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

Elisa Macchi*

Please, find the most recent version here.

October 15, 2021

Abstract

I study the economic value of obesity - a seemingly irrelevant but unhealthy status symbol in poor settings. Leveraging multiple experiments in Kampala (Uganda) randomizing decision-makers to see obese and not-obese manipulated portraits, I provide four results: i) obesity is perceived as a strong wealth signal, and unrelated to beauty, health...; ii) obesity facilitates access to credit: in a real-stake experiment with 146 credit institutions the obesity premium equals raising borrowers' self-reported earnings by 60%; iii) asymmetric information drives the premium, which falls significantly with more financial information availability; iv) obesity benefits and value are overestimated - inefficiently raising the cost of healthy behaviors.

*Department of Economics, MIT. Email: emacchi@mit.edu. I am grateful to my advisors David Yanagizawa-Drott, Lorenzo Casaburi, Joachim Voth, and Ernst Fehr, as well as to Alberto Alesina, Pietro Biroli, Ben Enke and Nathan Nunn for the support and encouragement during the course of this project. I also thank Emily Breza, Guy Grossman, Micheal Kremer, Guilherme Lichand, Michel Marechal, Gautam Rao, Heather Schofield, Florian Scheuer, Colin Sullivan, Roberto Weber, David Yang and participants at seminars and conferences at Harvard, Zurich, BREAD, DevPec, NEUDC, and ECBE for helpful discussions and feedback. Illen Aria and Giulio Molfese created the manipulated portraits. The field experiment would not have been possible without the invaluable support and cooperation of the Uganda Microfinance Regulatory Authority, of Innovation for Poverty Action (in particular, Carin Mirovitz, Elly Atuhumuza, Edmund Emulu and Patience Kyomuhendo) and International Growth Research and Evaluation Center (in particular, Joshua Bwiira and Lenny Gichia). Financial support from the Swiss National Science Foundation (grant 100018_165616) and the Swiss Re Foundation is gratefully acknowledged. The experiments were approved by the Ethics Committee of the Department of Economics of the University of Zurich and the Uganda National Council for Science and Technology. The experiments were preregistered at https://www.socialscienceregistry.org/trials/4806; https://www.socialscienceregistry.org/trials/4528

1 Introduction

People are willing to pay to look rich. The theory of conspicuous consumption goes back to Veblen in 1899. Recent experimental evidence confirms that people pay extra to acquire status goods (Bursztyn et al., 2017a). Despite the large literature on conspicuous consumption, we know little of the trade-offs of status investment and especially, we have no evidence on whether status can lead to benefits in market settings (Bursztyn and Jensen, 2017).

In poor countries, conspicuous consumption (Bloch et al., 2004; Rao, 2001) is relatively expensive —e.g., because of kinship taxation (Jakiela and Ozier, 2016; Squires, 2016), and comes at the cost of basic human-capital investment. At the same time, because screening costs are inefficiently high (Banerjee and Duflo, 2007), reliable wealth information is very scarce. In this paper, I hypothesize that when asymmetric information is large, agents may rely on status signals as imperfect proxies for wealth and thus, looking rich may lead to benefits in market settings.

Do seemingly irrelevant status indicators lead to benefits in market settings? If so, to which extent is it an efficient response to an information extraction problem? To address these questions, I study experimentally the wealth-signaling value and the credit market benefits of being obese in Kampala, the capital of Uganda. Obesity in low-income contexts can signal a person's status. Historically, prosperity has always meant having enough money to buy or own food. Today, this is still true in much of the developing world, where, unlike in richer countries, fat bodies are often positively perceived,[1] rich people are more likely to be obese,[2] and there exists a market for weight-gain programs.[3] To test for economic benefits, I focus on credit markets, an economically relevant market —credit constraints are a main barrier to poverty reduction —characterized by pervasive asymmetric information problems.[4]

Cars, clothes or watches may equally serve as a proxy for wealth. I focus on obesity

[1]Qualitative studies providing evidence of positive perception of fat bodies include: Anderson-Fye (2004) in Belize; Bosire et al. (2020) in South Africa; Chigbu et al. (2019) in Nigeria; Ettarh et al. (2013) in Nairobi, Kenya; Holdsworth et al. (2004) in urban Senegal; Popenoe (2012) among Arabs in Niger; Sobo (1994) in Jamaica.

[2]Figure J.10 plots obesity prevalence by income quintile and country income level.

[3]*Leblouh* or *gavage* describe the traditional practice, widespread among rich families in Kenya, Mauritania, Morocco, Niger, South Africa, and Uganda, of paying for daughters' to enter weight-gain programs.

[4]Lacking technological advancements, such as credit risk models, loan officers face both moral hazard and adverse selection problems (Karlan and Zinman, 2009). Evidence suggests that perhaps as a response to imperfect information (Banerjee, 2003) or because of higher returns to capital (De Mel et al., 2008), rich borrowers are favored in lending decisions in poor countries.

for two reasons. First, obesity is a seemingly irrelevant status signal in the context of credit. Body mass is not an obvious determinant of lending decisions, because it cannot be seized and has no collateral value; one could even identify obesity as a sign of poor credit risk. Second, obesity is particularly relevant to study. Obesity is a global health challenge[5] and the presence of monetary benefits may work as an incentive to gain (or not lose) weight, and raise the opportunity cost of healthy behaviors.[6]

My empirical strategy leverages a set of complementary experiments, involving borrowers and professional loan officers. My design cross-randomizes body mass, using weight-manipulated images, and the degree of asymmetric information in which decisions are taken, to test for the mechanism. I ask four questions: (i) Is obesity is perceived as a reliable wealth signal? (ii) Does obesity facilitate access to credit, because it serves as a proxy for wealth? (iii) Are obesity benefits common knowledge? and (iv) Are market outcomes shaped by correct beliefs about the obesity signal and benefits?

My first result is that Kampala residents use obesity as a proxy for wealth, and not of other traits commonly associate with obesity in the anthropology literature (e.g., beauty or health). In a survey experiment, I ask respondents to rate portraits —randomly presented either in the obese or normal-weight version —along several traits. Obesity causally increases portraits' wealth ratings, but has no effect on beauty, health, life expectancy, self-control or ability. The obesity signal is a strong —obese individuals are perceived as rich as lean people owning a car —and relevant —providing information on top of other signals. When portraits are accompanied by other status signals, e.g. place of residence or car ownership, the effect of obesity on wealth ratings is reduced, but remains significant.

Having established that obesity works as a strong and reliable wealth signal, I test for obesity economic benefits using a real-stake field experiment involving professional loan officers. Leveraging a cooperation with the Uganda Microfinance Regulatory Authority, I obtain contact information for the universe of financial institutions licensed to provide credit in Kampala. I recruit 238 loan officers from 147 institutions, about one-fourth of the initial population of interest.[7] I also recruit 180 prospective borrowers (Kampala

[5]Today more than 70% of the overweight and obese lives in developing countries, and more than 80% of obesity-related deaths happen in low- and middle-income countries (Shekar and Popkin, 2020).

[6]Body-mass index is the strongest predictor of wealth among a standard set of demographics such as age, gender, marriage status, pregnancy status, or education (DHS data, R^2 comparison in bivariate regressions). In a review of the literature, Yang et al. (2007) reports that 16% to 85% of Body Mass Index is 'heritable' and related to genetic similarities among twins.

[7]I select my population of interest to be formal and semi-formal financial institutions, active in the Greater Kampala Area, dealing with the general public and offering cash loans between \$ 250 to \$ 2'000

residents in need of a loan) to collect their demographics, financial characteristics and contact information.

In the credit experiment, loan officers review hypothetical borrowers' profiles during work hours and select those whose application they would like to discuss in person. Incentives come from borrowers' referrals: in a second step, I refer each loan officer to prospective borrowers whose profile matches their hypothetical choices. Loan officers are employees paid based on performance, or self-employed. Thus, they have incentives to select good borrowers and value the referrals. This incentive structure follows closely the Incentivized Resume Rating (IRR) recently developed by Kessler et al. (2019) to test for discrimination in hiring without deception.[8]

The design pinpoints the relationship between obesity, asymmetric information and credit by cross-randomizing borrowers' body mass and financial information in the hypothetical loan profiles. Along the obesity dimension, each profile is associated to (1) an obese or (2) a normal-weight borrower by including a manipulated portrait as the identifier (portraits are standard identifiers in financial documents in Uganda). Along the wealth information dimension, I exogenously vary the borrowers' wealth information included in the profiles, and each loan application is randomly assigned to two information arms: (1) no financial information, (2) self-reported financial information (occupation, collateral and earnings). When they include financial information, the profiles' content is cross-randomized between high or low debt-to-income ratio. In total, loan officers make 6,167 evaluations and in 4,419 times the profile includes financial information.

My results show that loan officers screen borrowers based on body mass and in turn, obese borrowers are granted easier access to credit. When a profile includes a borrower's portrait in its obese version (vs. the normal weight), loan officers perceive the borrower as more creditworthy and financially able, and the application as more likely to be approved. All else equal, loan officers end up being more likely to request the referral of obese borrowers (real-choice outcome).[9] The obesity premium is large —equivalent

(UGX 1 m to UGX 7 m). These selection criteria excludes commercial banks, which normally lend larger amounts. In total, there are 476 institutions. These institutions are heterogeneous in size, but the median employee is 4. If an institution participates, field officers interview 1 to 3 of their loan officers during work hours.

[8]In Kampala, loan officers deal with borrowers in person, making a correspondance study as in Bertrand and Mullainathan (2004) not feasible. The IRR allows to elicit incentive-compatible answers and additionally avoids deception. My application differs from Kessler et al. (2019) on two aspects. First, the setting and focus. To my knowledge, mine is the first application which (a) looks at credit markets, (b) in the context of a low-resource setting, and (c) tests for body-mass discrimination. Second, the design: I include a real-choice outcome and I test for the driver of discrimination, asymmetric information.

[9]The effect is exclusively on loan volume, and not on charged interest rates. Interestingly, I find that

to a 60% increase in a borrower's self-reported income —and aligned with loan officers' explicit beliefs on returns to obesity in access to credit.[10]

Asymmetric information drives obesity benefits: providing loan officers' with borrowers' self-reported financial information reduces the premium by two-thirds (a result significant at the 5% level). Unresolved asymmetric information probably explains the residual obesity premium. Likely the unresolved asymmetric information stems from the self-reported nature of the information. In fact, loan officers rate self-reported wealth information as not very reliable. In principle, taste-based discrimination could also explain the residual effect of obesity —e.g. a beauty premium as in Mobius and Rosenblat (2006). However, the results of the first experiment, where obese portraits were not perceived differently along any outcome except wealth, suggest this is not the case. Moreover, the obesity premium persists within same-sex loan officer/borrower pairs and is not driven by homophily in body mass. I interpret these results as consistent with loan officers engaging statistical discrimination.

The nature of the experimental design, based on hypothetical loan applications and weight-manipulated borrowers portraits, does not allow to test whether down-the-line obese borrowers are actually granted more credit or whether they have better returns to capital. To partially address this concern, I show that loan officers explicit beliefs on the returns to obesity in credit markets are consistent with the experimental results. The explicit beliefs, together the presence of real stakes, and the fact that obesity premium appears to matter on top of self-reported financial information, all point at the external validity of the results and suggest that being obese leads to actual substantial credit-market benefits in Kampala.

The results' implications crucially rest on people's accurate or inaccurate perception of the signal and the benefits. In the last part of the paper, I combine a simple model, additional tests, and experimental variation to further explore this aspect. I begin by investigating whether people hold accurate beliefs on obesity benefits in credit markets. I replicate the credit experiment with the general population asking respondents to guess loan officers' evaluations of the hypothetical loan profiles (incentivized second order beliefs). People are generally aware of obesity benefits in credit markets, yet hold biased beliefs which significantly overestimate obesity premium in access to credit. I find similar evidence of misperceptions when looking at whether people hold accurate beliefs on the obesity wealth signal. On the borrowers' side, I elicit laypeople's incentivized beliefs on

loan officers do not resort to screening using interest rate at this stage.

[10]Own survey data collected at the end of the credit experiment.

the earnings distribution by body mass in Kampala. On the loan officers side, guided by a simple framework, I estimate a revealed-preferences measure of loan officers' beliefs from their choices in the credit experiment.[11] As a benchmark, I collect complementary survey and anthropometric data to estimate the earnings distribution by body mass in Kampala. In Kampala, obese people earn around \$ 80/month more than normal weight people. According to my results, on both sides of the credit markets people hold inaccurate beliefs on what being obese means in terms of earnings. In particular, people place too much weight on obesity as a signal of wealth. While only suggestive, this is consistent with obese people being stereotyped as rich (Bordalo et al., 2016).

The evidence of misperception suggests that screening based on body mass is not necessarily efficient. In terms of credit allocation, both dispersion and overestimation may lead to distortions relative to a full information framework. In particular, 1) demand for credit may be too low among thin people and 2) the credit allocation may favor fat borrowers to an inefficient extent.[12] Moreover, the results suggests the presence of a trade-off between obesity health costs and financial benefits, which matters for the design obesity prevention policies in poor countries. Building on Allcott et al. (2019), I show that accounting for obesity monetary benefits reduces the optimal sugar tax when soda consumption is not regressive. Studying the incentives to gain weight in poor countries and understanding how obesity monetary benefits affect the take up of healthy behaviors are interesting avenues for future research.

This paper makes three contributions. First, it provides novel field-experimental evidence on the financial benefits of status indicators in a low-resource setting. The discussion on the hedonistic or instrumental nature of social concerns is open (Bursztyn and Jensen, 2017) and the experimental evidence on tangible rewards generated by social signals is limited to social interactions (Bursztyn et al., 2020; Nelissen and Meijers, 2011). Most field experiments testing for social image concerns do not investigate the benefits derived from signaling (Bursztyn et al., 2017b, 2019; Chandrasekhar et al.,

[11] The obesity premium in the experiment can be decomposed into a direct —i.e., taste-based discrimination (Becker, 1956) —and an indirect component —i.e., statistical discrimination (Arrow et al., 1973; Phelps, 1972), based on loan officers' beliefs of the earnings distribution by body mass. Exploiting the experimental cross-randomization of body mass and earnings, I infer loan officers' beliefs about the average earnings difference between obese and normal-weight borrowers and compare the distribution with the population value. My approach is conceptually close but distinct to Bohren et al. (2019). They propose either (i) eliciting agents beliefs, implying a large increase in survey time, or (ii) providing information about group characteristics. Based on discussions with partner micro-finance institutions, collecting statistics on loan performance by body mass appeared practically nonviable.

[12] Any conclusive statement on the effects of body mass screening on credit market efficiency hinges on returns to capital by borrowers' body mass and is beyond the scope of this paper.

2018; DellaVigna et al., 2016; Karing, 2018; Perez-Truglia and Cruces, 2017). A closely related paper is Bursztyn et al. (2017a), providing experimental evidence of demand for status in Indonesia. My results suggest that financial benefits may be driving, at least in part, the demand for status and thus help explaining phenomena like large expenditures in celebrations among the ultra poor (Banerjee and Duflo, 2007).[13] Second, the paper sheds light on the mechanism behind status signals' benefits —asymmetric information. Together with Cole et al. (2015) and Fisman et al. (2017), this is one of the few experimental studies looking at the supply side of lending decision in poor countries. While previous work —notably Giné et al. (2012) —studied the effect of reducing asymmetric information in credit markets, to the best of my knowledge this is the first paper to jointly randomize the degree asymmetric information with borrowers' information.[14] Third, this paper is the first to identify positive statistical discrimination by obesity in poor countries and thus, contributes to a literature on discrimination by body mass,[15] and on bias in consumer lending (Berkovec et al., 1994; Dobbie et al., 2018; Labie et al., 2015). Duarte et al. (2012), Pope and Sydnor (2011), and Ravina et al. (2008) also test for appearance discrimination in credit markets, but work in high-income setting, look at negative discrimination, and identify a different mechanism, e.g. taste or beauty bias. Finally, the paper provides experimental evidence on the socio-economic benefits of weight gain in poor countries and adds to our understanding of the obesity global epidemic. While a large literature focuses on the health and economic costs of obesity, to my knowledge, there is no other experimental evidence on its benefits.[16]

The paper is structured as follows. Section 2 describes the weight-manipulated portraits. Section 3 describes the beliefs experiment. Section 4 presents the credit experiment. In section 5, I test for awareness of benefits and beliefs accuracy among loan officers and borrowers using additional experimental evidence and a simple framework. Section 6 concludes discussing external validity and policy implications.

[13] Bursztyn et al. (2017a) provides evidence that (low) self-esteem may be a concurrent determinant of conspicuous consumption patterns.

[14] A field experiment with a similar design is Bartoš et al. (2016), showing that discrimination can arise from the decision makers' choose of the effort level to dedicate to an application.

[15] These works look at high-income countries and focus on negative discrimination. See Neumark (2018) for a review. For example, Rooth (2009) tests for *negative* obesity discrimination in hiring in Sweden.

[16] Most obesity literature focuses on high-income countries Cawley, 2004; Cawley and Meyerhoefer, 2012; Finkelstein et al., 2009, 2012). In the development context, Rosenzweig and Zhang (2019) studies the effects of education on healthy behaviors using twin data from rural China, and Giuntella et al. (2020) explores the effects of trade on obesity in Mexico. As obesity benefits imply rewards from extra calories, my findings relate to the puzzle of calorie under-investment in low-resource settings (Atkin, 2016; Schofield, 2014; Subramanian and Deaton, 1996).

2 Identifying the Causal Effect of Body-Mass Changes

Identifying the causal effect of obesity in an observational analysis is hard because body mass realizations are endogenous to preferences and constraints. An experimental design which randomly varies caloric intake would pose ethical challenges. To overcome both concerns, this paper identifies the causal effect of body mass by randomly varying whether the decision maker sees the "thinner" or "fatter" computer-manipulated version of a portrait. While other papers have used weight-manipulated portraits to test for negative discrimination by obesity in high-income settings (see Neumark (2018) for a review), my design innovates relative to the literature by comparing thinner and fatter manipulated portraits, rather than manipulated and originals. Comparing manipulated portraits allows me to identify the effect of *changes* in body mass, all else equal.[17]

The original portraits are 30 portraits of Kampala residents of Ugandan nationality and 4 computer-generated portraits of individuals of white race.[18] The portrayed individuals are stratified by gender, and are heterogeneous according to body mass, age, ethnicity, religion, and socio-economic status. To create the manipulated portraits I cooperate with two photographers, who manually create a "thinner" and "fatter" version of each portrait using a photo-morphing software. After discarding the originals, the final set of portraits is made of 34 pairs of weight-manipulated portraits, or 68 pictures.[19]

To measure the body mass variation across thinner and fatter portraits I elicit the portraits' perceived Body-Mass Index (BMI) from a set of 10 independent raters (Kampala residents).[20] To rate the perceived BMI, raters compare portraits with the figurative Body Size Scale for African Populations developed and validated in Cohen et al. (2015) (see Appendix Figure J.2). The portraits' perceived BMI, whose distribution is plotted in Appendix Figure J.3, ranges between 20 to 44 points. All "thinner" portraits are perceived to be at least normal weight ($BMI \geq 18.5$), while all "fatter" portraits are perceived to be at least obese ($BMI \geq 30$).[21] In particular, "fatter" have an average

[17]A caveat to this would be if manipulating weight up or down would affect perception differentially, an hypothesis which does not seem to be supported by informal ratings and checks.

[18]Kampala residents are recruited via focus groups; participants provide written consent and receive a digital copy of their portrait. The computer-generated portraits are obtained from an algorithm similar to https://thispersondoesnotexist.com/.

[19]Appendix Figure J.1 shows all the portraits' pairs presented one next to each other. While some of the portraits may look manipulated when showed one next to each other, several checks showed that people do not really perceive the portraits as odd when presented one-by-one as in the experiment.

[20]The BMI is a measure of whether someone is over- or underweight, calculated by dividing their weight in kilograms by the square of their height in metres.

[21]Notably, the perceived BMI distribution of the manipulated portraits is not much more extreme as compared with the BMI distribution in Kampala. In the city, obesity and overweight are much more

perceived BMI of 37 —class II obesity, while ”thinner” of 23 —normal weight. Thus, by varying whether a respondent sees a portrait in its thinner or fatter version, I identify the causal effect of obesity relatively to normal weight as the average treatment effect.

3 Obesity as a Signal of Wealth

Obesity positively correlates with wealth in the vast majority of low-income countries (Figure 1), and is the strongest wealth proxy among the observable individual characteristics recorded in Demographic and Health Survey (DHS) data —including age, gender, marital status, number of children, and rural/urban residence. In line with the data, abundant anecdotal evidence and qualitative evidence across time and space describe fatness as a sign of status in poor societies. Obesity and overweight have been found to signal high socio-economic status in ancient Europe. In current days, positive perception of fat bodies is reported by Anderson-Fye (2004) in Belize; Bosire et al. (2020) in South Africa; Chigbu et al. (2019) in Nigeria; Ettarh et al. (2013) in Nairobi, Kenya; Holdsworth et al. (2004) in urban Senegal; Popenoe (2012) among Arabs in Niger; Sobo (1994) in Jamaica; Ngaruiya et al. (2017) in Uganda.

While the evidence shows that obesity is associated with high social standing in low-income settings, the main assumption behind this paper's hypothesis —that people update their beliefs on others' wealth or earnings based on their obesity status —is not yet verified. Indeed, although obesity correlates with wealth in the data, people may not perceive body mass as a salient or reliable trait, and thus not take it into account when forming beliefs about others' wealth or earnings. On top of this, people may infer also other qualities independent of wealth which may indirectly affect their wealth beliefs. For example, in anthropology obesity is often described as a beauty trait, a sign of fertility, and good health in poor countries (see for example **??**), while in high-income countries, thinness is anecdotally associated with self-control and ability.[22]

3.1 Beliefs Experiment

To validate the assumption that raised body mass is perceived as a reliable wealth signal in Kampala, I design a survey experiment to test 1) whether obesity is perceived as a

prevalent than underweight. According to the Uganda Demographic and Health Survey, already in 2016 the share of overweight and obese women ($BMI > 25$) in Kampala was 41%, against a 5.3% underweight. Among men, the share of overweight and obese was around 22%, against 4.4% underweight.

[22] There is actually no conclusive evidence linking self control to body mass outcomes, as shown in the meta-analysis study **??**.

signal of wealth, as opposed to signaling other traits and 2) the relevance of the obesity signal against other typical signs of status like place of residence and car ownership.

Design In a survey experiment respondents see and rate random sequence of four portraits from the set of weight manipulated portraits. My design cross-randomizes obesity with other status signals, in a 2x3 design (Appendix Figure 2). Along the obesity dimension, for each portrait, respondents see either the fatter or thinner weight-manipulated version. The randomization is at the portrait level allows me to test whether on average obese portraits are rated differently as compared to not obese portraits, conditional on respondent and portrayed individual fixed effects. Along the second dimension, I randomize the amount of wealth signals available to the respondents. Respondents are assigned to two treatment arms. In the one-signal arm, all portraits are accompanied by age information only; in the multiple-signals arm, all portraits are accompanied by age information and another signal of wealth: respondents either learn that the person owns a car (rich type) or that the person lives in a slum (poor type). The signal type (rich or poor) is randomized at the portrait-individual level.

Outcomes Respondents rate each portrait along six characteristics in random order (first-order beliefs): wealth, beauty, health, longevity, self-control, ability to get things done, and trustworthiness. Of these characteristic, wealth is the pre-registered primary outcome.[23] The choice of the secondary outcomes was based on the most common qualities that are positively associated with obesity in poor countries in the anthropology literature (health, beauty, life expectancy) and those anecdotally negatively associated with obesity in high income countries (self-control, ability). Trustworthiness ex-ante could be a relevant confounder. While ultimately any list of traits cannot be comprehensive, the final choice was made to trade-off survey time and breadth.[24]

First-order beliefs —the main outcome of interest —cannot be incentivized. Although the variety of characteristics elicited reduces the likelihood that respondents guess the hypothesis under study, lack of monetary incentives may still raise concerns of experimenter demands biasing people's answers. To minimize these concerns, first the survey tools I include a decoy wealth signal: about a fourth of the portraits rated is of

[23] All secondary outcomes were pre-registered with the exception of trustworthiness, which was added during the experiment.

[24] These outcomes, including the distinction between primary and secondary, were pre-registered with the exception of trustworthiness which was included half-way into the experiment.

white race.[25] Second, I elicit a second set of outcomes: how they think other respondents rated each portrait (beliefs' about others beliefs). These answers are incentivized, as respondents receive a small bonus if their answer matches other respondents' most frequent ratings.[26]

Sample selection Respondents live in the districts of Kampala, Mukono and Wakiso, the districts which build for the largest population share of the Greater Kampala Metropolitan Area (Uganda Population and Housing Census 2014). To qualify for participation, respondents needed to be 18 year old or older and provide written consent. The sample is stratified by age group, socio-economic status, and gender. In fact, ex-ante obesity perception may depend on these characteristics. The anthropology literature highlights the relationship between poverty and social valorization of obesity, thus body mass perception may differ by socio-economic status.[27] Moeover, since obesity is often described as a sign of fertility (Popenoe, 2012), obesity perception may differ across women and men. Finally, younger people, likely more exposed to western media, may have updated their perception of body mass accordingly (**?**). Notably, the sample is not stratified by body mass.

