-signaling value of obesity does not systematically vary with the portrayed person's characteristics, like age or gender

implicit and explicit beliefs on obesity health risks: either risks are known but not salient or respondents are assuming a positive correlation between health and wealth.

Table 2—Portraits' Ratings by Obesity Status

	Wealth (1)	Beauty (2)	Health (3)	Life expectancy (4)	Self -control (5)	Ability (6)	Trust-worthiness (7)
Panel A. first-order beliefs							
Obese	0.699	0.113	0.005	−0.072	0.052	0.039	−0.358
	(0.077)	(0.081)	(0.088)	(0.079)	(0.083)	(0.093)	(0.691)
Multiple wealth signal	0.677	−0.234	−0.008	0.076	0.215	0.086	0.126
	(0.199)	(0.228)	(0.208)	(0.204)	(0.235)	(0.243)	(0.510)
Obese × *Multiple wealth signal*	−0.190	−0.032	0.014	−0.022	−0.089	−0.074	0.306
	(0.104)	(0.108)	(0.111)	(0.109)	(0.109)	(0.119)	(0.699)
Observations	1,699	1,699	1,699	1,699	1,699	1,699	679
Control mean: nonobese	2.23	2.27	2.34	2.46	2.37	2.51	2.34
Standard deviation	0.89	0.88	0.90	0.85	0.93	0.91	0.86
Panel B. beliefs about others' beliefs							
Obese	0.731	0.320	0.227	0.154	0.171	0.102	−0.504
	(0.079)	(0.082)	(0.090)	(0.093)	(0.090)	(0.091)	(0.441)
Multiple wealth signal	0.406	−0.370	0.178	0.055	−0.043	0.134	0.149
	(0.193)	(0.208)	(0.202)	(0.201)	(0.179)	(0.218)	(0.557)
Obese × *Multiple wealth signal*	−0.110	−0.081	0.007	−0.028	0.039	0.044	0.565
	(0.103)	(0.104)	(0.114)	(0.115)	(0.114)	(0.116)	(0.454)
Observations	1,699	1,699	1,699	1,699	1,699	1,699	679
Control mean: nonobese	2.30	2.27	2.32	2.42	2.35	2.49	2.28
Standard deviation	0.93	0.91	0.90	0.86	0.93	0.90	0.82

Notes: The table summarizes the main results from the beliefs experiment. All regressions include respondent and portrayed individual fixed effects. Outcome variables are standardized. For each portrait and outcome, respondents first rate the portrait according to their own beliefs and then, according to their best guess, the most frequent answer of other respondents (incentivized second-order beliefs). Wealth is the preregistered primary outcome. Health, beauty, self-control, ability, and life expectancy are preregistered secondary outcomes. Trustworthiness was not preregistered and was only elicited to 30 percent of the sample. *Obese* is a dummy for the weight-manipulated portrait being shown in the fatter version. *Multiple wealth signal* is a dummy equal to one when the respondent learns a second wealth signal on top of body mass, either place of residence (slum—poor type) or asset ownership (car, land title—rich type). Standard errors clustered at the respondent level in parentheses.

(online Appendix Table G2, columns 1 and 2). Moreover, incentivized beliefs about others' beliefs are broadly consistent with first-order beliefs.[28]

Since people often face more than one signal in real life, I exploit the variation in the number of provided signals across treatment arms to test for obesity relevance. I find that knowing about a person's assets or place of residence reduces the importance attributed to the obesity signal, but the interaction coefficient is small and not statistically different from zero (Table 2, panel A). Focusing on portraits accompanied by asset information or place of residence, obesity and other wealth signals do not appear to substitute each other. Instead, decision-makers appear to account for multiple signals independently (online Appendix Table G2, column 3). Thus, obesity is not only a strong signal but also a relevant one, providing additional information beyond other strong signs of status like place of residence or car ownership.

[28] Table 2, panel B shows that the effect of obesity on wealth ratings is twice as large and statistically different from the effect on any other outcome. The fact that the obesity wealth-signaling value is larger in the second-order beliefs regression than in the first-order beliefs regression may be consistent with pluralistic ignorance.

Taken together, these results show that people routinely use body size to update their beliefs on peoples' wealth and that the wealth-signaling value of obesity, β_1 in the wealth ratings regression, is large and reliable.

II. Credit Experiment: Obesity and Market Benefits

To understand whether being obese matters in economic interactions and to investigate the mechanism behind this, I focus on credit markets. Credit markets are an economically relevant and high-stakes market: distortions in credit screening can lead to inefficiencies both at the micro and macro level. Additionally, access to credit is a major channel to lift people out of poverty. From the perspective of testing for the mechanism, credit markets are typically characterized by information asymmetries, which in poor countries are emphasized by structural monitoring and screening challenges.[29]

A. *Credit Experiment*

In what follows, I describe the credit experiment, a real-stakes experiment involving professional loan officers employed in formal Kampala credit institutions.[30]

Credit Markets in Kampala.—The market for credit in Uganda is heterogeneous, with several types of financial institutions licensed to offer credit and a parallel informal lending market. In the credit experiment, I focus on formal financial institutions, which are classified into four tiers (Atuhumuza et al. 2020).[31] Most of these institutions commonly offer collateralized cash loans.

Some market features highlight the potential role for loan officers' first impression to affect credit outcomes. Loan applications are generally dealt in person, and loan officers have large discretionary power on approval decisions. Borrowers normally show up at a financial institution and wait until a loan officer accepts to meet them, a process that can take more than one day and can conclude in a no-meeting outcome. At this stage, loan officers know little to nothing about the client or the loan requested. It is only when the first meeting happens that the loan officer learns about the borrower financial situation, including the available collateral.

Most of the information the borrower provides during the first meeting is unverified, and usually it cannot be verified on the spot. Based on this unverified information, the loan officer decides whether to disregard the application or to start the verification process. Anecdotally, the verification is a time-consuming and effortful activity that entails verifying collateral ownership, interviewing family and neighbors, and making multiple trips to the home and/or place of business. Depending on

[29] The Ugandan credit market appears very similar to the setting described in Karlan and Zinman (2009), where loan officers face both adverse selection and moral hazard.

[30] The credit experiment was implemented in November 2019 in partnership with IPA Uganda and preregistered on the AEA registry (Macchi 2019a). The data are deposited with the AEA Data and Code Repository at ICPSR (Macchi 2023).

[31] I obtained the list of the universe of financial institutions licensed to provide credit from the Ugandan Microfinance Regulatory Authority (UMRA) or Bank of Uganda. When this experiment was conducted, the list included 25 commercial banks (tier 1); 5 credit institutions (tier 2); 5 deposit-taking microfinance institutions (MFIs, tier 3); and 2,000+ non-deposit-taking MFIs, moneylenders, and saving and credit cooperatives (tier 4).

the verification process outcome, the loan officer decides whether or not to continue with the loan approval process.

Based on qualitative interviews, loan officers expect richer people to be better borrowers.[32] From a disbursement perspective, richer borrowers can afford to borrow more. From a creditworthiness perspective, there is evidence that rich people have better returns to capital or wealth, in both poor and rich countries (De Mel, McKenzie, and Woodruff 2008; Fagereng et al. 2020). Moreover, because loans are fully collateralized—often the asset must be deposited at the institution—and require a guarantor, rich borrowers should not be more likely to engage in strategic default. Lastly, and anecdotally very relevant to the loan officers, richer borrowers have also an ex ante higher likelihood of success in the information verification stage because, for example, they are more likely to actually hold collateral.

Credit Institutions and Loan Officer Sample.—I focus on licensed institutions located in the Greater Kampala area, which are open to the general population and offer a standard set of loans: individual cash loans between USh 1 million and USh 7 million with a 6-month term to maturity and fully collateralized.[33] The population of interest counts 447 institutions.[34] Field officers visited each of these 447 institutions, confirmed eligibility, and asked for management consent to participate in a study aimed at improving matching between borrowers and lenders in Kampala.[35]

Although institutions must actively consent to participate, external validity concerns related to sample selection are minimal. The sample involves more than one-third of the original population (143 out of 447 institutions). Moreover, the participating institutions are broadly representative of the types of institutions providing personal loans in Kampala (Table 1). Most institutions offer both personal and business loans, and their size is heterogeneous, although, as in general in Uganda, most institutions are small (the median number of employees is four). The cost of credit is in line with the Ugandan monthly interest rate in 2019 (10–12 percent). For institutions consenting to participate, field officers asked to interview one to three loan officers. There were two requirements for participating: dealing directly with borrowers and providing written consent.

