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

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Abstract

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%, 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.

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1 Introduction

Status concerns are often seen as futile and potentially wasteful (Veblen, 1899; Frank, 1985; Hopkins and Kornienko, 2004; Bursztyn et al., 2017a). 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 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 (Figure 1) 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 socio-economic 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 et al., 2020; Shekar and

[1] In this paper, I use the word *fat* in support of the body-positivity movement's effort to de-stigmatize this word and to promote a concept of health at any size.

[2] Qualitative studies showing evidence of positive perception of fat bodies include, in addition to Uganda, the following: 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.

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-value = 0.00). To the contrary, I 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 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-value = 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 non-obese 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

[4] While the medical literature debates the existence of health risks of overweight, obesity, defined by the World Health Organization (WHO) as a body mass index (BMI) greater than 30, is associated with a higher risk of developing non-communicable 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, 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.

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

Resume Rating (IRR) recently developed by Kessler et al. (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-value $= 0.00$), more financially able (0.15 standard deviations, p-value $= 0.00$), and more likely to be approved (0.2 standard deviations, p-value $= 0.00$). 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-value $= 0.05$). The obesity premium is large, equivalent to the effect of a 60% 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-randomizes 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 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% to 70%.[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 ex-

[7]The IRR, developed to test for discrimination in hiring in the US, 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 et al. (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., 2018) 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 lower 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 2x2 design (Bertrand and Duflo, 2017), while I randomize both the profile quality and the overall amount of financial information provided (2x3 design). This is a cleaner test of statistical discrimination, which does not require me to assume substitution between signals.

[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 Appendix Table H.7. For example, more information available leads officers to value the requested loan amount *more*.

periment, 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% 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 the final part 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

[10]The beliefs experiment also suggests that the obesity premium is unlikely to be a trust premium as in Duarte et al. (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., 2008 and, less so, not being overweight in Pope and Sydnor, 2011) matters 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 and 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.

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

earnings of obese and normal weight people in the city (N = 124).[14] 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 et al., 2017b). Closely related to this paper is Bursztyn et al. (2017a), 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 et al. (2015) and Fisman et al. (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 et al., 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 socio-economic benefits of obesity in poor countries. Most of the obesity literature focuses on investigating the causes and costs in high-income countries (Cutler et al., 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).

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

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

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

2 Beliefs Experiment: Obesity as a Signal of Wealth

I first design the beliefs experiment to test (1) whether obesity is perceived as a salient signal of wealth, against other traits, and (2) to what extent obesity is a relevant signal when compared to other common status indicators.[17]

2.1 Beliefs Experiment

Sample selection Respondents live 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). They are at least 18 years old and provide written consent. I stratify the sample by age, gender, and socio-economic 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 et al., 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% male but is slightly richer and older than the Kampala average (National Population and Housing Census, 2014). 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 the 2016 Ugandan Demographic and Health Survey (DHS) and the WHO concerns about the rising overweight and obesity risk in urban Africa.

[17] The beliefs experiment was implemented in November 2019 in partnership with IGREC Uganda.

[18] To proxy for socio-economic 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 Appendix B.1.

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.[19] The original portraits are of 30 Kampala residents, plus 4 white-race individuals,[20] 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 portrait set is composed of 34 portrait pairs, each made of the thinner and fatter version of the same portrait. 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 (Appendix Figure G.1). Kampala residents perceive the thinner portraits as normal weight, while fatter portraits are perceived as obese (BMI greater than 30).[21] 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 Figure G.3, 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

[19] 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.

[20] White-race portraits are computer generated.

[21] To quantify the body mass variation, 10 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)'s Appendix Figure G.2). Using the scale, as detailed in 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.

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 2x3 design (Appendix Figure G.4). 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 six characteristics presented in random order: wealth, beauty, health, longevity, self-control (ability to resist to temptation), ability to get things done, and trustworthiness (a potential determinant of credit outcomes Duarte et al., 2012). Wealth is the pre-registered 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). 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.[22]

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 by other respondents (beliefs about others' beliefs).[23] Second, and more generally, people's

[22] All secondary outcomes were pre-registered except for trustworthiness, which was added during the data collection.

[23] 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

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.[24]

2.2 Beliefs Experiment 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 non-obese 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.[25] 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:

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

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.

Table 2 reports the regression analysis results. 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 coefficient of obesity on wealth ratings to the effects of obesity on the other ratings. The same portrait in its obese version is rated 0.7 standard deviations (p-value 0.000) wealthier as compared to its non-obese counterpart (Table 2, Panel A).

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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.

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

[25] In Uganda in 2016, there were 40 registered motor vehicles per 1,000 inhabitants. As a comparison, in the US 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.

In contrast, obese portraits are not perceived as more beautiful, healthier, or more likely to live a long life.[26] Obesity is also not associated with trust, the 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 (Appendix Table H.2, Columns 1 and 2). Moreover, incentivized beliefs about others' beliefs are broadly consistent with first-order beliefs.[27]

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 (Appendix Table H.2, 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.

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.

3 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

[26] 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 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.

[27] 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.

countries are emphasized by structural monitoring and screening challenges.[28]

3.1 Credit Experiment

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

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).[29] 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 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.[30] From a disbursement perspective, richer borrowers can afford to borrow more.

[28] 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.

[29] 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).

[30] Banerjee (2003) derives a theoretical framework to explain why asymmetric information can lead

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 et al., 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 six-month term to maturity and fully collateralized.[31] The population of interest counts 447 institutions.[32] 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.[33]

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%). 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% self-identify as loan officers, 14% own the business,

loan officers in poor countries to especially favor rich borrowers.

[31] 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).

[32] 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).

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

and 9% say they are the manager. About one-third are women, and 70% hold a bachelor's degree. Most loan officers earn between Ush 500,000 to 1 million per month, above the median monthly earnings for wage employees in urban areas (Ush 300,000 in the Uganda National Household Survey 2019/2020).

Looking at the tasks loan officers perform, the data confirm respondents' key role in the lending process: 74% directly approve loan applications, and 80% 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.[34] As previously mentioned, this incentive structure follows closely the IRR recently developed by Kessler et al. (2019) to test for discrimination in hiring without deception and is incentive compatible in this setting.[35]

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-

[34]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 borrower data set and select the best match. The procedure is detailed in Appendix C.3. Because the exercise occurs during work hours, loan officers also receive a small compensation for their time ($3).

[35]Kessler et al. (2019) ask employers to evaluate resumes they know to be hypothetical in order to be matched with real job seekers. In the resumes, 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.

quality borrowers, and who the owner approves for a loan may affect their profits. Most employed loan officers face a form of performance pay.[36] Consistent with the presence of stakes, loan officers spent, on average, two hours on the evaluation exercise and ask for a direct referral (versus referral to the institution) more than 80% of the time.

Borrower sample and hypothetical profiles On the borrower side, I collect information on 187 prospective borrowers.[37] Combining prospective borrower data and information from loan officer focus groups, I build 30 hypothetical borrower profiles.[38] 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 2. Because there is a thinner and a fatter version for each picture, in total there are 30 profiles pairs. Within each pair, profiles differ only in the borrower's body mass (see Appendix Figure G.6 for an example). These profiles are realistic because the layout is based on financial documents from two Ugandan commercial banks (Appendix Figure G.7) and the information comes from real 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 non-obese version of the same borrower portrait. This allows me to estimate the effect of obesity controlling for loan officer and borrower profile fixed effects.

[36] 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%), sales volume (30%), self-generated or total bank revenue (10%). For 18% 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.

[37] 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.

[38] The procedure is summarized in Table H.3 and is detailed in Appendix C.2.

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 2x3 design (Appendix Figure G.5).[39] 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.[40]

Appendix Table H.4 summarizes the realized borrower profile characteristics by the obesity status of the displayed borrower portrait. The obese and non-obese borrower profiles are nearly identical except for body mass: the difference is 14 BMI points, statistically different from zero. Obese and non-obese 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 relevant concern because the results rely on 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 consequences, I consider all outcomes as equally reliable. I also elicit,

[39] 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% of the cases. In the main analysis, I pool the two subtreatments.

[40] 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. Supporting the claim that the treatment arms' order is not confounding the results, Appendix C.4 shows there are no order effects, neither at baseline nor in the interaction with body mass.

as pre-registered 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.[41]

3.2 Credit Experiment Results

The main statistic of interest is the average rating difference between obese and non-obese 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 II).

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

$$\begin{aligned} Y_{ij}^k = \beta_0 + \beta_1 Obese_{ij} + \beta_2 FinancialInformation_{ij} + \\ + \beta_3 Obese_{ij} \cdot FinancialInformation_{ij} + \delta_i + \gamma_j + u_{ij}, \end{aligned} \tag{2}$$

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 officer 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 —

[41]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 Appendix C.1.

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 0.19 standard deviations (p-value = 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-value = 0.00, Column 2) and creditworthy (0.15 standard deviations, p-value = 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-value = 0.04, Column 4).[42] The results are robust to a randomization inference exercise (Appendix Figure G.8).

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 (Appendix Table H.5). Across outcomes, the obesity premium is either larger or comparable to a 60% increase in self-reported monthly income relative to the mean (Ush 1 million, about \$270–\$300 more).[43] 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% 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 term of likelihood ratios (Appendix Table H.9).[44] 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

[42]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% choose to do so.

[43]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 Table H.5 and represents the effect of a Ush 1 million increase in borrower's self-reported profits (60% 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).

[44]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.

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).

3.3 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 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*).[45]

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.[46] 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 financial information provided and suggests that it actually reduces the degree of asymmetric information.[47]

Second, providing additional financial information substantially and significantly re-

[45]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).

[46]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.

[47]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.

duces 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.[48] For *Approval likelihood*, providing self-reported financial information reduces the obesity premium by nearly 70% (p-value = 0.041). Thus, loan officers' behavior appears mostly consistent with statistical discrimination.[49]

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.[50]

Appendix Table 4 presents the results. 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).[51] Thus, most of the obesity premium appears to 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.

[48]For transparency, Appendix Table H.8 shows the results, splitting the financial information treatment arm by the timing of information provision. For most outcome, a statistical test cannot reject the null that providing financial information sequentially or at once have different effects on the way loan officers' consider obesity.

[49]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 non-financial information. As an alternative robustness check, in Appendix Table H.7 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.

[50]As shown in Appendix Table H.3, a low DTI ratio ranges between 0.3 and 0.4, while a high DTI ratio ranges between 0.9 and 1.05.

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

First, the financial information is self-reported and, on average, is perceived as not very reliable by the loan officers.[52] Notably, the same self-reported 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.[53] 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 (Appendix Table H.10). The size of the premium is also not systematically correlated with observable loan officer characteristics, as shown in Appendix Table H.11, including body size, confirming that the premium is inconsistent with homophily. Taken together, the results consistently point at loan officers engaging in statistical discrimination.

3.4 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% 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.[54] The fact that I can still detect an obesity

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

[53] 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.

[54] The baseline information (demographics, loan profile, appearance) is what is normally available to loan officers when choosing whom to meet, for example, among the prospective borrowers who have

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.[55]

Consistent with obesity benefits having real-life relevance, data from the Uganda National Panel Survey (UNPS) 2019 show a positive correlation between BMI and access to credit (Appendix Table H.14). Consistent with the credit experiment data (see binned scatterplot in Figure 3), being overweight is already associated with a higher likelihood of accessing credit and being obesity is associated to an additional premium. As a sanity check, column 2 shows that the weight gain premium observed in the UNPS 2019 is driven by borrowing from for-profit institutions as opposed to non-profit lending which should instead target the poor. 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.

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. (2019b) 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 this point in the following section, when I tackle the question about beliefs accuracy more generally.

4 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.

come to their office.

[55]Gauging the overall level of discrimination from single stages, in settings with subsequent screening stages, can be misleading (Bohren et al., 2019a). 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.

To answer this question, I replicate the credit experiment with a sample of Kampala residents (laypeople).[56] 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.[57] Specifically, I ask laypeople to make two main incentivized predictions for 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.[58] In theory, differences between guesses and the actual premium may also reflect a miscalibration of 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 (Appendix Figure G.12).

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 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.[59] To investigate beliefs accuracy, I then use,

[56] 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.

[57] 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 et al. (2019). In the application, I elicit beliefs implicitly. This is a conservative choice that can reduce the concerns of experimenter demands, likely more relevant among non-expert populations.

[58] 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.

[59] The plan was to elicit beliefs from the same sample of the beliefs experiment, via a follow-up

as a benchmark, the self-reported income of obese and normal weight people in the beliefs experiment.[60] 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 use the silhouette scale in Figure G.2 and I ask respondents to guess the average income of a group of people who look like a given silhouette and live in Kampala, as if they just met them on the street. This description mimics the recruitment of the beliefs experiment sample, which simply involved interviewing people on the street and taking their measurements.

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 \$110 per month more than the average normal weight person.[61] 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 \$230.