Field officers walked around the districts and enrolled respondents quasi-randomly until they reached the required number and composition.[28] The survey was described as part of a study in partnership with the University of Zurich focusing on how appearance affects individuals' perception in Uganda. Respondents received a small fixed fee in airtime as compensation for their time, plus a bonus depending on their answers. On top of this, field officers took respondents' weight and height, and respondents received their measurements, their BMI and their 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 work as a good incentives to participate. The final sample includes 511 Kampala residents. Table 1 summarizes the

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

[26]The portraits are introduced by the sentence: *"Imagine you just met this person for the first time in Kampala..."*. Each portrait is rated twice: the first time to elicit first-order beliefs; the second time, guessing other respondents' beliefs. The wording to elicit first-order beliefs is: *"How would you rate this person's $outcome? Please, provide your answer on a scale from 1 (not at all $outcome) to 4 (very $outcome)."* For beliefs' about others beliefs the wording is: *"How did other respondents rate this person's $outcome? Please provide your best guess of the most frequent answer on a scale from 1 (not at all $outcome) to 4 (very $outcome)."* Survey tools are in Appendix I.

[27]As a 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 dwell characteristic, access to credit and food security. The procedure is detailed in Appendix A).

[28]The survey was implemented in cooperation with IGREC Uganda.

descriptives. Because of the stratification, the sample is slightly older and richer than the Kampala average. In terms of body size, on average respondents are overweight (BMI 25.66). This data point is aligned with the data from body mass distribution in Kampala from the Uganda DHS 2016, again pointing at the rising overweight and obesity problems in urban areas in Africa.

3.2 Main Results: Obesity Wealth-Signaling Value

Figure 3 plots the average ratings by obesity status and Table 2 summarizes the corresponding regression analysis, including respondent and portrayed-individual fixed effects.[29]

The main statistic of interest is the difference in the wealth ratings of *Obese* and *Not Obese* portraits. The data shows that the very same portrait in its obese version is systematically rated as wealthier as compared to its normal weight counterpart (0.70 s.d). Instead, obese portraits are not perceived on average more beautiful, healthier nor more trustworthy; they are not rated differently in terms of life expectancy or ability; obesity status is also not associated with a lower self-control, described as ability to resist to temptation.[30] The beliefs experiment shows that obesity status is routinely perceived as a signal of being rich, but not of other traits.

Since people generally face many signals at once, one may worry that the obesity signal may be crowded out by other wealth signals, or that it may be so small as to be irrelevant. To investigate the relevance of obesity as a signal of wealth, I exploit the information variation across treatment arms. First, I benchmark the effect of obesity against the effect of a strong wealth signal, car ownership.[31] To do so, I compare the effect of car-ownership on wealth ratings in the multiple-signals arm, with the effect of obesity in the one-signal arm: the two coefficients are not statistically different from each other. Thus, the wealth-signaling gain from being obese is large: comparable to the gain derived from owning a car. Second, I look at whether the obesity coefficient on wealth ratings is systematically reduced by the presence of another signal. To do so, I pool all treatment arms and include an interaction term between the obesity dummy and a treatment-arm dummy. Providing more information about a person's assets or place

[29] The regression model is described in Appendix A.

[30] The beliefs about others' beliefs results are broadly consistent with the first-order beliefs: Table 2 Panel B shows that obesity is systematically more associated with wealth, than with any other effect (the effect is twice as large and statistically different).

[31] In Uganda in 2016 there were 40 registered motor vehicles per 1'000 inhabitants in 2016. As a comparison, in the US there were 838 *cars* per 1'000 inhabitants and in Switzerland 716.

of residence does reduce the importance of the obesity signal, but the effect is small and significant only at the 10% level (Figure 3 and Table 2). Thus, the obesity signal is a relevant one, which provides additional information beyond other strong signs of status like place of residence or car ownership. Finally, the importance of obesity as a wealth signal does not appear to vary by any of the pre-registered traits. In particular, obesity equally signals wealth for men and women.[32]

Discussion The beliefs experiment shows that Kampala residents routinely take into account a persons' body mass to build their wealth beliefs. The obesity signal is salient: without any experimenter prompt respondents associate obesity with wealth. The fact that obesity is exploited as a proxy for wealth appears to be common knowledge, as first and second-order beliefs are aligned). Finally, and most notably, the obesity signal appears very strong and reliable, as it provides additional information on top of other strong status signals like car ownership and place of residence. Taken together, these results suggest that obesity is routinely perceived as as a signal of wealth in real life interactions. In the next section, I move to investigating whether the wealth-signaling value of the obesity status signal actually translates into economic benefits from being obese and test for the asymmetric information channel.

4 Obesity Benefits in Credit Markets

To test whether obesity can provide financial benefits in market settings, I focus on credit markets. My hypothesis is that being obese can lead to economic benefits because agents rely on body mass —a status signal —as an imperfect but cheap proxy for wealth when verifying financial information is costly. Credit markets are a good setting to test for this hypothesis because, on top of being a context where benefits are relevant, they entail financial interactions where asymmetric information is pervasive, both in terms of adverse selection and moral hazard (Karlan and Zinman, 2009). Moreover, in poor countries, the rich have easier access to credit - thus being wealthy matters.[33]

[32] Additional results, including a separate analysis for white race portraits and the analysis of signals interactions, can be found in Appendix A.

[33] Understanding barriers to credit access has been the focus of a large literature in development economics. Karlan and Morduch (2010) provides a comprehensive review of the issue of accessing financial services in poor countries. Within this literature, Banerjee (2003) provides a theoretical framework to explain why asymmetric information leads loan officers favoring rich borrowers; more recently, De Mel et al. (2008) show experimentally that rich borrowers have also better returns to credit.

4.1 Credit Experiment

I design and implement a field experiment involving professional loan officers in Kampala (Uganda). In Uganda, loan officers' play a crucial role in the lending process, which is normally dealt in person. On top of meeting with borrowers multiple times, they also often take the final approval decision. Since most loan officers face a performance pay scheme, they have incentives to select the best borrowers. However, loan officers are normally also in charge of the field-investigative work to verify the information provided by prospective borrowers, thus also bearing the costs of the information verification.[34]

Institutions, Loan officers, and Borrowers Sample Institutions providing credit in Uganda are highly heterogeneous.[35] I obtained the listing of the universe of financial institutions *licensed* to provide credit in Uganda from the Ugandan Microfinance Regulatory Authority (UMRA). When the field work for this paper was conducted the listing included: 25 commercial banks, 4 credit institutions, 708 licensed moneylenders and 127 microfinance institutions. I restrict to institutions in Greater Kampala and, to allow for a relatively homogenous sample, I focus on those financial institutions which provide credit to the general population and specifically, individual and collateralized cash loans between $250 and $2500 with a 6-months term to maturity.[36] After excluding institutions in the pilot, my population of interest counts 447 institutions.[37]

IPA Uganda field officers visited each of the 447 institutions, checked the eligibility

[34]In Uganda, reliable financial information is lacking. For example, only 20% of Ugandan land titles - a common collateral - was registered in 2017. Although there exists a credit-score system, as of 2019 the majority of consumers are not included in that system. In this context, the cost of credit is high and credit rationing is widespread.

[35]Financial institutions which are legally allowed to provide credit are classified in four Tiers. Tier 1 institutions or commercial banks (25 institutions), that is formal credit institutions. Semi-formal institutions (Tier 2) are credit institutions not authorized to establish checking accounts or trade in foreign currency (4 institutions). Informal financial institutions include the remaining two tiers. Tier 3 includes the 5 institutions referred to as Microfinance Deposit-Taking Institutions (MDI). Tier 4 is a residual category that includes all other forms of lenders, including all MFIs that did not transform into MDIs. Tier 4 institutions are heterogeneous: moneylenders, companies, NGOs, or savings and credit cooperatives (SACCOs). The Uganda Microfinance Regulatory Authority (UMRA) encourages Tier 3 and Tier 4 to register to the official registrar. For an extensive description of the Ugandan credit market see Duggan (2016); Nilsson (2017); Sebudde et al. (2017).

[36]This category was defined after focus groups with multiple loan officers and branch managers. It excludes institutions which provide credit to certain professional categories (e.g., government employees), those providing mainly relatively large business loans (commercial banks), savings and credit cooperatives which mostly provide group loans, and informal moneylenders. While a 6-months term to maturity may seem short, the constraint actually only limited the inclusion of institutions granting shorter-term loans only.

[37]When an institution has multiple branches, I randomly select up to 4 branches and count each branch as one institution.

criteria and elicited from management the institutional consent to participate in a study in partnership with the University of Zurich. The study was presented as aimed at improving matching between borrowers and lenders in Kampala.[38] In total, more than one fourth of the visited institutions participate: 147 out of 447. This high turnout can be explained with the competitiveness of the Ugandan financial setting. The participating institutions, whose characteristics are summarized in Table 3, are broadly representative of the types of institutions providing personal loans in Kampala.[39] Most institutions offer both personal and business loans. The size, namely branches and employees number, is very heterogeneous but most institutions are rather small (median employees number is 4). The cost of credit is high but in line with the Ugandan average monthly interest rate (10%-12% in 2019).[40]

For each institution, 1 to 3 loan officers are interviewed. There are two requirements for participation: respondents need to be dealing with borrowers directly and provide written consent. The monetary incentives to participate are small ($1 fee); most relevantly, loan officers know that at the end of the study they will be referred to good prospective borrowers. The final sample includes 238 respondents, whose characteristics are summarized in Table 4. While for simplicity I refer to the respondents as loan officers, the occupation set is more diverse: 63% self-identify as loan officers; 13% own the business and 9% state to be the manager. The sample is relatively balanced in terms of gender (60% male); loan officers are also relatively young and educated, as about two-thirds hold a Bachelor degree. The monthly salary ranges between $ 135 to $ 270, above the median monthly wage in Kampala ($80 in the Ugandan Census 2014). Looking at loan officers' tasks 74% directly approve loan applications and 80% are in charge of verifying borrowers' information. Importantly, the verification process appears time consuming: loan officers spend on average about half of their working week verifying borrowers' information on the field.

[38]This is an accurate description and does not imply deception because at the end of the experiment, loan officers are matched with borrowers whose characteristics they like. I preferred not to draw people's attention on discrimination and in particular, body mass discrimination to reduce concerns of experimenter demands and selection.

[39]Except for the exclusion of commercial banks, and group loans institutions, all financial institutions tiers are represented. If anything, slightly oversample formal institutions as opposed to semi-formal ones In the actual population of financial institutions in Kampala, non-deposit deposit taking microfinance institutions account for the 1%, deposit-taking microfinance institutions account for the 0.12% and credit institutions account for the 0.15%.

[40]Ideally, one would want to compare the in-sample institutions with the full population. To do so, one would have needed to run a listing with all institutions, including those which did not want to participate in the study. This was logistically unfeasible.

The recruitment of the sample of prospective borrowers is simpler. At the end of the beliefs experiment, I collect information on the respondents' credit history, their need of a loan, and reason for borrowing. Then conditional on being a first-time borrower, I elicit consent to be included in the credit experiment sample. This allows me to collect a database with the information of 180 prospective borrowers, that is Kampala residents in need of a loan.

Design and Incentives In the credit experiment, the 254 professional loan officers evaluate 30 hypothetical loan applications each to be matched with real borrowers according to their preferences. This incentive structure follows closely the Incentivized Resume Rating (IRR) recently developed by Kessler et al. (2019) to test for discrimination in hiring without deception.[41] I provide the referrals by matching loan officers preferences with prospective borrowers from the borrowers' sample and then communicating to the borrowers the loan officers' name and contact information.[42]

Both financial business owners and loan officers care about referrals, because good clients can affect their earnings prospects. Credit markets in Kampala are characterized by many institutions competing for few high-quality borrowers. Owners' choices may affect their profits. Most employed loan officers face some form of performance pay.[43]

To pin down the relationship between obesity, access to credit, and asymmetric information, my design cross randomizes obesity and the degree of asymmetric information in the borrowers profiles. Along the first dimension, I vary borrowers' body mass by randomly assigning each loan officer to see a borrower's portrait in the either *Obese* or *Not Obese* version.[44] Along the second dimension, I vary the degree of asymmetric infor-

[41]In the original paper, Kessler et al. 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 demographics of hypothetical candidates. Their outcomes are employer preferences for candidates and employer beliefs about the likelihood candidates will accept job offers.

[42]The matching is born out of a machine learning algorithm which predicts the borrowers-lenders pairs with the best referral request probability, based on observables. I train a *Random Forest Classifier* on the experimental data. For each loan officer and borrower pairs, the algorithm predicts the likelihood that the loan officer would request the referral of that borrower. Following Kessler et al. (2019), to avoid implementing biased referrals, I include among the observable characteristics borrower's gender and body mass. I then apply the Classifier to the real prospective borrowers data and for each borrower I select the best match, that is: the loan officers with the highest referral request likelihood. Appendix C describes in detail the matching algorithm and the referrals' implementation.

[43]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%), revenue generated by self or bank on the whole (10%). For 18% of the loan officers, performance pay takes the form of yearly or quarterly bonuses if the person has done well or met a specific target.

[44]This randomization technique works neatly in this setting because it is customary to use portraits as

mation between borrowers and lenders by changing the amount and quality of borrowers' self-reported information in the application. Loan officers face two information options: a low-information arm, where profiles shown to loan officers only include demographics, a portrait, loan characteristics and the reason for the loan; a high-information arm, where profiles also include self-reported financial information and are randomly assigned to a high or low debt-to-income ratio. For each loan officer, the first 10 randomly selected profiles do not include any financial information; the last 20 include self-reported monthly revenues, monthly profits, collateral and occupation.[45] The result is a 2x3 design, described in Figure 5.[46] The idea underlying this design is that there are two reasons why loan officers may treat obese borrowers differently. First, they may have a preference for (or against) obese borrowers, which is unrelated to the fact that obesity is perceived as a proxy for wealth (*taste-based discrimination*). Second, they may borrowers' body mass may affect credit outcomes because loan officers' exploit obesity as a proxy for wealth. In the former case, one would not expect loan officers' preferences to be affected by the information environment. In the latter, instead, one would expect that the more information on a borrower's financial situation is available, the less loan officers would rely on body mass in their decisions.[47]

The experimental setup and loan officers' incentives are as close as possible to a real life setting. The lending process in Kampala normally begins with an in-person meeting between a loan officer and a borrower, which rules out the possibility of an audit

personal identifiers in financial documents, as shown in the financial documents templates in Appendix Figure J.4.

[45]Within the high- information arm applications were ex-ante divided into two sub-treatment arms of 10 applications each, in which either loan officers' opt in to see more information or the information is presented by default. The comparison between sub-treatments allows to understand at which point in the decision making process the discrimination bites. For example, loan officers may prefer to avoid seeing the information of applicants which they perceive as less creditworthy ex-ante. While the extra information was provided for free to the loan officers, it still takes some time for a loan officer to review it. The results show that loan officers opt in to receive more information about the applicants in 99% of the cases. In the analysis, I pool the two sub-treatments.

[46]Notably, while the order in which profiles are presented is random, the information treatments' order is not randomized. This design choice helped to clarify to the loan officers that the amount/type of information in the profiles was a design choice, and could not be attributed to a borrowers' strategic decision. In Appendix B I present evidence that the results are not driven by the order.

[47]Notably this test of statistical versus taste-based discrimination does not allow to identify the ”true” animus of the discrimination. Imagine that loan officers are biased towards obesity borrowers but that providing additional information makes it harder for them to justify their discrimination to other people or themselves, this outcome would be indistinguishable from actual statistical discrimination (loan officers would still look like profit-maximizing agents). In my setting, this is a relatively small concern applying an obesity premium does not appear to be at all stigmatized. This design limitation should be taken into account, however, if one would want to apply a similar design to another discrimination context.

study. Based on the self-reported information provided, loan officers decide whether or not to engage in the effortful and time-consuming task of verifying the borrower's information. Once the verification process is concluded, in some cases loan officers have full discretionality on loan approval, in others their choice is about recommending the applicant to the final stage of the loan approval process (credit committee evaluation). The first treatment arm mimics when a loan officer decides whom to meet, among the prospective borrowers in a waiting room. The second treatment arm mimics a situation in which, when meeting a borrower for the first time and collecting the self-reported information, a loan officer chooses whether or not to embark in the costly activity of verifying the borrowers' information on the field.[48]

Outcomes Loan officers evaluate each borrower profile according to six outcomes. I elicit three measures of beliefs (approval likelihood, borrowers' creditworthiness and financial ability) and the binary choice of being willing to meet with a borrower with similar characteristics. Given the incentive structure, the latter is a real choice outcome: if a loan officer chooses to meet a hypothetical borrower, then this increases the likelihood that she is referred to a real borrower with similar characteristics. The experiment also elicits two pre-registered secondary outcomes: interest rate charged conditional on approval, if a loan officer can charge discretionary interest rates and reliability of the self-reported financial information, when profiles include self-reported financial information.[49]

[48] According to the loan officers (Table 4), verifying the borrowers' information accounts for more than half of their working time (between 2 to 3 days per week) on average and includes multiple visits to the borrowers' home or business (96% of the respondents), verifying collateral (95%), talking to the neighbors, family members and employees (75%) as well as requiring formal documents (92%).

[49] The questions order is: Approval Likelihood, Creditworthiness, Interest Rate (if applicable), Financial Ability, Reliability (if applicable), Referral. The number, wording and scale of the questions were pre-registered. The wording is the following. Approval Likelihood: *Based on your first impression, how likely would you be to approve this loan application? (1-5, not at all likely - 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 - 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 - extremely likely)*; Info Reliability: *How reliable do you think the information provided by the applicant is? (1-5, not at all reliable - extremely reliable, not applicable if no additional info.)*; Referral: *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)*

Hypothetical Loan Profiles I build hypothetical loan profiles by cross-randomizing information from the prospective borrowers' sample and focus groups with loan officers. I cross-randomize the information to build 30 hypothetical borrower profiles.[50] Each profile includes blurred borrower's name and passport number, and Ugandan nationality. Moreover, each profile is randomly assigned to cross-randomized information on age, picture, loan profile and reason for loan. When a profile is assigned to the high-information treatment arm, it additionally includes self-reported financial information, that is borrowers' occupation, monthly revenues, monthly profits and collateral.[51] Most notably, each profile is assigned to a weight-manipulated portrait, so that for each profile there exist 30 pairs of borrower profiles, an *Obese* and a *Not-Obese* version, for a total of 60 loan profiles. Figure 6 shows one example of profiles' pair (no financial information). In the experiment, I randomize each respondent to see 30 hypothetical profiles and the randomization is stratified at the pair level to mitigate experimenter demands.

The hypothetical profiles are realistic. First, the profiles' template is based on a real financial document.[52] Second, the borrowers' portraits are selected from the pool of Kampala residents portraits. Third, to avoid that the combination of cross-randomized information may result in an unrealistic profile, the final set of 60 loan profiles is vetted by real loan officers.

4.2 Main Results: Obesity Premium in Access to Credit

Figure 7 plots the credit ratings by borrowers' body mass. The main statistic of interest is the difference in access to credit between *Obese* and *Not-Obese* borrowers.[53] Loan officers rate loan profiles associated with obese borrowers as more likely to be approved, more creditworthy and financially able, and finally, are more likely to requested the borrower for a referral (real-choice outcome). Plotting ratings by a continuous measure of body mass, the financial benefits from weight gain appears to be linearly increasing and the data shows no penalties associated to extreme BMI values (above and beyond

[50]The procedure is summarized in Table 5 and described in detail in Appendix B.

[51]The financial information is delivered by adding, at the bottom of the application, the following 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 [revenues amount]. The profits were [profits 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."*

[52]The templated used are displayed in Appendix Figure J.4.

[53]Table 6 shows the randomization works well and that loan profiles associated with *Obese* and *Not-Obese* borrowers are balanced across all observables, except body mass.

$BMI = 40$, i.e., obesity of degree II).[54]

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

$$Y_{ij}^{k} = \beta_0 + \beta_1 Obese_{ij} + \delta_i + \gamma_j + u_{ij}, \tag{1}$$

where i indexes the loan profile, j the loan officer and k is the outcome; Y_{ij}^{k} describes outcome k's rating of loan profile i by loan officer j; $Obese_{ij}$ is a dummy for loan profile i being associated with the *Obese* version of a borrowers' portrait when evaluated by loan officer j; δ_i are borrower pro fixed effects, and γ_j are loan-officer fixed effects. Standard errors are clustered at the loan officer level. For comparability, I standardize all outcome variables including the referral-request dummy. The coefficient of interest is β_1, which measures the obesity premium in access to credit.

Table 7, panel A, summarizes the results. The obesity premium is positive and statistically significant across all outcomes. The very same loan profile, when associated to an obese portraits, has a 0.11 s.d., (p-value 0.000) higher expected approval likelihood (Column 1). On average, obese borrowers are rated more financially able (0.12 s.d., p-value 0.000, Column 2) and creditworthy (0.09 s.d., p-value 0.000, Column 3). Consistent with the notion that loan officers' perceive obese borrowers as better borrowers, profiles including the obese version of a portrait are is 0.042 s.d. (p-value 0.019) more likely to be asked for a referral (Column 4). The results are robust to a randomization inference exercise (Appendix B).

To learn more about the relevance of the obesity premium, one can express the results in terms of odds that a borrower gets past first screening. The results imply that being obese raises the likelihood a loan officers asks you for a meeting to discuss a loan application by 2% (control mean: 74%), the likelihood a loan officers thinks you qualify for credit by 11% (46%), that you will put money to productive use by 5% (60%) and that you are rated creditworthy by 13% (47%). Moreover, exploiting the cross-randomized self-reported income information included two-thirds of the profiles, I can benchmark the gain in access to credit derived from being obese with the gains from declaring a larger income. Across all outcomes, the obesity premium is comparable (not statistically different) to a 60% increase in self-reported monthly income relative to the

[54]The model includes include loan officer fixed effects, and second-order polynomial in the manipulated pictures' BMI to allow for non linearity and control for observables.

borrowers' average income, or about $300.[55][56]

Taken together, the results show that obese borrowers have easier access to credit, and that the premium size is substantial. More generally, at least within the body mass range of the portraits, any level of weight gain - above and beyond the obesity BMI threshold - leads to significant credit-market benefits. The data is consistent with loan officers preferring fatter borrowers because they perceived them as better borrowers: the results on productivity and creditworthiness suggest that obese borrowers are perceived less risky, both in terms of moral hazard and adverse selection.

4.3 Mechanism: Asymmetric Information Drives Obesity Premium

Why do loan officers prefer obese borrowers? My hypothesis is that the obesity premium is a response to asymmetric information about borrowers' financial standing: obese borrowers are perceived as better borrowers because their body mass signals that they are rich.[57] While the statistical discrimination hypothesis is in line with the beliefs experiment —showing that obesity status, perhaps because it is a relatively hard trait to manipulate, is perceived as a reliable wealth signal —taste may also be a driver of the obesity premium. First, there may be other traits, not measured in the beliefs experiment and unrelated to a person's financial standing, which people associate with both obesity and creditworthiness. Second, professional loan officers may just have different preferences and beliefs compared to the general population (Palacios-Huerta and Volij, 2008). As discussed in the design section, my approach to disentangle between statistical and taste-based discrimination is to vary the degree of asymmetric information between borrowers and lenders by providing or not self-reported information about borrowers' earnings, occupation, and collateral. The idea is that if loan officers were profit-maximizing agents which exploit obesity as a way to screen for rich borrowers, then the more financial information about a borrower, the lower the need for each signal and thus the importance of body mass. Instead, if loan officers prefer obese borrowers

[55]The comparison is obtained from comparing the regression coefficient of obesity and of self-reported monthly income in two separate but identical models, each including loan officers and profile fixed effects, using Stata's *suest* and *test*. The p-value of the test is 0.5803. The borrowers' average income in the profiles is ca. $480.

[56]Interestingly, I find that obese borrowers are not charged systematically different interest rates. This is mainly explained by loan officers' not screening based on interest rate. While about half of the loan officers can charge discretionary interest rates, only 5% of the loan officers actually choose to do so at this stage.

[57]In low-income countries, evidence suggests that credit markets favor rich borrowers. While this is likely partly due to imperfect information and contracting problems ((Banerjee, 2003)), there is also some evidence that rich borrowers have higher returns to capital (De Mel et al., 2008).

for reasons orthogonal to the wealth-signaling value of obesity, then obesity premium should be invariant to the amount of financial information.

To compare the obesity premium when loan officers have more or less information about a borrowers' financial standing I estimate the following model:

$$Y_{ij}^{k} = \theta_0 + \theta_1 Obese_{ij} + \theta_2 FinancialInfo_{ij} + \theta_3 FinancialInfo_{ij} \cdot Obese_{ij} + \delta_i + \gamma_j + v_{ij}, \qquad (2)$$

As in equation (1), i indexes the loan profile, j the loan officer, and k the outcome. Y_{ij}^{k} is outcome k rating for loan application i by loan officer j. $Obese_{ij}$ is a dummy for whether application i is associated with an *Obese* portrait when evaluated by loan officer j. $FinancialInfo_{ij}$ is a dummy for loan profile i being assigned to include self-reported financial information, when evaluated by loan officer j. δ_i are loan-profile fixed effects, and γ_j are loan-officer fixed effects. All outcomes are standardized. Standard errors are clustered at the loan officer level. θ_1 is the obesity premium in the absence of self-reported wealth information; θ_2 captures the relevance of the additional information provided; θ_3 measures the effect of reducing asymmetric information on the obesity premium.