The final sample includes 238 professional loan officers, whose characteristics are summarized in Table 1. I refer to the respondents as loan officers, but the self-reported occupation set is more diverse: 63 percent self-identify as loan officers, 14 percent own the business, and 9 percent say they are the manager. About one-third are women, and 70 percent hold a bachelor's degree. Most loan officers earn between USh 500,000 and USh 1 million per month, above the median monthly

[32] Banerjee (2003) derives a theoretical framework to explain why asymmetric information can lead loan officers in poor countries to especially favor rich borrowers.

[33] These are selection criteria aimed at creating a homogeneous sample, defined based on focus groups with loan officers and branch managers. On top of informal lenders, the selection excludes institutions that provide credit to certain professional categories (e.g., government employees); those providing relatively large loans, like commercial banks, savings, and credit cooperatives that provide group loans; and lenders offering very short-term loans (e.g., daily loans).

[34] When an institution has multiple branches, I randomly select up to four branches and count each branch as one institution (as does UMRA in the original listing).

[35] The experiment was implemented in partnership with Uganda's Innovation for Poverty Action.

earnings for wage employees in urban areas (USh 300,000 in the Uganda National Population and Housing Census 2014 [Uganda Bureau of Statistics 2016]).

Looking at the tasks loan officers perform, the data confirm respondents' key role in the lending process: 74 percent directly approve loan applications, and 80 percent verify borrower information. Loan officers spend, on average, about half of their working week verifying borrower information: they travel to interview prospective borrower neighbors, family members, and employees and to verify collateral property and value. According to the loan officers, what matters most in getting a loan is collateral (average rating of 2.92, on a scale from 1 to 3), followed by income, guarantor, occupation, nationality, and age.

Flow and Incentives.—In the experiment, I ask loan officers to evaluate the 30 borrower profiles during their working time. The aim is to choose the borrowers they would like to meet with to discuss a loan application. While loan officers know that the profiles are hypothetical, the incentives are as close as possible to a real-life lending decision. At the end of the study, loan officers are actually referred to real prospective borrowers (from the 187 prospective borrowers pool), and I inform loan officers that the referrals will be implemented so that the referred borrowers' characteristics match their choices in the experiment.[36] As previously mentioned, this incentive structure follows closely the IRR recently developed by Kessler, Low, and Sullivan (2019) to test for discrimination in hiring without deception and is incentive compatible in this setting.[37]

Loan officers care about referrals because good borrowers have lower expected verification costs. Moreover, good clients can improve their earnings prospects. Credit markets in Kampala are characterized by many institutions competing for few high-quality borrowers, and who the owner approves for a loan may affect their profits. Most employed loan officers face a form of performance pay.[38] Consistent with the presence of stakes, loan officers spent, on average, two hours on the evaluation exercise and asked for a direct referral (versus referral to the institution) more than 80 percent of the time.

[36] To implement the referrals, I provide borrowers with the name and contact information of the loan officer who would be most likely to meet them to discuss a loan application. The matching is based on observable characteristics except borrower gender and body mass. This choice was a response to the ethical concern of avoiding implementing a biased credit outcome. I train a simple machine learning algorithm (*random forest classifier*) on the experimental data to identify borrower characteristics that give the highest referral request probability for each loan officer. I then apply the algorithm to the 187 prospective borrowers dataset and select the best match. The procedure is detailed in online Appendix C3. Because the exercise occurs during work hours, loan officers also receive a small compensation for their time (US$3).

[37] Kessler, Low, and Sullivan (2019) ask employers to evaluate résumés they know to be hypothetical in order to be matched with real job seekers. In the résumés, they randomize human capital characteristics and the demographics of hypothetical candidates. Their outcomes are employer preferences for candidates and employer beliefs about the likelihood candidates will accept job offers, measured using a cardinal scale.

[38] The relevant performance metric varies across institutions: performance is measured in terms of either quality or quantity of borrowers secured or both. In the sample, the type of performance pay varies among portfolio performance (30 percent), sales volume (30 percent), self-generated or total bank revenue (10 percent). For 18 percent of the loan officers, performance pay takes the form of yearly or quarterly bonuses if the person has done well or has met a specific target.

Borrower Sample and Hypothetical Profiles.—On the borrower side, I collect information on 187 prospective borrowers.[39] Combining prospective borrower data and information from loan officer focus groups, I build 30 hypothetical borrower profiles.[40] Each profile is associated with a name and passport number (blurred) and is cross-randomized to a date of birth, nationality (all Ugandans), loan information (reason for loan, amount, time to maturity), and self-reported financial information (occupation, monthly revenue, monthly profits, and collateral).

Finally, I assign to each profile a portrait—a standard identifier in financial documents in Uganda. The portraits are randomly selected from the set of weight-manipulated portraits of Kampala residents described in Section I. Because there is a thinner and a fatter version for each picture, in total there are 30 profile pairs. Within each pair, profiles differ only in the borrower's body mass (see Appendix Figure A3 for an example). These profiles are realistic because the layout is based on financial documents from two Ugandan commercial banks (Appendix Figure A2) and the information comes from real prospective borrowers. Nonetheless, to make sure there are no unrealistic combinations due to the randomization, the final set of loan profiles is vetted by loan officers during piloting.

Design.—To pin down the relationship between obesity, access to credit, and asymmetric information, the design cross-randomizes borrower obesity status and the degree of asymmetric information between borrowers and lenders. Along the first dimension, I vary borrower body mass by randomly assigning each loan officer to see a loan profile associated with the obese or nonobese version of the same borrower portrait. This allows me to estimate the effect of obesity controlling for loan officer and borrower profile fixed effects.

Along the second dimension, I vary whether the profile displays the borrower self-reported financial information and if so, the quality of that information. In particular, borrowers are randomly assigned to have a low or high debt-to-income ratio (DTI) and a larger or smaller collateral. The resulting experimental design is a 2×3 design (online Appendix Figure G4).[41] For each loan officer, of the 30 profiles evaluated in total, the first 10 randomly selected profiles display the borrower demographics and loan application information (reason, amount, time to maturity). The last 20 randomly selected profiles also display self-reported monthly revenue, monthly profits, collateral, and occupation information.[42]

Table A1 in the Appendix summarizes the realized borrower profile characteristics by the obesity status of the displayed borrower portrait. The obese and nonobese

[39] To identify a population of prospective borrowers, at the end of the beliefs experiment, I collect information on the respondent's credit history and need for a loan. I also elicit consent to be included in a study aimed at improving borrower and lender matching in Kampala.

[40] The procedure is summarized in online Appendix Table G3 and is detailed in online Appendix C2.

[41] When financial information is provided, I also vary whether loan officers can opt in to see more information (10 to 20) or if the information is presented by default (20 to 30). Ex ante, this allows me to test for attention discrimination (Bartoš et al. 2016). In practice, however, the additional information cost is minimal (forgone time), and loan officers opt in to receive more information about the applicants in 99 percent of the cases. In the main analysis, I pool the two subtreatments.

[42] The order of treatment arms was not randomized, which helped loan officers clarify that respondents providing, or not providing, financial information was a design choice rather than strategic decisions of the borrower. Online Appendix Table G4 supports the claim that the treatment arms' order is not confounding the results. For more details see online Appendix C4.

borrower profiles are nearly identical except for body mass: the difference is 14 BMI points, statistically different from 0. Obese and nonobese borrowers have the same average profits and collateral, suggesting that the cross-randomization with financial information worked well. Profiles differ according to the average likelihood of selling clothes or owning a jewelry shop as an occupation. These differences are driven by the small number of profiles within each obesity-gender-occupation cell due to some of the occupations being gender specific. This is not a threat to identification because the randomization is within subject and results rely on both loan officer and profile fixed effects.

Outcomes.—Loan officers evaluate each profile according to four primary outcomes: three cardinal measures (*Approval likelihood*, *Creditworthiness*, and *Financial ability*) and the binary choice of asking to meet with a borrower with similar characteristics. Given the matching algorithm structure, the latter is the actual real choice outcome: choosing to meet a hypothetical borrower increases the likelihood that the loan officer is referred to a real borrower with those characteristics. Importantly, loan officers are only informed that matching is based on their choices but do not know of the algorithm details. As a consequence, I consider all outcomes as equally reliable. I also elicit, as preregistered secondary outcomes, the interest rate charged conditional on approval and, when profiles include self-reported financial information, beliefs on the reliability of the self-reported financial information.[43]

B. *Main Results*

The main statistic of interest is the average rating difference between obese and nonobese borrowers, all else equal. Figure 3 plots the average credit ratings by borrower obesity status (binary) and the predicted credit ratings by BMI (continuous). The left-hand side of the graphs shows that across all main outcomes, obese borrowers have better credit ratings, and these ratings translate into better access to credit because obese borrower profiles are also more frequently asked for a referral (real choice outcome). It also shows the obesity premium is strongest in the absence of financial information but that obesity still matters when borrowers provide self-reported information on income, collateral, and occupation. The right-hand side shows that the credit market benefits of weight gain are linearly increasing in body mass: the benefits start when individuals are overweight, and loan officers do not penalize extreme BMI values, those above and beyond 40 BMI points (obesity of degree III).