The results are robust to removing potential outliers, for example, by winsorizing 1% of the beliefs distribution. The estimated average difference on the winsorized sample is still almost twice as large as the true difference (\$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 \$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 gen-

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in-person survey. Due to the COVID-19 pandemic, the survey had to be run remotely. The interviews, then, were partly run partly on the phone and partly online. The phone sample is a random sample of the beliefs experiment sample. This initial approach had limitations, because we could not refer to the visual body mass scale. We therefore switched to an online sample, recruited by IGREC field officers through WhatsApp. The sample description is in Appendix D.1 and in Appendix Table H.12.

[60] 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 socio-economic 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.

[61] The average monthly income of normal weight and obese people in the beliefs experiment is \$106 and \$217, respectively. These numbers are based on the subset of respondents in the beliefs experiment with a BMI between 16 and 21 ($n = 93$)—the BMI range in Figures 1 and 4)—and those whose BMI is between 32 and 43 ($n = 55$)—the BMI range of Figures 7 and 9. I chose these two ranges because Figure 2 is the normal weight figure for which I elicit income beliefs and Figure 8 is the obese one.

eral 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' 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 H.14, 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 (Appendix Table H.11)—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.[62]

Bias and heuristics may be one reason why people hold systematically inaccurate

[62]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 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 the 30 loan applications. I find that T and E together can explain only a very small part of the total variation in P: the $R2$ in a bivariate regression ranges between 1% and 5% across the four primary outcomes (Appendix Table H.13). Note that this estimation is very data intensive as it is based on only 30 data points per loan officer.

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. (2019b), suggests this is often not the case. Learning traps are particularly relevant under "pluralistic ignorance" (Katz et al., 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).

5 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 non-obese ones in a small-scale experiment set in rural Malawi.[63] This suggests that obesity socio-economic benefits exist in settings

[63] Appendix Figure G.9 shows the Malawi results. The same experiment in a small-scale Amazon

where body mass positively correlates with wealth or earnings (Figure 1, Panel B) and asymmetric information is widespread.

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 et al. (2019), I find that the higher the monetary benefits of weight gain, the lower the optimal sugar tax for Uganda.[64] Second, indirectly, because they can influence people's behavior, as suggested by qualitative interviews.[65] The identified cultural-specific perception of obesity highlights the need for more research on both ends of the malnutrition spectrum in poor countries.

MTurk pilot with US workers gives opposite and smaller effect magnitudes (Appendix Figure G.10).

[64]See Appendix F.

[65]In an open-ended survey question, "commanding respect or prestige" and "showing off wealth" were respondents' most common reasons for why people may want to gain weight (Appendix Figure G.11). 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.

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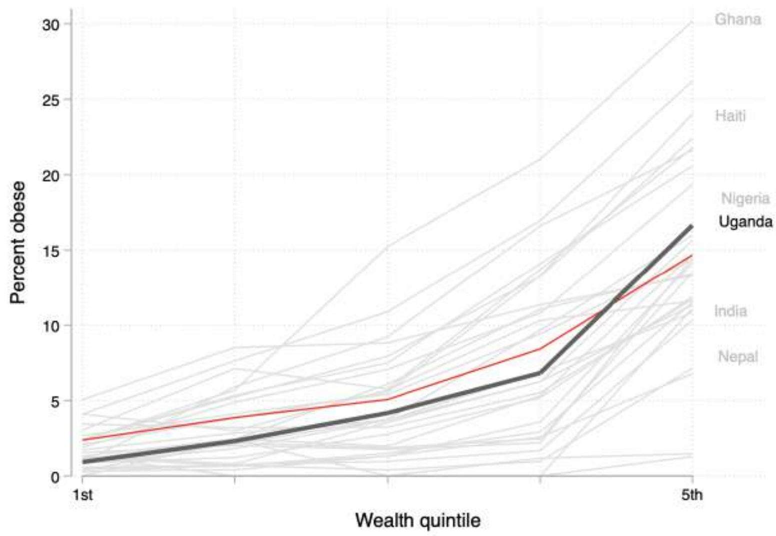
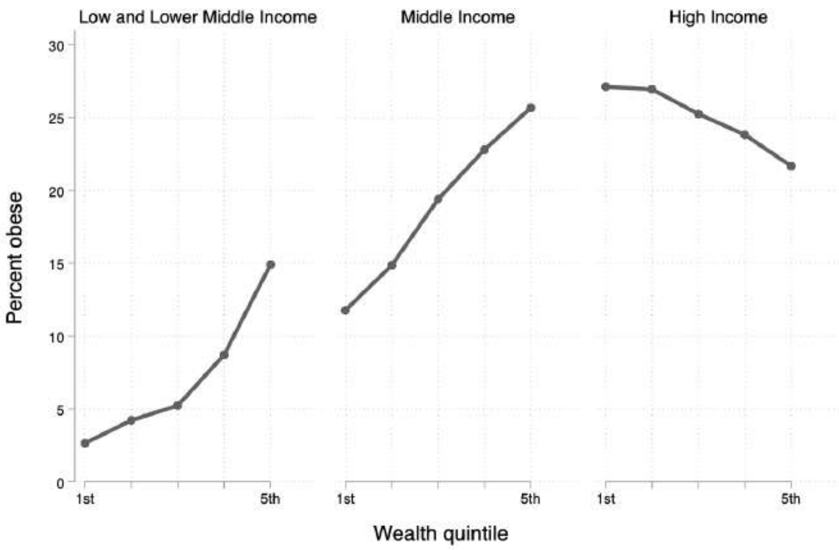
Figures

Figure 1: Obesity Prevalence by Wealth Quintile

(a) Low- and Lower-Middle-Income Countries



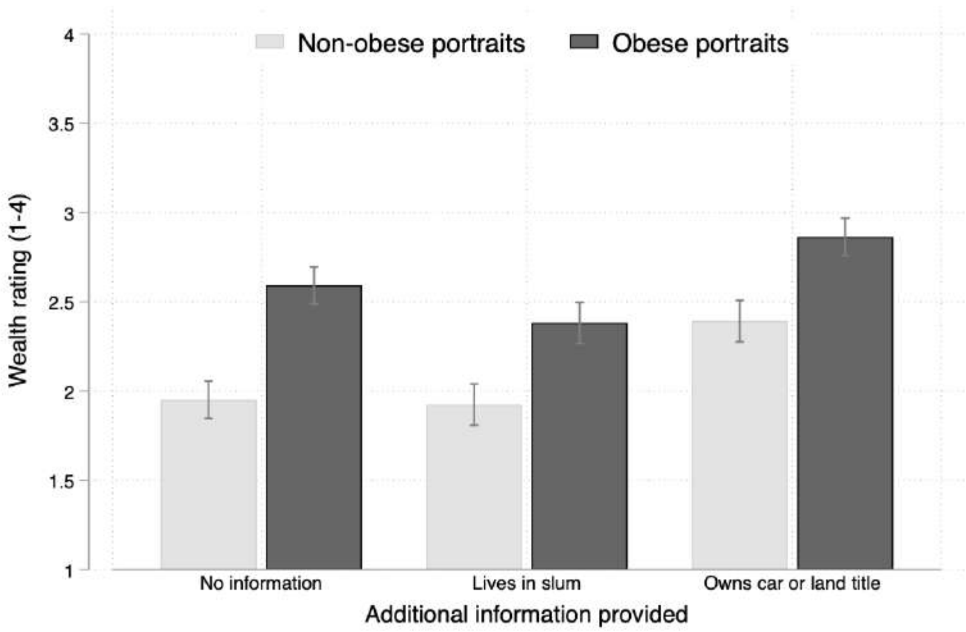
(b) By Country Income Level



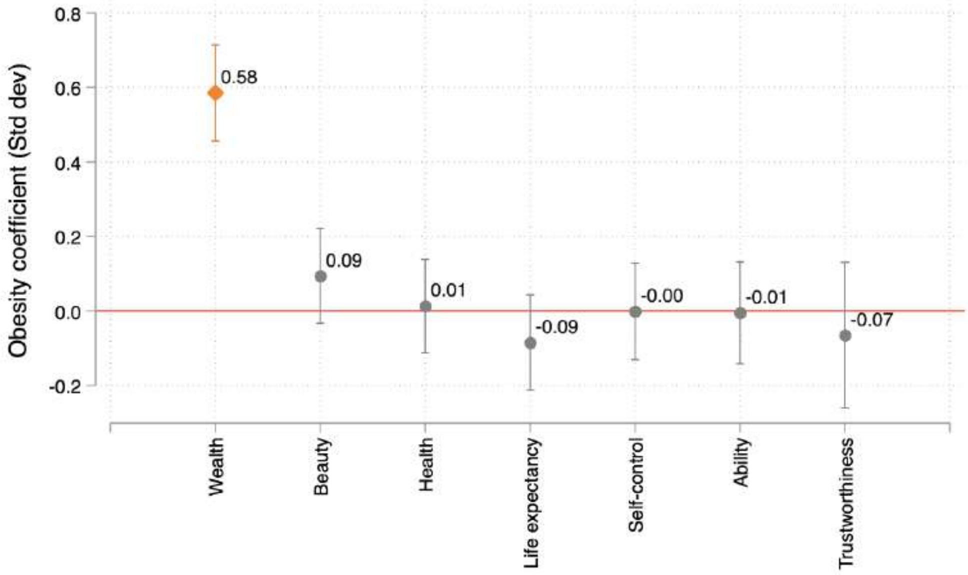
Notes: Panel A plots the percent of obese respondents by wealth quintile, from the most recent DHS wave as of 2019 (2010–2016) for low- and lower-middle-income countries: Armenia, Bangladesh, Benin, Bolivia, Burkina Faso, Burundi, Cambodia, Cameroon, Comoros, DRC Congo, Ethiopia, Gambia, Ghana, Guinea, Haiti, India, Ivory Coast, 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 body mass index greater than or equal to 30 (WHO definition). Panel B aggregates at the country income level and includes DHS data of middle-income countries, Eurostat, and CDC data.

Figure 2: Beliefs Experiment Results

(a) Portrait Wealth Ratings by Obesity Status and Other Wealth Signals



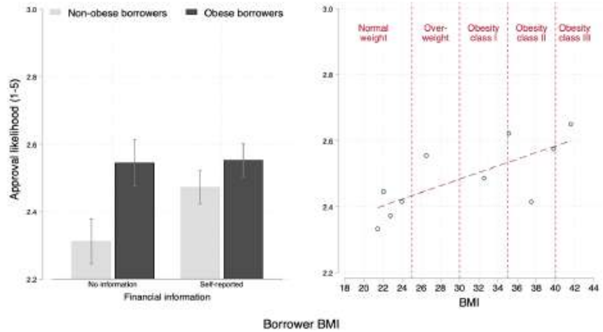
(b) Effect of Obesity Status on Portrait Ratings



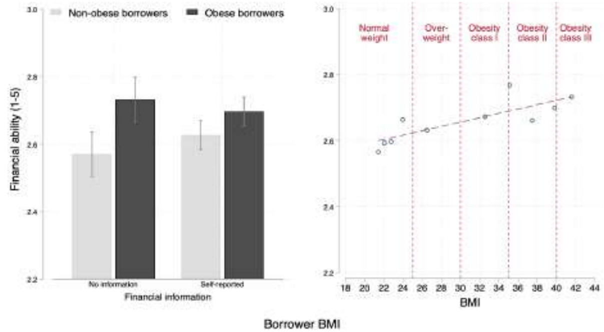
Notes: The figure plots the main beliefs experiment results. The bars are 95% confidence intervals. A total of 511 respondents rate three to four black-race portraits each, for a total of 1,699 observations. Wealth ratings are the pre-registered primary outcome. Panel A plots the raw wealth ratings data, 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 including all the evaluations, with and without additional wealth information, standardize outcomes, portrait-pair and respondent fixed effects, and standard errors clustered at the respondent level.