Table 7, panel B, summarizes the regression analysis and provides two main results. First, providing additional self-reported financial information overall improves access to credit. Since, as described in Table 5, the financial information provided is either sufficiently good to grant approval or borderline, this result provides a sanity check that the self-reported financial information is valuable for the loan officers and does reduce the degree of asymmetric information. Second, providing additional financial information indeed substantially and significantly reduces the obesity premium. Relative to the obesity premium absent self-reported financial information (θ_1), the obesity premium drops by nearly two-thirds when profiles include self-reported financial information: across all outcomes, the interaction between obesity and financial information (θ_3) is negative and mostly statistically significant (p-value range: 0.002-0.371). For example, focusing on Approval Likelihood rating providing self-reported financial information reduces the obesity premium by nearly 70% (p-value: 0.041).

I interpret these results as to say that providing more financial information reduces the obesity premium, and thus that asymmetric information is a driver of the obesity premium. Loan officers' behavior is not consistent with a pure taste-based discrimination model and at least two-thirds of the obesity premium can explained by statistical discrimination.[58]

From a theoretical perspective, both residual asymmetric information and taste-based discrimination (e.g. a beauty premium) could explain the residual obesity premium. Since the financial information is self-reported (unverified) loan officers are likely to face residual asymmetric information. Instead, I find no empirical evidence in support of taste-based discrimination: the results of the first experiment does not point at beauty, health or trustworthiness premia and the residual premium is not explained by homophily in body size.[59] Consistent with this interpretation, on average, loan officers do not fully trust applicants' self-reported financial information. The self-reported information is perceived as not very reliable (the average reliability rating is 1.98, on a scale from 1 to 5).[60]

The presence of a residual obesity premium in the presence of self-reported financial information suggests that obesity matters even when lenders can access some other type of signal of wealth. To add to this analysis one can ask whether obesity and other signals complement or substitute each other. Taking a perspective similar to Börgers et al. (2013), I define two signals as complement if there is a premium in access to credit for displaying both good signals jointly. Instead, I define two signals as substitutes if there are decreasing returns in access to credit to acquiring the second good signal, conditional on possessing already the first one. My design allows me to test for this by testing for the interaction between obesity status and a relatively good or low Debt-to-Income ratio, within the Financial Information treatment arm.[61] Table 8 summarizes the results of the analysis. The interaction coefficient is small and not statistically different from zero, suggesting that the obesity premium is comparable among rich- and poor-

[58]Inattention may be confounding this analysis: when additional financial information is provided loan officers may pay mechanically less attention to all the baseline characteristics including borrowers' body mass. Including a third treatment arm where non-financial borrower information was provided would have provided a clean robustness check but was not feasible due to sample size restrictions. As an alternative approach in Appendix Table J.4 I present a set of regressions where I test for the effect of self-reported financial information on the cross-randomized characteristics included in the baseline loan profiles. The sign of interaction term is not systematically negative, thus confirming that inattention is unlikely to be driving the results.

[59]In Table **??** I explore heterogeneity in the obesity premium. For each measure of access to credit, I split the sample according to the loan officers' median obesity premium and compare loan officers whose obesity premium is above and below median across all characteristics I collect.

[60]Interestingly, the very same self-reported information is perceived as more reliable when associated to an obese borrower. This is again in line with statistical discrimination, because the financial information included in the borrowers' profiles describes on average richer individuals than the Kampala average.

[61]The reference category are applications with a relatively bad or high Debt-to-Income ratio. Notably, among these applications the ratio is often still good enough to be granted credit.

looking borrowers. Thus obesity and other wealth signals appear to be accounted for independently.

4.4 Discussion

The credit experiment shows that loan officers are more willing to meet with obese borrowers, all else equal, and rate their loan applications as more likely to be approved because they perceive obese borrowers as more financially able and creditworthy. The nature of the experimental design, based on hypothetical loan applications and weight-manipulated borrowers portraits, does not allow to test whether down-the-line obese borrowers are actually granted more credit or whether they have better returns to capital. However, the presence of real stakes, the size of the premium, and the fact that obesity premium appears to matter on top of self-reported financial information, all point at the external validity of the results and suggest that being obese leads to actual substantial credit-market benefits in Kampala. Accordingly, loan officers themselves are aware of the positive obesity discrimination in credit markets: loan officers' explicit beliefs on returns to weight-gain in credit markets are qualitatively aligned with the experimental results as shown in Figure 9.[62]

The obesity premium appears unrelated to personal taste and rather due to profit-maximizing agents engaging in statistical discrimination in response to asymmetric information. My results show that the more financial information available on the market, the less loan officers exploit obesity as a reliable signal of wealth. Loan officers' behavior aligns with the predictions of an attention discrimination model (Bartoš et al., 2016) in which, because verifying information is costly, loan officers screen borrowers based on expected net benefits and prefer borrowers which in their view have ex-ante higher perceived probability of verification success.

5 Beliefs Accuracy

Both the general population and trained professionals routinely build their beliefs on people's wealth based on obesity, a seemingly economically irrelevant sign of status. In turn, being obese leads to financial benefits in market interactions, like the lending process, where agents are trying to screen for wealth but verifying information is costly. The implications of these results both for health policy and market efficiency hinge on

[62] The explicit beliefs elicitation is described in Appendix G.

whether beliefs about returns to obesity and the value of obesity as a signal are accurate. In what follows, I use additional survey evidence, experimental variation, and a simple model to investigate beliefs accuracy among the general population and loan officers.

I start by testing experimentally for awareness and accurate perception of obesity benefits in credit markets. Then, I move on to investigate whether people have accurate beliefs on the value of obesity as a wealth signal. I elicit incentivized beliefs from the general population and using a simple theoretical framework I derive and estimate a revealed-preference measure of loan officers' beliefs. Overall, the analyses show evidence of misperception, in particular in the direction of people overestimating the importance of being obese.

5.1 (Mis-)Perception of Obesity Benefits in Credit Markets

To understand whether people hold accurate beliefs on the obesity credit market benefits, I replicate the credit experiment with the sample of Kampala residents from the beliefs experiment.[63] In the replication, the field officer describe to the respondents the original credit experiment (except the results). Then, respondents are shown 4 randomly selected loan profiles and are asked to guess loan officers' ratings. The second order beliefs are incentivized, and body mass or obesity never need to be mentioned to the respondents, thus reducing experimenter demands concerns.

For each loan profile, I elicit three main outcomes: 1) the number of loan officers which requested the referral of a similar applicant (0 to 10), 2) the most common loan officers' approval-likelihood rating (1 to 5), and 3) if they would recommend to a borrower with similar characteristics to apply for a loan, based on their assessment of the loan officers' interest (yes/no). Notice that the latter outcome is not incentivized.

The results, summarized in Fig. 10, show that the general population are fully aware of obesity benefits in access to credit. Respondents systematically guess that the very same loan profile and borrower, when associated to an *Obese* portrait, was more often requested for a referral by the loan officers and that its approval likelihood rating in the original credit experiment was higher. Comparing the average loan officers' obesity bias with the lay people's predictions shows that lay people overestimate the obesity premium in credit by a factor of 2. The size of the overestimation is four times larger among overweight respondents. This result is particularly surprising when thinking that

[63] In the same session, respondents first take part in the beliefs experiment, and later to the credit experiment. Note that, if respondents see a given portrait in the beliefs experiment, they will not see the portrait again in the credit experiment.

the magnitude of the estimated obesity premium is already quite sizable. Focusing on loan application with no financial information and the approval likelihood outcome, loan officers apply an obesity premium of about 20%, while laypeople estimate the premium to be around 50%. These results show that on the borrowers side people are aware of returns to obesity but that they systematically and largely overestimate them. Since, respondents are also more likely to recommend to obese borrowers to apply for loans, the fact that people overestimate obesity benefits in credit markets may lead to distortions in the demand for credit.

5.2 (Mis-)Perception of the Obesity Wealth Signal: General Population

To test for the accurate or inaccurate perception of obesity as a weight signal, I elicit incentivized beliefs on the correlation between body mass and earnings from a sample of the general population of Kampala residents.[64]. To elicit beliefs on the earning distribution by body mass, I exploit the figurative Body Size Scale for African Populations designed and validated in Cohen et al. (2015). To incentivize beliefs, I use the measured body mass and self-reported monthly earnings distribution, as it emerges from my own survey data (Beliefs Experiment). The results —displayed in Table 9 —show that also the general population holds inaccurate beliefs on the correlation between earnings and obesity and overestimate the average income difference between obese and not-obese individuals. According to my data, an obese person in Kampala earns on average ca. US$80/month more, as compared to a not-obese person. Instead, Kampala residents overestimate this difference to be about US $250. Interestingly, the overestimation is largest among overweight and obese respondents. The results show that in general people place too much *weight* on obesity as a signal of wealth.

Loan Officers While the general population holds inaccurate beliefs on obesity as a wealth signal, loan officers may have more precise beliefs either because of their training, or because of their choices' stakes. While the credit experiment is not designed to test for the efficiency consequences of obesity discrimination, neither socially nor from the perspective of credit institutions' profits, the experimental data can help to disentangle

[64]The sample, described in the Appendix, is a small sample of 49 Kampala residents. The beliefs elicitation experiment was run as an online phone survey. I collected this data after the completion of the credit experiment. Due to Covid-19 restrictions, it was not possible to recruit more people and to run the survey in person.

between accurate and inaccurate statistical discrimination by testing for beliefs accuracy. Intuitively, testing for beliefs accuracy means testing for whether loan officers' beliefs about the correlation between obesity and the relevant measure of being rich, say monthly earnings, are on average correct.[65] The test requires two ingredients: 1) data on the actual correlation between earnings and body mass, and 2) loan officers' beliefs on such correlation. Since in the experiment, I do not elicit loan officers' beliefs on the obese and earning correlation explicitly, my measure of beliefs is a revealed-preference measure from loan officers' decisions in the credit experiment. To understand the specific test that my experimental data allows for, it is useful to think of loan officers' decision in the credit experiment through the lenses of a simple theoretical framework.

Theoretical framework I focus on loan officers' evaluation of a borrower's creditworthiness.[66] When financial information is available, I assume that perceived creditworthiness depends on demographics, obesity status, income, and an unobservable, normally-distributed error component u_{ij}.[67] Let j denote the loan officer and i the borrower, then:

$$C_{ij} = \alpha_j \mathbb{1}(BMI_i \geq 30) + \eta_j Y_i + \mathbf{X}_i \beta_j + u_{ij}, \tag{3}$$

When income is unobservable, instead, I assume that loan officers' officers form beliefs about Y_i. So the evaluation function becomes:

$$C_{ij} = \alpha_j \mathbb{1}(BMI_i \geq 30) + \gamma_j E(Y_i | \mathbb{1}(BMI_i \geq 30), \mathbf{X}_i) + \mathbf{X}_i \beta_j + v_{ij}, \tag{4}$$

From the perspective of the experimenter, loan officers' beliefs about the borrowers' income are a latent variable. Thus, exploiting the omitted variable bias formula, the observed obesity premium when no information is available can be decomposed into a direct effect and an indirect effect, mediated by loan officers' beliefs the income distribution given body mass:

[65] A reduced-form test of accurate versus inaccurate statistical discrimination entails testing whether obese borrowers all else equal have better credit outcomes (Outcomes' Test). If not, assuming to exclude taste-based discrimination, one could argue that loan officers engage in inaccurate statistical discrimination and hold biased beliefs. I prefer the direct test of accurate beliefs for two reasons. First, it is agnostic on the presence of taste-based discrimination. Second, it is a more precise test of the mechanism. Imagine that loan officers held inaccurate beliefs on the importance of being rich for loan performance, but had accurate beliefs on what obesity signals in terms of wealth: loan officers would be accurately statistically discriminating by body mass, and still the Outcomes' Test would be biased.

[66] In Appendix **??** I present a micro-foundation for this framework.

[67] This framework makes strong simplifying assumptions. For example, the loan officer likely exploits other measures of wealth, on top of income. Since in the experiment all the available financial information is cross-randomized, the simplification does not compromise the generality of the model.

$$\alpha_j = \delta_j + \gamma_j \Big(E_j(Y_i|BMI_i \geq 30, X_i) - E_j(Y_i|BMI_i < 30, X_i) \Big) = \delta_j + \gamma_j \phi_j, \tag{5}$$

where δ_j is the direct causal effect of obesity on creditworthiness, γ_j, is the causal effect of earnings on perceived creditworthiness and ϕ_j is j's estimate of the average difference in monthly income between obese and not obese borrowers.[68]

This framework produces a summary statistic for loan officers' beliefs about the correlation between earnings and obesity, and thus, a simple test for loan officers' beliefs accuracy. Loan officers' beliefs are summarized by ϕ_j, loan officers' expectation of the average income difference between obese and not obese borrowers. By estimating the ϕ_j distribution and comparing it with the average income difference between obese and not-obese individuals in Kampala one can learn the share of loan officers that engage in inaccurate statistical discrimination.

Estimation My experimental design allows me to estimate the distribution of loan officers' beliefs ϕ_j by exploiting the cross-randomization of body mass and self-reported income in the credit experiment. To do so, I finally need to make an assumption on how loan officers' update their beliefs on borrowers' income. Let W be a dummy for an application including self-reported income information, I assume that loan officers form their expectations as follows:

$$E_j(Y_i|BMI_i, \mathbf{X}_i, \tilde{Y}_i) = (1 - W)(\mathbb{1}(BMI_i \geq 30) + X_i) + W(\lambda \tilde{Y}_i)), \tag{6}$$

That is, when no income signal is available, loan officers form their beliefs about borrowers' income based on demographics, while when self-reported income is available, expected borrowers' income depends only on self-reported borrowers' income. This is equivalent to assuming that body mass does not affect income beliefs directly when self-reported income is available. This assumption is necessary for estimating the beliefs, but is a strong assumption. For example, λ, the extent to which loan officers' rely on the self-reported information, is likely increasing in body mass (loan officers perceive obese borrowers' self-reported income as more reliable). To limit these concerns, I focus the estimation on applications whose self-reported income is rated as reliable or very reliable and act as if loan officers' fully trust the self-reported income provided ($\lambda = 1$). I later

[68]Under the additional simplifying assumption that obesity affects creditworthiness only through financial characteristics, and not e.g. through an health channel, we can intepret δ_j as taste-based discrimination (Becker, 1956) and $\gamma_j * \phi_j$ can be intepreted as statistical discrimination (Arrow et al., 1973; Phelps, 1972).

discussed relaxing this assumption.

Under this additional functional form assumption, the credit experiment allows me to estimate α_j, δ_j and γ_j. To see this more clearly, plugging equation (6) into equation (4) gives:

$$\begin{cases} C_{ij} = \alpha_j \mathbb{1}(BMI_i \geq 30) + X_i\beta_j + u_{ij}, & \text{if} W = 0 \\ C_{ij} = \delta_j \mathbb{1}(BMI_i \geq 30) + \tilde{Y}_i\gamma_j + X_i\beta_j + v_{ij}, & \text{if } W = 1, \end{cases} \tag{7}$$

α_j is estimated as the obesity premium for loan applications which do not include self-reported financial information. δ_j is the obesity premium conditional on self-reported income information, while γ_j is the income premium conditional on obesity. I exploit the estimates of α_j, δ_j and γ_j to back out the loan officers beliefs distribution (ϕ_j), according to the premium decomposition in equation (5).

Limitations The analysis has two main limitations. First, the estimates are noisy as they are based on a relatively small sample (for each loan officer, I only measure 30 choices). Second, the results rests on the assumption of linear separability between the effect of body mass and self-reported income. This assumption is a strong one, however it seems supported by the data in that throughout the analysis I find that agents account for obesity and other wealth signals independently in their evaluations. Notably, the framework does *not* require that obesity cannot affect creditworthiness through other financial characteristics (e.g. wealth, or partners' income). In fact, the cross-randomization of body mass and self-reported earnings allows to net out of this effect by capturing it in δ_j.

Benchmark data The benchmark statistic is the average monthly income difference between obese and not-obese people Kampala ($\phi = E(Y_i|BMI_i \geq 30, X_i) - E(Y_i|BMI_i < 30, X_i)$). To estimate it, I collect anthropometric data (height, weight) and self-reported income for a sample of 511 Kampala residents (beliefs experiment).[69] According to the data I collect data, obese people in Kampala earn on average \$ 80/month more as compared to normal weight one. The sample is not representative. However, to my knowledge, other than the Uganda DHS, no publicly available and representative survey collecting both body mass and financial information. In the DHS, income is measured with a household level, asset-based and standardized wealth index which is hard to compare with the experimental monthly monetary income information. The income and

[69] At the end of the beliefs experiment section, field officers record respondents' body mass (measured using a scale and a height board) and self-reported monthly income.

body mass correlation in my data is nonetheless comparable to the Uganda DHS one suggesting that concerns about representativeness should be minor.[70]

Results Loan officers' beliefs distribution is plotted in Figure 11, panel B. The distribution is very dispersed, with loan officers both vastly overestimating and underestimating the true income difference between Obese and Not Obese individuals. Indeed, most loan officers hold inaccurate beliefs on the average income difference of obese and not obese individuals. Fewer than 12% of the loan officers (19 out of 161) and about 8% of the lay people (4 out of 49) hold beliefs within a 10% confidence interval from the true distribution mean of $81.[71] On average people appear to overestimate the true income difference, however due to the small sample size and extremely dispersed distribution the loan officers' beliefs mean is not actually statistically different from the truth.

6 Conclusion and Policy Implications

In this paper, I show experimentally that being obese substantially improves access to credit in the urban area of Kampala (Uganda) because being obese signals wealth and loan officers rely on the body mass signal to screen borrowers in real-stake lending decisions when verifying financial information is costly. In terms of magnitude, the obesity wealth-signalling value is large —comparable to owning a car, and obesity benefits are substantial —equivalent to a 60% increase in self-reported income. To pin down the asymmetric mechanism I show that obesity is not associated with potential confounders such as beauty, health, self-control or trustworthiness, and most importantly, that reducing the degree of asymmetric information between borrowers and lenders causally reduces the obesity premium. I conclude that returns to obesity cannot be explained by a pure taste-based discrimination model, e.g. a beauty-premium story, but are instead consistent with a model of statistical discrimination. While body mass indeed correlates with earnings and wealth in Kampala, and thus screening by obesity may be consistent with profit-maximizing behavior, I find evidence of large misperception. Experimental data shows that borrowers overestimate returns to obesity in access to credit and that people put too much weight on obesity as a signal of wealth.

[70] Standardizing the income measures in both data I find that the conditional distribution of income given body mass is 0.04 s.d. in my data and 0.03 s.d in the Uganda DHS 2016 (Kampala region).

[71] The estimates are based on a sample of 161 loan officers obtained by focusing on loan officers with no missing loan applications evaluated (30 observation per loan officer, and excluding loan applications which perceived below-average reliable).

Since obesity is well-known to be a status signal in low-income countries today, as in Europe in the past, I interpret my results as the first experimental evidence that seemingly irrelevant status symbols have sizable financial benefits in poor countries, and to identify the mechanism: status signals provide wealth information in a context where asymmetric information is pervasive. While relying on signals may reduce the cost of information verification, the results on beliefs accuracy show that this screening on status signals is not necessarily efficient as people can vastly misperceive the signal. Moreover, when the signal is unhealthy, as in the case of obesity, financial benefits can work as an incentive to engage in unhealthy behaviors.

External Validity I expect that obesity status to lead to financial benefits in financial interactions with lacking financial information (e.g. credit scores, property registry), and in countries at similar stage of the nutritional transition —low- and lower-middle income countries (Appendix Figure J.10). In line with these predictions, a replication of the Beliefs Experiment involving 300 women in rural Malawi finds that obese people are perceived as wealthier (no beauty or health effect) and more creditworthy (see Appendix H). The result that status signals lead to market benefits in response to asymmetric information mechanism is more general and likely to apply to other sign of status and economic interactions, beyond obesity and credit markets. For example, financial returns to status may help explaining large conspicuous consumption patterns among the poor (Banerjee and Duflo, 2007).

Policy implications The analysis leads to a number of policy relevant considerations. First, concerning credit markets efficiency and financial inclusion, the paper suggests that improving financial information reliability or changing agents incentives to put more verification effort could raise credit-market efficiency in poor countries, avoiding that agents rely on noisy signals, such as obesity. Second, the results point at socio-economic incentives to be obese in poor settings. The existence of financial benefits generates a trade-off with obesity health costs that directly and indirectly affects the effectiveness of obesity prevention policies. Directly, building on the optimal sin tax framework of Allcott et al. (2019), I show that accounting for monetary benefits of soda consumption (through weight gain) significantly reduces the optimal sugar tax in Uganda.[72] Indirectly,

[72]The estimate is based on survey data on sugar beverages consumption, body mass, nutritional knowledge and prices in Uganda, as well as data from Allcott et al. (2019). I account only for financial benefits in access to credit, in partial equilibrium approach. I model the benefits as a subsidy to SSB consumption. The details are in Appendix F.

the presence of financial benefits affects the uptake of healthy behaviors at the margin. This is likely the case given that anecdotally there are countless daily micro-interactions where being obese provides benefits, beyond credit markets. Consistently, in open ended questionnaires, people mention showing off wealth and status as the main reason why people gain weight in Kampala as shown in Appendix Figure J.8 and Table J.11.

Quantifying the efficiency costs of screening by status signals for credit markets, the importance of status concerns and related monetary benefits for healthy behaviors and to which extent the conspicuous nature of food consumption can explain the obesity epidemic in poor countries is beyond the scope of this paper, but may provide interesting avenues for future research.

References

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky, "Regressive sin taxes, with an application to the optimal soda tax," *The Quarterly Journal of Economics*, 2019, *134* (3), 1557–1626.

Anderson-Fye, Eileen P, "A "Coca-Cola" shape: Cultural change, body image, and eating disorders in San Andres, Belize," *Culture, Medicine and Psychiatry*, 2004, *28* (4), 561–595.

Arrow, Kenneth et al., "The theory of discrimination," *Discrimination in labor markets*, 1973, *3* (10), 3–33.

Atkin, David, "The caloric costs of culture: Evidence from Indian migrants," *American Economic Review*, 2016, *106* (4), 1144–81.

Banerjee, Abhijit V, "Contracting constraints, credit markets, and economic development," *ECONOMETRIC SOCIETY MONOGRAPHS*, 2003, *37*, 1–46.

— **and Esther Duflo**, "The economic lives of the poor," *Journal of economic perspectives*, 2007, *21* (1), 141–168.

Bartoš, Vojtěch, Michal Bauer, Julie Chytilová, and Filip Matějka, "Attention discrimination: Theory and field experiments with monitoring information acquisition," *American Economic Review*, 2016, *106* (6), 1437–75.

Becker, Gary S, *The economics of discrimination*, University of Chicago press, 1956.

Berkovec, James A, Glenn B Canner, Stuart A Gabriel, and Timothy H Hannan, "Race, redlining, and residential mortgage loan performance," *The Journal of Real Estate Finance and Economics*, 1994, *9* (3), 263–294.

Bertrand, Marianne and Sendhil Mullainathan, "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination," *American economic review*, 2004, *94* (4), 991–1013.

Biroli, Pietro, Teodora Boneva, Akash Raja, and Christopher Rauh, "Parental beliefs about returns to child health investments," *Journal of Econometrics*, 2020.

Bloch, Francis, Vijayendra Rao, and Sonalde Desai, "Wedding celebrations as conspicuous consumption signaling social status in rural India," *Journal of Human Resources*, 2004, *39* (3), 675–695.

Bohren, J Aislinn, Kareem Haggag, Alex Imas, and Devin G Pope, "Inaccurate statistical discrimination," Technical Report, National Bureau of Economic Research 2019.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer, "Stereotypes," *The Quarterly Journal of Economics*, 2016, *131* (4), 1753–1794.

Börgers, Tilman, Angel Hernando-Veciana, and Daniel Krähmer, "When are signals complements or substitutes?," *Journal of Economic Theory*, 2013, *148* (1), 165–195.

Bosire, Edna N, Emmanuel Cohen, Agnes Erzse, Susan J Goldstein, Karen J Hofman, and Shane A Norris, "'I'd say I'm fat, I'm not obese': obesity normalisation in urban-poor South Africa," *Public Health Nutrition*, 2020, *23* (9), 1515–1526.

Bursztyn, Leonardo and Robert Jensen, "Social Image and Economic Behavior in the Field: Identifying, Understanding, and Shaping Social Pressure," *Annual Review of Economics*, 2017, *9* (1), 131–153.

_ , Bruno Ferman, Stefano Fiorin, Martin Kanz, and Gautam Rao, "Status Goods: Experimental Evidence from Platinum Credit Cards*," *The Quarterly Journal of Economics*, 12 2017, *133* (3), 1561–1595.

_ , Georgy Egorov, and Robert Jensen, "Cool to be smart or smart to be cool? Understanding peer pressure in education," *The Review of Economic Studies*, 2019, *86* (4), 1487–1526.

_ , _ , and Stefano Fiorin, "From extreme to mainstream: The erosion of social norms," *American Economic Review*, 2020, *110* (11), 3522–48.