To quantify the obesity premium, I estimate the following regression model:

$$Y_{ij}^{k} = \beta_0 + \beta_1 Obese_{ij} + \beta_2 FinancialInformation_{ij} + \beta_3 Obese_{ij} \times FinancialInformation_{ij} + \delta_i + \gamma_j + u_{ij},$$

[43] The order is the following: *Approval likelihood*, *Creditworthiness*, *Interest rate* (if loan officer has discretion), *Financial ability*, *Reliability* (if applicable), and *Referral request*. The wording is in online Appendix C1.

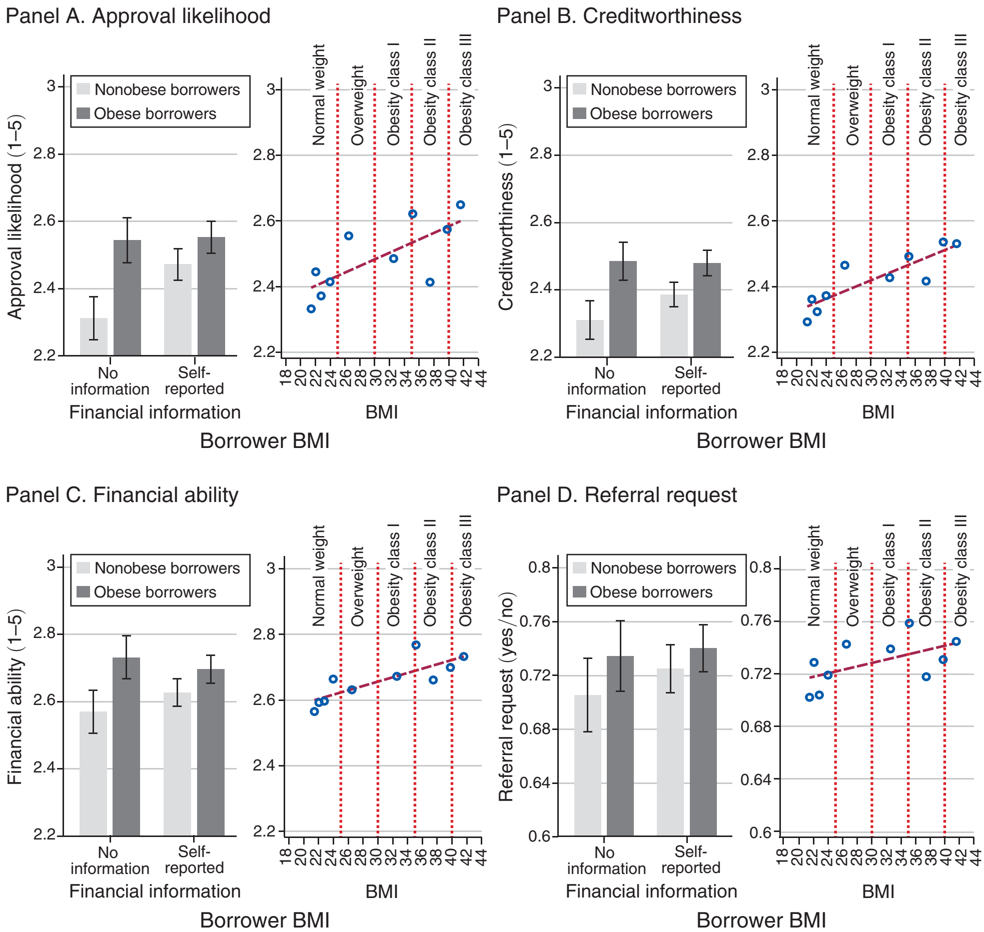

Figure 3. Obesity Premium in Access to Credit

Notes: The graphs summarize the main results from the credit experiment. Respondents are 238 loan officers engaging in 6,645 borrower profile evaluations. Each profile is evaluated along the four primary outcomes. Ratings are on a scale from one to five ("not at all" to "very"), while referral request is a real choice outcome (no/yes). The left-hand-side graphs plot the raw data by borrower obesity status and information provided. The bars are 95 percent confidence intervals. The right-hand-side graphs plot the binned scatterplot of a continuous measure of body mass (BMI, kg/m²) using Stata's *binscatter*. The number of bins specified is ten. Both dependent and independent variables are residualized on borrower profile and loan officer dummies.

where Y_{ij}^k describes outcome k's rating of profile i by loan officer j and $Obese_{ij}$ is a dummy variable for loan profile i being associated with the obese version of a borrower portrait when evaluated by loan officer j. $FinancialInformation_{ij}$ indicates whether profile i included self-reported information on collateral, occupation, revenue, and profits when shown to loan officer j. δ_i are profile fixed effects, and γ_j are loan officer fixed effects. Standard errors are clustered at the loan officer level, and for comparability, I standardize all outcome variables, including the *Referral request* dummy. The coefficient β_1 captures the preferred measure of the obesity premium in access to credit: the premium charged by loan officers absent any financial information about the borrower. It is common for loan officers to make the first decisions in the screening process—namely, whether or not to start the process at all and engage in a first one-to-one meeting—based on very little information. Normally, loan officers know what type of loan the person wants to request and have seen the person in their offices' waiting room (the loan application process is dealt in person).

Table 3 summarizes the estimation results. The obesity coefficient is positive and statistically significant across all outcomes. When associated with obese portraits, the same profile has a higher expected approval likelihood of 0.2 standard deviations ($p = 0.00$, column 1). Consistent with the notion that loan officers perceive obese borrowers as better borrowers, obese borrowers are rated more financially able (0.18 standard deviations, $p = 0.00$, column 2) and creditworthy (0.15 standard deviations, $p = 0.00$, column 3).

Obesity actually leads to easier access to credit: profiles including the obese version of a portrait are more likely to be asked for a referral by 0.07 standard deviations ($p = 0.04$, column 4).[44] The results are robust to a randomization inference exercise (online Appendix Figure G5).

The estimated obesity premium is large. To see this, I can benchmark the gain in access to credit derived from being obese with the benefits of a larger self-reported income (online Appendix Table G5). Across outcomes, the obesity premium is either larger or comparable to a 60 percent increase in self-reported monthly income relative to the mean (USh 1 million, about US\$270–US\$300 more).[45] In percentage terms, the chances that a loan officer asks an obese borrower for a meeting are 3 percentage points higher relative to an average likelihood of 70.5 percent among normal-weight borrowers.

To get a sense of how these results compare with the literature on discrimination, I can express the obesity premium in terms of likelihood ratios (online Appendix Table G7).[46] The obesity access-to-credit likelihood ratio ranges between 1.04 and 1.44 (1.02 and 1.24 when financial information is provided). In absolute value, the estimates are either larger or in line with the obesity penalty found in US peer-to-peer lending markets: in Pope and Sydnor (2011) the funding likelihood ratio of not overweight versus severely overweight is 1.02 (marginally significant). The effect magnitude is also broadly in line with the (negative) effect of obesity in Rooth (2009), a correspondence study on obesity discrimination in hiring in Sweden (1.21 to 1.25).

C. *Mechanism behind the Obesity Premium*

So far, the credit experiment shows that obesity leads to market benefits. My hypothesis is that the obesity premium is a response to an information extraction

[44] Loan officers do not seem to screen using interest rates at this stage of the lending process. About half of them can charge discretionary interest rates, but only 5 percent choose to do so.

[45] Since self-reported profits are randomized, I simply test whether the obesity coefficient in equation (2) (β_1) is statistically smaller or equal to the self-reported profits' coefficient in the corresponding regression model reported in online Appendix Table G4 and represents the effect of a Ush1 million increase in borrower's self-reported profits (60 percent increase relative to the average earnings in the profiles). I use Stata's *suest* and *test*. For all outcomes except *Referral request*, I can reject the hypothesis that the obesity coefficient is smaller or equal to the profit coefficient (the one-sided p-values range between 0.017 and 0.029). For *Referral request*, the test cannot reject the null hypothesis that the obesity coefficient is smaller or equal to the profit coefficient (two-sided p-value: 0.833).

[46] This is straightforward for *Referral request*, a binary outcome. For the cardinal outcomes, I compute the ratio between the likelihood being rated as very likely or extremely likely (rating 4 or 5) to be approved, pay back, or use money productively.