Figure 3: Obesity Premium in Access to Credit

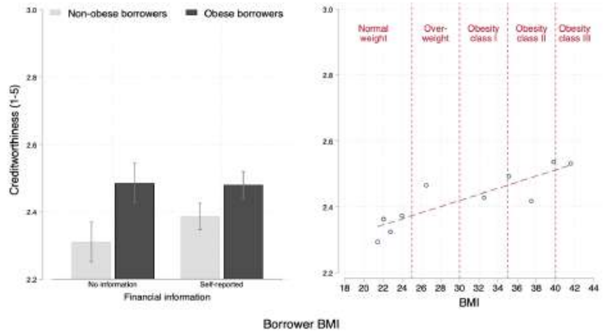
(a) Approval Likelihood



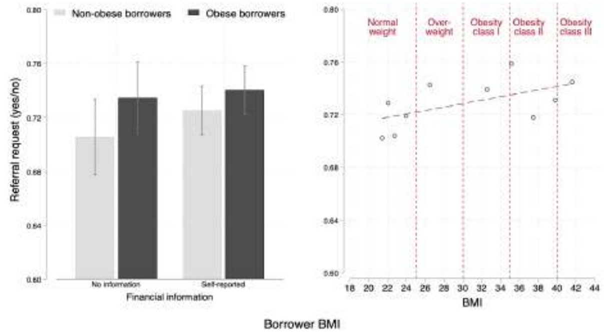
(b) Financial Ability



(c) Creditworthiness

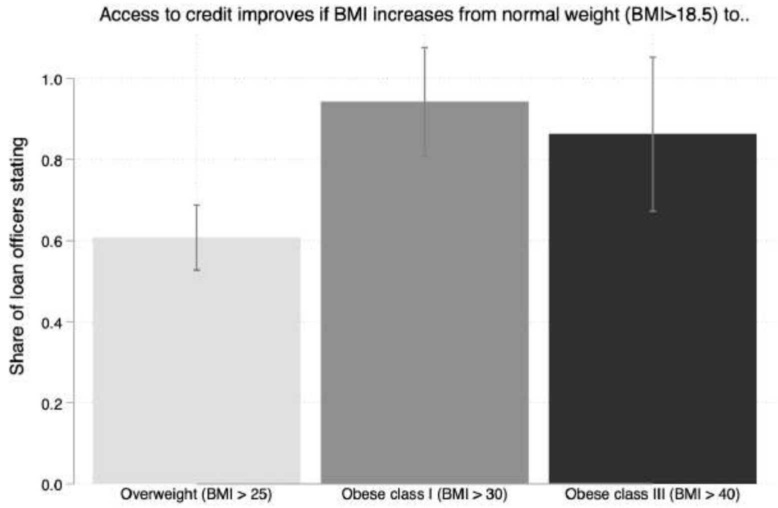


(d) Referral Request



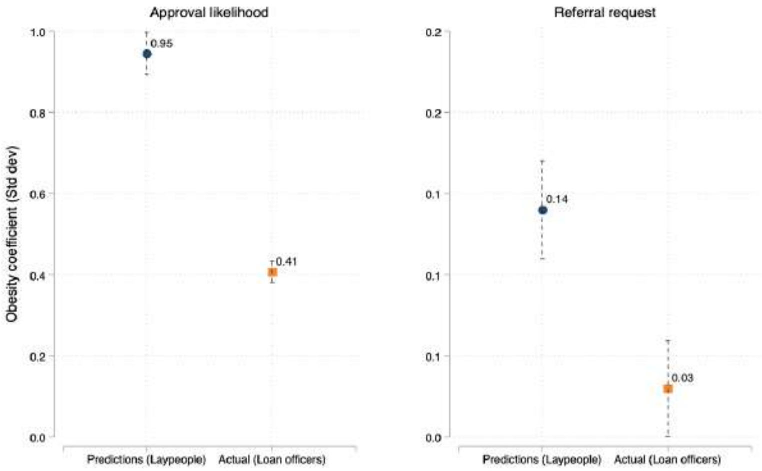
Notes: The graphs summarize the main results from the credit experiment. Respondents are 238 loan officers engaging in 6,645 borrower profile evaluations. Each profile is evaluated along four primary outcomes (in this order): likelihood of approval (*Approval likelihood*), probability of repayment (*Creditworthiness*), ability use money productively (*Financial ability*), and *Referral request*, that is, the choice of meeting a borrower with similar characteristics. Ratings are on a scale from one to five (not at all to very), and referral request is a real choice outcome (no/yes). The left-hand side graphs plot the raw data by borrower obesity status and degree of asymmetric information. The bars are 95% 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 10. Both dependent and independent variables are residualized on individual borrower profile and loan officer dummies.

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



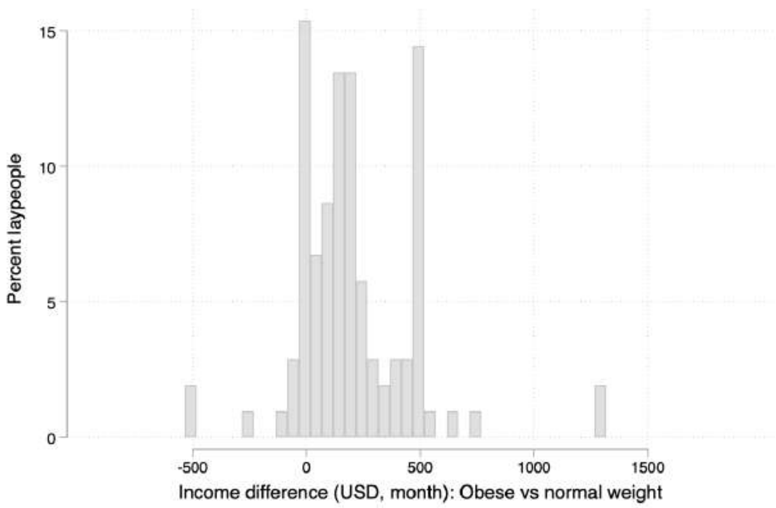
Notes: The graph plots loan officers' explicit beliefs on returns to BMI in access to credit, coded from their answers to an open ended survey question. At the end of the credit experiment, loan officers are shown three body-sized silhouettes (overweight, obese of degree I, and obese of degree III) in pair comparisons and have to state which silhouette in the pair has a higher likelihood of getting a loan. The silhouettes' comparisons are 1) normal weight and overweight, 2) overweight and obese degree I, and 3) 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.

Figure 5: Perceived (Laypeople) vs. Actual (Loan Officers) Premium in Credit Markets



Note: 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 (1) loan officers' most frequent *Approval likelihood* rating and (2) 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.

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 is from the beliefs accuracy survey (N=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.

Tables

Table 1: Descriptive Statistics

	Beliefs Experiment		Credit Experiment			
Variables	*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
Wakiso	0.33	0.47	0.19	0.40	0.18	0.39
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/m2)	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		
Ush 500k to 1 mil(.)	0.13	0.34	0.40	0.49		
Ush 1 to 1.5 mil(.)	0.03	0.17	0.22	0.42		
Ush 1.5 to 2 mil(.)	0.03	0.16	0.04	0.20		
over Ush 2 mil(.)	0.06	0.24	0.02	0.14		
Role: Loan officer			0.63	0.48		
Owner			0.14	0.35		
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		
Provide product information			0.95	0.21		
Review personal information			0.95	0.21		
Review financial information			0.91	0.29		
Refer borrowers to next step			0.80	0.40		
Recruit new borrowers			0.75	0.43		
Approve borrowers			0.74	0.44		
Collect credit			0.68	0.47		
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
Microfinance institution					0.22	0.41
Non-deposit-taking MFIs					0.14	0.35
Licensed moneylenders					0.64	0.48
Branches					6.09	21.94
Employees per branch					6.18	6.54
Offer both personal and business loans					0.90	0.31
Interest rate for Ush 1 million loan					11.82	7.07
Ush 5 million loan					11.90	7.27
Ush 7 million loan					11.62	7.15
Observations	511		238		143	

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

Table 2: Portraits' Ratings by Obesity Status

	(1) Wealth	(2) Beauty	(3) Health	(4) Life expectancy	(5) Self -control	(6) Ability	(7) Trust-worthiness
First-order beliefs							
Obese	0.699	0.320	0.005	-0.072	0.052	0.039	-0.358
	(0.077)	(0.082)	(0.088)	(0.079)	(0.083)	(0.093)	(0.691)
Additional wealth signal	0.677	-0.370	-0.008	0.076	0.215	0.086	0.126
	(0.199)	(0.208)	(0.208)	(0.204)	(0.235)	(0.243)	(0.510)
Obese × Additional wealth signal	-0.190	-0.081	0.014	-0.022	-0.089	-0.074	0.306
	(0.104)	(0.104)	(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: non-obese	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
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)
Additional 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 × Additional 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: non-obese	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 pre-registered primary outcome. Health, beauty, self-control, ability, and life expectancy are pre-registered secondary outcomes. Trustworthiness was not pre-registered and was only elicited to 30% of the sample. *Obese* is a dummy for the weight-manipulated portrait being in shown in the fatter version. *Additional wealth signal* is a dummy equal to 1 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.

Table 3: Obesity Premium in Access to Credit

	(1) Approval likelihood	(2) Financial ability	(3) Credit-worthiness	(4) Referral request	(5) Information reliability
Obese	0.199	0.180	0.151	0.066	0.043
	(0.034)	(0.037)	(0.038)	(0.033)	(0.017)
Self-reported financial info	0.168	0.118	0.105	0.048	0.000
	(0.040)	(0.041)	(0.042)	(0.049)	(.)
Obese × Self-reported financial info	-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 =0	0.000	0.000	0.000	0.044	

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 the meet with a similar applicant. *Reliability info* 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.

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

	(1) Approval likelihood	(2) Financial ability	(3) Credit-worthiness	(4) Referral request
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: non-obese	2.423	2.362	2.609	0.719
Standard deviation	1.169	0.965	1.060	0.445
p-value: Obese + Obese x High DTI = 0	0.001	0.000	0.002	0.012
p-value: Obese + Obese x 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% and 40%; *High DTI ratio* indicates DTI ratios between 90% and 105%. The omitted category represents profiles not reporting any income information. While anecdotally borrowers with DTI ratios as high as 95% 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 non standardized dependent variable.

A Weight-Manipulated Portraits

To implement the photo-morphing, I work with two photographers who manually create a thinner and fatter version of each portrait using computer software. The originals are 30 Kampala resident portraits (Ugandan nationality) and 4 portraits of white-race individuals. Kampala residents are recruited via focus groups; participants provide written consent and receive a digital copy of their portrait. White-race portraits are computer generated and obtained from an algorithm similar to https://thispersondoesnotexist.com/.

Half of the portrayed individuals are women, and the minimum age is 20 years. Portraits are heterogeneous according to initial body size, age, ethnicity, religion, and socio-economic status. After discarding the originals, the final set is composed of 34 weight-manipulated portraits' pairs, each made of the thinner and fatter version of the same portrait (Appendix Figure G.1).

On average, thinner portraits are perceived as normal weight, while fatter portraits are portrayed as obese. To quantify the body mass variation across thinner and fatter portraits, I elicit the portraits' perceived BMI among 10 independent raters (Kampala residents). To rate portraits' perceived BMIs, raters compare each portrait to the figurative Body Size Scale for African Populations developed and validated in Cohen et al. (2015).

The portraits' perceived BMIs range from 20 to 44 points. Importantly, none of the thinner portraits are perceived to be underweight ($BMI < 18.5$), and all the fatter portraits are perceived to be obese ($BMI \geq 30$).[66] Thus, the experimental average treatment effect captures the effect of obesity relatively to normal weight, which is estimated in the data using a dummy equal to 1 if the portrait is shown in the obese version.

B Beliefs Experiment

B.1 Respondents' Wards of Residence

The wards are selected at random from the list of all wards in the districts of Kampala, Mukono, and Wakiso (Greater Kampala). The selection is stratified by quintiles of a poverty index at the ward level, which I use to proxy for socio-economic status for the respondents. I build this ward-level poverty index from Ugandan census data. From the universe of wards in Greater Kampala, I then drop one industrial area, the two richest neighborhoods (Kololo and Muyenga), and the wards counting less than 2% of the population. The final list has 99 wards.

Using ward-level aggregate data from the 2014 Ugandan census, I create a poverty index averaging four variables: share of households with no decent dwelling, share of households living on less than two meals per day, share of households that do not have a

[66] Appendix Figure G.2 displays the body size scale and the rating procedure. The perceived body mass distribution is plotted in Appendix Figure G.3. Notably, the manipulated portraits' BMI distribution is only mildly skewed to the right compared to the actual BMI distribution in Kampala. Today in the city, obesity and overweight are more prevalent than underweight. In the Uganda DHS 2016, the share of overweight and obese women ($BMI > 25$) in Kampala was 41% and 22%, against 5.3% and 4.4% underweight.

bank account, and share of illiterate adults. The poverty index ranges from 5, richest, to 42, poorest, (sd: 5.75). I define poverty index quintiles and randomly select 10 wards from each of the first, third, and fifth quintiles. Appendix Table H.1 provides a list of selected wards and their characteristics.

C Credit Experiment

C.1 Outcome Wording

The outcome wording is as follows: *Approval likelihood*: "Based on your first impression, how likely would you be to approve this loan application? (1–5, not at all likely to extremely likely); *Interest rate*: "If you had to approve this loan application, which interest rate would you charge? (standard, higher, lower, not applicable)"; *Creditworthiness*: "Creditworthiness describes how likely a person is to repay a financial obligation according to the terms of the agreement. Based on your first impression, how would you rate the person's creditworthiness? (1–5, not at all likely to extremely likely)"; *Financial ability*: "Based on your first impression, how likely do you think this person would be to put the loan money to productive use? (1–5, not at all likely to extremely likely)"; *Information reliability*: "How reliable do you think the information provided by the applicant is? (1–5, not at all reliable to extremely reliable, not applicable if no additional info)"; and *Referral request*: "Based on your first impression, would you like us to refer you to a similar applicant to meet and discuss his/her loan application? (yes/no)."

C.2 Hypothetical Borrower Profiles

Using information from loan officer focus groups and data from 187 real prospective borrowers in Kampala, I build 30 hypothetical profiles. To cross-randomize the information in the applications, I use Python *numpy.random* and the *itertools.cycle* functions. Each profile includes a set of borrower characteristics and the borrower's portrait, selected from the weight-manipulated portrait set (black race only). I stratify the information randomization by body mass and, as the signaling power of body mass might differ for men and women, by gender.