_ , Thomas Fujiwara, and Amanda Pallais, "'Acting Wife': Marriage Market Incentives and Labor Market Investments," *American Economic Review*, 2017, *107* (11), 3288–3319.

Cawley, John, "The impact of obesity on wages," *Journal of Human resources*, 2004, *39* (2), 451–474.

_ and Chad Meyerhoefer, "The medical care costs of obesity: an instrumental variables approach," *Journal of health economics*, 2012, *31* (1), 219–230.

Chandrasekhar, Arun G, Benjamin Golub, and He Yang, "Signaling, shame, and silence in social learning," Technical Report, National Bureau of Economic Research 2018.

Chigbu, CO, UU Aniebue, U Berger, and KG Parhofer, "Impact of perceptions of body size on obesity and weight management behaviour: a large representative population study in an African setting," *Journal of Public Health*, 2019.

Cohen, Emmanuel, Jonathan Y. Bernard, Amandine Ponty, Amadou Ndao, Norbert Amougou, Rihlat Saïd-Mohamed, and Patrick Pasquet, "Development and validation of the body size scale for assessing body weight perception in African populations," *PLoS ONE*, 2015, *10* (11), 1–14.

Cole, Shawn, Martin Kanz, and Leora Klapper, "Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers," *The Journal of Finance*, 2015, *70* (2), 537–575.

DellaVigna, Stefano, John A List, Ulrike Malmendier, and Gautam Rao, "Voting to tell others," *The Review of Economic Studies*, 2016, *84* (1), 143–181.

Dobbie, Will, Andres Liberman, Daniel Paravisini, and Vikram Pathania, "Measuring bias in consumer lending," Technical Report, National Bureau of Economic Research 2018.

Duarte, Jefferson, Stephan Siegel, and Lance Young, "Trust and credit: The role of appearance in peer-to-peer lending," *The Review of Financial Studies*, 2012, *25* (8), 2455–2484.

Duggan, Catherine SM, "Doing bad by doing good? theft and abuse by lenders in the microfinance markets of Uganda," *Studies in Comparative International Development*, 2016, *51* (2), 189–208.

Ettarh, Remare, Steven Van de Vijver, Sam Oti, and Catherine Kyobutungi, "Overweight, obesity, and perception of body image among slum residents in Nairobi, Kenya, 2008–2009," *Preventing chronic disease*, 2013, *10.*

Finkelstein, Eric A, Justin G Trogdon, Joel W Cohen, and William Dietz, "Annual Medical Spending Attributable To Obesity: Payer-And Service-Specific Estimates: Amid calls for health reform, real cost savings are more likely to be achieved through reducing obesity and related risk factors.," *Health affairs*, 2009, *28* (Suppl1), w822–w831.

_ , Olga A Khavjou, Hope Thompson, Justin G Trogdon, Liping Pan, Bettylou Sherry, and William Dietz, "Obesity and severe obesity forecasts through 2030," *American journal of preventive medicine*, 2012, *42* (6), 563–570.

Fisman, Raymond, Daniel Paravisini, and Vikrant Vig, "Cultural proximity and loan outcomes," *American Economic Review*, 2017, *107* (2), 457–92.

Giné, Xavier, Jessica Goldberg, and Dean Yang, "Credit market consequences of improved personal identification: Field experimental evidence from Malawi," *American Economic Review*, 2012, *102* (6), 2923–54.

Giuntella, Osea, Matthias Rieger, and Lorenzo Rotunno, "Weight gains from trade in foods: Evidence from Mexico," *Journal of International Economics*, 2020, *122*, 103277.

Holdsworth, M, A Gartner, E Landais, B Maire, and F Delpeuch, "Perceptions of healthy and desirable body size in urban Senegalese women," *International journal of obesity*, 2004, *28* (12), 1561–1568.

Jakiela, Pamela and Owen Ozier, "Does Africa need a rotten kin theorem? Experimental evidence from village economies," *The Review of Economic Studies*, 2016, *83* (1), 231–268.

Karing, Anne, "Social Signaling and Childhood Immunization : A Field Experiment in Sierra Leone," *Mimeo*, 2018.

Karlan, Dean and Jonathan Morduch, "Chapter 71 - Access to Finance," in Dani Rodrik and Mark Rosenzweig, eds., *Handbooks in Economics*, Vol. 5 of *Handbook of Development Economics*, Elsevier, 2010, pp. 4703–4784.

— **and Jonathan Zinman**, "Observing unobservables: Identifying information asymmetries with a consumer credit field experiment," *Econometrica*, 2009, *77* (6), 1993–2008.

Kessler, Judd B, Corinne Low, and Colin D Sullivan, "Incentivized resume rating: Eliciting employer preferences without deception," *American Economic Review*, 2019, *109* (11), 3713–44.

Labie, Marc, Pierre-Guillaume Méon, Roy Mersland, and Ariane Szafarz, "Discrimination by microcredit officers: Theory and evidence on disability in Uganda," *The Quarterly Review of Economics and Finance*, 2015, *58*, 44–55.

Mel, Suresh De, David McKenzie, and Christopher Woodruff, "Returns to capital in microenterprises: evidence from a field experiment," *The quarterly journal of Economics*, 2008, *123* (4), 1329–1372.

Mobius, Markus M and Tanya S Rosenblat, "Why beauty matters," *American Economic Review*, 2006, *96* (1), 222–235.

Mullainathan, Sendhil and Jann Spiess, "Machine learning: an applied econometric approach," *Journal of Economic Perspectives*, 2017, *31* (2), 87–106.

Nelissen, Rob MA and Marijn HC Meijers, "Social benefits of luxury brands as costly signals of wealth and status," *Evolution and human behavior*, 2011, *32* (5), 343–355.

Neumark, David, "Experimental research on labor market discrimination," *Journal of Economic Literature*, 2018, *56* (3), 799–866.

Ngaruiya, Christine, Alison Hayward, Lori Post, and Hani Mowafi, "Obesity as a form of malnutrition: over-nutrition on the Uganda "malnutrition" agenda," *Pan African Medical Journal*, 2017, *28* (1).

Nilsson, Annika, "Housing Finance in Kampala, Uganda: To Borrow or Not to Borrow." PhD dissertation, KTH Royal Institute of Technology 2017.

Palacios-Huerta, Ignacio and Oscar Volij, "Experientia docet: Professionals play minimax in laboratory experiments," *Econometrica*, 2008, *76* (1), 71–115.

Perez-Truglia, Ricardo and Guillermo Cruces, "Partisan interactions: Evidence from a field experiment in the united states," *Journal of Political Economy*, 2017, *125* (4), 1208–1243.

Phelps, Edmund S, "The statistical theory of racism and sexism," *The american economic review*, 1972, *62* (4), 659–661.

Pope, Devin G and Justin R Sydnor, "What's in a Picture? Evidence of Discrimination from Prosper. com," *Journal of Human resources*, 2011, *46* (1), 53–92.

Popenoe, Rebecca, *Feeding desire: Fatness, beauty and sexuality among a Saharan people*, Routledge, 2012.

Rao, Vijayendra, "Celebrations as social investments: Festival expenditures, unit price variation and social status in rural India," *Journal of Development Studies*, 2001, *38* (1), 71–97.

Ravina, Enrichetta et al., "Love & loans: The effect of beauty and personal characteristics in credit markets," *Journal of Finance*, 2008.

Rooth, Dan-Olof, "Obesity, attractiveness, and differential treatment in hiring a field experiment," *Journal of human resources*, 2009, *44* (3), 710–735.

Rosenzweig, Mark R and Junsen Zhang, "The Effects of Schooling on Costless Health Maintenance: Overweight Adolescents and Children in Rural China," Technical Report, National Bureau of Economic Research 2019.

Schofield, Heather, "The economic costs of low caloric intake: Evidence from India," *Unpublished Manuscript*, 2014.

Sebudde, Rachel K, Valeriya Goffe, Dorothy Daka, and Mehnaz S Safavian, "Step by step: let's solve the finance puzzle to accelerate growth and shared prosperity," Technical Report, The World Bank 2017.

Shekar, Meera and Barry Popkin, *Obesity: health and economic consequences of an impending global challenge*, World Bank Publications, 2020.

Sobo, E, "The sweetness of fat: Health, procreation, and sociability in rural Jamaica. New Brunswick," *NJ: Rutgers University Press. Srull, TK, & Wyer, RS (1979). The role of category accessibility in the interpretation of information about persons: Some determinants and implications. Journal of Personality and Social Psychology*, 1994, *37*, 1660–1672.

Squires, Munir, "Kinship taxation as a constraint to microenterprise growth: experimental evidence from Kenya," *Unpublished paper*, 2016.

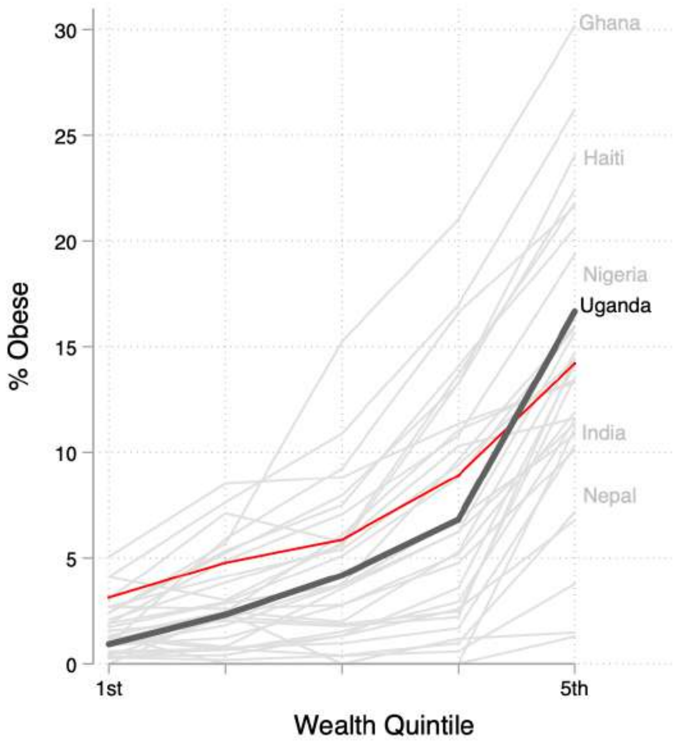
Subramanian, Shankar and Angus Deaton, "The demand for food and calories," *Journal of political economy*, 1996, *104* (1), 133–162.

Veblen, Thorstein, *The theory of the leisure class: An economic study of institutions*, Aakar Books, 1899.

Yang, Wenjie, Tanika Kelly, and Jiang He, "Genetic epidemiology of obesity," *Epidemiologic reviews*, 2007, *29* (1), 49–61.

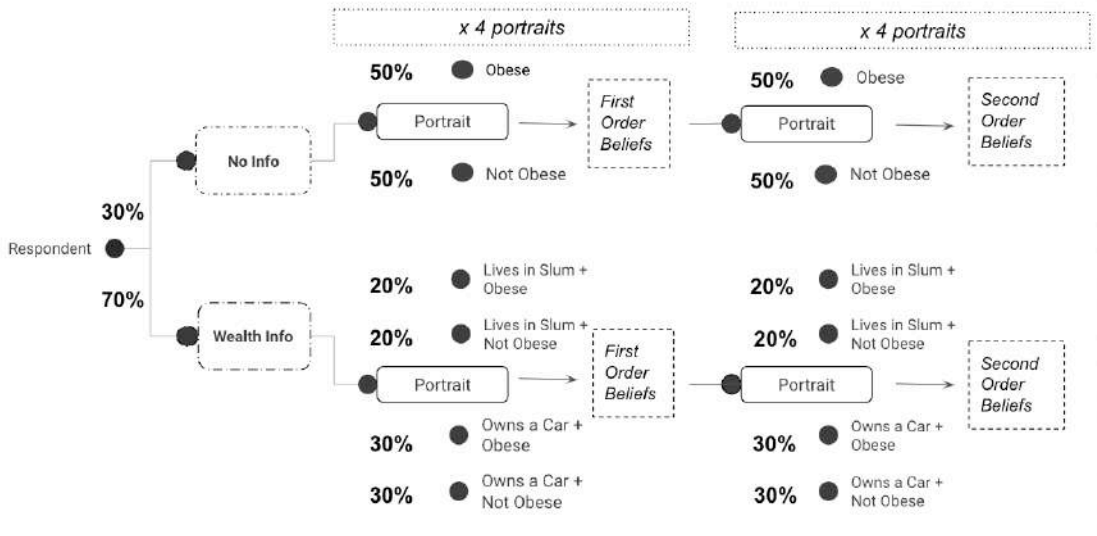
7 Figures

Figure 1: Obesity prevalence by wealth quintile, low- and lower-middle income countries.



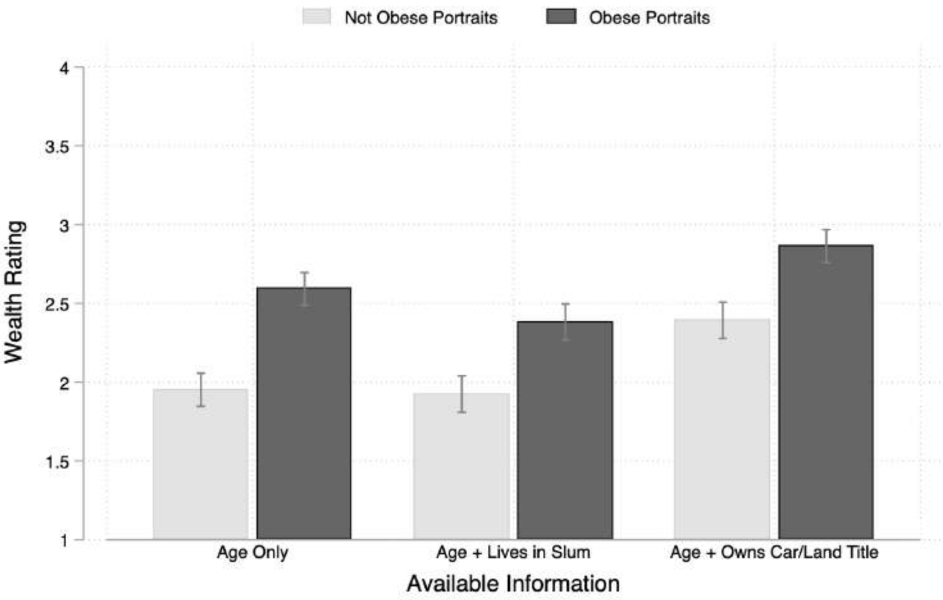
Note: Data from the most recent DHS wave in 2019 (2005-2016). Countries: Armenia, Bangladesh, Benin, Bolivia, Burkina Faso, Burundi, Cambodia, Cameroon,Comoros, DRC Congo, Ethiopia, Gambia, Ghana, Guinea, Haiti, India, Ivory Coast, Kenya, Kyrgyzstan, Liberia, Lesotho, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Tajikistan, Tanzania, Timor-Leste, Togo, Uganda, Uzbekistan, Zambia, Zimbabwe. The red line plots the average at the quintile level. Obesity is defined as a body-mass index (BMI) greater or equal than 30 (WHO definition).

Figure 2: Beliefs Experiment: Design



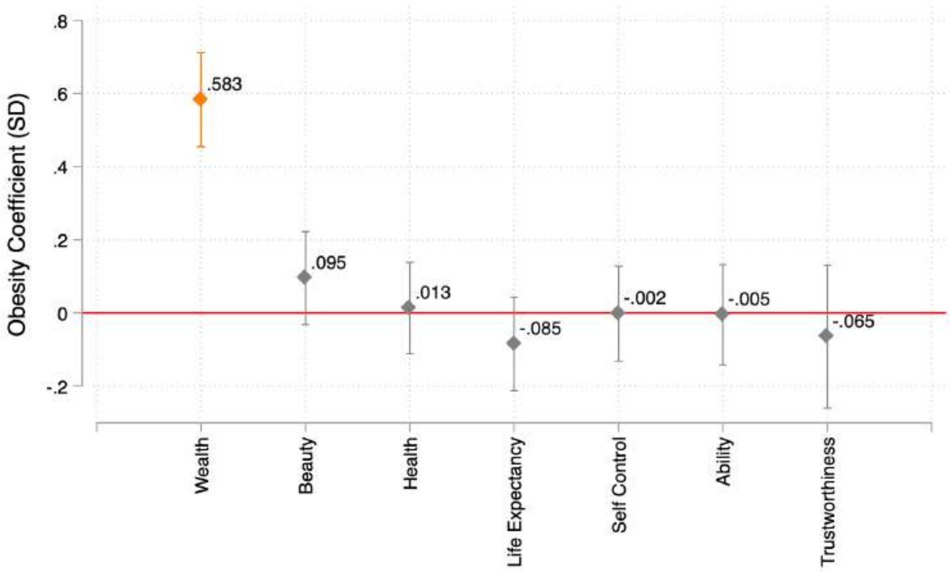
Note: The graph summarizes the Beliefs Experiment design. Respondent rate 3 to 4 black-race portraits each. Portraits were randomly selected from the manipulated portraits set, and shown to each respondent in the obese or the not-obese version. Randomization is at the individual level. Respondents randomly assigned to the No Information Arm learn only the age of the portrayed individual. Those assigned to the Wealth Information Arm learn additionally about an asset the person owns (car or land title), or where the person lives (slum). All portraits are first rated in terms of first-order beliefs (unincentivized) and later in terms of second-order beliefs (incentivized).

Figure 3: Wealth Ratings (First-Order Beliefs) by Portrait's Obesity Status and Wealth Information



Note: Data from Beliefs Experiment. 511 respondent rate 3 to 4 black-race portraits each, for a total of 1,699 observations. Portraits were randomly selected from the manipulated portraits set, and shown in the obese or the not-obese version. Wealth is the primary outcome of the experiment (pre-registered). About two-thirds of the respondents receive additional wealth signals about the respondents, in the form of asset ownership or place of residence.

Figure 4: Effect of Portrait's Obesity Status on Portrait's Ratings



Note: Data from Beliefs Experiment. First-order beliefs. 511 respondent rate 3 to 4 black-race portraits each, for a total of 1,699 observations. Portraits were randomly selected from the manipulated portraits set, and shown in the obese or the not-obese version. Plotted is the obesity coefficient from a regression including portrayed-individual and respondent fixed effects. All outcomes are standardized and standard errors are clustered at the respondent level. The regressions pool both respondents which receive no additional wealth information and those which learn about asset ownership or place of residence.

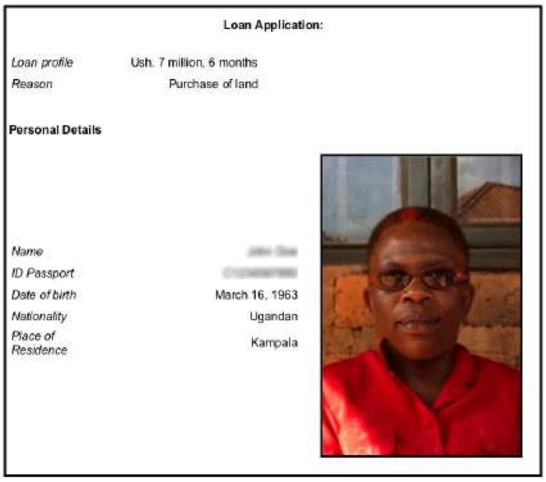
Figure 5: Credit Experiment: Design Matrix

	Degree of Asymmetric Information		
	Borrower's Profile: No Financial Information *(demographics + loan details)*	Borrower's Profile: Financial Information (+ self-reported profits, collateral, occupation)	
Borrower's Body Mass (Portrait)	Obese	Obese / Low Debt-To-Income	Obese / High Debt-To-Income
	Not Obese	Not Obese / Low Debt-To-Income	Not Obese / High Debt-To-Income
	10 applications	20 applications	

Note: The figure outlines the Credit Experiment design. Loan officers evaluate 30 hypothetical borrowers profiles each. Each profile includes the borrowers' picture, demographics and loan profile information (reason for loan, type of loan, loan amount). For each applicant, a loan officer is randomly assigned to see the portrait either in the not-obese or in the obese version. A borrowers' body mass is cross-randomized with the amount of information provided. The first 10 application only include the above-described baseline information. The last 20 applications evaluated included self-reported financial information (revenues, profits, collateral and occupation). Profits information was randomized to give a high (95%) or low (35%) Debt-To-Income ratio. Loan officers evaluated the applications along 4 primary outcomes (in this order): likelihood of approval (Approval Likelihood), probability of repayment (Creditworthiness), ability to put money to productive use (Finacial Ability) and Referral Request, the choice of being referred to an applicant with similar characteristics. Referral Request is a real choice outcome. All outcomes are on a scale from 1 to 5 (not at all, very), except Referral Request (0-1 dummy, no/yes).

Figure 6: Example of Borrowers' Profile

(a) Not Obese Borrower


Loan Application:

Loan profile Ush. 7 million, 6 months
Reason Purchase of land

Personal Details

Name
ID Passport
Date of birth March 16, 1963
Nationality Ugandan
Place of Residence Kampala

(b) Obese Borrower

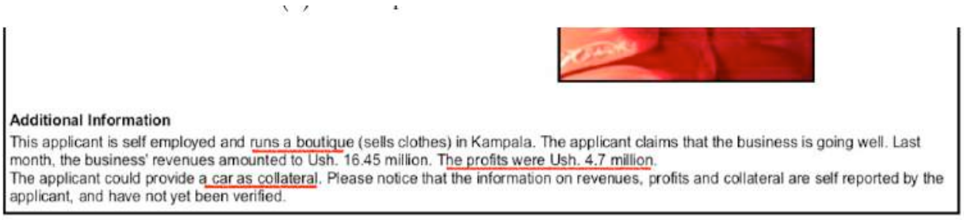

Loan Application:

Loan profile Ush. 7 million, 6 months
Reason Purchase of land

Personal Details

Name
ID Passport
Date of birth March 16, 1963
Nationality Ugandan
Place of Residence Kampala

(c) Self-Reported Financial Information

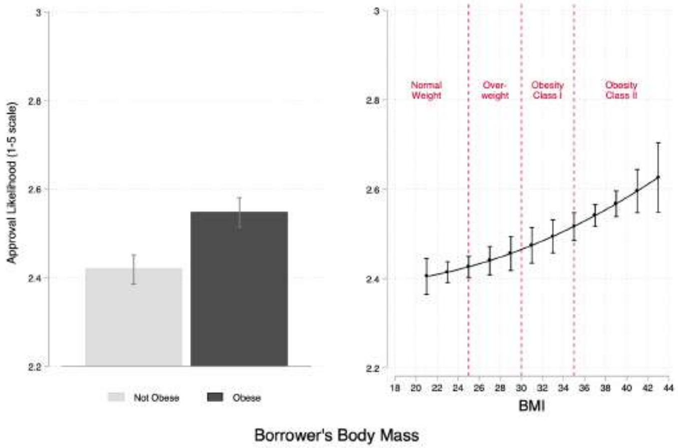

Additional Information

This applicant is self employed and runs a boutique (sells clothes) in Kampala. The applicant claims that the business is going well. Last month, the business' revenues amounted to Ush. 16.45 million. The profits were Ush. 4.7 million.
The applicant could provide a car as collateral. Please notice that the information on revenues, profits and collateral are self reported by the applicant, and have not yet been verified.

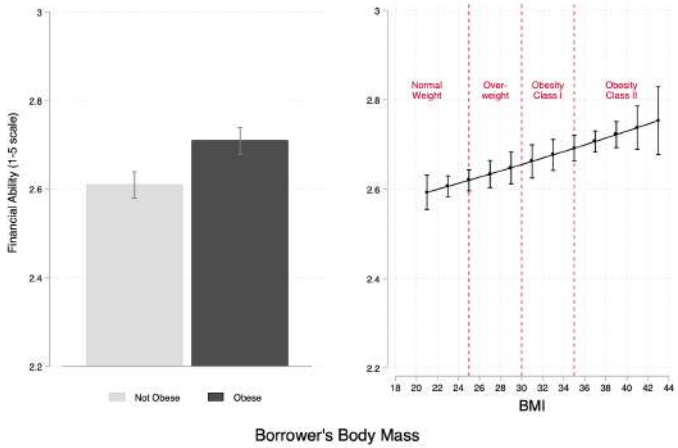
Note: The figure presents one of the 30 hypothetical borrowers profile sets created for the Credit Experiment. Panel (a) is the not-obese version; panel (b) is the obese version; panel (c) displays the self-reported financial information.