Table 3—Obesity Premium in Access to Credit

	Approval likelihood (1)	Financial ability (2)	Credit-worthiness (3)	Referral request (4)	Information reliability (5)
Obese	0.199	0.180	0.151	0.066	0.043
	(0.034)	(0.037)	(0.038)	(0.033)	(0.017)
Self-reported	0.168	0.118	0.105	0.048	0.000
	(0.040)	(0.041)	(0.042)	(0.049)	(.)
Obese × *Self-reported*	−0.129	−0.082	−0.084	−0.031	0.000
	(0.038)	(0.041)	(0.043)	(0.038)	(.)
Observations	6,645	6,645	6,645	6,645	4,438
Control mean: not obese	2.423	2.362	2.609	0.719	2.015
Standard deviation	1.169	0.965	1.060	0.445	1.078
p-value: *Obese* + *Obese* × *Financial Information* = 0	0.001	0.000	0.006	0.105	

Notes: The table summarizes the main results of the credit experiment. All regressions include borrower profile and loan officer fixed effects. Outcomes are standardized. *Approval likelihood* is the perceived likelihood of approving the application (1–5 scale). *Creditworthiness* is the borrower's perceived creditworthiness (1–5 scale). *Financial ability* is the borrower's perceived ability to put money to productive use (1–5 scale). *Referral request* is a dummy equal to one for the loan officer asking to meet with a similar applicant. *Information reliability* is loan officers' perceived reliability of the financial information provided (1–5 scale), a question that only applied to profiles reporting financial information. *Obese* is a dummy equal to one if the profile displays the borrower portrait in the fatter version. *Financial information* is a dummy for the profile being randomly assigned to include self-reported financial information when shown to the loan officer. Standard errors clustered at the loan officer level in parentheses.

problem: in the absence of verified financial information, obesity reliably indicates that a borrower is rich (as shown in the beliefs experiment) and thus more creditworthy (*statistical discrimination*). A competing explanation is that loan officers prefer obese borrowers for reasons, for example, homophily or attractiveness, unrelated to the obesity wealth signal (*taste-based discrimination*).[47]

To test for statistical discrimination, my design varies the degree of asymmetric information between loan officers and borrowers. The prediction is that borrowers' financial information should reduce the premium under statistical discrimination but should not affect loan officers' idiosyncratic preferences for obese borrowers in any way.[48] Table 3 shows the results. The financial information coefficient captures the asymmetric information variation in the experiment; its interaction with obesity captures the effect of a reduction in asymmetric information on the obesity premium. There are two takeaways. First, the financial information coefficient is positive and significant, meaning that profiles that include self-reported financial information have easier access to credit. This confirms that loan officers value the

[47] While the beliefs experiment results do not highlight a beauty or trust premium associated with obesity, loan officers' preferences may differ from the general population (Palacios-Huerta and Volij 2008).

[48] This design cannot identify the discriminator's animus. Imagine loan officers are biased toward obese borrowers, but when more financial information is available, their bias is harder to justify (to other people or themselves). Then, they would respond less to obesity when information is available, and their behavior would be indistinguishable from "true" statistical discrimination. In my setting, this is relatively less of a concern because most loan officers feel comfortable in admitting that they screen by body size. However, if one were to apply a similar design to a context where discrimination is stigmatized (e.g., gender or race discrimination), this limitation may be more relevant.

financial information provided and suggests that it actually reduces the degree of asymmetric information.[49]

Second, providing additional financial information substantially and significantly reduces the obesity premium: the interaction between obesity and financial information is negative and always statistically significant (except for *Referral request*, which is negative but not statistically significant). Overall, the obesity premium drops by a range between half and two-thirds when loan officers evaluate profiles that include self-reported financial information.[50] For *Approval likelihood*, providing self-reported financial information reduces the obesity premium by nearly 70 percent ($p = 0.041$). Thus, loan officers' behavior appears mostly consistent with statistical discrimination.[51]

Following standard tests of statistical discrimination, I can also test whether the obesity premium varies systematically by borrowers' quality, via a regression allowing for heterogeneity in the borrower DTI ratio. This is possible because, conditional on receiving financial information, the design randomly varies the quality of the financial information shared. Quality variation in the profiles comes mainly from the DTI ratio, defined implicitly from the combination of self-reported income and loan amount requested.[52]

Table 4 presents the results of the heterogeneity analysis. Most of the obesity premium is driven by lower-quality borrowers (high DTI ratio). The test of joint significance between obesity and a high DTI ratio can always reject the null. In contrast, the coefficient of the obesity and low DTI ratio interaction is significant and large enough to undo the main effect for most outcomes. This implies that loan officers mostly respond to obesity when confronting a lower-quality borrower but not as much when confronting a higher-quality one. These results are again consistent with the statistical discrimination interpretation, where obese borrowers are seen as better borrowers (Bertrand and Duflo 2017).[53] Thus, most of the obesity premium appears to be the result of statistical discrimination.

As for the residual obesity premium, in theory, both residual asymmetric information and taste-based discrimination could explain it. Evidence suggests, however, that the residual premium is also driven by unresolved asymmetric information, for two reasons. First, the financial information is self-reported and, on average, is perceived as not very reliable by the loan officers.[54] Notably, the same self-reported

[49] One may find it surprising that loan officers respond to self-reported financial information. However, the information value of collateral information is not zero, for example, because borrowers have to deposit the physical collateral (e.g., car) at the institution. For information-like profits, loan officers anecdotally factor cheap talk to some degree but, perhaps because any excessive overstatement would be easy to detect upon verification, still find the numbers informative.

[50] For transparency, online Appendix Table G6 shows the results, splitting the financial information treatment arm by the timing of information provision. For most outcomes, a statistical test cannot reject the null that providing financial information sequentially or at once has different effects on the way loan officers consider obesity.

[51] Inattention is an alternative explanation for the results: when there is more information, loan officers may pay mechanically less attention to all the baseline characteristics, including body mass. The ideal experiment to test for this hypothesis would be to have a third arm providing nonfinancial information. As an alternative robustness check, in Appendix Table A2 I test for the effect of self-reported financial information on all the cross-randomized characteristics included in the baseline borrower profiles. Reassuringly, I find that the interaction term's sign varies and is not systematically negative.

[52] As shown in online Appendix Table G3, a low DTI ratio ranges between 0.3 and 0.4, while a high DTI ratio ranges between 0.9 and 1.05.

[53] I thank an anonymous referee for suggesting this analysis.

[54] The average reliability rating is 1.98 on a scale from 1 to 5.

Table 4—Obesity Premium in Access to Credit by Borrower Type

	Approval likelihood (1)	Financial ability (2)	Credit-worthiness (3)	Referral request (4)
Obese	0.199	0.180	0.151	0.066
	(0.034)	(0.036)	(0.038)	(0.033)
High DTI ratio	−0.168	−0.078	−0.100	−0.162
	(0.050)	(0.053)	(0.053)	(0.058)
Low DTI ratio	0.501	0.312	0.307	0.257
	(0.052)	(0.052)	(0.051)	(0.057)
Obese × *High DTI ratio*	−0.107	−0.053	−0.046	0.006
	(0.041)	(0.046)	(0.049)	(0.041)
Obese × *Low DTI ratio*	−0.152	−0.113	−0.123	−0.070
	(0.045)	(0.044)	(0.049)	(0.044)
Observations	6,645	6,645	6,645	6,645
Control mean: nonobese	2.423	2.362	2.609	0.719
Standard deviation	1.169	0.965	1.060	0.445
p-value: *Obese* + *Obese* × *High DTI* = 0	0.001	0.000	0.002	0.012
p-value: *Obese* + *Obese* × *Low DTI* = 0	0.149	0.038	0.428	0.899

Notes: All regressions include borrower profile and loan officer fixed effects. All outcomes are standardized for comparability. *Obese* is a dummy equal to one if the application included the obese version of the original picture. *DTI ratio* is a categorical variable. *Low DTI ratio* indicates borrowers reported DTI ratios between 30 percent and 40 percent; *High DTI ratio* indicates DTI ratios between 90 percent and 105 percent. The omitted category represents profiles not reporting any income information. While anecdotally borrowers with DTI ratios as high as 95 percent can be approved, these high values indicate relatively low borrower quality. Standard errors clustered at the loan officer level in parentheses. *Standard deviation* refers to the nonstandardized dependent variable.

information is perceived as more reliable when associated with an obese borrower (Table 3, column 5), providing additional evidence that loan officer behavior is consistent with statistical discrimination.[55] Second, loan officers declare to consider other information not included in the profiles, such as the existence of a guarantor, in their decision-making (see Table 1).