The procedure is as follows. First, the hypothetical borrower's body mass and gender are randomly assigned (male/female, thin/fat). Then, the following happens:

- **Portrait:** Each portrait is randomly selected from the set of 30 black-race original portraits, conditional on gender.
- **Loan profile and reason for loan:** There are three different loan profiles: Ush 1 million, Ush 5 million, and Ush 7 million. The reason for the loan was either business or personal. All loan profiles have a six-month term to maturity, and loans could be personal or for business. Business was left generic, while the reasons for personal loans included home improvements, purchase of land, purchase of an animal, and purchase of an asset (e.g., a fridge or car). Loan profile and reason for loan randomization is stratified by the borrower's gender and body mass.

- **Name, passport ID, nationality, and place of residence:** Name and passport ID are included to increase realism but are blurred. Nationality is always Ugandan as most credit institutions would not issue loans to non-Ugandan citizens. Place of residence is always Kampala as most loan officers would be skeptical about issuing a loan to people living in another city. All applications include a date of birth, where the year of birth is the actual year of birth of the portrayed individual, while month and day are randomly selected. This information was not randomized.

- **Occupation:** The information was randomized conditional on the applicant's gender. Typical female occupations include being an owner of the following: a retail and mobile money shop, a boutique, a jewelry shop, an agricultural produce and drug shop, or a hardware store. Typical male occupations include owning a retail shop and mobile money business, owning a phone accessory and movie shop, selling clothes (owning a boutique), running a poultry and egg business, and running a dairy project. The set of occupations were vetted in focus groups with loan officers. All the hypothetical loan applicants were self-employed because employees normally have a line of credit with their employer.

- **Monthly income:** Income information is provided in the form of last month's self-reported revenue and profits, which are randomly assigned conditional on loan profile and the borrower's gender and body mass and type. I first randomly assign each profile to a type: good (low DTI ratio) or bad (high DTI ratio). I then compute the monthly repayments based on the average interest rate in Kampala and determine monthly profits according to the formula $MonthlyRepayment = X \cdot MonthlyProfits$. If the borrower type is good, X is randomly selected from [0.3; 0.35; 0.37; 0.4]; if the borrower type is bad, X is randomly selected from [0.9; 0.95; 0.97; 1.05]. Notably, "bad" borrowers are relatively defined and could still be considered for a loan. It is not uncommon to approve loans such that $X = 0.95$ or $X = 1$. This made the profiles realistic: borrowers with no chance of being approved would normally not apply or would lie. Moreover, it raised loan officers' stakes by showing they could access a good pool of borrowers by participating in the experiment.

- **Collateral:** Collateral is randomly assigned conditional on the borrower's body mass, gender, and loan profile. For loan profiles of Ush 1 million, the choice is between motorcycle and land title. For loans of Ush 5 million and above, the choice is either car or land title.

The financial information is displayed at the bottom of the loan profile, using the sentence "This applicant is self employed and runs a [occupation type] in Kampala. The applicant claims that the business is going well. Last month, the business revenues amounted to [revenue amount]. The profits were [profit amount]. The applicant could provide a [collateral type] as collateral. Please notice that the information on revenues, profits and collateral are self reported by the applicant, and have not yet been verified."

C.3 Implementation of Borrower Referrals

To refer loan officers to real borrower referrals that match their preferences, I use their choices in the credit experiment. The matching is borne out of a machine learning algorithm that accounts for all observable characteristics except gender and body mass. I exclude these characteristic to avoid implementing biased referrals, following Kessler et al. (2019). This choice may be seen as deceptive since loan officers may expect body mass or gender to matter. I believe the ethical concerns to be minimal since I do not specify the characteristics based on which I match borrowers and lenders and since a perfect match would never be feasible and would be justified by the need of avoiding biased credit outcomes.

To implement the procedure, I use R and the code mostly relies on *Tidymodels*.[67]

Introduction to the Machine Learning Problem The problem of matching new borrowers with loan officers based on loan officer preferences is a supervised machine learning algorithm problem. Supervised machine learning revolves around the problem of predicting out-of-sample y from in-sample x. One needs to predict loan officers' preferences for new borrowers (out of sample) based on the preferences they expressed on hypothetical borrowers in the

[67] The code is available upon request.

credit experiment (in sample). Since my measure of loan officers' preferences is the binary choice of requesting, or not, to meet with the hypothetical borrower, I train a supervised classification algorithm.

To implement this matching, in short, I train a set of competing classification models on the experimental data and select the optimal model to identify loan officers' preferences. Then, I apply it to the new database of real prospective borrowers to predict which borrowers would be more likely to get a meeting with a given loan officer. The real prospective borrowers are 187 Kampala residents who need a loan. For each new borrower, I select the loan officer who has the highest probability of requesting a meeting with that borrower. Finally, the details of the loan officers are communicated to that borrower with a phone call in spring 2020. Depending on the loan officers' stated choice, I refer the borrower to either the institution or a specific loan officer.

Data Description The loan officer preferences data are based on 238 loan officers, evaluating between 4 to 30 applications each. To improve on referral quality, I exclude profiles for which the loan officer has no information on the applicants' financial information. The total number of observations is 4,419.

Machine learning algorithms search automatically for the variables, and interactions among them, that best predict the outcome of interest. One must decide how to select, encode, and transform the underlying variables before they are fed to the machine learning algorithm. I include all loan officers and firm characteristics recorded in the credit experiment. For the borrower characteristics, I include all the characteristics in the profile except 1) gender and body mass because of ethical reasons and 2) occupation, which was elicited as an open question to the new borrowers. Including the occupation information requires making some assumptions on how to code the self-reported occupations of the prospective borrowers, which does not seem worthwhile considering that algorithm performances are quite good even without occupation information.

The preferences data include the following:

- Loan officers: age, body mass, gender, education, self-reported financial knowledge, financial knowledge score, experience, role (dummies for manager or owner), employed/self-employed status, monthly income, family members, activities performed, perceived stress of the verification procedure, dummies for factors influencing loan officer choices (age, gender, income, nationality, appearance, education, guarantor, collateral, occupation), number of applicants met daily, number of applicants approved daily, dummies for actions implemented to verify the applicants, performance pay, and relevance of the performance pay.

- Financial institutions: institution name, tier, district, organization size, interest rate for 1 million, 5 million, and 7 million loan types offered.

- Borrowers: age, monthly profits, collateral, loan reason (business, personal), loan amount, place of residence, and nationality.

Moreover, the data include outcome information: loan officers' choice to meet, or not meet, a borrower with similar characteristics (meeting request).

The data on real prospective borrowers come from a subsample of the beliefs experiment respondents. These are 187 individuals from the 511 respondents in the beliefs experiment who said they need a loan and agreed to be contacted with information on where to apply for a loan. The data include age, monthly income, collateral, requested loan amount, requested loan type, requested loan reason, place of residence, and nationality.

Setup and Pre-Processing I split the preferences database into a training set and a test data set, stratifying over the outcome variable. This is because "meeting request" classes in the preferences database are unbalanced: 76% are in class 1 (wants to meet), and 24% are in class 0 (does not want to meet). The test sample contains 20% of the observations. After selecting the relevant variables, I convert the education, financial knowledge, loan amount, and the stress variable to ordered factors as well as convert all string variables and numerical dummies to factor variables.

After the initial pre-processing, each model has its unique preprocessing steps. In *Tidymodels*, these steps are defined in the respective recipe. In most models, I include polynomials of degree 3 for continuous variables (loan officers' and applicants' age, loan officers' body mass, borrower profits). I standardize all predictors and remove those with no variation. When necessary (e.g., in Lasso), I create dummies for all non-continuous predictors and impute all missing values with a nearest neighbor procedure.

Training Process and Model Selection I use the training set to tune the hyper parameters of each model. I first select the models and parameter combinations that result in the highest AUC on the training data set. I then use the test data set to compare the different models and select the preferred model. The performance of the preferred model on unseen data is be assessed on the test data. but before that, I tune the algorithm parameters on the trained data. I use fivefold cross validation and a two-step procedure to find the optimal parameter: first, I use a semi-random set of parameter values for the first grid. In a second step, based on the results from this first grid, I used Bayes optimization to estimate additional models around the parameter combinations that resulted in the highest AUC in the first tuning step.

The models with the highest test AUCs are the gradient boosting classifiers (extreme gradient boosting) followed very closely by a random forest classifier. Gradient boosting models are more complex, require more careful tuning, and are prone to overfitting. Given the limited test data available, I chose to rely on the simpler random forest model. The preferred random forest model is run with the ranger engine and includes polynomial variables for age and BMI of the loan officer as well as age and profits of the applicants. It also imputes missing data using nearest neighbors (three neighbors), uses numeric scores for all ordered categorical variables, and reduces the number of levels of variables by grouping infrequent categories into a new "other" category. I fit the random forest model with optimal parameters one last time to the entire available data.

Matching and Referrals To match borrowers and lenders, I merge the borrower data with the preferences data. Then, I apply the trained model to the merged database to predict a meeting request probability for each borrower-loan officer pair. The result of the classification exercise, the probability score, is a variable between 0 and 1, indicating the probability that a given loan officer would want to meet that applicant. Finally, I select those matches that are classified as positive by the algorithm, and among these I select the best match (the highest probability score). The process is successful, and I obtain a recommendation for each prospective borrower.

C.4 Robustness Checks

No Evidence of Order Effects In the credit experiment, the order of the information treatment is not randomized: loan officers first evaluate profiles without information and later evaluate profiles with self-reported financial information. Randomizing the order may have induced loan officers to think that the amount of information displayed was a strategic choice of the borrower rather than a design choice. For example, they may have assumed that borrowers who did not present collateral information had no collateral.

At the same time, one may worry that lack of treatment randomization could bias the results, if evaluating an application has spillovers on future evaluations (e.g., if people get tired). To investigate whether this is a relevant concern, I test whether applications presented later to loan officers (within a given arm) are rated systematically differently. I generate a dummy variable that indicates whether a given application was displayed in the first half (1–5) or in the second half (6–10) and test for the heterogeneity by order at baseline, and in the effect of body mass in a regression including both loan officer and information treatment fixed effects. Appendix Table H.6 summarizes the results: there is no evidence of order effects, and, most notably, there is no significant interaction of order with body mass.

Randomization Inference The credit experiment results are consistent, large, and therefore unlikely to have occurred by chance. In this section, I demonstrate this with a simulation exercise following Athey and Imbens (2017), who recommend randomization-based statistical inference for significance tests. This approach calculates the likelihood of obtaining the observed treatment effects by random chance, where the randomness comes from an assignment of a fixed number of units (in our case, high schools) to treatment rather than from the random sampling of a population.

I focus on the main results: the benefits in access to credit in the pooled analysis. Using the experimental data, I re-assign the applications' obesity status using the same procedure used in the original randomization, and I estimate treatment effects based on this reassignment. I repeat this procedure 10,000 times to generate a distribution of potential treatment effects that could be due to baseline differences of applications and loan officers when they are combined together. For each outcome, I calculate the share of the 10,000 simulated treatment-control differences that is larger in absolute value than the difference observed in the actual random assignment discussed throughout the paper. This proportion represents the randomization-based p-value.

The results are summarized in Figure G.8, where I plot the distribution of treatment effects from the 10,000 iterations for a selection of outcomes. The dashed vertical line in each graph plots the actual treatment effect. The analysis confirms that the findings cannot be explained by random differences between the loan officers and applications including a portrait in its obese version.

D Perception of Obesity Benefits and Wealth-Signaling Value

D.1 Second Laypeople Sample

In Spring 2020, I ran an additional survey to elicit laypeople's beliefs on the income distribution by body size in Kampala. This survey was not pre-registered. The initial idea was to interview a random sub-sample of the respondents of the beliefs experiment, via an in-person follow-up survey. Because of COVID-19, this was not feasible. Therefore, we initially switched to an online phone survey. We interviewed 49 respondents of the 511, but quickly realized that this approach made it complicated to refer to visual aids such as the Body Size Scale for African Populations. Because anyway we had to rely on sending these images via WhatsApp, we decided to switch to an online survey. We enroll respondents via WhatsaApp, from a sample of Kampala residents who provided their phone numbers to IGREC and agreed to take part in phone and online surveys in the future. Respondents had to provide consent and received a small compensation for completing the survey. We enrolled additionally 79 respondents.

In the analysis, I pool the online and phone samples; Appendix Table H.12 provides the summary statistics for the 124 respondents. In the phone survey, I also elicited willingness to pay for nutritional advice and respondents' beliefs on reasons for weight gain in Kampala. Thus, the data plotted in Figure G.11 come from the online subsample of this sample.