Figure 7: Obesity Premium in Access to Credit

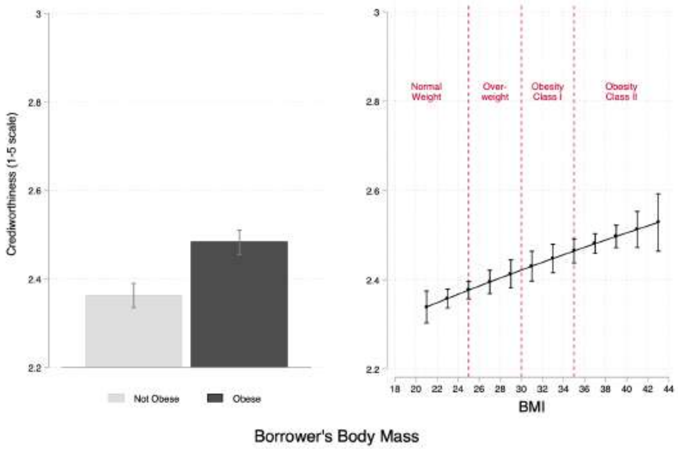
(a) Approval Likelihood



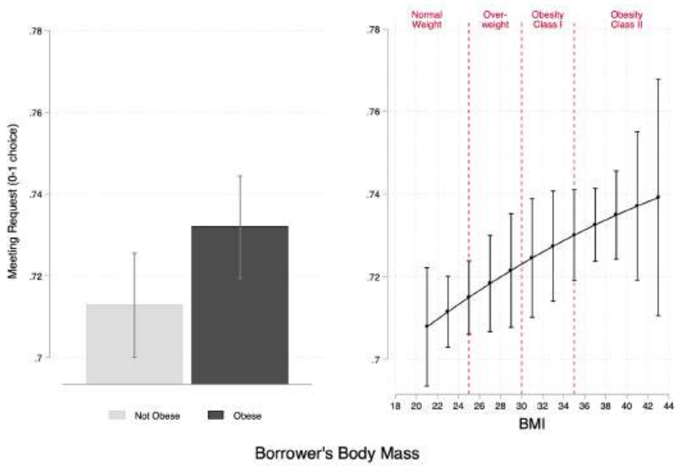
(b) Financial Ability



(c) Creditworthiness

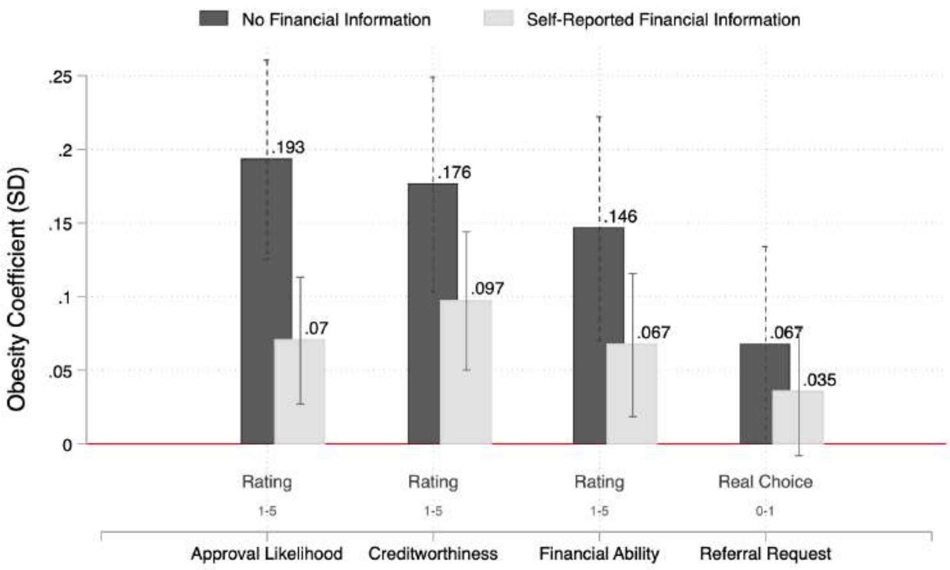


(d) Referral Request



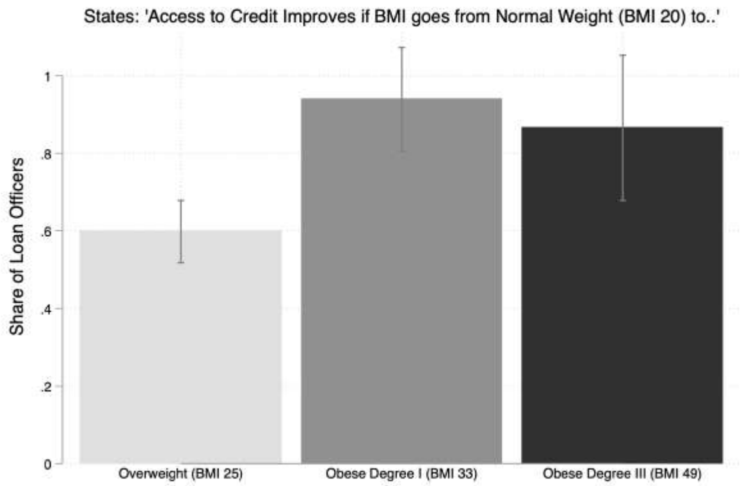
Note: The graphs summarizes the main results from the Credit Experiment. The left-hand side graphs plot the raw profiles evaluation data by dichotomous obesity status (10% CI). The right-hand side graphs plot the predicted access to credit associated to a continuous measure of body mass (BMI, kg/m2) using Stata's *marginsplot*. The regressions includes a double polynomial in BMI, application and loan officers fixed effects. Respondents are 238 loan officers, for a total of 6,645 borrowers' profiles evaluations.

Figure 8: Obesity Premium by Degree of Asymmetric Information



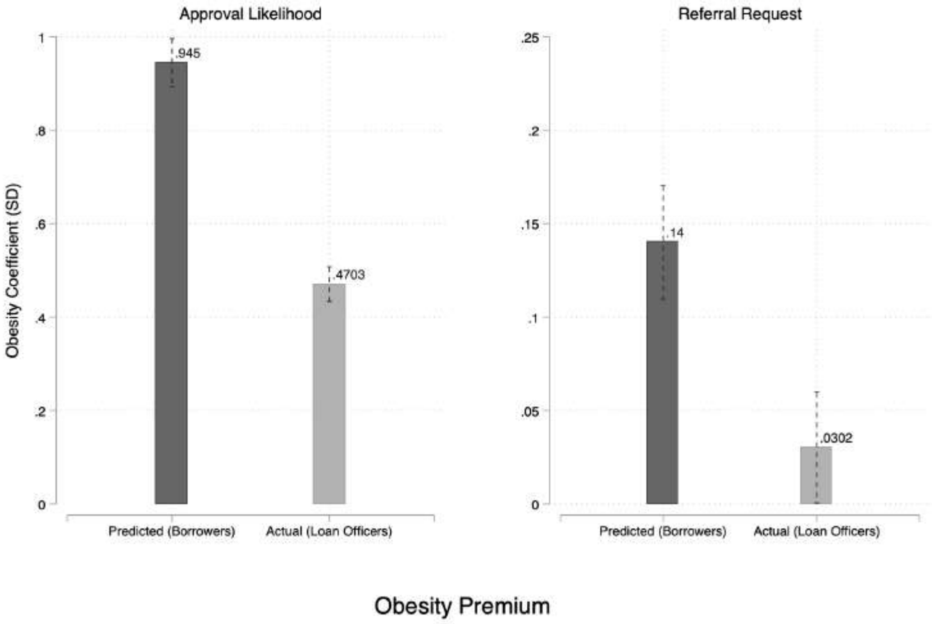
Note: The figure shows how the obesity premium in the Credit Experiment varies according to the amount of borrowers' financial information provided to the loan officers. The obesity premium is defined as the obesity coefficient in a regression including application and loan officers fixed effects, estimated separately on the subset of observations with and without financial information. The dependent variables are the main experimental outcomes, standardized. In 2,079 of the evaluations, the profiles did not include any financial information. In 4,566 of the evaluations, the profiles included self-reported information on revenues, profits, occupation and collateral.

Figure 9: Loan Officers Explicit Beliefs on Returns to Body Mass in Access to Credit



Note: The figure plots the loan officers explicit beliefs on returns to BMI in access to credit. At the end of the credit experiment, loan officers are shown 3 silhouettes pairs from the Cohen Body Size Scale for Assessing Body Weight Perception in African Populations. For each pair, they state which silhouette would have higher likelihood to get a loan. The wording is: *"Imagine a person which looks like Sil. X and one that looks like Sil. Y, which person would be more likely to be considered for a loan?".* The question is open ended. Answers are coded as follows: "-1" if the lower BMI silhouette has easier access," 0" if same likelihood, and "1" if the higher BMI silhouette has easier access. The paired silhouettes' BMI are: 1) 20 and 25; 2) 25 and 33; 3) 33 and 49.

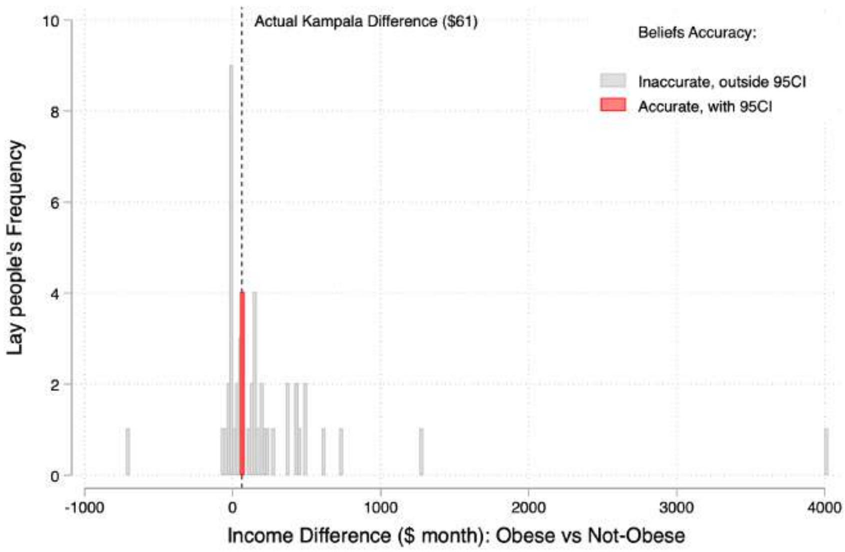
Figure 10: Beliefs Accuracy: Predicted Obesity Premium (Laypeople) Overestimates True Premium (Loan Officers)



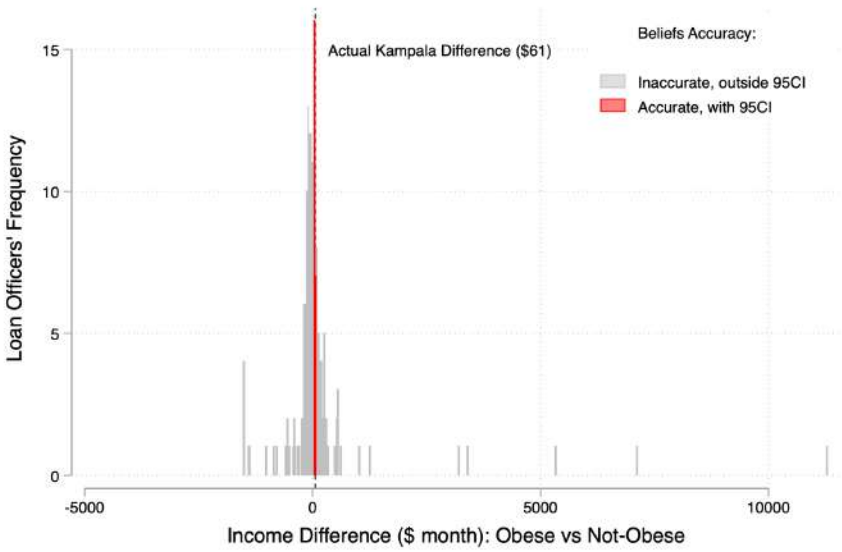
Note: The figure compares the predicted obesity premium with the actual obesity premium measured in the loan officers' Credit Experiment. The predicted premium comes from an incentivized experiment involving 511 Kampala residents (beliefs experiment sample). Respondents are shown randomly selected loan applications from the credit experiment 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 second-order beliefs are incentivized. The predicted obesity premium is the coefficient of the dummy on each outcome, in a regression including respondent and applications fixed effects. The actual premium are the equivalent statistics from the Credit Experiment.

Figure 11: Beliefs Accuracy: Obesity as a Signal of Earnings

(a) Lay People's Beliefs Distribution



(b) Loan Officers' Estimated Revealed-Preference Beliefs Distribution



Note: The histogram plots the beliefs distribution on the monthly income difference between obese and not-obese individuals among lay people and loan officers. In panel (a) I plot the incentivized beliefs of a sample of 49 Kampala residents. Respondents see the Cohen Body Size Scale for African populations and guess the monthly income of a normal weight and an obese silhouette. Answers are incentivized using own survey data. In panel (b) I plot the revealed-preference loan officers' beliefs distribution estimated using from loan officers' choices in the credit experiment. I estimate the beliefs for the 202 loan officers which evaluate all 30 loan applications. The dashed line indicates the average monthly income difference between obese and not obese Kampala residents (own survey data). The red bars indicate the beliefs within 90% confidence interval from Kampala average monthly income difference. Fewer than 12% of the loan officers and about 8% of the lay people hold accurate beliefs, according to this definition.

8 Tables

Table 1: Kampala Residents Sample, Summary Statistics

VARIABLES	(1) mean	(2) sd	(3) p50	(4) min	(5) max
District: Kampala	0.63	0.48	1.00	0.00	1.00
Wakiso	0.33	0.47	0.00	0.00	1.00
Mukono	0.03	0.18	0.00	0.00	1.00
Age	37.54	13.30	35.00	20.00	95.00
Height, cm	163.05	12.00	163.00	0.00	191.00
Weight, kg	68.52	15.25	66.00	0.00	172.55
Body-Mass Index (kg/m2)	25.66	5.28	24.61	15.43	46.87
Gender: Male	1.50	0.50	1.00	1.00	2.00
Education: Primary	0.41	0.49	0.00	0.00	1.00
O Level	0.31	0.46	0.00	0.00	1.00
A Level	0.10	0.30	0.00	0.00	1.00
Certificate	0.05	0.23	0.00	0.00	1.00
Diploma	0.06	0.25	0.00	0.00	1.00
Bachelor	0.06	0.24	0.00	0.00	1.00
Master/PhD	0.00	0.06	0.00	0.00	1.00
Personal Income, $	126.34	200.84	67.50	0.00	1,620.00
Household Income, $	187.34	281.06	94.50	0.00	1,890.00
Marital Status: Single	0.28	0.45	0.00	0.00	1.00
Married	0.41	0.49	0.00	0.00	1.00
Living as married	0.13	0.34	0.00	0.00	1.00
Separated	0.10	0.31	0.00	0.00	1.00
Divorced	0.02	0.15	0.00	0.00	1.00
Widowed	0.05	0.22	0.00	0.00	1.00

Notes: The table displays summary statistics for the 511 Kampala residents participating to the *Beliefs Experiment*. Information is self-reported with the exception of weight and height, which are measured by the field officer at the end of the survey using a heigh board and a scale.

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***	0.113	0.005	-0.072	0.052	0.039	-0.358
	(0.093)	(0.098)	(0.106)	(0.095)	(0.099)	(0.112)	(0.806)
Additional Wealth Signal	0.677***	-0.234	-0.008	0.076	0.215	0.086	0.126
	(0.239)	(0.273)	(0.250)	(0.245)	(0.283)	(0.292)	(0.594)
Obese × Additional Wealth Signal	-0.190	-0.032	0.014	-0.022	-0.089	-0.074	0.306
	(0.125)	(0.129)	(0.133)	(0.131)	(0.131)	(0.143)	(0.815)
Obs.	1699	1699	1699	1699	1699	1699	679
Beliefs about Others' Beliefs							
Obese	0.731***	0.320***	0.227**	0.154	0.171	0.102	-0.504
	(0.094)	(0.098)	(0.109)	(0.111)	(0.108)	(0.109)	(0.514)
Additional Wealth Signal	0.406*	-0.370	0.178	0.055	-0.043	0.134	0.149
	(0.232)	(0.249)	(0.243)	(0.242)	(0.215)	(0.262)	(0.650)
Obese × Additional Wealth Signal	-0.110	-0.081	0.007	-0.028	0.039	0.044	0.565
	(0.124)	(0.125)	(0.137)	(0.138)	(0.136)	(0.140)	(0.530)
Obs.	1699	1699	1699	1699	1699	1699	679

Notes: * p<0.1, ** p<0.05, *** p<0.01. All regressions include respondent, rating order and portrayed individual fixed effects. Standard errors are clustered at the respondent level. Outcome variables are elicited on a scale from 1 to 4, and then standardized. *Obese Portrait* is a dummy taking value 1 when the rated portrait is randomly assigned to be the higher-body mass version of the original portrait, and 0 when the rated portrait is randomly assigned to be the lower-body mass version. *Additional Wealth Signal* is a dummy taking value 1 when the respondent gets a second wealth signal on top of body mass, either place of residence or asset ownership. For each portrait and outcome, respondents first rated the portrait according to their own beliefs, and then according to their best guess the most frequent answer of other respondent (incentivized second-order beliefs). Wealth is the pre-registered primary outcome. Health, beauty, self-control, ability, life-expectancy are pre-registered secondary outcomes. Trustworthiness was not preregistered and only elicited to 30% of the sample.

Table 3: Financial Institutions Sample, Summary Statistics

VARIABLES	(1) mean	(2) sd	(3) p50	(4) min	(5) max
Tier 2: Credit Instititutions	0.02	0.13	0.00	0.00	1.00
Tier 3: NDT MFI	0.11	0.32	0.00	0.00	1.00
Tier 4: MFI	0.30	0.46	0.00	0.00	1.00
Tier 4: Moneylenders	0.57	0.50	1.00	0.00	1.00
Total Branches	6.07	18.25	1.00	0.00	160.00
Employees per Branch	6.73	6.58	4.00	0.00	50.00
District: Kampala	0.78	0.42	1.00	0.00	1.00
Wakiso	0.20	0.40	0.00	0.00	1.00
Mukono	0.02	0.15	0.00	0.00	1.00
Interest Rate: Profile 1	11.83	7.39	10.00	1.50	40.00
Profile 2	11.77	7.57	10.00	1.50	40.00
Profile 3	11.27	7.29	10.00	2.00	40.00
Offers Personal Loans	0.92	0.27	1.00	0.00	1.00
Offers Business Loans	0.97	0.18	1.00	0.00	1.00

Notes: The table reports summary statistics for the 146 financial institutions participating. Institution type relates to the tiered structure as follows. Credit Institutions are Tier 2; Non-Deposit Taking Microfinance Institutions are Tier 3; Micro-Finance insitututions and Moneylenders are Tier 4. Tier 1 institutions (Commercial Banks) are not included in the sample. Tier 2 and Tier 3 institutions are purposefully oversampled with respect to the true distribution of financial institutions in Kampala. (Tier 2 are the 0.1 percent, and Tier 3 the 1 percent). To obtain this sample, field officers visit a listing of 476 financial institutions licensed to provide credit in Kampala and offering standard loans between 1 million to 7 million Ugandan shillings (USD 250-2000) to the general population. The institutions' listing is obtained thanks to a cooperation with the Uganda Microfinance Regulatory Authority. Profile 1 to Profile 3 refer to the three loan profiles which loan officers evaluate in the credit experiment, namely 6 months loan for 1 million, 5 million and 7 million Ugandan shillings.

Table 4: Loan Officers Sample, Summary Statistics

VARIABLES	(1) mean	(2) sd	(3) p50	(4) min	(5) max
Age	31.27	7.19	30.00	16.00	69.00
Gender: Male	0.59	0.49	1.00	0.00	1.00
BMI	24.28	4.58	23.40	16.16	43.57
Education (Years)	15.32	2.04	16.00	0.00	18.00
Family Size	3.46	2.14	3.00	0.00	12.00
Salary: Under 500,000 (USD 135)	0.32	0.47	0.00	0.00	1.00
Salary: 500,000 to 1 million (USD 270)	0.40	0.49	0.00	0.00	1.00
Salary: 1 to 1.5 million (USD 405)	0.22	0.42	0.00	0.00	1.00
Salary: 1.5 to 2 million (USD 540)	0.04	0.21	0.00	0.00	1.00
Salary: Over 2 million	0.01	0.12	0.00	0.00	1.00
Performance pay or self-employed	0.90	0.30	1.00	0.00	1.00
Role: Owner	0.14	0.34	0.00	0.00	1.00
Role: Manager	0.10	0.29	0.00	0.00	1.00
Role: Loan Officer	0.63	0.48	1.00	0.00	1.00
Experience (Years)	2.67	2.77	2.00	0.00	11.00
Interest Rate Discretionality	0.56	0.50	1.00	0.00	1.00
Financial Knowledge (Self-Reported)	1.24	0.47	1.00	1.00	3.00
Task: receive borrowers	0.88	0.32	1.00	0.00	1.00
Task: provide product information	0.95	0.21	1.00	0.00	1.00
Task: review personal information	0.95	0.21	1.00	0.00	1.00
Task: review financial information	0.91	0.29	1.00	0.00	1.00
Task: refer borrowers to next step	0.80	0.40	1.00	0.00	1.00
Task: recruit new borrowers	0.75	0.43	1.00	0.00	1.00
Task: approve borrowers	0.74	0.44	1.00	0.00	1.00
Task: collect credit	0.68	0.47	1.00	0.00	1.00
Task: verify financial information	0.82	0.38	1.00	0.00	1.00
Days/week to verify information	2.33	1.45	2.00	0.00	5.00
Matters for Loan: Occupation	2.76	0.49	3.00	1.00	3.00
Matters for Loan: Income	2.92	0.33	3.00	1.00	3.00
Matters for Loan: Gender	1.26	0.57	1.00	1.00	3.00
Matters for Loan: Age	2.12	0.67	2.00	1.00	3.00
Matters for Loan: Collateral	2.92	0.29	3.00	1.00	3.00
Matters for Loan: Guarantor	2.79	0.46	3.00	1.00	3.00
Matters for Loan: Education	1.22	0.45	1.00	1.00	3.00
Matters for Loan: Nationality	2.15	0.82	2.00	1.00	3.00
Matters for Loan: Appearance	1.31	0.50	1.00	1.00	3.00
Borrowers Met, Daily	8.05	8.53	5.00	1.00	60.00
Borrowers Approved, Daily	4.30	4.61	3.00	0.00	30.00

Notes: The table reports descriptive statistics for the 238 loan officers participating to the credit experiment. *BMI* is noted by enumerator using the Body Size Scale for Assessing Body Weight Perception in African Populations (Cohen et al., 2013).

Table 5: Hypothetical Loan Applications 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 (ca $270)* *Ush 5 million (ca $1,400)* *Ush 7 million (ca $1,900)*
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 describes the information included in the hypothetical loan application and the corresponding cross-randomization rules. The content information are of typical loan profiles and are obtained from focus groups with multiple loan officers.

Table 6: Loan Profiles Characteristics: Covariates Balance

	Not Obese		Obese		P-value of Difference		
	Mean	SD	Mean	SD	Diff	Standard	RI
BMI value	23.34	1.94	37.31	3.40	13.962	0.00	0.00
Age	36.50	9.36	36.88	9.61	0.382	0.18	0.07
Gender: Male	0.50	0.50	0.50	0.50	0.005	0.36	0.71
Collateral: Car	0.33	0.47	0.33	0.47	0.000	0.97	0.99
Collateral: Land Title	0.50	0.50	0.49	0.50	-0.007	0.14	0.59
Collateral: Motorcycle	0.17	0.37	0.17	0.38	0.007	0.11	0.46
Occ: Agri Shop	0.10	0.30	0.10	0.30	-0.000	0.94	0.96
Occ: Sells Clothes	0.19	0.39	0.21	0.41	0.022	0.04	0.04
Occ: Diary Project	0.10	0.30	0.10	0.30	0.000	0.98	0.98
Occ: Hardware Store	0.09	0.29	0.10	0.30	0.007	0.11	0.35
Occ: Jewelry Shop	0.11	0.31	0.09	0.29	-0.018	0.02	0.03
Occ: Retail and Mobile Money	0.21	0.41	0.19	0.40	-0.014	0.03	0.19
Occ: Phone and Movies Shop	0.10	0.29	0.10	0.30	0.004	0.43	0.67
Occ: Poultry and Eggs	0.10	0.30	0.10	0.30	-0.000	0.92	0.96
Revenues (UGX m)	5.85	4.80	5.77	4.75	-0.087	0.14	0.49
Profits (UGX m)	1.67	1.37	1.65	1.36	-0.025	0.14	0.49
Order in Arm	5.51	2.82	5.49	2.91	-0.021	0.36	0.75
Reason: Business	0.21	0.41	0.20	0.40	-0.008	0.16	0.38
Reason: Home Improv.	0.23	0.42	0.22	0.42	-0.005	0.35	0.69
Reason: Purchase Animal	0.17	0.37	0.17	0.38	0.007	0.11	0.46
Reason: Purchase Asset	0.17	0.38	0.17	0.38	0.000	0.89	0.96
Reason: Purchase Land	0.23	0.42	0.23	0.42	0.005	0.26	0.63
Loan Profile: 1 million	0.34	0.47	0.34	0.48	0.008	0.20	0.50
Loan Profile: 5 million	0.34	0.47	0.33	0.47	-0.012	0.07	0.30
Loan Profile: 7 million	0.33	0.47	0.33	0.47	0.004	0.59	0.73
Observations	6,645						

Notes: Note: The *Obese* (*Not-Obese*) column indicates if a borrower's profile was randomly assigned to the higher (lower) body mass 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. BMI of the pictures is evaluated by 10 third-party Ugandan raters using the Body Size Scale for Assessing Body Weight Perception in African Populations (Cohen et al. 2013) and averaged at the portrait level. The content of the applications is randomly assigned as described in Table 5.