In contrast, I find no empirical evidence in support of taste-based discrimination. The results of the beliefs experiment do not suggest any beauty, health, or trustworthiness premium. In the credit experiment, the obesity premium is stronger for male borrowers and persists in same-sex borrower/lender pairs (online Appendix Table G8). The size of the premium is also not systematically correlated with observable loan officer characteristics, as shown in online Appendix Table G9, including body size, confirming that the premium is inconsistent with homophily. Taken together, the results consistently point at loan officers engaging in statistical discrimination.

[55] People who apply for loans need a minimum of collateral, which makes them, on average, wealthier as compared to a random draw of the population. In fact, the self-reported income in the profiles is above average, and all prospective borrowers state to own some collateral.

D. *Discussion and External Validity*

Loan officers in the credit experiment prefer obese borrowers, all else equal, and their behavior is consistent with statistical discrimination. They see obese borrowers as richer and therefore more creditworthy. Obesity also likely matters outside the experimental setting, for real-life credit outcomes. First, the experiment has real stakes, and since I never refer explicitly to obesity, experimenter demands are unlikely. Second, the information loan officers face is as close as possible to real life.

Third, and most notably, when asked directly, both the general population and the loan officers say they expect obese people to have better credit outcomes as compared to normal-weight people. For example, in an open-ended question at the end of the experiment, about 90 percent of the loan officers state that an obese borrower is more likely to get a loan as compared to a normal-weight borrower (Figure 4). Based on the results, the obesity premium will be larger at earlier screening stages, when little to no financial information is available.[56] The fact that I can still detect an obesity premium even conditional on self-reported financial information, however, means that obesity also matters at later stages of the lending process and implies pervasive effects on credit market outcomes.[57]

Consistent with obesity benefits having real-life relevance, data from the Uganda National Panel Survey (UNPS) 2019–2020 show a positive correlation between BMI and access to credit.[58] The analysis is summarized in Appendix Table A3. First, in the nationally representative data in column 1, being overweight is associated with a higher likelihood of accessing credit (0.11 percentage points, p 0.047), and being obese appears to be associated with an additional premium (0.07 percentage points, p 0.204). These results are in line with the credit experiment results (see binned scatterplot in Figure 3). Second, the weight gain premium observed in the nationally representative data is driven by borrowing from for-profit institutions as opposed to nonprofit lending. Indeed, there is no statistically significant weight premium for respondents who borrow from nonprofit lenders, which normally target the poor and thus are not likely to screen for wealthy borrowers (Appendix Table A3, column 2). This result provides additional support to the fact that loan officers value obesity because it is a proxy for wealth.[59]

One limitation of the design is that it does not allow me to test whether statistical discrimination is accurate or inaccurate. Indeed, tests of inaccurate statistical discrimination as in Bohren et al. (forthcoming) are outcome based, but in the credit experiment I cannot measure borrowers' outcomes by design because profiles are hypothetical. More data on loan performance by body size, or appearance in general, would be needed to fully conclude whether loan officers are biased. I will return to

[56] The baseline information (demographics, loan profile, appearance) is what is normally available to loan officers when choosing whom to meet, as described in Section IIA, paragraph "Credit Markets in Kampala."

[57] Gauging the overall level of discrimination from single stages, in settings with subsequent screening stages, can be misleading (Bohren, Imas, and Rosenberg 2019). Absent information on obesity discrimination at future stages, a weighted sum of the obesity discrimination in the two treatment arms could be a lower bound to the overall discrimination in Kampala credit markets.

[58] Uganda Bureau of Statistics (2021).

[59] Note that the correlational premium appears larger than the experimentally identified one both in absolute terms and in percentages. This is consistent with both omitted variable bias or selection, whereby obese/overweight borrowers are more likely to apply for credit, as they expect to have better chances.

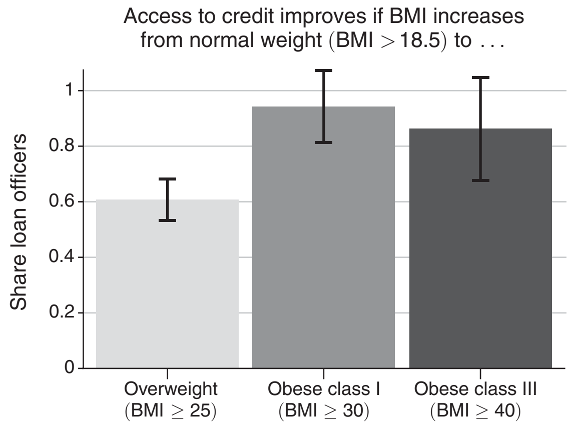

Figure 4. Loan Officers' Explicit Beliefs on Returns to Body Mass in Access to Credit

Notes: The graph plots loan officers' explicit beliefs on returns to BMI in access to credit, coded from their answers to an open-ended survey question. At the end of the credit experiment, loan officers are shown three body-sized silhouettes (overweight, obese of degree I, and obese of degree III) in pair comparisons and have to state which silhouette in the pair has a higher likelihood of getting a loan. The silhouettes' comparisons are (i) normal weight and overweight, (ii) overweight and obese degree I, and (iii) obese of degrees I and III. The question asks, If a person moves from Silhouette A to B, would he or she be more, less, or equally likely to be considered for a loan? The graph plots the cumulative share of answers coded as "more likely" relative to normal weight.

this point in the following section, when I tackle the question about beliefs accuracy more generally.

III. Beliefs Accuracy

This paper shows that agents rely on obesity as a signal of wealth or earnings when information is scarce. In such a statistical discrimination framework, the accuracy of beliefs about benefits and the signaling value of obesity is relevant to qualify these findings. Are people aware of obesity benefits in credit markets, and are beliefs about the obesity premium or the wealth-signaling value of obesity correct? In what follows, I use additional experimental variation and survey evidence to answer these questions.

I first ask if the general population is aware of the obesity premium in credit markets. To answer this question, I replicate the credit experiment with a sample of Kampala residents (laypeople).[60] In the replication, laypeople see four randomly selected hypothetical loan profiles and guess loan officers' ratings in the original credit experiment (no financial information arm). Before guessing, they are given information on the credit experiment, except for the results and the fact that portraits are manipulated. I then test for misperception by comparing the obesity premium for laypeople's guesses with the actual obesity premium in the original credit experiment.[61] Specifically, I ask laypeople to make two main incentivized predictions for

[60] These are the same people from the beliefs experiment. In the same session, respondents first answer the beliefs experiment section and then the credit experiment replication section. By design, respondents cannot see the same portrait twice.

[61] This exercise is an example of relating research to the views of the general public as a way to qualify research findings, as advocated in DellaVigna, Pope, and Vivalt (2019). In the application, I elicit beliefs implicitly. This is a

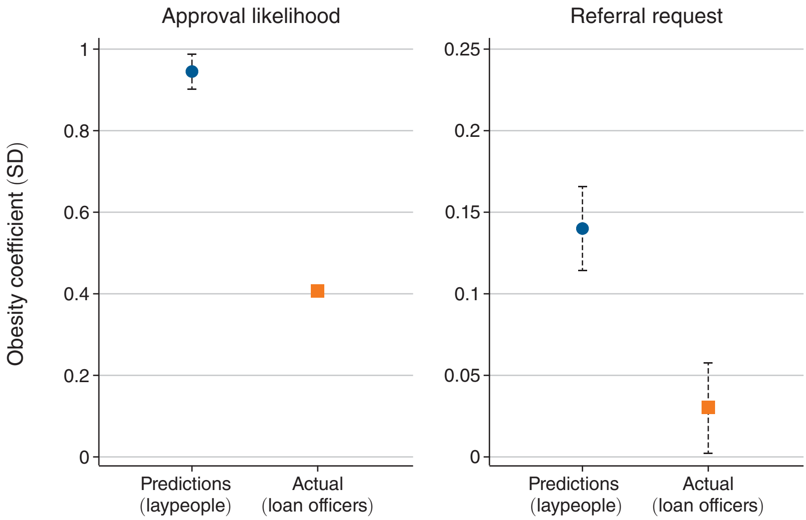

FIGURE 5. PERCEIVED (LAYPEOPLE) VERSUS ACTUAL (LOAN OFFICERS) PREMIUM IN CREDIT MARKETS

Notes: The figure compares laypeople's perceived obesity premium with the actual obesity premium. The perceived premium comes from an incentivized experiment with 511 Kampala residents. Respondents are shown randomly selected borrower profiles and guess (i) loan officers' most frequent *Approval likelihood* rating and (ii) the share of loan officers asking to be referred to a borrower with similar characteristics (*Referral request*). The perceived premium (dots) is the effect of laypeople's obesity evaluations (conditional on layperson and profile fixed effects). The actual premium (squares) is the equivalent coefficient estimated on loan officers' evaluations in the credit experiment. Laypeople overestimate the obesity premium in approval likelihood and referral request by more than two and four times, respectively.

each profile: (i) the number of loan officers who requested the referral of a similar applicant (scale: 0 to 10) and (ii) the most common loan officers' approval likelihood rating (scale: 1 to 5).