E External Validity

E.1 Replication in Malawi

This paper tests a theory—that obesity is perceived as a signal of wealth—whose processes are defined in general terms and is therefore is likely to find application in contexts characterized by a similar stage in the nutritional transition, that is, with a similar positive BMI and wealth correlation. To investigate the external validity of these findings, I conduct a similar, smaller-scale survey experiment with 241 women in rural Malawi. Different from the Ugandan survey experiment, the Malawi survey exploits only two portraits (1 man and 1 woman), for a total of four photo-morphed pictures. I elicit only second-order beliefs (not incentivized). For each picture, the respondents are asked to guess how many out of 10 people would rate the individual as wealthy, would rate the individual as beautiful, would give credit to the individual, would go on a date with the person, or would respect the individuals' admonitions.

Obese individuals are around 30 percentage points more likely to be perceived as wealthy and slightly more likely to be perceived as creditworthy. Similarly, the effects on other outcomes are not statistically significant (Appendix Figure G.9). Comparative with the Ugandan sample, the Malawi sample is substantially poorer and less educated. These results, combined with the extensive qualitative literature showing evidence of positive perception of fat bodies across developing countries and, in the past, in Europe or the US, suggests that obesity is perceived as a signal of wealth in poor countries in general.

E.2 Replication on Amazon MTurk (US)

To further investigate the external validity of the results, I investigate whether obesity is exploited as a wealth signal in a high-income country setting. First, since obesity and wealth are negatively correlated in rich countries today, obesity would be a signal of being poor. Most notably, however, if the results on the asymmetric information mechanism are correct, one should not expect people to rely much on appearance because of the existence of better verification technologies.

To test for these predictions, I replicate the beliefs experiment on Amazon MTurk in Spring 2020. I select respondents to be US residents. I recruit 37 respondents, each rating 3 portraits for a total of 111 observations. This is a small sample, but a similar-sized pilot in Uganda was able to detect statistically significant effects of obesity on wealth beliefs. Each respondent rates each portrait both in terms of first- and second-order beliefs, and their answers are not incentivized.

Respondents rate portraits in terms of nine characteristics; seven traits (wealth, beauty, health, life expectancy, self-control, ability, and trustworthiness) are the very same as in the original beliefs experiment. The remaining two allow me to measure obesity premium or penalty in credit markets: creditworthiness and willingness to lend money. All responses are on a scale from 1 to 4, as in the original experiment. Appendix Figure G.10 shows the results. Obese portraits are associated with worse ratings along all outcomes. The difference in ratings, however, is not statistically different from zero except for beauty. The effects are also in smaller in magnitude as compared to the Ugandan experiment. I interpret these results as suggestive that obesity is stigmatized in the US context, but it is not exploited as a wealth signal as in poor countries, likely because of lower asymmetric information problems.

F Sugar Beverage Tax and Weight Gain Benefits

Building on Allcott et al. (2019), henceforth ALT, I now describe how accounting for the obesity benefits can affect the calibration of obesity prevention policies by focusing on the optimal sugar beverage tax example. ALT develops a theoretical framework for optimal sin taxes and exploits it to estimate the optimal soda tax in the US. The strength of this framework is that it delivers empirically implementable sufficient statistics formulas for the optimal commodity tax, which can be estimated in a wide variety of empirical applications. To estimate how accounting for obesity benefits would affect the optimal sugar tax (beverages) in the Ugandan context, I proceed in two steps: (1) I exploit equation (3) to estimate a benchmark for the Ugandan sugar tax in the absence of monetary obesity benefits, and I (2) introduce obesity benefits and investigate how the tax is affected.

The equation for the optimal sin tax in the ALT framework (given a fixed income tax) is

$$t \approx \frac{\bar{\gamma}(1+\sigma) + e - \frac{p}{\bar{s}\bar{\zeta}^c}((Cov[g(z);s(z)] + A)}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}((Cov[g(z);s(z)] + A)}, \tag{3}$$

where $A = E(\frac{T'(z(\theta))}{1-T'(z(\theta)}\zeta_z(\theta)\bar{s}(\theta)\epsilon(\theta))$. $\bar{\gamma}$ is the bias, σ is the redistributive effect of the corrective motive, e measures the externality from the sin good consumption, $g(z)$ are welfare weights, $T(z)$ is the income tax, $\bar{\zeta}^c$ is the compensated price elasticity, and ζ_z is the compensated elasticity of income relative to the marginal tax.

The Ugandan context differs from the US one for three main reasons. First, own survey data show that in Uganda, contrary to the US, soda consumption correlates positively with income. It follows that a sugar beverage tax is not regressive. Thus, $\sigma \leq 0$ and the correlation between welfare weights and sugary beverage consumption is negative. Second, health care cost externalities are likely lower because of the absence of a large health care system. Finally, there is low-state capacity to collect taxes. Because of these three differences, I make the following parametric assumptions: 1) $\sigma = 0$, 2) $e = 0$, and 3) $A = 0$. Thus, the equation for the optimal tax for Uganda simplifies to

$$t_{uga} \approx \frac{\bar{\gamma} - \frac{p}{\bar{s}\bar{\zeta}^c}(Cov[g(z); s(z)])}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}(Cov[g(z); s(z)])}. \tag{4}$$

How do obesity benefits enter the optimal sugar beverage tax? My results show there are two types of benefits, social and financial The social benefits are that sugary beverage consumption increases people's BMI and higher BMI individuals are perceived as wealthier. The financial benefits are that obese people have easier access to credit or other monetary returns.

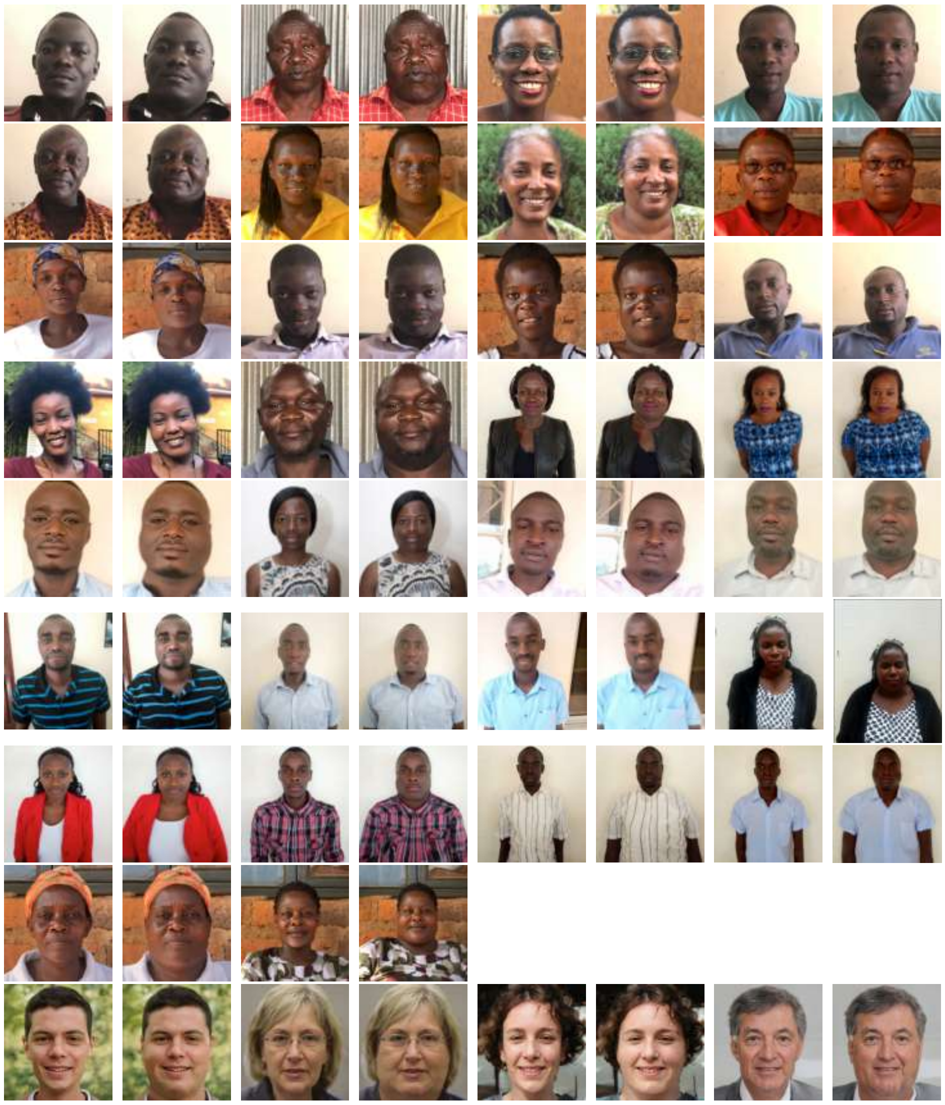
Social benefits enter the utility function and are captured in the elasticity of sugar beverage consumption in Equation (4). As far as monetary benefits are concerned, this is equivalent to a subsidy in sugar beverage consumption equal to the expected returns per unit consumed ($p' = p - E(b)$). The optimal sugar beverage tax accounting for financial benefits is

$$t^b_{uga} \approx \frac{\bar{\gamma} - \frac{(p-E(b))}{\bar{s}\bar{\zeta}^c}(Cov[g(z);s(z)])}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}(Cov[g(z);s(z)])}. \tag{5}$$

The effect of financial benefits on the tax depends on $(Cov[g(z);s(z)])$, that is, the correlation between welfare weights and sugar beverage consumption. When $(Cov[g(z);s(z)]) > 0$, like in the US where poor people (higher welfare weights) consume more soda on average, the larger the financial benefits, the higher the optimal tax. When $(Cov[g(z);s(z)]) < 0$, like in Uganda where rich people (lower welfare weights) consume more soda, the larger the financial benefits, the lower the optimal tax.

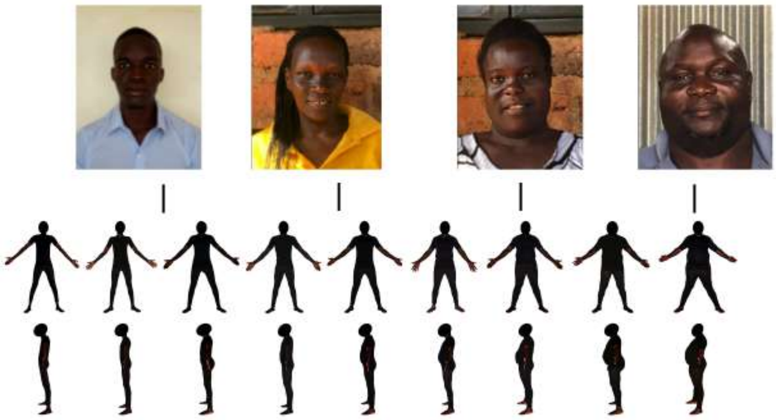
G Appendix Figures

Figure G.1: Weight-Manipulated Portraits



Notes: The figure displays the 34 manipulated portraits used in the analysis. The original portraits (not displayed) have been manually manipulated by two experts using a photo-morphing software to create thinner and fatter versions. The black-race original portraits are of Kampala residents, and the white-race original portraits are computer generated.

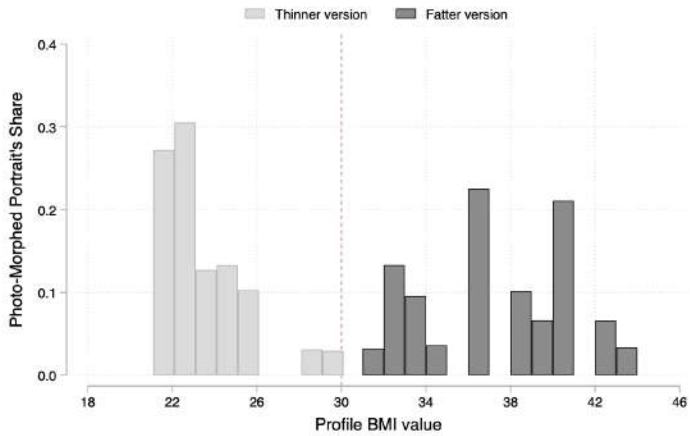
Figure G.2: Linking Weight-Manipulated Portraits to a Perceived BMI Value



1.09	1.55	1.87	2.50	3.18	3.90	4.64	6.19	7.97	Endomorphy
9.93	10.00	10.76	18.91	19.74	24.89	30.83	36.53	36.96	Body Fat (%)
16.89	19.17	21.72	24.09	25.76	27.97	32.87	39.03	43.24	BMI

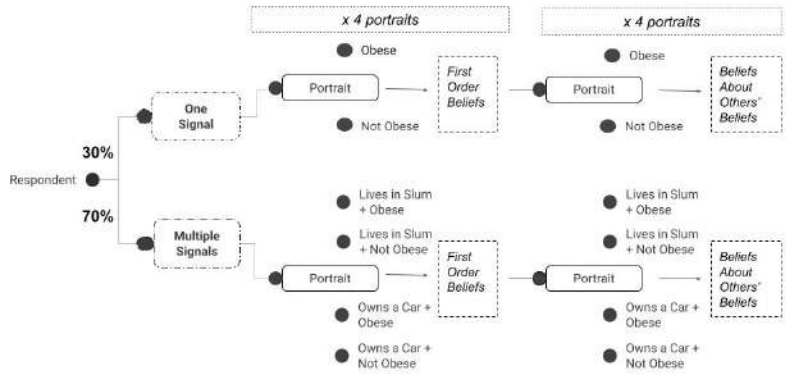
Notes: Ten independent Ugandan raters match each weight-manipulated portrait using the Body Size Scale for African Populations, developed and validated by Cohen et al. (2015). I take the ratings average at the portrait level and compute the corresponding BMI using the conversion model.