Table 7: Obesity Premium in Access to Credit

	(1) Approval Likelihood	(2) Financial Ability	(3) Credit-worthiness	(4) Referral Request
Panel A: Pooled Information Treatments				
Obese	0.110***	0.123***	0.093***	0.045**
	(0.019)	(0.021)	(0.022)	(0.019)
Observations	6645	6645	6645	6645
Panel B: By Borrowers' Information Provided				
Obese	0.199***	0.180***	0.151***	0.066**
	(0.035)	(0.037)	(0.039)	(0.033)
Self-Reported Financial Info	0.166***	0.105**	0.085*	0.065
	(0.045)	(0.046)	(0.047)	(0.052)
Obese × Self-Reported Financial Info	-0.129***	-0.082**	-0.084*	-0.031
	(0.039)	(0.041)	(0.044)	(0.039)
Observations	6645	6645	6645	6645

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. All regressions include application, and loan officer fixed effects. Standard errors are clustered at the loan officer level. All outcomes are standardized, including *Referral Request*, a dummy taking value 1 when the loan officer chooses the meet with a similar applicant (real choice outcome). *Approval Likelihood* is the self-reported likelihood of approving the application (1-5 scale). *Creditworthiness* is the perceived creditworthiness of the applicant (1-5 scale). *Financial ability* is the perceived ability of the applicant to put money to good use (1-5 scale). *Obese* is a dummy taking value one if the application included the high-body-mass version of the original picture. *Self-Reported Financial Info* is a dummy taking value one if the application was randomly assigned to include self-reported financial information.

Table 8: Obesity Premium by Borrower's Type (Low DTI - High DTI)

	(1) Approval Likelihood	(2) Financial Ability	(3) Credit-worthiness	(4) Referral Request
Obese	0.091***	0.126***	0.102***	0.071**
	(0.027)	(0.031)	(0.034)	(0.029)
Low DTI Ratio	0.608***	0.431***	0.300***	0.251**
	(0.124)	(0.109)	(0.114)	(0.114)
Obese × Low DTI Ratio	-0.043	-0.057	-0.072	-0.074**
	(0.042)	(0.043)	(0.049)	(0.038)
Observations	4566	4566	4566	4566

Notes: * p<0.1, ** p<0.05, *** p<0.01. All regressions include borrower profile and loan officer fixed effects. Standard errors are clustered at the loan officer level. Regressions include only profiles assigned to show borrowers' self-reported financial information. This heterogeneity analiysis was pre-registered. *Approval Likelihood* is the self-reported likelihood of approving the application (1-5 scale). *Creditworthiness* is the perceived creditworthiness of the applicant (1-5 scale). *Financial ability* is the perceived ability of the applicant to put money to good use (1-5 scale). *Referral Request* is a dummy taking value 1 when the loan officer chooses the meet with a similar applicant (real choice outcome). All outcomes are standardized for comparability *Obese* is a dummy taking value one if the application included the high-body-mass version of the original picture. *Low DTI Ratio* is a dummy taking value 1 if the borrowers' self-reported financial information indicates that the borrower has a low Debt to Income ratio (good type).

Table 9: Obesity signal perception among Kampala residents (laypeople)

Kampala Monthly Income Distribution by Body Mass

	Actual		
	Below Median Income	Above Median Income	Mean Income
Body Mass	%	%	USD
Obese	43.0	57.0	259
Normal weight	50.2	49.8	166
Likelihood ratio		**1.14**	
	Predicted		
	Below median	Above median	Mean Income
Body Mass	%	%	USD
Obese	24.5	75.5	350
Normal weight	77.6	22.4	104
Likelihood ratio		**3.34**	

Note: The table displays the monthly earnings distribution by body mass in Kampala. The top panel displays self-reported earnings data from a self-administered survey of 511 individuals in Kampala. While the survey is not designed to be representative, the correlation between earnings and body mass is comparable to the correlation between an asset-based wealth index and body mass in the Uganda 2016 DHS data (Kampala region). The bottom panel displays the equivalent predicted statistics from a sample of 96 Kampala residents. The predictions are incentivized with the true values. The results show that laypeople overestimate the correlation between obesity and earnings in the population.

Appendix

A Beliefs Experiment

A.1 Wards Selection

In this appendix, I describe how I select the wards from which I sample respondents in the beliefs experiment. The wards are selected randomly from the list of all wards in the districts of Kampala, Mukono and Wakiso (Greater Kampala). To ensure variation in terms of socio-economic status, I stratify the wards based on a ward-level poverty-index I create from Ugandan Census data. I build the index as follows. From alll the wards in the Greater Kampala, I drop one industrial area, the two richest neighborhoods (Kololo and Muyenga), and the wards counting less than 2% of the Greater Kampala population. The final list includes 99 wards. Using ward-level aggregate data from the Ugandan 2014 census, I create a poverty index averaging 4 variables: share of households with no decent dwelling, share of households living on less than 2 meals per day, share of households which do not have a bank account and share of illiterate adults. The poverty index ranges from 5, richest, to 42, poorest, (sd: 5.75). To implement the stratification, I rank the wards and split the sample according to poverty index quintile. To maximize variation, I randomly select 10 wards from each of the first, third and fifth quintile. The final list of selected wards and their characteristics is in Table J.1.

A.2 Main analysis

The coefficient of interest is β_1 in the following specification:

$$Y_{ij}^{k} = \beta_0 + \beta_1 HighBM_{ij} + \alpha_i + \gamma_j + u_{ij}, \tag{8}$$

where i indexes the application and j the respondent. Y_{ij}^{k} is the rating with respect to outcome k of picture i by respondent j. $Obese_{ij}$ is a dummy taking value 1 if picture i is displayed to respondent j in the Obese version. $Order_{ij}$ is a categorical variable indicating if the picture was shown as the first, second, third or fourth picture to respondent i. α_i are portrayed-individual fixed effects, and γ_j are respondent fixed effects. Standard errors are clustered at the respondent level. Results are summarized in Table 2.

B Credit Experiment

B.1 Building hypothetical loan applications

In this appendix, I describe how I build the hypothetical loan applications. Table 5 summarizes the step-by-step randomization procedure. Each application includes a set of borrowers' characteristics and the borrowers' portrait. For each application there exist two versions, which are identical except for the portrait version included (obese, not obese). I build 30 original applications, for a total of 60 applications.

To cross-randomize the information in the applications I use Python *numpy.random* and the *itertools.cycle* functions. I select portraits from the set of manipulated portraits (black race only). I stratify the randomization by body mass, and as the signaling power of body mass might differ for men and women, by gender. The additional borrowers' information is cross-randomized simultaneously within each application: that is, each application can be presented to a loan officer either including or not including financial information.

In what follows, I describe the information included and the corresponding randomization structure. I begin with the baseline information, included in all applications:

- **BMI, gender and age:** The information about gender and BMI is conveyed using a picture. For each application, a picture is selected from the set of 30 passport-style pictures of individuals living in Kampala described in Section 3. In each application, the picture is selected conditional on gender and body mass (randomly assigned). Body mass of the applicant is selected between high and low BMI. If high BMI (low BMI) is selected, then the picture included in the application will be the high BMI (low BMI) photo-morphed version of that picture. As far as age information is concerned, 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.
- **Loan profile and reason for loan** There are three different loan profiles: UGX 1 million ($ 270), UGX 5 million ($ 1,350), UGX 7 million ($ 1,900). [73] The chosen repayment time was of 6 months for all loan profiles. The reason for the loan was randomly assigned to be either business or personal. Business was left open, while for personal loans the choice set included home improvements, purchase of land, purchase of an animal and purchase of an asset (for example, a fridge or car). Both loan profile and reason for loan were stratified by gender and body mass (high/low).
- **Name, Passport ID, Nationality and Place of Residence** The information on name, passport ID, nationality and place of residence is not randomized. Name and passport ID are included to increase realism, but are blurred. Nationality is always Ugandan, as most loan officers 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.

As far as the financial information is concerned, I included the following information:

- **Occupation:** All the hypothetical loan applicants are self-employed. This is because most

[73] According to the Uganda Finscope Survey in 2013, the 75 percentile of loan amounts did not exceed UGX 500,000. However, bank customers in urban areas were more than twice as likely to access loans of more than UGS 1 million compared to borrowers in rural areas. If anything, the selected loan amounts are relatively large. This choice was made to increase loan officers' stakes and attention.

employed individuals would have a direct and more convenient credit line with their employer. This choice hardly limits the external validity of the results because the share of self-employed work in Uganda, as in many other low income countries, is much larger than the employed one. For example, self-employed individuals as percent of total employment in Uganda were 85. 30% in 2017 according to estimates of the International Labour Organization. The occupations included in the applications have been vetted in focus groups and are assigned conditional on gender. Female-typical occupations include owning a retail and mobile money shop, owning a boutique, owning a jewelry shop, owning an agricultural produce and drug shop, owning a hardware store. Male-typical occupations include: owning a retail shop and mobile money business, owning a phone accessories and movies shop, selling clothes (owning a boutique), running a poultry and eggs business, running a dairy project.

- **Monthly Income:** Because applicants are self-employed, income information is provided in the form of last month's self-reported revenues and profits. Each application is randomly assigned to be high or low income. Then, profits and revenues are randomly assigned conditional on the income realization and the loan profile. For each loan profile, I compute the monthly repayment rate based on the average interest rate in Kampala. Then, I determine monthly profits according to the formula $MonthlyRepayment = X \cdot MonthlyProfits$. If the application is a high income application, X is randomly selected between [0.3; 0.35; 0.37; 0.4]; if the application is a low income application, X is randomly selected between [0.9; 0.95; 0.97; 1-05]. [74]
- **Collateral:** Collateral is assigned conditional on loan profile. For loan profiles of UGX 1 million, the choice is between motorcycle and land title. For loans of UGX 5 million or above, the choice is either car or land title.

The financial information is delivered by adding, at the bottom of the application, the following 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 [revenues amount]. The profits were [profits 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. "*

B.2 Robustness Checks

B.2.1 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

[74] It is not uncommon, especially among informal lenders, to approve of loans such that $X = 0.95$ or $X = 1$.

Imbens (2017) and Young (2019), 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 assignment of a fixed number of units (in our case, high schools) to treatment, rather than from random sampling from 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 J.5, 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 findings cannot be explained by random differences between the loan officers and applications including a portrait in its obese version.

B.2.2 Beauty bias

In principle, the obesity premium could be a beauty premium. Beauty bias can lead to strong distortions as shown in Mobius and Rosenblat (2006). If obese individuals are perceived as more beautiful, that may explain why loan officers are more lenient towards them. Both the beliefs experiment results, showing that laypeople do not perceive obese borrowers as more beautiful, and the fact that the obesity premium is mostly driven by asymmetric information suggest this is unlikely. In this appendix, I further show that a cross-gender attractiveness cannot explain the obesity premium: in Table J.5 I restrict the sample to male loan officers evaluating male borrowers and show that results are qualitatively unaffected.

B.2.3 Heterogeneity by order in which the applications are presented.

In the credit experiment, the information treatment order is not randomized. The reason is that, during pilot activities, loan officers appeared confused when asked to evaluate first applications including financial information, followed by applications with no financial information. However, one may be worried that the lack of randomization may bias the results. In this appendix, I look into how the moment in which an application was presented to loan officers (within a given arm) affects the results. The idea is that if evaluating an application has spillovers on future evaluations, this should happen both within and across arms. To test for this hypothesis, I generate a dummy variable which indicates whether a given application was displayed in the first half (n. 1 to n. 5 included) or in the second half (n. 6 to n. 10 included). I use this dummy to investigate heterogeneity in the effect of body mass by order in which the applications were presented. Table J.2 summarizes the results: the effect of body mass on access to credit is equivalent in applications in the first half and applications in the second half of each arm.

B.3 Additional Results

B.3.1 Variation in timing of financial information provision

In this appendix, I investigate how variation in the moment in which financial information is revealed to the loan officers affects bias. As described in the main text, the credit experiments randomly varies amount and quality of the borrowers' financial information in the applications. Within the financial information arm, the design also varied whether receiving the extra information was a loan officers' choice or was exogenous provided. In practice, in half of the applications, loan officers' were asked whether they wanted to learn additional information on the applicant; for the remaining half, they were shown the financial information right away. The results show that 99% of loan officers always chose to learn additional information. Thus, loan officers do not exploit their opportunity to choose whether to receive additional information to hide discrimination. Because there is basically no difference in selection between the two sub-arm, in the main analysis I pool all the data. Yet, this variation can be exploited to understand the effect of timing of information provision on the effect of body mass. In fact, when the information was provided exogenously, all the information was provided at once; instead, when loan officers had the choice, they first saw the baseline information, and then the financial information. The results in Table J.3 show that the interaction coefficient is negative but insignificant. This result may be policy relevant because they suggest that presenting all the information at once may reduce body mass discrimination; however, given the small effect size, further research is needed to make more conclusive claims.

C Real borrowers' referrals

In the credit experiment, I incentivize loan officers' evaluation of the hypothetical loan application by referring them to real borrowers' referrals which match their preferences, as they emerged from the hypothetical evaluation exercise. In this appendix, I describe how I implement the referrals. The matching is based on observable characteristics and is obtained using a machine learning algorithm. To implement the procedure I use R and my code mostly relies on *Tidymodels*.[75]

C.1 Introduction to the machine learning problem

The problem of matching new borrowers with loan officers, based on the preferences loan officers' expressed on the hypothetical borrowers set is a very good application of supervised machine

[75] Code available upon request.

learning algorithms. Supervised machine learning revolves around the problem of predicting y from x. As noted in Mullainathan and Spiess (2017), the appeal of machine learning is that it manages to uncover general patterns and does particularly well in out-of-sample predictions. Referring good (new) borrowers to the loan officers requires an out-of-sample prediction: one needs to predict loan officers' preferences for new borrowers (out-of-sample) based on the preferences they expressed on hypothetical borrowers in the credit experiment.

In what follows, I outline the machine learning procedure I exploit to implement this matching. My measure of loan officers' preferences is the loan officers' binary choice to meet with the applicant. This makes the prediction problem a supervised *classification* problem. In short, I will train a set of competing classification models on the hypothetical loan applications evaluation data. I select the optimal model (more on this in the details) and apply it to a new dataframe of real prospective borrowers to predict which borrowers which loan officers would be more likely to get a meeting with a loan officer and those who wouldn't. The real prospective borrowers are 187 Kampala residents which are in need of 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. The referral procedure was implemented in Spring 2020.

C.2 Data description

The full credit experiment data on loan officers preferences includes 254 loan officers, evaluating from 4 to 30 applications each. From these data, I exclude applications for which the loan officer has no information on the applicants' income. The amount of information in these applications is very low and therefore not relevant for the prediction exercise. The total number of observations is 4,299.

Machine learning searches automatically for the variables, and interactions among them, who best predict the outcome of interest. Practically, then, one must decide how to select, encode and transform the underlying variables before they are fed to the machine learning algorithm.

First, I select all loan officers and firm characteristics recorded in the credit experiment. Concerning the applicants characteristics, I select all the characteristics for which there exists a counterpart in the new borrowers' data.[76]

The final database includes:

- Loan officers characteristics: age, gender, BMI, 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

[76] I exclude occupation, which was elicited as an open question to the new borrowers. Including the occupation information requires making some assumptions to link borrower occupations which are similar to the hypothetical applications choices. Since the performance of the algorithm are quite satisfying even in the absence of occupation information, I prefer to keep the implementation simpler and exclude occupation information.

of the verification procedure, dummies for factors influencing loan officers 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.

- Firm characteristics: institution name, tier, district, organization size, interest rate for 1 million, 5 million and 7 million loan, loan types offered
- Applicant's characteristics: age, monthly profits, loan reason (business, personal), loan amount. [77]

The new borrowers' data is a subsample of a stratified random sample (gender, age, residence ward) of 511 Kampala residents. The subsample corresponds to the 187 individuals which stated to be in need of a loan. For each prospective borrower, I consider only the following information: age, monthly income, body mass, requested loan amount, requested loan type.

C.3 Setup and pre-processing

I split the Credit Experiment data in a training set and a test data set, stratifying over the outcome variable). This has to do with the fact that most times, loan officers want to meet the client and hence classes in the training database are unbalanced: 76% - class 1 (meet); 24% class 0 (do not meet). The test sample contains 20% of the observations. After selecting the relevant variables, I convert to ordered factors the education, financial knowledge, loan amount and the stress variable. I convert all string variables and numerical dummies to factor variables. After this initial pre-processing, each model has its unique pre-processing 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, borrowers' profits). I standardize all predictors and remove those with no variation. When necessary (for example, in the Lasso), I create dummies for all non continuous predictors and impute all missing values with a nearest neighbor procedure.

C.4 Training process and model selection

The training set is used to tune the hyperparameters of each model. I select the models and parameter combinations that result in the highest AUC on the training data set. I use the test data set to compare the different models and select the preferred model.

The performance of the preferred model on unseen data will be assessed on the test data. Before doing that, I tune the algorithm parameters on the train data. I use 5-fold 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

[77] Following Kessler et al. 2019, I exclude gender and body mass to avoid discriminatory outcomes.

resulted in the highest AUC in the first tuning step. Table J.10 shows the estimated models and their respective performance. I select the model with the highest AUC on the test data as my preferred model. The models with the highest test AUC are the Gradient Boosting classifier (extreme gradient boosting) followed very closely by a Random Forest classifier. Gradient Boosting models are more complex objects, require more careful tuning and are prone to overfitting. Since I have a limited set of test data available, I prefer to rely on the Random Forest model. The preferred Random Forest model is run with the ranger engine, 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 (3 neighbors). It 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.

After selecting the preferred model, I fit the Random Forest model with optimal parameters one more time to the entire available data in order to let the fit use as many data points as possible.

C.5 Matching and referrals

To assign the correct referral to each prospective borrower I proceed as follows. First, I merge the new borrowers' data with the loan officers and firms characteristics data. In such a way, I can compare across loan officers' predictions for each borrower. Second, I clean the resulting data according to the I apply the trained model described in the previous section to the new merged data and compute the predicted scores for each borrower-loan officers pair. The probability score is the result of the classification exercise. This variable is a score, between 0 and 1, indicating the probability that a given loan officer would want to meet that applicant. Third, I select only those matches which 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. Depending on the loan officers' preferences, the actual referral entails either the institution's name and address, or additionally includes the contact information of a specific loan officer. Referrals are communicated to the prospective borrowers via a phone survey, implemented in Spring 2020.

D Credit Discrimination Model

In this appendix, I describe the credit discrimination model which provides the micro-foundation to my theoretical framework. Formally, consider a loan officer j who evaluates borrower i's profitability π_{ij}, and chooses whether to undertake a costly verification action $v_{ij} \in 0, 1$ in order to learn about i's true repayment probability α_i. Assume: (A1) loan officer j chooses $v_{ij} = 1$ if $\pi_{ij} > 0$; (A2) there is asymmetric information about borrowers' income, Y_i; (A3) ij depends on body mass (BMI_i), self-reported income ($\tilde{Y_i}$) and other observable characteristics (X_i); (A4) α_i is linear in the observable and unobservable characteristics, and $\tilde{Y_i}$ is a linear in Y_i.

Assumptions A1 and A2 tie the model to the setting. Loan officers have financial incentives to select profitable borrowers; in their first meeting, loan officers cannot verify the self-reported borrowers information. Assumption A3 allows for discrimination by body mass. Assumption A4 simplifies the framework without loss of generality. I define loan officer j expected profitability of borrower i as:

$$\pi_{ij}(\alpha_i, Y_i; BMI_i; \mathbf{X_i}; R_i; t_i) = p_{ij}R_i - t_i \tag{9}$$

where p_{ij} is the repayment probability of borrower i, in j's expectation; R_i is the total repayment amount if the loan is granted; t_i is the cost of credit. Ex-ante the true probability of repayment α_i is unobservable, therefore loan officers form expectations based on the observables (body mass, self-reported income and other borrower's characteristics). Under A1-A4:

$$\begin{aligned} p_{ij} &= E_j(\alpha_i|\tilde{Y_i}, BMI_i, X_i) = E_j(\beta_i Y_i + \gamma_i BMI_i + \theta_i X_i + u_i|\tilde{Y_i}, BMI_i, X_i)) = \\ &= \int_k (\beta_i Y_i + \gamma_i BMI_i + \theta_i X_i + u_i|\tilde{Y_i}, BMI_i, X_i)) \cdot g_j(Y_{ik}|\tilde{Y_i}, BMI_i, X_i)), \end{aligned} \tag{10}$$

where Y_{ik} are all borrower i's possible income levels, and $g_j(Y_{ik}|\tilde{Y_i}, BMI_i, X_i))$ is the probability distribution associated by loan officer j with each borrower income level, given borrower i's body mass and other characteristics. To the eyes of an observer, v_{ij} is observable, but π_{ij} and, more relevantly, p_{ij} are latent variables. To the eyes of the experimenter, however, p_{ij} is observable: in the credit experiment, I elicit loan officers' perceived probability of repayment for each borrower, the outcome Creditworthiness.

Thus, I model body-mass discrimination as that the overall effect of body mass on perceived probability of repayment, and positive body-mass discrimination as: $\frac{dpi_{ij}}{dBMI_i} > 0$.

To explore the determinants of discrimination, the total effect of body mass on repayment probability can be decomposed into a direct effect, and an indirect effect: a change in BMI shifts the distribution over borrowers' income, as perceived by the loan officer. Under A1-A4, the decomposition simplifies to:

$$\frac{dp_{ij}}{dBMI_i} = \gamma_i + \beta_i \frac{\delta E_j(Y_i|\tilde{Y_i}, BMI_i, \mathbf{X_i})}{dBMI_i}, \tag{11}$$

where $\frac{dp_{ij}}{dBMI_i}$ is the total obesity premium, γ_i is the effect of body mass, given self-reported income and β_i is the effect of income, given body mass. $\frac{\delta E_j(Y_i|\tilde{Y_i}, BMI_i, \mathbf{X_i})}{dBMI_i}$ is the average shift in the expected income distribution due to a marginal increase in a borrowers' BMI, from the perspective of the loan officers.

- In a pure taste-based discrimination framework, discrimination arises as the direct effect of body mass on creditworthiness, conditional on income, that is $\gamma_i > 0$ and $\frac{\delta E_j(Y_i|\tilde{Y_i}, BMI_i, \mathbf{X_i})}{dBMI_i} = 0$;
- In a statistical discrimination framework, loan officers exploit body mass to infer about borrowers' income. Thus, the perceived income distribution depends on body mass: $g_j(Y_{ik}|\tilde{Y_i}, BMI_i, X_i)) \neq$

$g_j(Y_{ik}|\tilde{Y}_i, X_i))$.

- In an accurate statistical discrimination model, beliefs on the conditional income distribution are accurate: $\frac{\delta E_j(Y_i|\tilde{Y}_i, BMI_i, \mathbf{X_i})}{dBMI_i} = \frac{\delta E(Y_i|\tilde{Y}_i, BMI_i, \mathbf{X_i})}{dBMI_i}$.
- In an inaccurate statistical discrimination model, beliefs on the conditional income distribution are inaccurate: $\frac{\delta E_j(Y_i|\tilde{Y}_i, BMI_i, \mathbf{X_i})}{dBMI_i} \neq \frac{\delta E(Y_i|\tilde{Y}_i, BMI_i, \mathbf{X_i})}{dBMI_i}$.

E Obesity benefits and body mass realizations: information experiment pilot

Obesity benefits raise the opportunity cost of engaging in healthy behaviors. Building on the observed correlation between perceived obesity benefits and body mass, and in particular, on the results showing that obesity benefits are overestimated among laypeople, I design a simple information provision experiment to test whether informing about the true benefits of obesity affects willingness to engage in healthy behaviors. In what follows, I present this design and outline some preliminary results from piloting activities run in Spring 2020.[78]

The design is as follows. First, I elicit priors along a set of dimensions, including ideal body size, reasons to lose or gain weight in Kampala, obesity and income correlation, and the health costs of obesity. Then, I allocate respondents to one of three informational treatment arms: (T1) respondents learn that a study has found that obesity leads to sizable benefits in access to credit in Kampala; (T2) respondents learn that according to a recent study most people overestimate the benefits of obesity in terms of access to credit in Kampala; (T3) respondents learn that according to a recent study the costs of weight gain start with mild overweight.[79] Then, the study is over. As a thank you for their time, respondents can enter a lottery which gives them the opportunity to receive nutritional support (randomly assigned between nutritional supplements or nutritional advice) at a subsidized rate. If they win the lottery, they can either purchase the nutritional support or keep the won amount. I measure demand for willingness to pay to receive support using the Becker–DeGroot–Marschak procedure.

The aim of the design is to test whether informing about overestimation of obesity benefits increases willingness to engage in healthy behaviors, proxied by willingness to pay for nutritional support. My main comparison of interest is between T1 and T2. Relative to a pure control design, this approach allows me to control for the fact that, by providing information on obesity benefits overestimation, I implicitly confirm the presence of obesity benefits. The comparison between T2 and T3 allows to benchmark the effect against a standard obesity health costs treatment. Some steps in the design are aimed to limit experimenter demand concerns: first, I elicit some priors using open ended questions (e.g., reasons to lose or gain weight); second, the experiment is structured so that the information-provision and the willingness to pay for the products are

[78] Because of the Covid-19 outbreak, respondents are recruited using snowball sampling techniques and the surveys are administered either online using phone-surveys and Whatsapp.