Figure 5 summarizes the results. Laypeople are aware of obesity benefits in credit markets but overestimate them substantially. The implicit obesity premium guessed by laypeople is significantly larger than the actual one for both outcomes. In regard to approval likelihood, laypeople overestimate by a factor of two, and the extent of the overestimation is stronger for referral requests. Those who are themselves overweight or obese overestimate the premium more.[62] In theory, differences between guesses and the actual premium may also reflect inaccurate beliefs on the elasticity or variation in lending decisions. The data, however, provide little support to this alternative explanation, as loan officers do not systematically overestimate the importance of other traits for lending (online Appendix Figure G8).

Having established that laypeople overestimate the obesity premium in credit markets, I next ask whether they also hold inaccurate beliefs about obesity's wealth-signaling value. To answer this question, I elicit laypeople's incentivized beliefs on the earnings of obese and normal-weight people in Kampala. Since most

conservative choice that can reduce the concerns of experimenter demands, likely more relevant among nonexpert populations.

[62] The estimates are obtained from a regression model including both respondent and profile fixed effects. For comparability, the credit experiment benchmark is estimated on the subsample of loan profiles displayed without financial information.

people are not used to associating BMI values to body sizes, I elicit income guesses referring to a normal-weight and an obese silhouette from the Body Size Scale for African Populations. In this beliefs survey, I interview 124 Kampala residents.[63] To investigate beliefs accuracy, I then use, as a benchmark, the self-reported income of obese and normal-weight people in the beliefs experiment.[64] For each of the 511 respondents in the beliefs experiment, I measure height and weight using a weight scale and a height board and ask about self-reported monthly earnings. The beliefs elicitation is incentive compatible. To elicit beliefs, I ask respondents to guess the income of people who live in Kampala and who look like certain silhouettes in the Cohen et al. (2015) Body Size Scale, as if they just met them on the street.[65]

To test for misperception, I use the beliefs data to estimate, for each respondent, the perceived average income difference between obese and normal-weight people. Figure 6 plots the distribution. According to my benchmark data, the average obese person in Kampala earns about US$110 per month more than the average normal-weight person.[66] Laypeople's beliefs are heterogeneous, but on average they overestimate the true value by two to three times. The average layperson estimates the average income difference to be about US$230.

The results are robust to removing potential outliers, for example, by winsorizing 1 percent of the beliefs distribution. The estimated average difference on the winsorized sample is still almost twice as large as the true difference (US$206). Misperception also appears unlikely to be due to people misunderstanding the exercise. Laypeople are accurate when they guess the income of normal-weight people in Kampala (the average guess is US$114), but they overestimate the income of Kampala residents who are obese. Thus, laypeople overestimate the wealth-signaling value of obesity.

The evidence of overestimating the obesity wealth-signaling value among the general population could imply that loan officers also place too much weight on obesity in lending decisions. At the same time, experts—loan officers in this case—may have more accurate beliefs relative to the general population because of their training or the stakes involved (Palacios-Huerta and Volij 2008). The credit experiment is not set to provide a definitive answer to this question. First, I do not elicit loan officers'

[63] The original plan was to elicit beliefs from the same sample of respondents from the beliefs experiment in a follow-up in-person survey. Due to the COVID-19 pandemic, the survey had to be run remotely. The first 49 interviews were run on the phone. This initial approach had limitations because it was complicated to refer to the visual body mass scale. We therefore switched to an online Qualtrics survey. As many of the respondents in the beliefs experiment did not own a smartphone, we recruited a new sample ($N = 75$) recruited through WhatsApp. The sample characteristics are in online Appendix Table G11. More details can be found in online Appendix D1.

[64] Ideally, the benchmark data would come from a nationally representative survey. However, to my knowledge, there are no publicly available data on body mass and personal income for Kampala or Uganda. The DHS measure of socioeconomic status is an asset-based wealth index at the household level, which is a relative measure and an intuitive one to guess. The UNPS 2019 elicits personal income (wage) only for employees, a small share of the population, who also tend to be less likely to be obese. Self-employment income is defined as revenue at the household level only.

[65] Respondents are informed that the closer their answer was to the average income of a randomly selected group of Kampala residents with that body size, the higher the likelihood of receiving a bonus. This description mimics the recruitment of the beliefs experiment sample, which simply involved interviewing people on the street and taking their measurements.

[66] The average monthly income of normal-weight and obese people in the beliefs experiment is US$106 and US$217, respectively. These numbers are based on the subset of respondents in the beliefs experiment with a BMI between 16 and 21 ($n = 93$) and those whose BMI is between 32 and 43 ($n = 55$). I chose these two ranges to match the BMI range of the silhouettes in the Body Size Scale that I use to elicit income beliefs (Silhouette 2 and Silhouette 8) and displayed in online Appendix Figure G3.

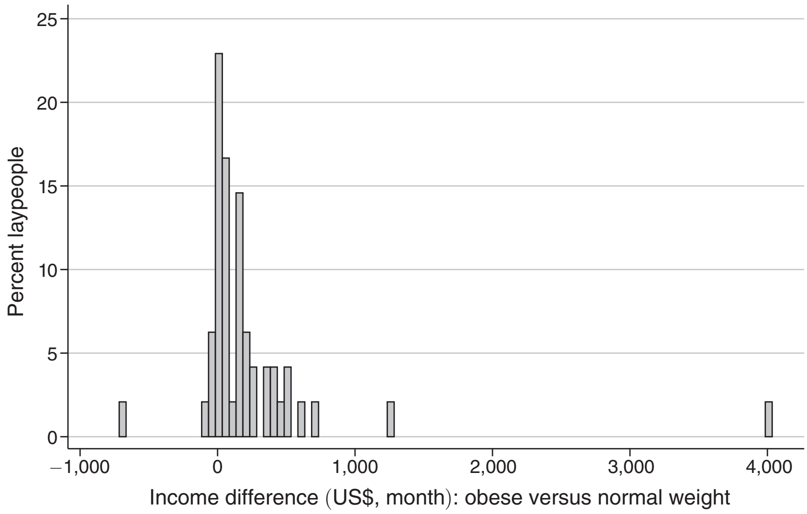

FIGURE 6. BELIEFS ON EARNINGS PREMIUM ASSOCIATED WITH OBESITY

Notes: The histogram plots the distribution of laypeople's beliefs on difference in monthly income between obese and normal-weight Kampala residents. The data are from the beliefs accuracy survey (Observations = 124). Beliefs are elicited by asking respondents to guess the monthly income of a randomly selected normal-weight and obese Kampala resident using the Body Size Scale for African Populations (Silhouette 2 and Silhouette 8). To build the beliefs distribution, for each respondent I take the difference between the two guesses. The plotted distribution is winsorized at the 99 percent level.

beliefs on earnings by body size. Second, outcome-based tests of accurate statistical discrimination are unfeasible by design: I cannot measure loan performance because the borrowers are hypothetical. Looking at UNPS 2019 data, there is some suggestive evidence that a heavier weight may have some correlation with creditworthiness. The repayment likelihood—the likelihood that a person has made payments into repaying a debt during the previous year, conditional on borrowing—positively correlates with BMI (Appendix Table A3, column 3). Yet, lacking an identification strategy to account for selection and omitted variable bias, the evidence should be taken as purely descriptive and does not allow to conclude whether loan officers' preference for obese borrowers is justified on average by their performance.

Moreover, the fact that the obesity premium is very heterogeneous across loan officers may provide some suggestive evidence of inaccurate beliefs. Indeed, under statistical discrimination, accurate beliefs would imply a homogeneous obesity premium across loan officers (Akerlof 1976): borrowers with the same BMI should face the same premium, independent of the loan officer. While measurement error is likely driving at least some part of the heterogeneity, the fact that a large part of the premium variation cannot be explained by loan officers' performance pay (online Appendix Table G9)—by the set of portraits evaluated, by unobservables, nor by each loan officer's perceived importance of financial information for access to credit—suggests that differences in beliefs may explain a substantial part of this variance.[67]

[67] Because loan officers evaluate 30 profiles each, I can estimate the total obesity premium (P) for each loan officer. Exploiting the cross-randomization of obesity, and the amount of financial information at the loan officer

Bias and heuristics may be one reason why people hold systematically inaccurate beliefs (Fiske 1998). For example, both the overestimation of the obesity premium and the wealth-signaling value are consistent with a stereotyping model as in Bordalo et al. (2016), where heavier weight is a representative trait of rich people. Another explanation could be lack of information. Without credit scores, even loan officers may not have enough data to build accurate beliefs. Learning could mitigate inaccurate beliefs, but the literature, summarized in Bohren et al. (forthcoming), suggests this is often not the case. Learning traps are particularly relevant under "pluralistic ignorance" (Katz, Allport, and Jenness 1931), a phenomenon consistent with the evidence according to which people think the obesity signal is more relevant to others than to themselves (Table 2, panel B).