Figure G.3: 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 cut-off (BMI = 30).

Figure G.4: Beliefs Experiment Design



Notes: The graph summarizes the beliefs experiment design. Respondents rate four portraits each along with seven characteristics in random order. Portraits are selected from the weight-manipulated portrait set and are randomly displayed in the obese or non-obese version. Body mass randomization is at the respondent portrait level. Respondents can be assigned either to the "one-signal" arm to see the portrait and learn only the individual's age. Respondents assigned to the "multiple signals" arm learn about asset ownership (car or land title— rich type) or place of residence (whether the person lives in a slum—poor type). The four portraits are first rated in terms of first-order beliefs (non-incentivized) and then in terms of beliefs about others' beliefs (incentivized).

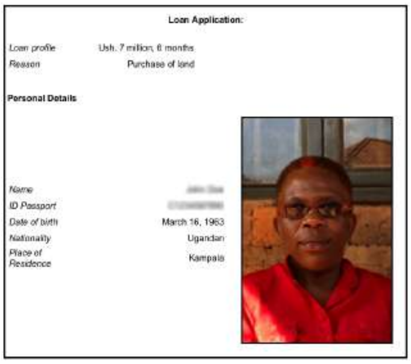
Figure G.5: Credit Experiment Design

		Borrower's Body Mass (Portrait)			
Degree of Asymmetric Information	*Demographics + loan profile information* [10 profiles]	Obese		Not-obese	
	+ self-reported financial information [20 profiles]	Obese / Low DTI	Obese / High DTI	Not-obese / Low DTI	Not-obese / High DTI

Notes: The figure outlines the credit experiment design. Loan officers each evaluate 30 hypothetical borrower profiles, which include a portrait. For each borrower profile, a loan officer is randomly assigned to see the portrait either in the non-obese or obese version. The borrower BMI is cross-randomized with the amount of information provided. The first 10 applications evaluated display the borrower's picture plus demographics and loan profile details: reason for loan, type of loan, and loan amount. The last 20 applications evaluated display in addition self-reported financial information: revenue, profits, collateral, and occupation. Profits were randomized to induce a high bad or low debt-to-income ratio (DTI).

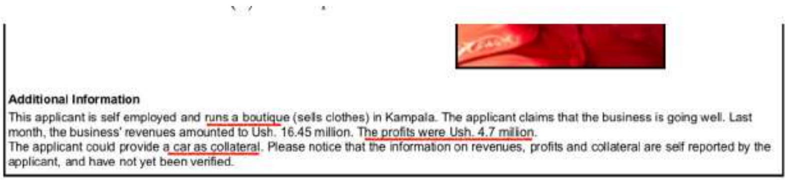
Figure G.6: Example of Borrower Profile

(a) Non-obese borrower



(b) Obese borrower

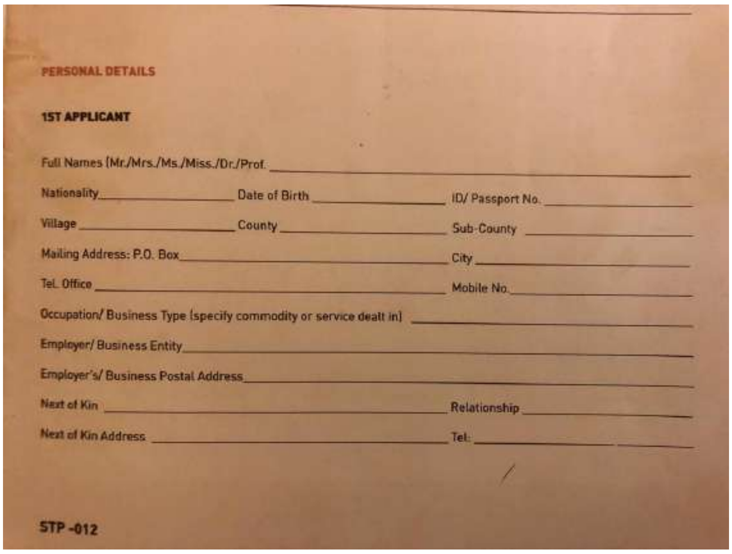
(c) Self-reported financial information



Notes: The figure presents one 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 depends on the treatment assignment (see Appendix Figure G.5).

Figure G.7: Financial Documents Used as Profiles' Templates

Template A



PERSONAL DETAILS

1ST APPLICANT

Full Names (Mr./Mrs./Ms./Miss./Dr./Prof. ____

Nationality ____ Date of Birth ____ ID/ Passport No. ____

Village ____ County ____ Sub-County ____

Mailing Address: P.O. Box ____ City ____

Tel. Office ____ Mobile No. ____

Occupation/ Business Type (specify commodity or service dealt in) ____

Employer/ Business Entity ____

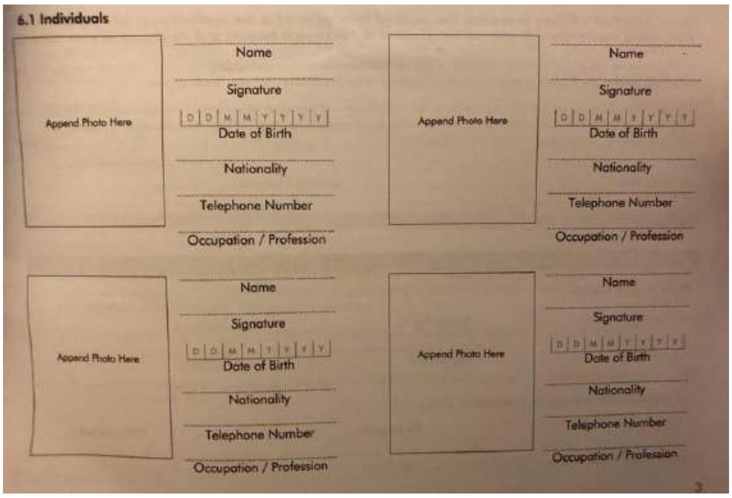
Employer's/ Business Postal Address ____

Next of Kin ____ Relationship ____

Next of Kin Address ____ Tel: ____

STP -012

Template B



6.1 Individuals

Append Photo Here

Name

Signature

D D M M Y Y Y Y

Date of Birth

Nationality

Telephone Number

Occupation / Profession

Append Photo Here

Name

Signature

D D M M Y Y Y Y

Date of Birth

Nationality

Telephone Number

Occupation / Profession

Append Photo Here

Name

Signature

D D M M Y Y Y Y

Date of Birth

Nationality

Telephone Number

Occupation / Profession

Append Photo Here

Name

Signature

D D M M Y Y Y Y

Date of Birth

Nationality

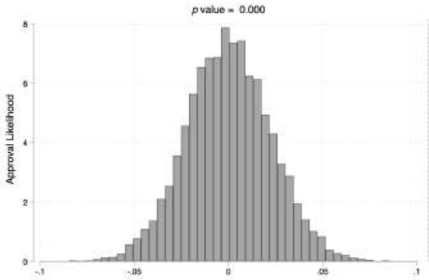
Telephone Number

Occupation / Profession

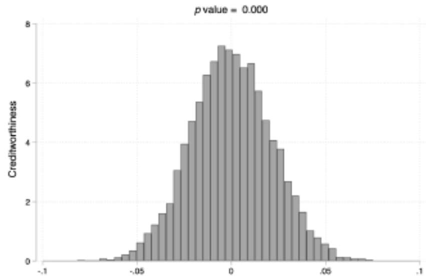
Notes: The figure shows photos of financial applications from two major Ugandan commercial banks that were used to design the hypothetical profiles. The applicant is always supposed to provide a picture, which in Template A is attached to the application.

Figure G.8: Randomization Inference Exercise for Obesity Premium

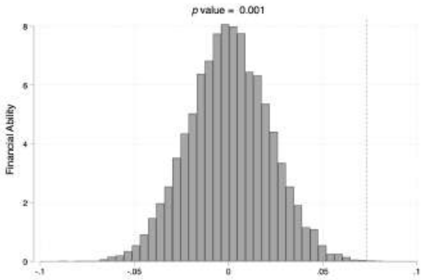
(a) Approval likelihood



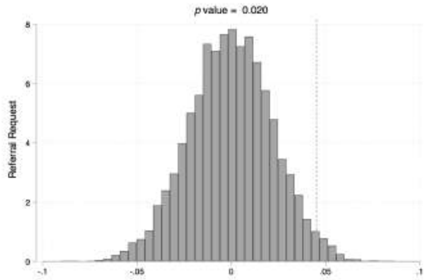
(b) Creditworthiness



(c) Financial ability

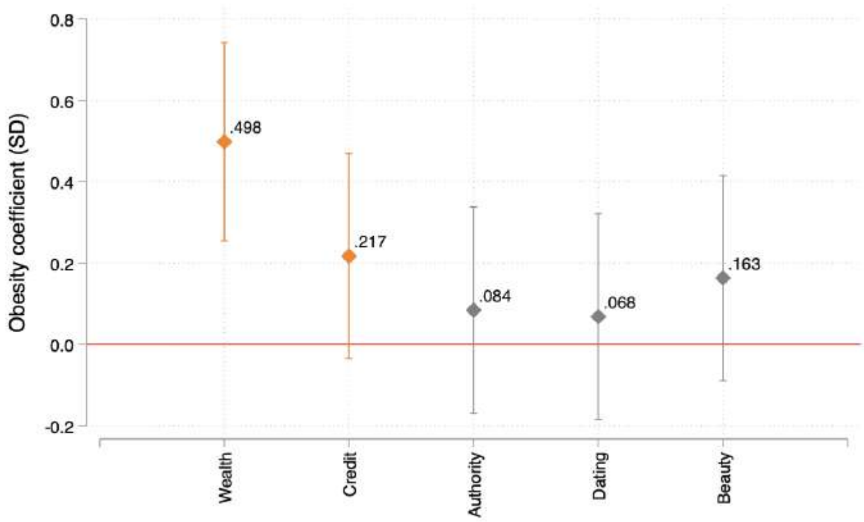


(d) Referral request



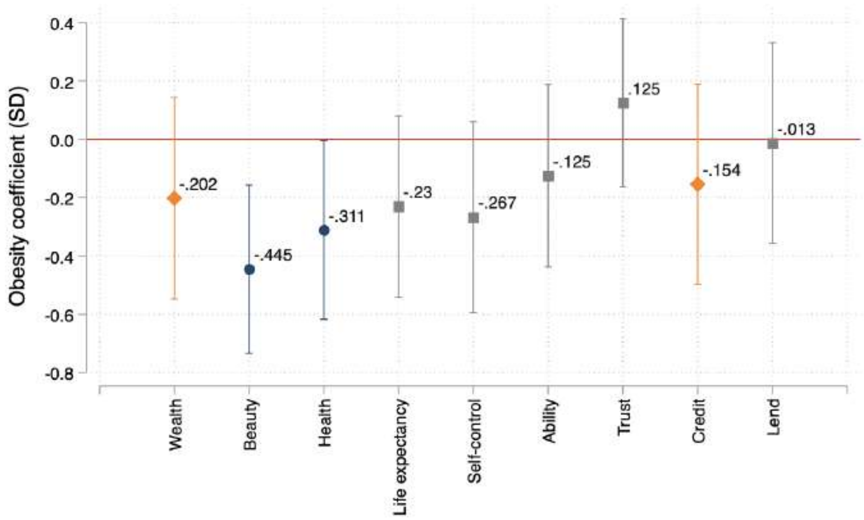
Notes: The figure shows a simulation exercise following Athey and Imbens (2017). Outcome variables are standardized. Each simulated treatment effect comes from randomly assigning profiles to the "obese" treatment using the same randomization algorithm used for the true assignment and then running a regression of the outcome on the "obese" status, including borrower profile and loan officer fixed effects. The dashed line is the estimated effect. The reported p-value is calculated as the number of simulated effects greater in absolute value than the estimated effect.