[79] The treatment wordings are in Appendix I.

presented as separate events; third, I do not explicitly ask for posterior beliefs. Instead, after providing the information, I ask respondents to rate how much they trust the results of the study.

Exploratory results, based on a sample of 40 respondents and 121 observations, are summarized in Fig. J.11. Informing about obesity benefits overestimation increases willingness to pay for nutritional support. This effect is smaller in magnitude, when compared to the informing about obesity costs. The lowest willingness to pay is associated with confirmation of obesity benefits in access to credit. These results are preliminary and need to be taken with a grain of salt: the sample size is extremely small and the results are not statistically significant. Yet, the results are encouraging in that correcting beliefs about obesity benefits may indeed be successful at encouraging healthier behaviors. Larger scale implementation may investigate the complementarity of health costs and benefits messages.

F Sugar beverages tax in the presence of obesity benefits

In this appendix I build on Allcott et al. (2019), henceforth ALT, to describe how accounting for the obesity benefits affect the optimal sugar tax.

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.

In this appendix, I exploit this sufficient-statistic approach 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 (12) to estimate to obtain a benchmark for the Ugandan sugar tax in the absence of monetary obesity benefits; (2) I introduce obesity benefits and compare the tax is affected.

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

$$t \approx \frac{\bar{\gamma}(1+\sigma) + e - \frac{p}{\bar{s}\bar{\zeta}^c}((Cov[g(z);s(z)] + A)}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}((Cov[g(z);s(z)] + A)} \tag{12}$$

where $A = E(\frac{T'(z(\theta))}{1-T'(z(\theta)}\zeta_z(\theta)\bar{s}(\theta)\epsilon(\theta))$.

In equation (12), $\bar{\gamma}$ 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, ζ_z the compensated elasticity of income relative to the marginal tax.

From the perspective of the benchmark tax estimation, the Ugandan context differs from the US one for three main reasons. First, in Uganda, contrary to the US, soda consumption correlates positively with income. It follows that sin taxes are not regressive and thus that $\sigma \leq 0$ and that the correlation between welfare weights and sugary beverages consumption is negative. For simplicity, I set $\sigma = 0$. Second, health care costs externalities are likely to be lower because of the absence of a large health care system, and thus for simplicity I assume $e = 0$. Finally, I assume $A = 0$ (low-state capacity to collect taxes).

Under these assumptions, the equation for the optimal tax simplifies to:

$$t_{uga} \approx \frac{\bar{\gamma} - \frac{p}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)])}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)])}. \tag{13}$$

How do obesity benefits enter equation (13)? My results show there exists two types of benefits:

1. Social benefits: sugary beverages consumption increases people's BMI and higher BMI individuals are perceived as wealthier. [80]
2. Financial benefits: obese borrowers have easier access to credit.

I assume that social benefits enter the utility function and in equation (13) they are captured in the elasticity of soda consumption. As far as monetary benefits are concerned, this is equivalent to a subsidy in soda's consumption equal to the expected returns per unit consumed ($p' = p - E(b)$). The equation for the optimal sugar beverages tax accounting for financial benefits can be written as:

$$t^b_{uga} \approx \frac{\bar{\gamma} - \frac{(p-E(b))}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)])}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)])}. \tag{14}$$

The effect of financial benefits on the tax is ex-ante ambiguous and depends on $(Cov[g(z); s(z)])$, that is the correlation between welfare weights and sugar beverages consumption. When $(Cov[g(z); s(z)]) > 0$, for example 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.

To understand whether accounting for obesity benefits can have sizable effects on the tax, I implement a simple calibration of the Ugandan optimal soda taxes, not accounting for obesity benefits (t_{uga}) and accounting for benefits (t^b_{uga}). In the levels, these calibrations should be taken with a grain of salt as the estimates are subject to severe data limitations. In short, the estimate of the soda tax is based on soda consumption data, data on preferences for sodas, soda prices, data to compute the welfare weights, and when accounting for obesity benefits, data on financial returns to soda consumption. My data limitations rely in soda consumption data and the welfare weights. For example, while ALT exploit soda purchase data (Nielsen Homescan Data), I only have self-reported soda consumption and income data from a non-representative survey of Kampala residents. This has two main consequences: first, I cannot estimate bias as in ALT, rather I can only build an average bias estimate; second, I cannot estimate the sugary

[80] There could be additional direct status benefits related to sugar beverages consumption (since these beverages are generally expensive). Since my experimental results do not directly measure these benefits I abstract from them in this application. Hence, the estimates will provide a lower bound for the effect of obesity benefits.

beverages elasticity. My solution to this limitation is to exploit the corresponding ALT US value in lieu of the statistics which are unavailable for Uganda. This strong assumption mainly affects the level of benchmark in equation (13), while the goal of this estimation exercise is the effect of accounting for obesity benefits, that is the difference between equation (13) and equation (14).

For what concerns preferences for sodas I implement a nutritional survey data which follows the Nutritional Survey implemented in ALT but modified to fit the Ugandan context, with the help of a local nutritionist. For what concerns the estimate of the financial benefits of soda consumption, I exploit the credit experiment of the obesity premium in access to credit to estimate the monetary benefits of obesity, and the correlation between body mass and soda consumption from the self-reported survey data. In practice, I assume that $E(b) = \bar{b} = \frac{\delta Benefits}{\delta BMI} \cdot \frac{\delta BMI}{\delta soda}$.

In sum, I make the following assumptions to compute the standard soda tax:

- Elasticity: as in the US.
- Bias ($\bar{\gamma}$): as in the US.
- $A = 0$
- $e = 0$
- $\sigma = 0$
- $Cov(g(z), s(z))$ from self-reported soda consumption data in Kampala (Uganda), assuming that welfare weights are decreasing in monthly earnings.
- $\bar{s}$: from self-reported consumption data;
- p = 2,300 UGX/liter (US$ 0.62).

Under these assumptions, the optimal sugar tax in Uganda is US$ 1.02 cents per ounce of soda (t_{uga}), while the estimate of (t^b_{uga}) is US$ 0.7 cents per ounce, a reduction of 15%. While the levels of these estimates are unlikely to be meaningful for policy, this estimation exercise shows clearly that accounting for obesity financial benefits can have sizable effect on the optimal soda tax. In particular, it shows that when soda consumption is larger among the wealthier, the optimal soda tax is decreasing in the amount of financial benefits.

G Explicit beliefs on obesity benefits and costs

G.1 Obesity benefits in the dating and job market

In the beliefs experiment I also elicit people's explicit beliefs on returns to obesity in other markets: the dating market and the labor market. After the beliefs experiment and the credit experiment replication, I elicited four questions on obesity benefits in the job market, the dating market, the credit market and the probability of developing cardiovascular diseases. To define body mass I referred to the Body Size Scale for African Populations. The questions exploited the wording: *"If someone had a figure like Silhouette X and increased to Silhouette Y, do you think he/she would be more or less likely to develop a cardiovascular disease. (Man: more/less/equally likely; Woman: more/less/equally likely)"* and the comparisons allowed for were normal weight to overweight; overweight to obese; obese of degree I to obese of degree II. Appendix Figure J.6 summarizes the results. First, laypeople's explicit beliefs on returns to weight gain in credit markets are aligned with the implicit beliefs. This confirms once again that people are aware of obesity benefits in credit markets. Second, while there are some benefits to gain weight up to overweight also in dating and the job market, obesity benefits are strongest in the credit markets. This is likely explained by the fact that credit markets are those where wealth screening is the strongest.

G.2 Obesity costs

In this section I describe the survey evidence suggesting that individuals are aware of the health costs of obesity and overweight, as well as of of unhealthy eating or lack of exercising. To elicit beliefs, I exploit the hypothetical investment scenarios following Biroli et al. (2020). I measure individual beliefs about the returns to health investments by eliciting individuals beliefs about the returns to (i) following a recommended-calorie diet and (ii) exercising regularly. The main difference from Biroli et al. (2020) is that I directly elicit adults' beliefs on returns to healthy/unhealthy behaviors of adults from age 30 to age 65. The scenario elicitation procedure is as follows. I present individuals with different hypothetical scenarios based on 10 hypothetical individuals living in Kampala, all of whom are 30 years old and are of average height and weight. To elicit perceived likelihoods, I ask respondents to report how many of the 10 hypothetical individuals presented in the scenarios they think will experience a certain outcome. For each scenario I am interested in three different outcomes namely being dead at age 65, being overweight at age 65 (conditional on being alive), and having a heart disease at age 65. Respondents are randomly assigned to either the Eating or Exercise scenario. Then, they are presented with two hypothetical investment scenarios varying in either food consumption or exercise levels.

The Eating or Exercise scenarios vary along one of two dimensions: (i) the calorie intake of the individual from ages 30-65 (Eating), and (ii) the amount of exercise undertaken daily by the individual from ages 30-65 (Exercise). For calorie intake, I consider two levels: the healthy amount ("two traditional Ugandan meals per day", the modal calories intake) and the unhealthy amount ("three traditional Ugandan meals per day plus a snack"). I cannot refer to recommended calories intake because most people are not familiar with the concept of calories. Similarly for exercise, the healthy behavior is defined as 60 minutes of exercise every day, while the unhealthy one is 0 minutes of exercise. The results are summarized in Appendix Figure J.7. Respondents understand the consequences of unhealthy behaviors related to overeating and lack of exercising. They also understand the BMI production function. For what concerns the scenario on exercising, the only one comparable to the results of Biroli et al. (2020), the effects of unhealthy behaviors are comparable in magnitude and if something slightly larger (overweight: 4,500 against 2,800;

cardiovascular disease: 4,520 against 2,579), except for the mortality effect (0.300 against 1.477). The mortality effect is substantially lower because the average life expectancy in Uganda is below 65 years old.

H Beliefs Experiment in Malawi

The paper tests a theory - that obesity is perceived as a signal of wealth - whose processes are defined in general terms, and which therefore is likely to find application in contexts characterized by a similar stage in the nutritional transition, i.e. with a similar positive BMI and wealth correlation (Popkin, 2001). However, the evidence provided so far is limited to Uganda, leading to the concern that these results may result from the specific Ugandan cultural context. In this appendix, I focus on investigating how widespread the perception of obesity as a signal of wealth is.

I conduct a similar, smaller scale survey experiment with 241 women in rural Malawi. Differently from the Ugandan survey experiment, the Malawi one exploits only 2 portraits (1 men and 1 woman), for a total of 4 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 p.p. more likely to be perceived wealthy and slightly more likely to be perceived creditworthy. Similarly, the effects on other outcomes are not statistically significant (Table J.9). Comparatively with the Ugandan sample, the Malawi one is substantially poorer and less educated. These results, together with the set of qualitative and descriptive results discussed in introduction, suggest that the results have external validity for Sub Saharan Africa and more generally for low-resources settings.

I Survey Tools

I.1 Information Provision Experiment

In this section, I report the wording of the information texts provided to respondents in the information experiment:

- Treatment 1: *People and families make decisions based on their environment or community. Many people in Kampala think that one person's body size affects the way people think of him or her. Recently IGREC, together with Elisa Macchi and the University of Zurich ran a study on this topic. The results showed that indeed this is true: Talking both with real loan officers and with normal people on the street, they learned that a person's weight matters for important decisions such as getting a loan or how wealthy the others think you are.*

- Treatment 2: *Several studies from the World Health Organization show that overweight and obesity are strongly associated with severe health conditions including heart disease, stroke, diabetes and high blood pressure. Many people think that obesity or high overweight start causing problems only when a person's weight is extremely high, for example when a person's body mass is like S9. This is not true. Doctors say that already a little bit of extra weight increases the chances of developing diabetes, heart disease and high blood pressure.*
- Control: *People and families make decisions based on their environment or community. Many people in Kampala think that one person's body size affects the way people think of him or her. Recently the results of a study of IGREC, together with Elisa Macchi and the University of Zurich showed that this is mostly only a belief. For example most people do not find overweight people neither more attractive, nor healthier, nor better at getting things done or more trustworthy. Also, people overestimate how easy it is for an obese person to get a loan. Once a loan officer learns self-reported information on a person's income, then weight does not matter much.*

Product description:

A: *The product is a set of easy-to-follow nutritional rules elaborated by a nutritionist. These tricks and guidelines will help you not to gain weight if normal weight or to lose weight if you are overweight.*

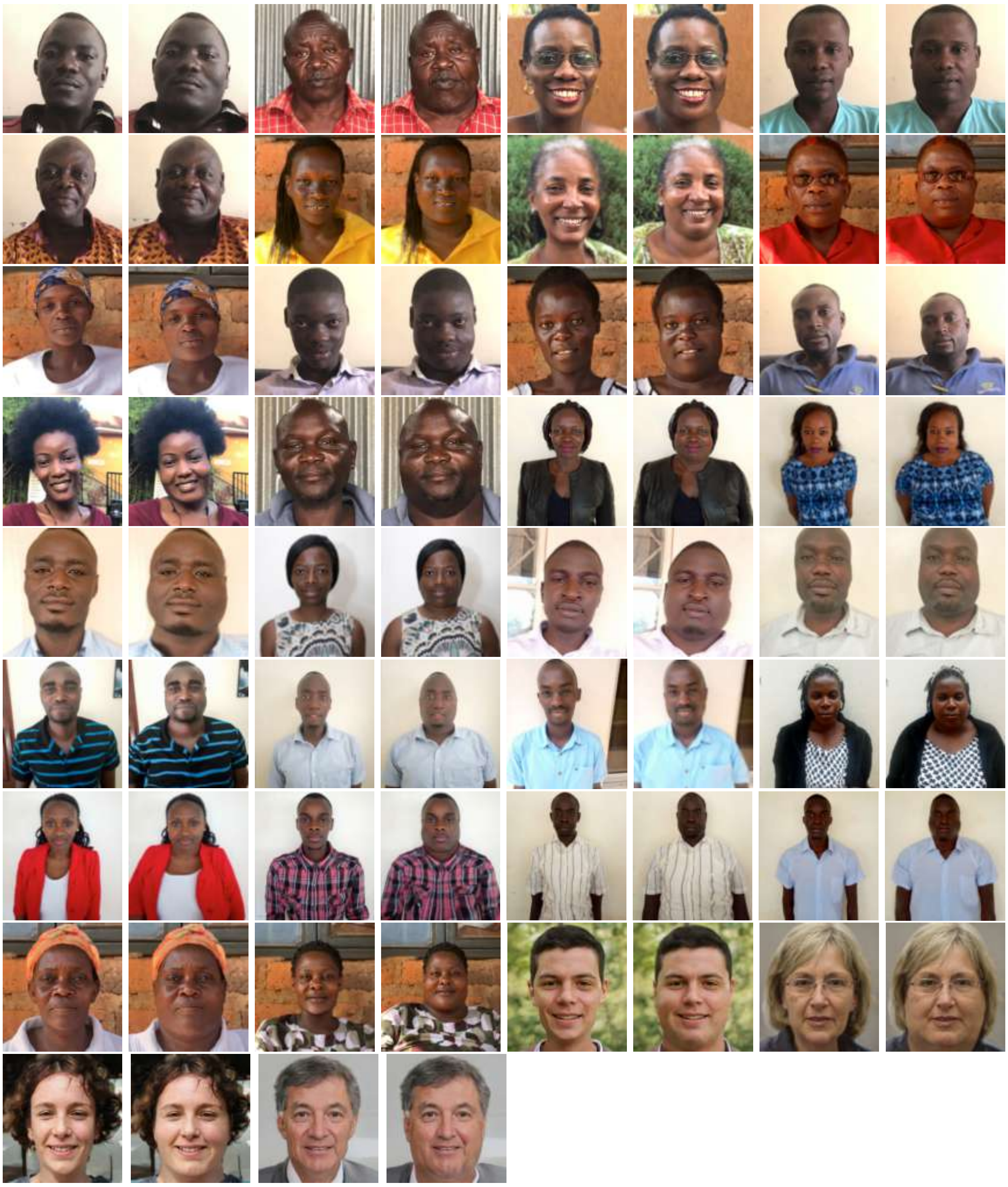
B: *The product is a highly nutrient drink. This is a drink which is filled with nutrients and energy. If you drink it regularly and keep your current diet, this drink can will help you keep up your weight or even gain some weight. This is perfect for individuals who need extra nutrition.*

Willingness to pay (BDM) wording:

- *"Now we are going to give you the opportunity to enter a lottery in which you may earn between UGX 0 and UGX 7'000 that you will receive at the end of the lockdown. If you win in the lottery, you will have the possibility to either receive the lottery price in money money and be free to use it to spend it on whatever you want, or to purchase $product. $product has a market value of US$ 20. You will not find out what amount you have earned in the lottery until the end of the interview. Before the lottery, For different amounts, I will ask you whether you would like to receive the full amount after the lockdown or receive a $product after the lockdown. At the end of the interview, the amount you have earned in the lottery will be revealed and you will receive your choice for that amount."*

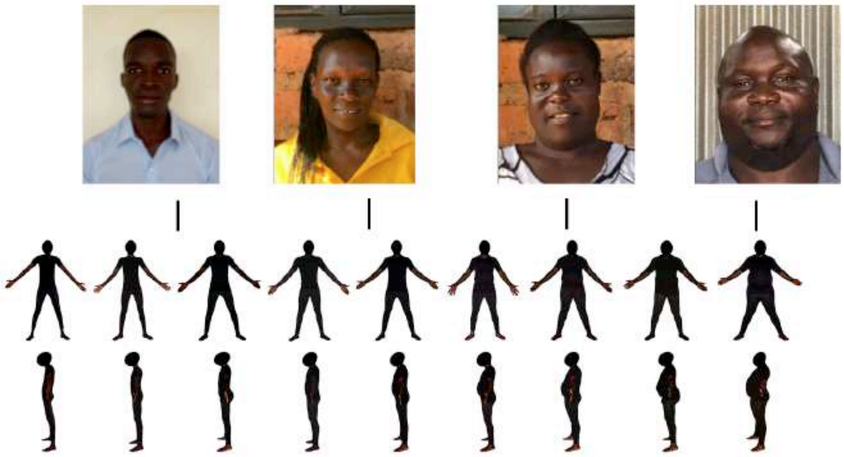
J Appendix Figures

Figure J.1: Weight-Manipulated Portraits



Note: The figure displays the 34 manipulated portraits exploited in the analysis. An original portrait (not displayed) has been manually manipulated by two independent photo-morphing expert to create a lower body mass and a higher body mass version. The black race original portraits are of Kampala residents. The white race original portraits are computer generated.

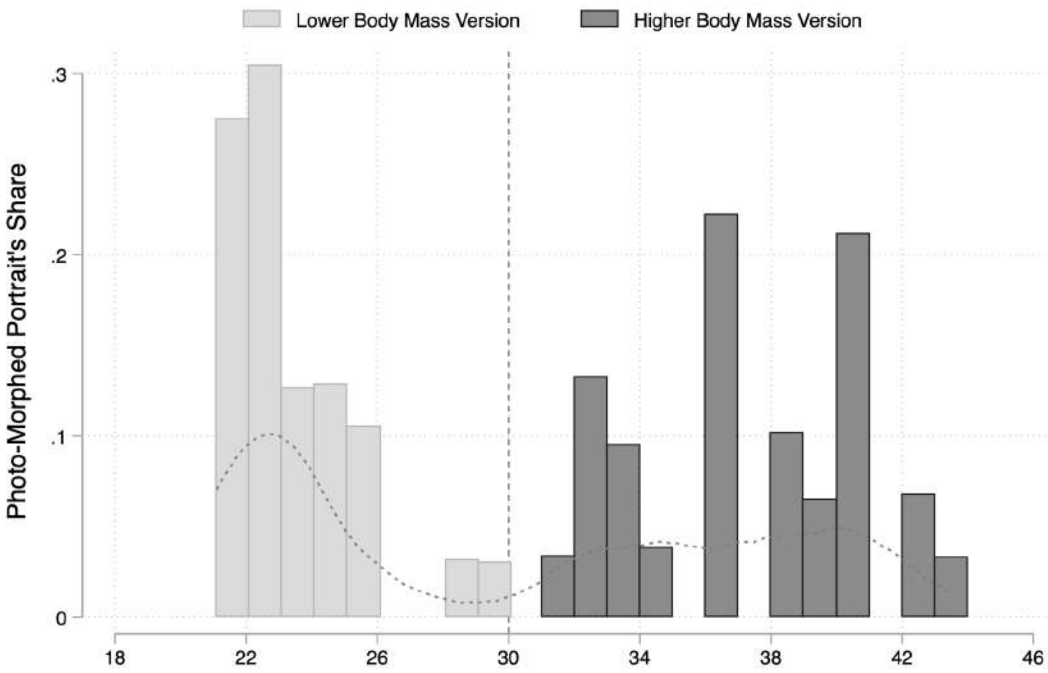
Figure J.2: Procedure to link portraits to a perceived BMI value using the Body Size Scale for Assessing Body Weight Perception in African Populations



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 (%)
16.39	19.17	21.72	24.09	25.76	27.97	32.37	39.03	43.24	BMI

Note: Portraits were matched to a BMI value with the help of 10 independent Ugandan raters. Each rater was shown the full set of pictures and the Body Size Scale shown above. The rates associated each picture to a silhouette. Then, I averaged the ratings across raters and associated a BMI to each picture using the conversion model described in Cohen et al. 2015.

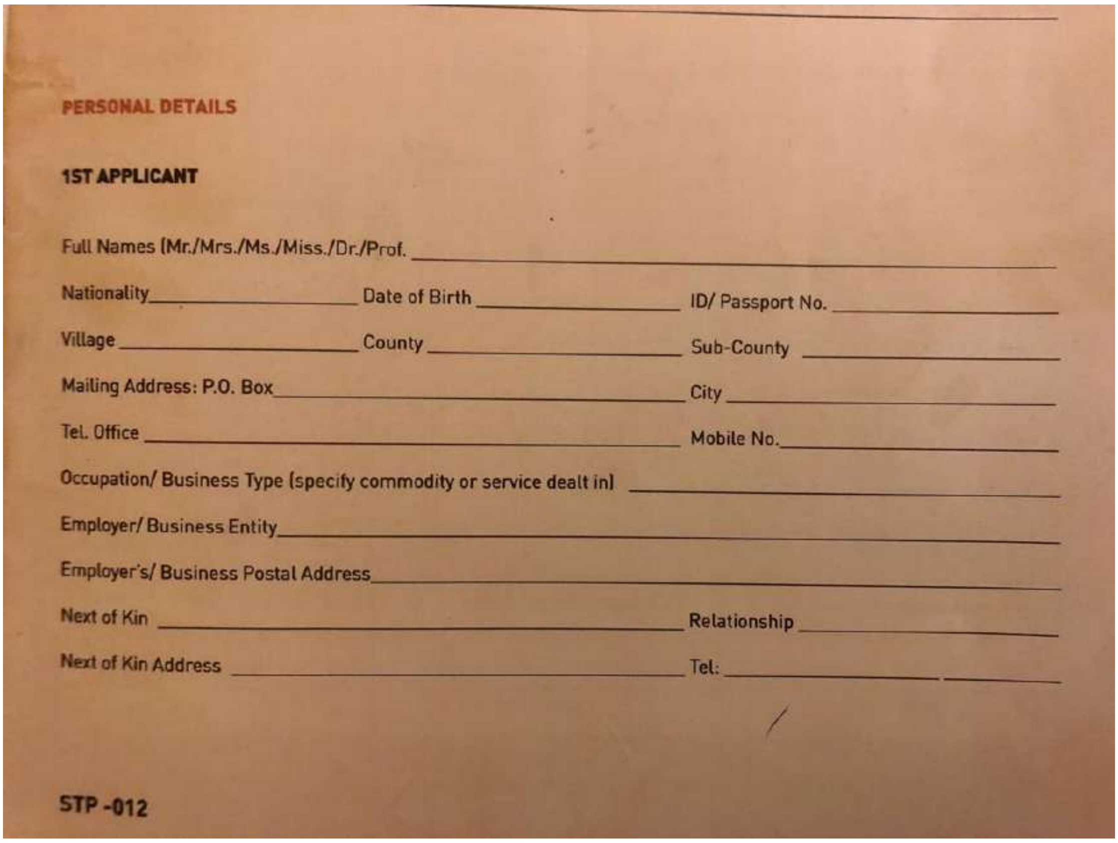
Figure J.3: Perceived Body-Mass Index Distribution of Manipulated Portraits



Note: Binned histogram of the 60 manipulated portraits (black-race only). Bin width: 1 BMI point. The x-axis starts at 18, which is the WHO threshold for normal weight. The red dashed line signals the WHO obesity cut-off, BMI = 30.