IV. Conclusion and Implications for Policy

Exploiting an experiment with loan officers from many credit institutions, this paper shows that being obese largely increases one's chances of accessing credit in Kampala, Uganda. Looking at the mechanism, loan officers screen borrowers by body mass in response to asymmetric information (statistical discrimination). The underlying reason, as shown in a separate beliefs experiment, is that, in this context, obesity is perceived as a strong and reliable wealth signal. While these beliefs may be compatible with standard models of Bayesian updating (rich people are more likely to be obese in Kampala), additional experimental and survey evidence shows that people largely overestimate both obesity wealth-signaling value and its credit market benefits.

I interpret these results as to show that in poor countries visible signs of status, like obesity, provide information about a person's financial standing. In turn, this generates sizable market benefits because this noisy information, likely because of its accessibility, becomes valuable in settings with severe incomplete information problems, as in the studied credit context. The identified mechanism appears general enough to suggest that in poor countries status symbols lead to benefits in other interactions too.

The estimated obesity credit market benefits likely signal a host of underlying benefits to being obese in poor countries. Different from existing qualitative accounts of the positive perception of heavier weight, my experimental results causally identify the benefits and credibly pin down the wealth-signaling channel. While the main results are drawn from the one setting (Kampala), I find that obese portraits are similarly rated as wealthier and more creditworthy than nonobese ones in a small-scale

level, I can estimate the residual premium (T) capturing any potential preference for obese borrowers orthogonal to the financial information value of obesity and the effect of unobservable borrower characteristics that may be associated with obesity. Finally, because I also cross-randomize obesity with the quality of the financial information provided, I can estimate the effect of self-reported earnings, and collateral on creditworthiness (E), capturing differences in loan officer beliefs on the importance of wealth/earnings for credit. I focus on the 165 loan officers who evaluate all 30 loan applications. I find that T and E together can explain only a very small part of the total variation in P: the R^2 in a bivariate regression ranges between 1 percent and 5 percent across the four primary outcomes (online Appendix Table G11). Note that this estimation is very data intensive, as it is based on only 30 data points per loan officer.

experiment set in rural Malawi.[68] This suggests that obesity socioeconomic benefits exist in settings where body mass positively correlates with wealth or earnings and asymmetric information is widespread, as in many low-income countries.

The efficiency implications of screening by body mass are ambiguous. Easy-to-access financial information may reduce the cost of credit, but inaccurate beliefs can lead to an inefficient demand and supply of credit relative to a full information framework. The nature of the credit experiment, based on hypothetical profiles, does not allow me to test for whether obese borrowers have better performance. While facilitating loan officers' access to accurate information at earlier stages of the screening process is likely to improve efficiency, this paper cannot say whether, for example, banning visual identifiers in loan applications would lead to an improved allocation of credit. Other work is needed to quantify the efficiency implications of screening by status symbols.

Obesity benefits—which, at least in the context of credit, appear to be large and salient—also affect health policy in poor countries. First, directly, because they induce a trade-off with the associated health risks of obesity, which affects the calibration of anti-malnutrition policies. As an example, in the sin tax framework of Allcott, Lockwood, and Taubinsky (2019), I find that the higher the monetary benefits of weight gain, the lower the optimal sugar tax for Uganda.[69] Second, indirectly, because they can influence people's behavior. Indeed, qualitative interviews revealed that respondents most commonly associated weight gain with the desire to command respect or prestige and show off wealth (Appendix Figure 4)[70] The identified cultural-specific perception of obesity highlights the need for more research on both ends of the malnutrition spectrum in poor countries.

[68] Online Appendix Figure G6 shows the Malawi results. The same experiment in a small-scale Amazon MTurk pilot with US workers gives opposite and smaller effect magnitudes (online Appendix Figure G7).

[69] See online Appendix F.

[70] I note that the fact that people may change their behavior in response to weight benefits does not imply that weight stigma should be considered a strategy to prevent obesity.

Appendix A

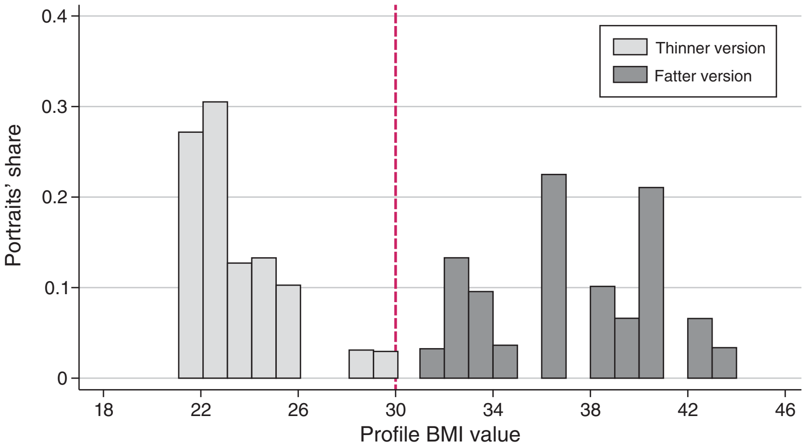

Figure A1. Weight-Manipulated Portraits' Perceived BMI Distribution

Notes: Binned histogram of the 60 manipulated portraits (Black-race only). Bin width: 1 BMI point. The x-axis starts at 18 BMI points, the threshold for normal weight (WHO). The vertical dashed line indicates the obesity cutoff (BMI = 30).

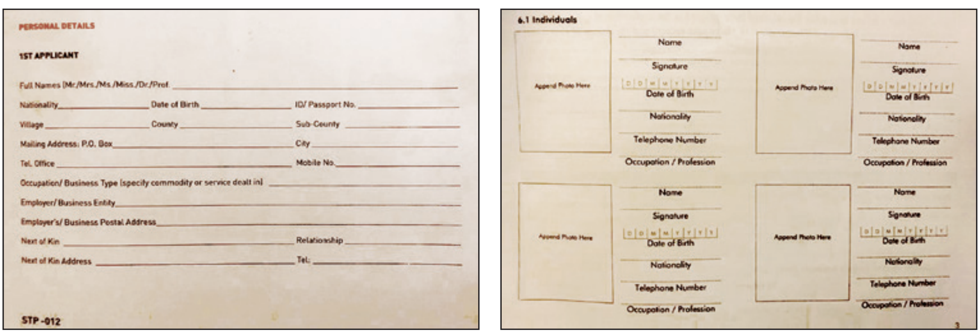

Figure A2. Financial Documents Used as Profiles' Templates

Notes: The figure shows photos of financial applications from two major Ugandan commercial banks that were used to design the hypothetical profiles. The applicant is always supposed to provide a picture, which in the left panel is attached to the application.