Figure G.9: Beliefs Experiment Replication in Malawi



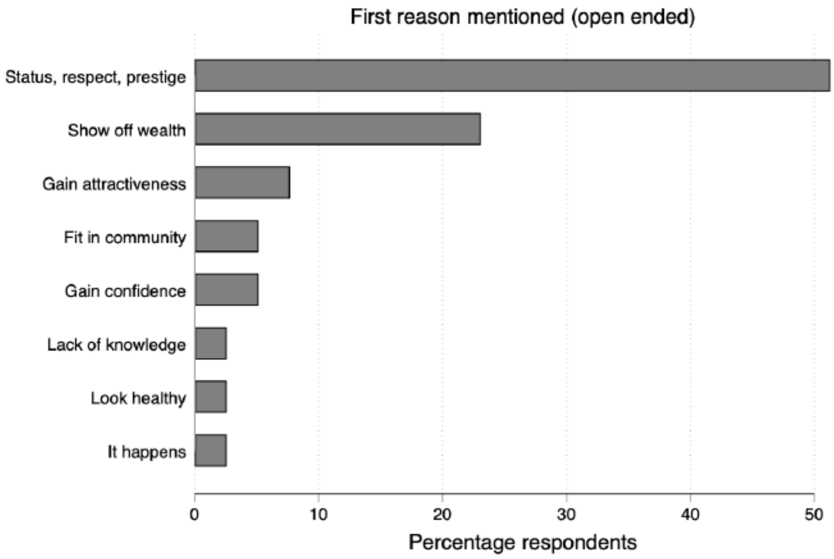
Notes: The figure shows the results from a small-scale experiment in rural Malawi to investigate external validity on a rural, poorer sample. The respondents are 241 women. The paradigm is conceptually equivalent to the beliefs experiment. The main difference is that a) women rate one picture each and b) the portraits are portrait drawings from Project Implicit instead of portraits. I use two pairs of fat/thin drawing portraits, one male and one female. The outcomes measured are second-order beliefs elicited using the wording: "How many out of 10 individuals would...: 1) rate the individual as wealthy, 2) lend money, 3) listen to a monition, 4) go on a date, or 5) rate the individual as attractive."

Figure G.10: Beliefs Experiment Replication on Amazon MTurk



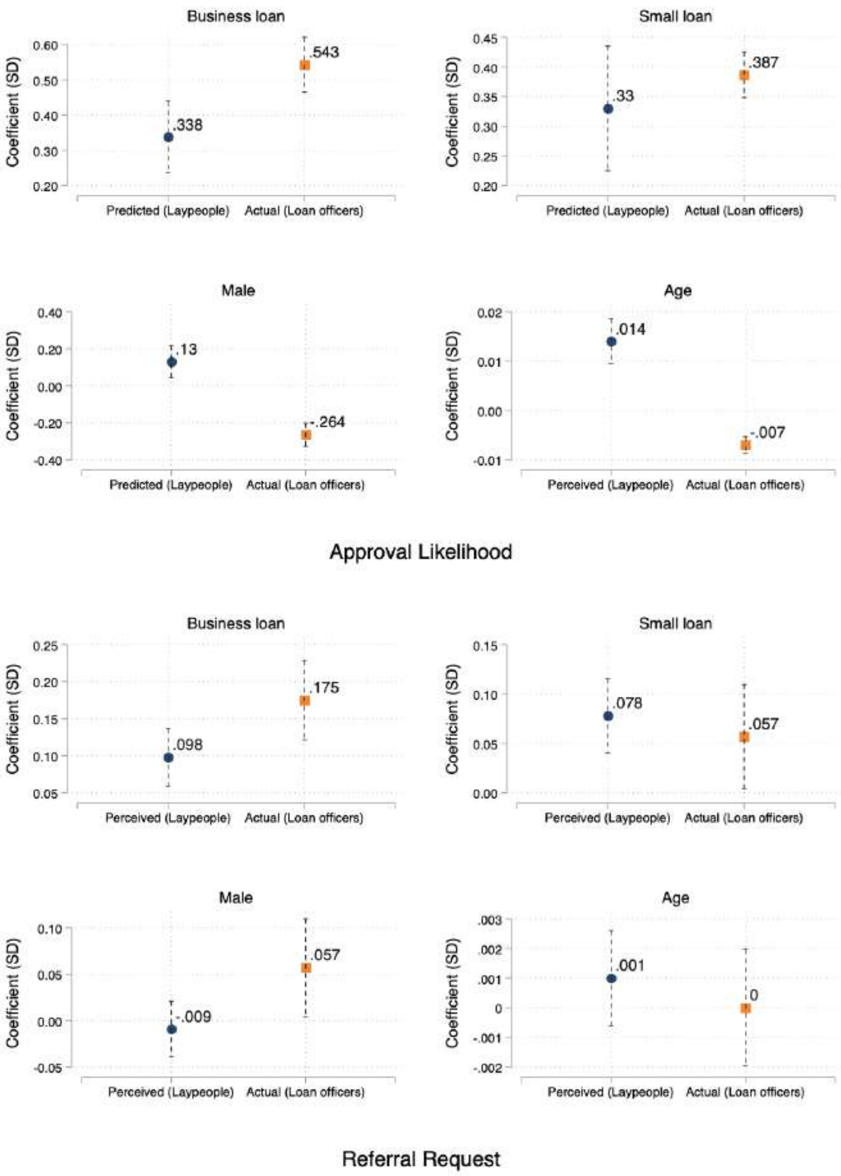
Notes: The figure plots first-order beliefs from a beliefs experiment on Amazon MTurk. The survey involves 37 respondents, for a total 111 portrait evaluations. This is a small sample, but a similar-sized pilot in Uganda had produced statistically significant results. The ratings are elicited on a 1–4 scale, using the same wording as in the original experiment. Portraits are randomly shown either in the obese or non-obese version, stratified by race (black, white). The results show that people appear to engage in (negative) obesity discrimination and second-order beliefs are aligned with first-order beliefs.

Figure G.11: 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 Appendix Table H.15, and the sample is described in Appendix D.1.

Figure G.12: Predicted vs. Actual Effects of Non-Financial Profile Characteristics



Notes: The figure plots laypeople's guesses of the effect of each baseline characteristic on credit outcomes in the borrower profiles, and the actual coefficient in the credit experiment. The laypeople respondents are the same respondents of the beliefs experiment.

H Appendix Tables

Table H.1: Randomly Selected Wards in Greater Kampala for Recruiting for Beliefs Experiment Sample

District	Subcounty	Ward	Pop. share (%)	Poverty index	Quintile
Kampala	Kawempe Division	Makerere University	0.25	5	1
Kampala	Nakawa Division	Kiwatule	0.75	12	1
Kampala	Kawempe Division	Makerere II	0.66	13	1
Kampala	Nakawa Division	Bukoto II	1.01	13	1
Kampala	Rubaga Division	Lubaga	0.99	13	1
Kampala	Nakawa Division	Mutungo	2.87	14	1
Kampala	Central Division	Bukesa	0.40	15	1
Kampala	Makindye Division	Luwafu	0.87	15	1
Kampala	Makindye Division	Salaama	1.47	15	1
Kampala	Central Division	Kamwokya II	0.83	18	3
Kampala	Kawempe Division	Kanyanya	1.19	18	3
Kampala	Kawempe Division	Kawempe II	1.03	18	3
Kampala	Kawempe Division	Mpererwe	0.27	18	3
Kampala	Nakawa Division	Butabika	0.87	18	3
Kampala	Nakawa Division	Mbuya I	1.13	18	3
Kampala	Rubaga Division	Kabowa	1.76	18	3
Kampala	Kawempe Division	Wandegeya	0.32	23	5
Kampala	Central Division	Kisenyi II	0.37	25	5
Kampala	Makindye Division	Katwe II	0.60	26	5
Mukono	Central Division	Namumira Anthony	0.93	18	3
Wakiso	Nansana Division	Nansana West	1.08	15	1
Wakiso	Nansana Division	Kazo	1.48	18	3
Wakiso	Ndejje Division	Ndejje	2.28	18	3
Wakiso	Kasangati Town Council	Kiteezi	0.741	22	5
Wakiso	Kasangati Town Council	Wattuba	0.61	22	5
Wakiso	Kasangati Town Council	Kabubbu	0.61	25	5
Wakiso	Kasangati Town Council	Nangabo	0.39	26	5
Wakiso	Kasangati Town Council	Katadde	0.36	33	5
Wakiso	Mende	Bakka	0.28	41	5
Wakiso	Mende	Mende	0.25	42	5

Notes: The table shows the wards visited to recruit respondents for the beliefs experiment. The selection procedure is described in Appendix B.1.

Table H.3: Hypothetical Borrower Profiles Content

Information	Randomization	Conditionality	Options
Body mass	Randomized		*High* *Low*
Gender	Stratified by BM		*Male* *Female*
Picture	Stratified by BM	Women Men	*Pic n1 to n15* *Pic n16 to n30*
Loan profile	Stratified by BM and gender		*Ush 1 million* *Ush 5 million* *Ush 7 million*
Reason for loan	Stratified by BM and gender		*Business* *Home improvement* *Purchase of animal* *Purchase of land* *Purchase of asset*
Date of birth	Not randomized	Based on picture's age	
Residence	Not randomized		*Kampala*
Nationality	Not randomized		*Ugandan*
Occupation	Stratified by BM	Women	*Retail shop and mobile money* *Boutique (sells clothes)* *Jewelry shop* *Agri produce and drug shop* *Hardware store*
		Men	*Retail and mobile money shop* *Phone acc. and movies shop* *Poultry and eggs business* *Boutique (sells clothes)* *Diary project*
Income	Stratified by BM and gender		*High* *Low*
Monthly profits		Low debt-to-income ratio	*DTI = [30, 35, 37, 40]*
Revenues = 3.5 profits	Not randomized	High debt-to-income ratio	*DTI = [90, 95, 97, 1.05]*
Collateral	Strat. by BM and gender	Ush 7 or 5 million	*Car* *Land title*
		Ush 1 million	*Motorcycle* *Land title*

Notes: The table summarizes the procedure for building the hypothetical profiles. The content information comes from real prospective borrowers and typical loan profiles from focus groups with loan officers.

Table H.2: Heterogeneity in Obesity Wealth-Signaling Value

	(1) Wealth	(2) Wealth	(3) Wealth
Obese	0.600	0.548	0.732
	(0.074)	(0.193)	(0.078)
Male	0.070		
	(0.076)		
Obese × Male	0.042		
	(0.099)		
Age		0.011	
		(0.004)	
Obese × Age		0.002	
		(0.005)	
Additional wealth signal			0.652
			(0.194)
Obese × Additional wealth signal			-0.184
			(0.108)
Observations	1,699	1,699	1,699

Notes: Data are from the beliefs experiment. The table summarizes the wealth-signaling value of obesity by portrait's gender (column 1), portrait's age (column 2), and presence of an additional wealth signal in the portrait's description (column 3). In column 3, the additional wealth signal can be either "living in a slum" or "owning a car" or "owning a land title". *Wealth* are first-order beliefs on the portrayed individual's wealth (1 to 5 scale, standardized). All regressions include respondent fixed effects. Standard errors clustered at the respondent level in parentheses.

Table H.4: Borrower Profiles' Covariates

	Non-obese		Obese		P-value of Difference		
	Mean	SD	Mean	SD	Diff	Standard	RI
Profile BMI value	23.34	1.93	37.30	3.40	13.958	0.00	0.00
Age	36.53	9.35	36.89	9.58	0.354	0.21	0.14
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
Land title	0.50	0.50	0.50	0.50	-0.006	0.19	0.63
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
Sells clothes	0.19	0.39	0.21	0.41	0.020	0.06	0.04
Diary project	0.10	0.30	0.10	0.30	-0.001	0.91	0.91
Hardware store	0.10	0.30	0.10	0.31	0.007	0.12	0.34
Jewelry shop	0.11	0.31	0.09	0.29	-0.016	0.03	0.03
Mobile money shop	0.21	0.41	0.19	0.40	-0.012	0.05	0.22
Phone/movies shop	0.10	0.30	0.10	0.30	0.001	0.84	0.91
Poultry and eggs	0.10	0.30	0.10	0.30	-0.001	0.79	0.87
Profile revenues UGX ml	5.91	4.81	5.83	4.77	-0.078	0.17	0.53
Profile profits UGX ml	1.69	1.37	1.67	1.36	-0.022	0.17	0.53
Profile order in arm	5.51	2.84	5.50	2.90	-0.010	0.72	0.91
Reason for loan: Business	0.20	0.40	0.20	0.40	-0.006	0.33	0.54
Home improvement	0.24	0.42	0.23	0.42	-0.004	0.38	0.70
Purchase animal	0.17	0.37	0.17	0.38	0.004	0.39	0.65
Purchase asset	0.17	0.37	0.17	0.37	0.002	0.66	0.81
Purchase land	0.23	0.42	0.23	0.42	0.004	0.39	0.70
Loan amount: Ush 1 mil(.)	0.33	0.47	0.34	0.47	0.006	0.32	0.60
Ush 5 mil(.)	0.34	0.47	0.33	0.47	-0.011	0.07	0.32
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 "Obese" ("Non-obese") columns indicate if a borrower's profile displayed the thinner or 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. BMIs of the pictures are evaluated by 10 third-party Ugandan raters using the Body Size Scale for Assessing Body Weight Perception in African Populations (Cohen et al., 2015) and are averaged at the portrait level. The profile information is cross-randomized following the procedure described in Table H.3.

Table H.5: Earnings Premium in Credit Experiment

	(1) Approval likelihood	(2) Financial ability	(3) Credit-worthiness	(4) Referral request	(5) Information reliability
Profits Ush mil(.)	0.125	0.097	0.076	0.055	0.021
	(0.017)	(0.014)	(0.014)	(0.015)	(0.008)
Observations	4,566	4,566	4,566	4,566	4,438

Notes: Data are from the credit experiment. *Profits* is a continuous variable indicating the self-reported profits (Ush million) reported on the profile and applies only to profiles randomly selected to display additional information. Outcomes are standardized. Regressions include loan officer fixed effects. Standard errors clustered at the loan officer level in parentheses.

Table H.6: Obesity Premium by Profiles' Rating Order

	(1) Approval likelihood	(2) Financial ability	(3) Credit-worthiness	(4) Referral request
Obese	0.111	0.099	0.080	0.017
	(0.037)	(0.032)	(0.033)	(0.012)
Second half	-0.006	-0.020	-0.024	-0.005
	(0.036)	(0.035)	(0.032)	(0.013)
Obese $\times$ Second half	0.037	0.043	0.040	0.006
	(0.061)	(0.050)	(0.047)	(0.021)
Observations	6,645	6,645	6,645	6,645

Notes: Data are from the credit experiment. *Obese* is a dummy equal to one if the borrower profiles included the obese version of the original picture. *Second half* is a dummy equal to one if the profile was the 5th to the 10th profile rated, within each arm. Regressions include loan officer and information arm fixed effects. Standard errors clustered at the loan officer level in parentheses.

Table H.7: Inattention Robustness (Effect of Financial Information on Other Profile Characteristics)

	(1) Approval likelihood	(2) Approval likelihood	(3) Approval likelihood	(4) Approval likelihood
Self-reported financial info	0.168	0.043	-0.027	-0.153
	(0.040)	(0.096)	(0.050)	(0.058)
Obese × Self-reported financial info	-0.129			
	(0.038)			
Self-reported financial info × Profile age		0.002		
		(0.003)		
Ush. 5 million × Self-reported financial info			0.202	
			(0.058)	
Ush. 7 million × Self-reported financial info			0.190	
			(0.069)	
Home improvements × Self-reported financial info				0.565
				(0.074)
Purchase of an animal × Self-reported financial info				-0.021
				(0.085)
Purchase of an asset × Self-reported financial info				0.275
				(0.086)
Purchase of land × Self-reported financial info				0.352
				(0.069)
Observations	6,645	6,645	6,645	6,645

Notes: Data are from the credit experiment. The regressions' outcome is the *Approval likelihood* (1–5), standardized. *Self-reported financial info* 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 H.8: Obesity Premium by Timing of Financial Information Provision

	(1) Approval likelihood	(2) Financial ability	(3) Credit-worthiness	(4) Referral request
Obese	0.233	0.174	0.160	0.030
	(0.041)	(0.036)	(0.041)	(0.015)
Sequential information	0.191	0.124	0.130	0.008
	(0.048)	(0.041)	(0.047)	(0.023)
All information at once	0.203	0.103	0.091	0.035
	(0.057)	(0.046)	(0.051)	(0.024)
Obese $\times$ Sequential information	-0.135	-0.077	-0.089	-0.002
	(0.049)	(0.044)	(0.051)	(0.021)
Obese $\times$ All information at once	-0.167	-0.082	-0.089	-0.027
	(0.056)	(0.047)	(0.053)	(0.018)
Observations	6,645	6,645	6,645	6,645
p-value: Obese x Sequential information = Obese x All information at once	0.541	0.911	0.994	0.166

Notes: Data are from the credit experiment. The estimation focuses on profiles that displayed additional financial information. *Obese* is a dummy for the profile being associated with a fatter weight-manipulated portrait. *Sequential information* indicates that the baseline information is shown first and then the financial information is provided. *All information at once* indicates that both baseline and financial information is shown immediately. The excluded category are profiles where picture and demographic information are not shown. Regressions include borrower profile and loan officer fixed effects. Standard errors clustered at the loan officer level in parentheses.

Table H.9: Credit Experiment Likelihood Ratios

Outcome	Rate obese	Rate non-obese	Ratio
No financial information [N = 2,079]			
Approval likelihood ≥ 4	20.78 %	14.86 %	1.4
Creditworthiness ≥ 4	11.89 %	8.86 %	1.34
Productivity ≥ 4	24.34 %	20.26 %	1.2
Referral request $= 1$	73.49 %	70.5 %	1.04
Financial information [N = 4,566]			
Approval likelihood ≥ 4	23.44 %	21.59 %	1.09
Creditworthiness ≥ 4	12.8 %	10.38 %	1.23
Productivity ≥ 4	22.07 %	19.76 %	1.12
Referral request $= 1$	74.04 %	72.48 %	1.02

Notes: Data are from the credit experiment. The panel above reports data for profiles that were randomized not to display borrower financial information, while the panel below focuses on the profiles that displayed financial information. For the categorical variables, a rating equal to four meant "very high or likely," while a rating equal to five meant "extremely high or likely."

Table H.10: Obesity Premium for Male Loan Officers Rating Male Borrowers

	(1) Approval likelihood	(2) Financial ability	(3) Credit-worthiness	(4) Referral request
Obese	0.196	0.143	0.145	0.089
	(0.042)	(0.045)	(0.044)	(0.042)
Observations	1,977	1,977	1,977	1,977

Notes: Data are from the credit experiment. The sample is restricted to male loan officers rating male borrower profiles. Outcomes are standardized. Standard errors clustered at the loan officer level in parentheses.

Table H.11: Obesity Premium Heterogeneity by Loan Officer Characteristics

Approval likelihood	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Age	BMI	Education	Experience	Days verify	Gender	Owner	Performance pay: Any	Performance pay: Sales volume
Obese	-0.034	0.154	0.106	0.090	0.041	0.071	0.104	0.047	0.123
	(0.095)	(0.103)	(0.222)	(0.026)	(0.041)	(0.024)	(0.020)	(0.065)	(0.023)
Obese × Age	0.005								
	(0.003)								
Obese × Loan officer BMI		-0.002							
		(0.004)							
Obese × Education (years)			0.000						
			(0.014)						
Obese × Experience (years)				0.007					
				(0.006)					
Obese × Days/week to verify information					0.033				
					(0.016)				
Obese × Male						0.064			
						(0.037)			
Obese × Owner							0.036		
							(0.061)		
Obese × Performance pay								0.068	
								(0.068)	
Obese × Performance pay = Sales volume									-0.045
									(0.041)
Observations	5,363	6,645	6,645	6,645	5,469	6,645	6,645	6,645	6,645

Notes: Data are from the credit experiment. The table summarizes the heterogeneity analysis in the obesity premium by loan officers characteristics and reports the interaction effects of each corresponding saturated model. The outcome is *Approval likelihood* (1–5 scale, standardized), the perceived likelihood of approving the loan application. *Obese* is a dummy equal to one if the profile displays the borrower portrait in the obese version. All regressions include borrower profile fixed effects. Standard errors clustered at the loan officer level in parentheses.

Table H.12: Summary Statistics: Belief Accuracy Sample

	(1)	(2)	(3)
VARIABLES	Mean	SD	Median
Gender: Female	0.61	0.49	1.00
Age: 18 to 24	0.25	0.43	0.00
25 to 35	0.49	0.50	0.00
35 to 44	0.18	0.38	0.00
55 to 64	0.04	0.19	0.00
Education: Primary school	0.02	0.13	0.00
Secondary school	0.11	0.31	0.00
Professional degree	0.65	0.48	1.00
Some college	0.02	0.13	0.00
Two year degree	0.21	0.41	0.00
Personal income: Far below average	0.11	0.31	0.00
Moderately below average	0.07	0.26	0.00
Slightly below average	0.23	0.42	0.00
Average	0.28	0.45	0.00
Slightly above average	0.12	0.33	0.00
Moderately above average	0.14	0.35	0.00
Far above average	0.05	0.23	0.00
Personal income (month, Ush million)	0.66	0.71	0.40
BMI	26.62	6.72	25.84

Notes: The table displays summary statistics for the 124 Kampala residents who were part of the beliefs accuracy survey. Because of COVID-19, the survey was run partly on the phone (49) and partly online (79).

Table H.13: Obesity Premium Heterogeneity: R-Squared Analysis

Dep var: Obesity premium	(1) Approval likelihood	(2) Financial ability	(3) Credit-worthiness	(4) Referral request
Residual premium	0.197	0.250	0.098	0.173
	(0.090)	(0.090)	(0.092)	(0.087)
Earnings, self-reported	0.157	0.336	0.178	0.189
	(0.109)	(0.147)	(0.163)	(0.118)
Car collateral	-0.055	0.103	-0.067	-0.048
	(0.058)	(0.071)	(0.076)	(0.057)
Land collateral	0.088	-0.112	0.045	0.043
	(0.055)	(0.068)	(0.072)	(0.053)
Constant	0.127	0.115	0.119	0.035
	(0.035)	(0.039)	(0.039)	(0.032)
Observations	238	238	238	238
R2	0.041	0.060	0.020	0.038

Notes: Data are from the credit experiment. The table summarizes the results of a multivariate regression to investigate the extent to which the variance of the obesity premium can be explained by variation in observable borrower financial characteristics and variation in the residual premium, conditional on learning about a borrower self-reported characteristics. The data is from the credit experiment. The regressions are estimated at the loan officer level. The dependent variable is the estimated obesity premium for each access to credit outcome. The residual premium is the estimated obesity premium for the given outcome, conditional on providing additional financial information. *Earnings*, *Land collateral*, and *Car collateral* are the estimated effects on the given access to credit outcome of self-reported earnings, car collateral, and land collateral. Regressions include fixed effects for the set of portraits evaluated, and control for borrower age and gender.

Table H.14: Body Mass and Access to Credit Correlation in the Uganda National Panel Survey 2019

	(1) Borrowed	(2) Borrowed	(3) Repaid
Normal weight	0.069		0.100
	(0.013)		(0.020)
Overweight	0.116		0.031
	(0.017)		(0.025)
Obese	0.062		0.212
	(0.017)		(0.027)
BMI		0.007	
		(0.001)	
Non-profit institution		1.115	
		(0.044)	
Non-profit institution × BMI		-0.013	
		(0.002)	
Observations	14,236	14,236	3,633
p-value: BMI + Non-profit institution x BMI >= 0		0.000	

Notes: Data are from the Uganda National Panel Survey 2019. The table displays the correlation between individual body mass and access to credit and repayment. The outcome in column 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 1 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. Non-profit institutions include institutions classified as NGOs but also ROSCAs, welfare fund, burial society, VSLAs. The regressions include district and household fixed effects, and control for gender, age and gender specific age trends.

Table H.15: Reasons Why People Think Other People Want to Gain or Lose Weight in Kampala

Want to gain	Want to lose
To be more respected and look presentable in the society.	To avoid diseases like pressure
They want to appear wealthy and command that respect of economic bulls	To maintain healthy living. Overweight make ones body vulnerable to diseases like pressure
So that they appear attractive and respected. Its common for unmarried people. Most ladies don't want to introduce slimy men (...)	Sexual pleasure. Slender people enjoy sex very well as compared to overweight people
To look wealthy	To avoid diseases
To be respected in public	To easily do work without getting tired
Most of them say fat people are respected on account that they are loaded (they have money)	To be healthy. You know very fat people are easily attacked by diseases like the heart disease
Just like myself, they feel you can look cash but after gaining the weight you start battling to reduce it	To live healthier
In Kampala its commonly known that people with money have the weight (...)	To look smarter though most times weight people don't want to lose weight. (...)
Respect	To avoid diseases like pressure and other heart related diseases
Prestige. Fat people are respected even in terms of finances	To be more healthy
Financial-such other people should look at them as wealthy	To be more fit
To look rich and show that they doing well financially	Feeling to appear healthy
To look more representable and wealthy	To be healthy and lighter
Fat people are assumed to have money and are respected	Overweight is associated with diseases so most people do it to prevent easy attacks
Peer pressure fit in community	Be fit for some jobs
To be more respected	To be healthy and fit
They are ignorant	People may mistake n you to be wealth
It just happens as they Eat fatty foods and do not do exercise	Avoid sickness related to over weight
To gain respect	Avoid sickness associated with over weight
Earn more respect, self confidence	Fighting the attack of diseases and be more flexible
They want to be seen as different and attractive	To be more flexible and attractive
Get respect in community	Get rid of sickness associated with obesity
To look rich	Healthier
To gain more respect from people around them	To be more flexible, and to be in good shape
So that they can look good with some weight	To fight disease attack
To fit in community	Fit in community
So that they can respect them	To look more attractive
Gain more respect	Avoid diseases like pressure and diabetes
Fit in group	Fit in society pear pressure
Get more respect	Fear to sicknesses
To earn more respect	Fighting not to get diseases
To gain more respect	To be in shape and flexible
Due to Inferiority complex	Portability
So that they don't under rate them	To fight disease and look attractive
To earn more respect	They don't want to be attacked by diseases and be fit
To earn more respect	Fear of getting diseases
So that they can be more attractive	Not to get diseases
So that they can be respected	To be in good shape
Earn more respect, to gain some big status	They look more flexible

Notes: Data from the laypeople phone sample ($N = 49$), with 10 missing responses. Each respondent is asked an open-ended question on reasons for why people in Kampala may want to gain weight and may want to lose weight.