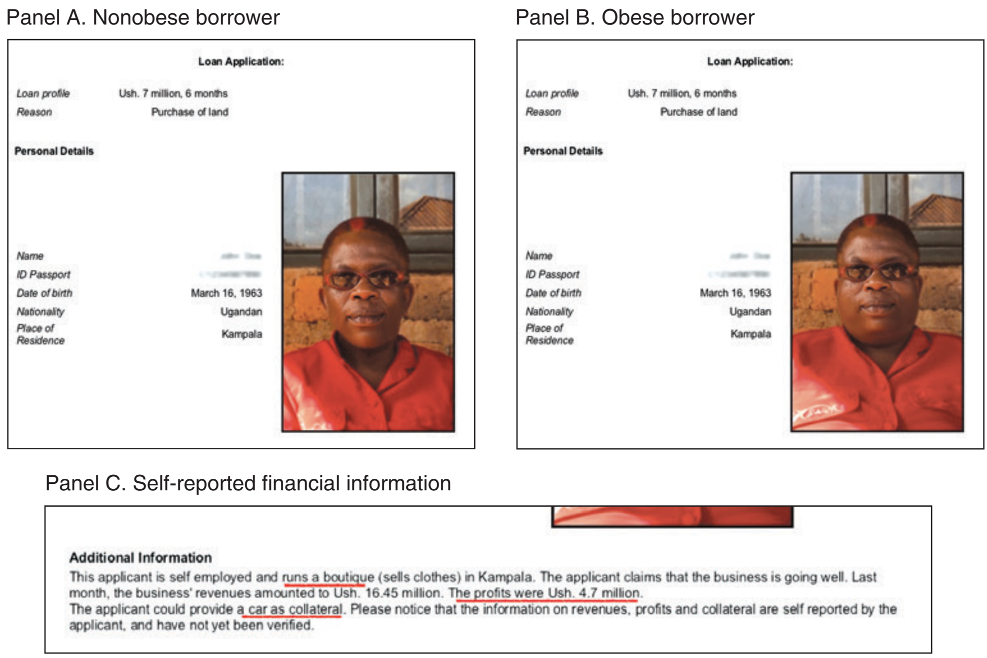

FIGURE A3. EXAMPLE OF BORROWER PROFILE

Notes: The figure presents 1 of the 30 hypothetical profiles. Panels A and B present the thinner and fatter version at baseline (no information). Panel C shows the additional financial information. The displayed portrait and amount of information depend on the treatment assignment.

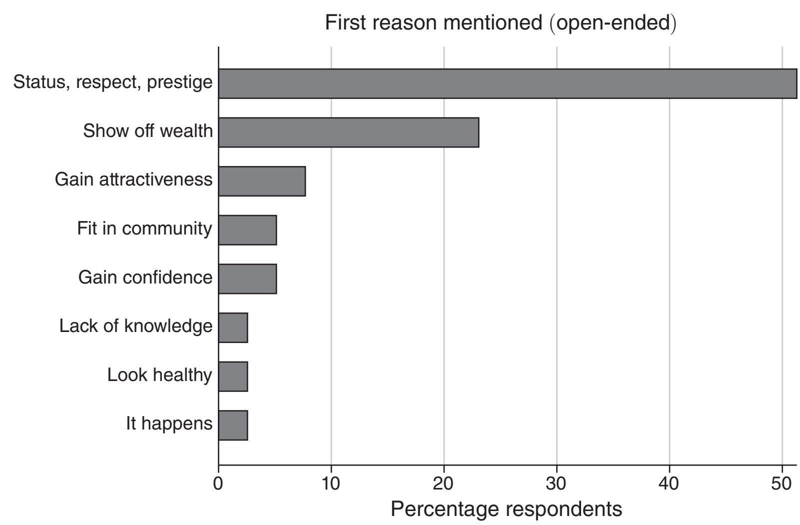

FIGURE A4. REASONS FOR WEIGHT GAIN IN KAMPALA

Notes: The figure plots the distribution of reasons why Kampala residents think people want to gain weight. These categories are based on the first answers to the open-ended question "In Kampala, what are the most common reasons why normal weight people may want to (put effort to) gain weight? Please answer with your best guesses of the 3 main reasons." Respondents are 49 Kampala residents interviewed in the beliefs accuracy sample (phone survey). Ten answers are missing. The open-ended answers are tabulated in online Appendix Table G12.

Table A1—Borrower Profiles' Covariates

	Nonobese		Obese		p-value of difference		
	Mean	SD	Mean	SD	Diff	Standard	RI
BMI	23.34	1.93	37.30	3.40	13.96	0.00	0.00
Age	36.53	9.35	36.89	9.58	0.354	0.21	0.14
Gender: male	0.50	0.50	0.50	0.50	0.003	0.54	0.83
Collateral: car	0.33	0.47	0.33	0.47	0.002	0.77	0.87
Collateral: land title	0.50	0.50	0.50	0.50	−0.006	0.19	0.63
Collateral: motorcycle	0.17	0.37	0.17	0.38	0.004	0.39	0.65
Occupation: produce shop	0.10	0.30	0.10	0.30	0.003	0.57	0.72
Occupation: sells clothes	0.19	0.39	0.21	0.41	0.020	0.06	0.04
Occupation: dairy project	0.10	0.30	0.10	0.30	−0.001	0.91	0.91
Occupation: hardware store	0.10	0.30	0.10	0.31	0.007	0.12	0.34
Occupation: jewelry shop	0.11	0.31	0.09	0.29	−0.016	0.03	0.03
Occupation: mobile money shop	0.21	0.41	0.19	0.40	−0.012	0.05	0.22
Occupation: phone/movies shop	0.10	0.30	0.10	0.30	0.001	0.84	0.91
Occupation: poultry and eggs	0.10	0.30	0.10	0.30	−0.001	0.79	0.87
Revenues USh mil(·)	5.91	4.81	5.83	4.77	−0.078	0.17	0.53
Profits USh mil(·)	1.69	1.37	1.67	1.36	−0.022	0.17	0.53
Order in arm	5.51	2.84	5.50	2.90	−0.010	0.72	0.91
Reason: business	0.20	0.40	0.20	0.40	−0.006	0.33	0.54
Reason: home improvement	0.24	0.42	0.23	0.42	−0.004	0.38	0.70
Reason: purchase animal	0.17	0.37	0.17	0.38	0.004	0.39	0.65
Reason: purchase asset	0.17	0.37	0.17	0.37	0.002	0.66	0.81
Reason: purchase land	0.23	0.42	0.23	0.42	0.004	0.39	0.70
Amount: USh 1 mil(·)	0.33	0.47	0.34	0.47	0.006	0.32	0.60
Amount: USh 5 mil(·)	0.34	0.47	0.33	0.47	−0.011	0.07	0.32
Amount: USh 7 mil(·)	0.33	0.47	0.33	0.47	0.005	0.45	0.67
Observations	6,645						

Notes: Data are from the credit experiment. The "Nonobese" ("Obese") columns indicate if a borrower's profile displayed the thinner (fatter) weight-manipulated portrait. The "p-value of difference" column reports the difference, the standard p-value, and the randomization inference p-value based on 5,000 replications.

Table A2—Inattention Robustness
(Effect of Financial Information on Other Profile Characteristics)

	Approval likelihood (1)	Approval likelihood (2)	Approval likelihood (3)	Approval likelihood (4)
Obese × *Financial information*	−0.129			
	(0.038)			
Age × *Financial information*		0.002		
		(0.003)		
USh 5 million × *Financial information*			0.202	
			(0.058)	
USh 7 million × *Financial information*			0.190	
			(0.069)	
Home improvements × *Financial information*				0.565
				(0.074)
Purchase of an animal × *Financial information*				−0.021
				(0.085)
Purchase of an asset × *Financial information*				0.275
				(0.086)
Purchase of land × *Financial information*				0.352
				(0.069)
Observations	6,645	6,645	6,645	6,645

Notes: Data are from the credit experiment. The table reports the interaction effects of each corresponding saturated model. The regressions' outcome is the *Approval likelihood* (1–5), standardized. *Financial information* is a dummy equal to one if the application was randomly assigned to include self-reported financial information. *Obese* is a dummy for the borrower profile being associated with a fatter weight-manipulated portrait. *Age* is a continuous variable indicating borrowers' age in years. *USh 5 million* or *USh 7 million* are dummies for the loan amount. The residual category is *USh 1 million*. *Home improvements*, *Purchase of land*, *Purchase of an asset*, and *Purchase of an animal* are dummies for the loan reason. All regressions include borrower profile and loan officer fixed effects. Standard errors clustered at the loan officer level in parentheses.

Table A3—Body Mass and Access to Credit Correlation in the Uganda National Panel Survey, 2019

	Borrowed (1)	Borrowed (2)	Repaid (3)
Normal weight	0.067		0.125
	(0.045)		(0.105)
Overweight	0.111		0.008
	(0.056)		(0.129)
Obese	0.070		0.272
	(0.055)		(0.133)
BMI		0.008	
		(0.003)	
Nonprofit institution		1.126	
		(0.143)	
Nonprofit institution × *BMI*		−0.014	
		(0.006)	
Observations	2,181	2,181	237
p-value: *BMI* + *Nonprofit institution* × *BMI* = 0		0.126	

Notes: Data are from the Uganda National Panel Survey, 2019–2020. The table displays the correlation between individual body mass and access to credit, and credit repayment. The outcome in columns 1 and 2 is a binary variable taking value 1 if the respondent has borrowed in the last 12 months. The outcome in column 3 is a binary variable taking value one if the respondent during the last year has repaid some of the money borrowed, conditional on having borrowed during the last year. In column 2, the regression model allows for heterogeneity depending on whether the lending institution is for-profit or not. The regressions include district and household fixed effects and control for gender, age, and gender-specific age trends.

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