Figure J.4: Borrowers 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 ______

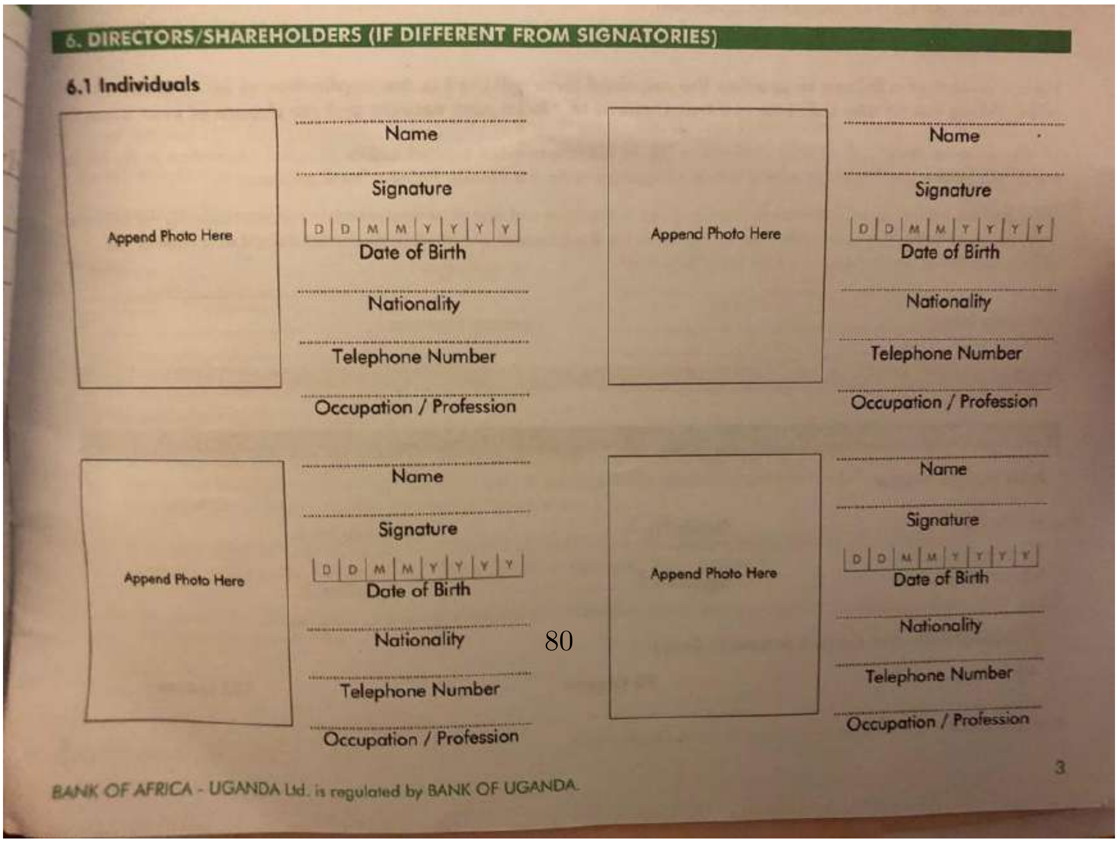
Employer's/ Business Postal Address ______

Next of Kin ______ Relationship ______

Next of Kin Address ______ Tel: ______

STP -012

Template B



6. DIRECTORS/SHAREHOLDERS (IF DIFFERENT FROM SIGNATORIES)

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

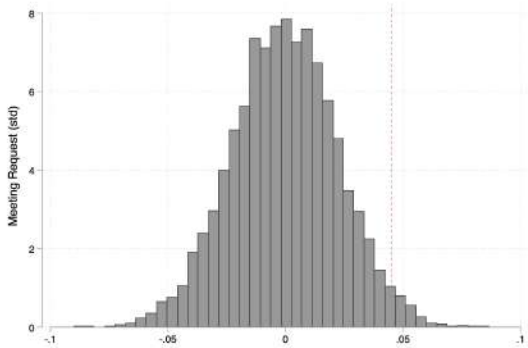
Telephone Number

Occupation / Profession

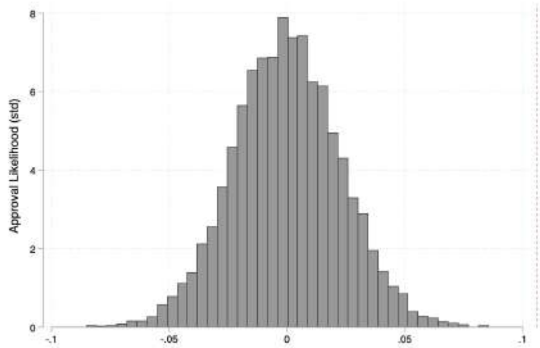
BANK OF AFRICA - UGANDA Ltd. is regulated by BANK OF UGANDA.

3

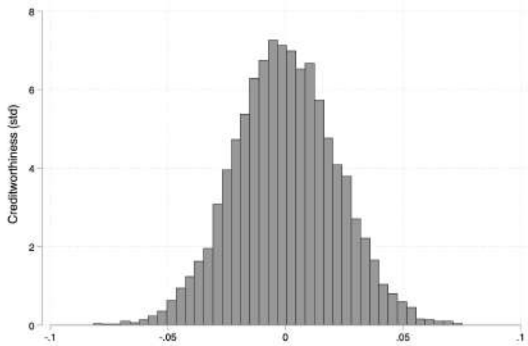
Figure J.5: Randomization Inference Robustness: Obesity Premium in Access to Credit



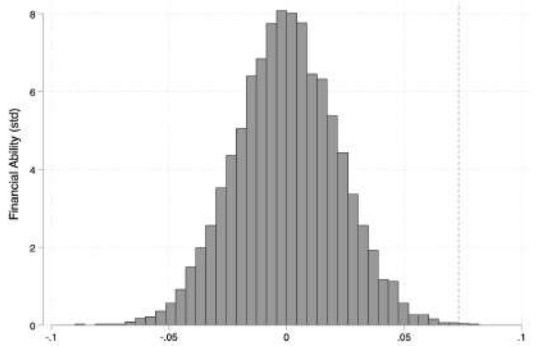
(a) Meeting Request (z)



(b) Approval Likelihood (z)



(c) Creditworthiness (z)

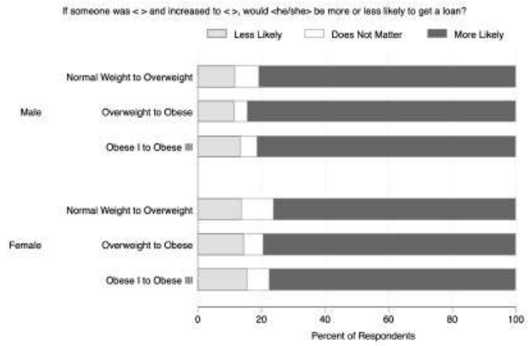


(d) Financial Ability (z)

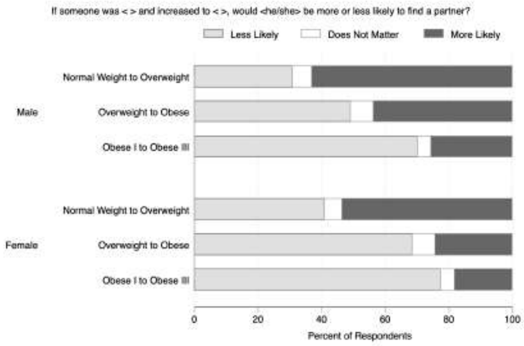
Note: Treatment effect distribution from 10,000 simulations.

Figure J.6: Explicit beliefs on returns to weight gain in credit, dating, and job market (general population).

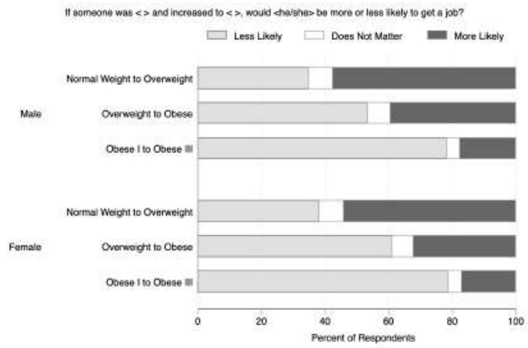
(a) Credit



(b) Dating

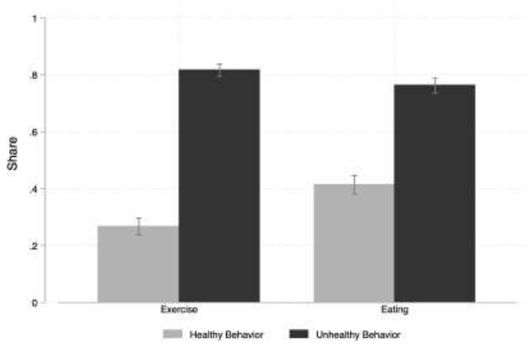


(c) Job Market

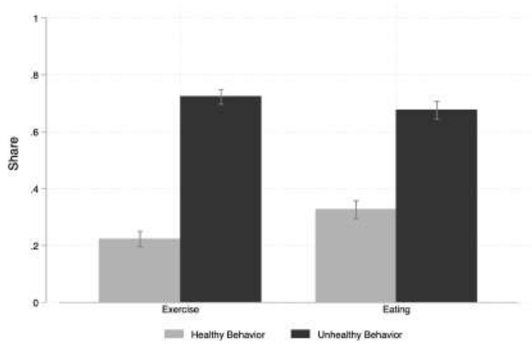


Note: Kampala residents sample, N=511. The beliefs were elicited in random order at the end of the Beliefs Experiment.

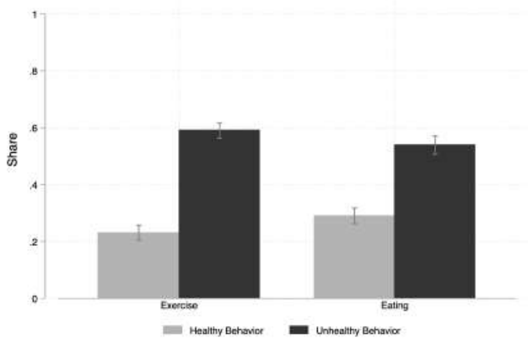
Figure J.7: Explicit beliefs on the health consequences of over-nutrition and lack of exercising



(a) Overweight prevalence (age 65)



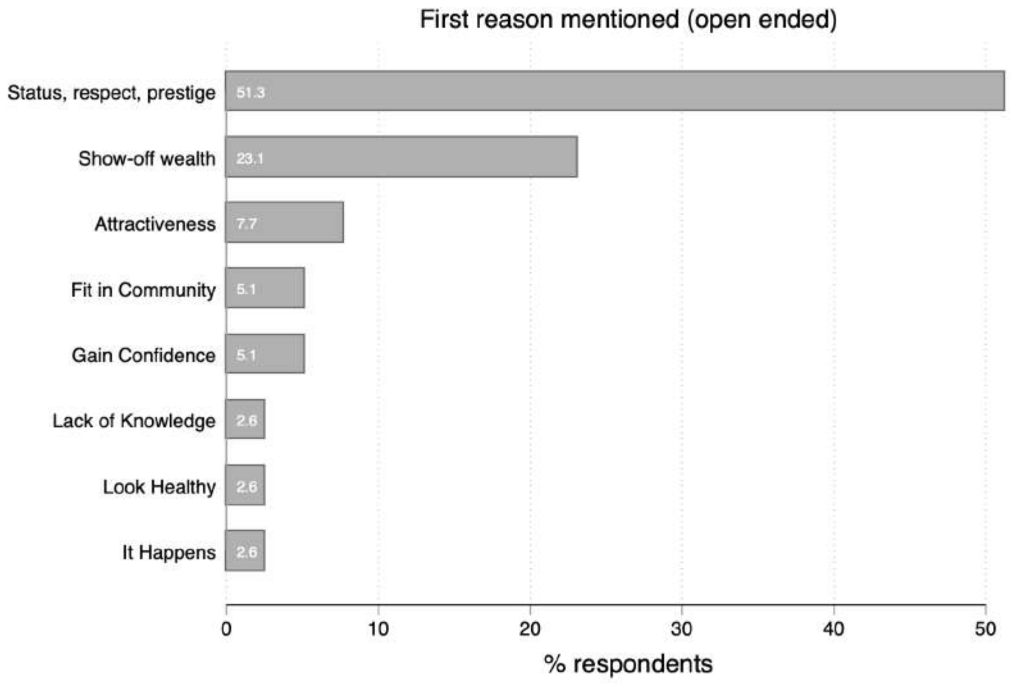
(b) Cardiovascular disease prevalence (age 65)



(c) Death likelihood (age 65)

Note: beliefs are elicited exploiting hypothetical investment scenarios, a strategy which builds on Biroli et al. (2020). I measure beliefs' about the returns to (i) following a recommended-calorie diet and (ii) exercising regularly. Respondents are presented with different hypothetical scenarios based on 10 hypothetical individuals living in Kampala, all of whom are 30 years old and are of average height and weight. Each scenario varies either the calorie intake of the individual from ages 30-65 (Eating), or the amount of exercise undertaken daily (Exercise). For the Eating variation, the healthy behavior is eating ”two traditional Ugandan meals per day” (modal calories intake) and the unhealthy one is eating ”three traditional Ugandan meals per day plus a snack”. For the Exercise variation, the healthy behavior is 60 minutes of exercise every day, while the unhealthy one is 0 minutes of exercise. To elicit perceived likelihoods, I ask respondents to report how many of the 10 hypothetical individuals presented in the scenarios they think will experience each outcome.

Figure J.8: ”Why do normal weight people put effort to gain weight?” (open question)



Note: The figure categorizes the open-ended answers to the questions: ”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 guess. ” Respondents are Kampala residents, N=49.

Figure J.9: ROC Curve Comparison

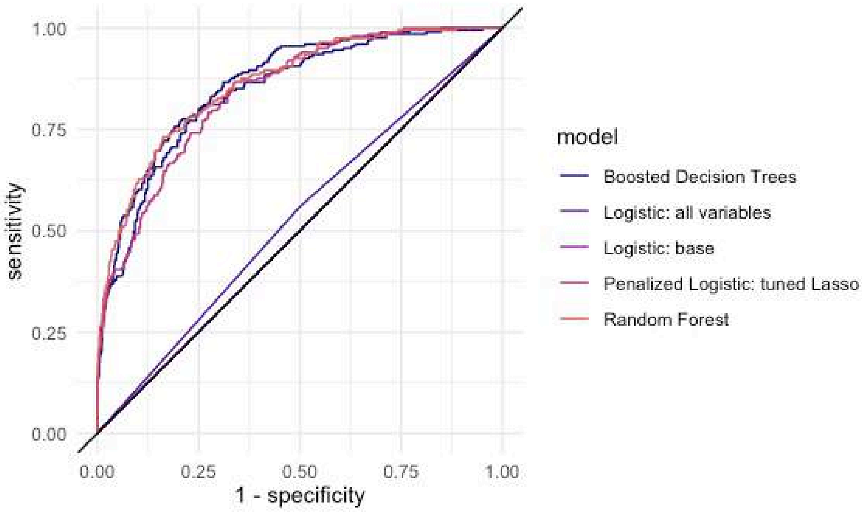
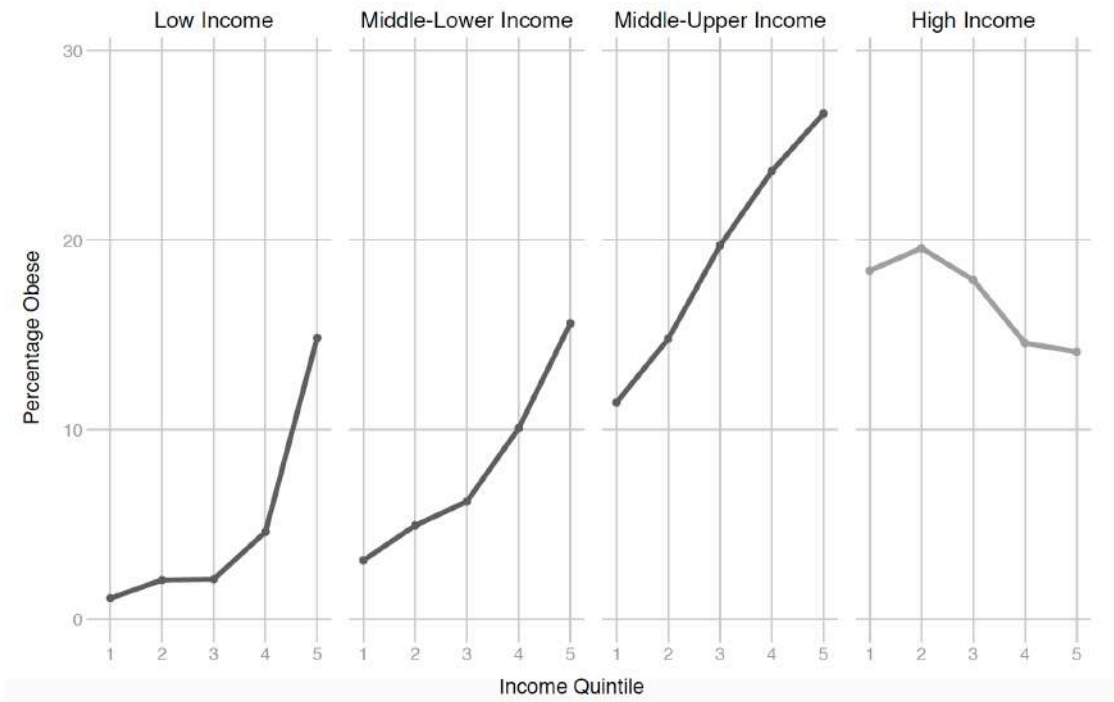
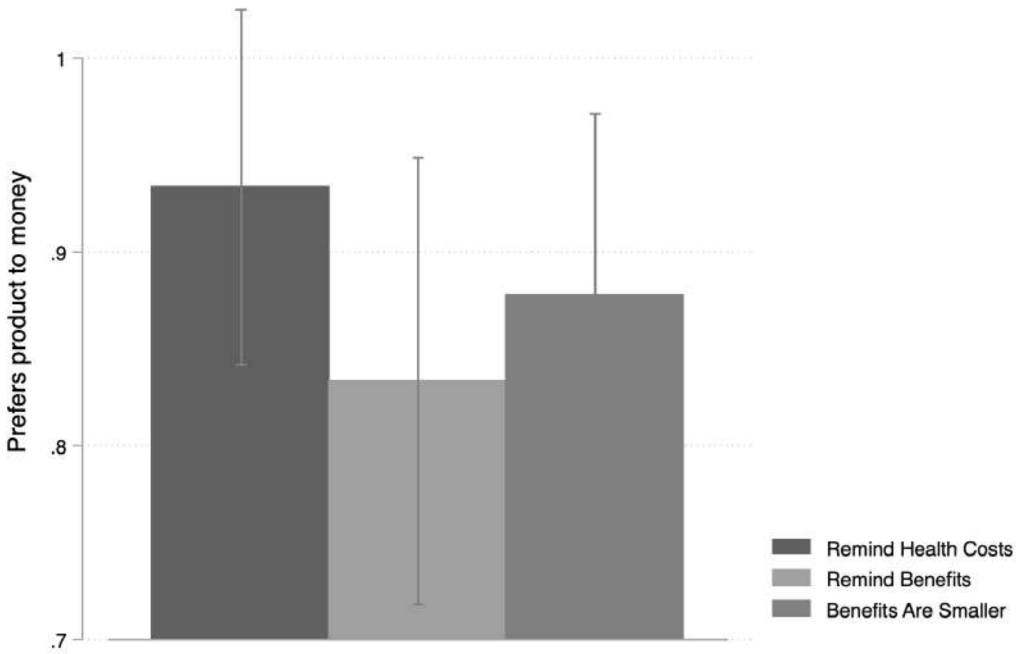


Figure J.10: Obesity Prevalence by Income Quintile and Country Income Level



Source: DHS surveys (2010-2017), CDC, Eurostat

Figure J.11: Willingness to Pay for Nutritional Advice by Information Treatment



Own pilot data. Phone survey with 39 respondents. Respondents receive information about returns to obesity in credit markets or information about the health cost of obesity and overweight. The outcome is the willingness to pay for a pamphlet of nutritional advice. Answers are incentivized. Survey tools are in Appendix I.

.

Table J.1: Selected Wards (GKMA)

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

Table J.2: Obesity Premium by Order of Borrowers' Profile Rating

	(1) Meeting Request	(2) Approval Likelihood	(3) Financial Ability	(4) Credit- worthiness
Obese	0.038	0.100***	0.116***	0.081**
	(0.030)	(0.033)	(0.035)	(0.032)
Second-Half	0.124	0.300***	0.275***	0.105
	(0.101)	(0.104)	(0.093)	(0.093)
Obese Applicant × Second-Half	0.006	0.018	0.024	0.012
	(0.049)	(0.052)	(0.053)	(0.045)
Observations	6299	6259	6195	6230

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. P-values are clustered at the loan officer level. *Meeting Request* the standardized value of a dummy taking value 1 when the loan officer chooses the meet with a similar applicant (referral). *Approval Likelihood* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). Regressions include application, loan officer and information arm fixed effects. *Obese* is a dummy taking value one if the borrower profiles included the obese version of the original picture. *Second-Half* is a dummy taking value one if the profile was the 5th to the 10th profile rated, within each arm.

Table J.3: Obesity Premium by Information Provision Timing

	(1) Meeting Request	(2) Approval Likelihood	(3) Financial Ability	(4) Credit-worthiness	(5) Access to Credit
Obese=1	0.032	0.067**	0.096***	0.058*	0.049
	(0.034)	(0.034)	(0.035)	(0.035)	(0.034)
Timing=1	0.051	-0.006	-0.032	-0.051	0.060
	(0.037)	(0.041)	(0.038)	(0.035)	(0.037)
Obese=1 $\times$ Timing=1	-0.009	-0.005	0.006	0.008	-0.033
	(0.044)	(0.048)	(0.048)	(0.046)	(0.044)
Observations	4307	4273	4236	4253	4218

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. P-values are clustered at the loan officer level. The regressions only include applications which reported additional wealth information. *Meeting Request* the standardized value of a dummy taking value 1 when the loan officer chooses the meet with a similar applicant (real choice outcome). *Approval Likelihood* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). *Interest rate* is probability of assigning an interest rate higher than the standard one (standardized). The question is only applicable to loan officers which have interest rate discretionality for a given loan profile. *Access to Credit* is an index of access to credit based on *Referral Request*, *Approval Likelihood*, *Creditworthiness*,*Financial ability*. Regressions include application and loan officer fixed effects. The interaction term estimates the differential effect of a *Obese* borrower profile when all the information is presented at the same time with respect to a situation in which loan officers are first shown the demographics and later learn the wealth information.

Table J.4: Importance of Baseline Profile Characteristics by Self-Reported Financial Information

	(1) Approval Likelihood	(2) Approval Likelihood	(3) Approval Likelihood	(4) Approval Likelihood
Obese	0.199***			
	(0.035)			
Self-Reported Financial Info	0.166***	0.041	-0.029	-0.156**
	(0.045)	(0.099)	(0.053)	(0.062)
Not Obese × Self-Reported Financial Info	0.000			
	(.)			
Obese × Self-Reported Financial Info	-0.129***			
	(0.039)			
Age		-0.035***		
		(0.012)		
Self-Reported Financial Info × Age		0.002		
		(0.003)		
Ush. 5 million			-0.103	
			(0.089)	
Ush. 7 million			0.137	
			(0.100)	
Ush. 5 million × Self-Reported Financial Info			0.202***	
			(0.059)	
Ush. 7 million × Self-Reported Financial Info			0.190***	
			(0.070)	
Home improvements				-0.159
				(0.097)
Purchase of an animal				-0.026
				(0.100)
Purchase of an asset				-0.569***
				(0.102)
Purchase of land				-0.130
				(0.097)
Home improvements × Self-Reported Financial Info				0.565***
				(0.076)
Purchase of an animal × Self-Reported Financial Info				-0.021
				(0.087)
Purchase of an asset × Self-Reported Financial Info				0.275***
				(0.087)
Purchase of land × Self-Reported Financial Info				0.352***
				(0.070)
Constant	-0.316***	1.177***	-0.116*	0.014
	(0.065)	(0.448)	(0.068)	(0.062)
Observations	6645	6645	6645	6645

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. The table compares how providing additional financial infomation interacts with body mass and the other baseline characteristics. The results show that providing additional financial information does necessarily reduce the importance of each characteristic for approval likelihood, as one would have expected if the effects were driven by inattention. The regressions' outcome is the Approval Likelihood rating, standardized. All regressions include application, and loan officer fixed effects. Standard errors are clustered at the loan officer level. *Self-Reported Financial Info* is a dummy taking value one if the application was randomly assigned to include self-reported financial information. The first column shows the borrowers' body mass and information interaction, the second column looks at borrowers' age, the third column focuses on loan profiles, and the fourth column looks at reasons for loan.

Table J.5: Obesity Premium in Access to Credit: Male Loan Officers Evaluating Male Borrower Profiles

	(1) Referral Request	(2) Approval Likelihood	(3) Financial Ability	(4) Credit-worthiness	(5) Access to Credit
Obese	0.040**	0.109***	0.128***	0.087***	0.042**
	(0.019)	(0.021)	(0.023)	(0.023)	(0.020)
Observations	6299	6259	6195	6230	6167

Notes: * p<0.1, ** p< 0.05, *** p<0.01. P-values are clustered at the loan officer level. *Referral request* is a dummy taking value 1 when the LO chooses to be referred an applicant similar to the hypothetical one. *Approve* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). *Access to Credit* is an index of access to credit based on the main outcomes. *Obese* is a dummy taking value one if the application included the high-body-mass version of the original picture. Regressions include application fixed effects, loan officer fixed effects and fixed effects for the information included in the application. Sample restricted to male loan officers rating male borrowers profile.

Table J.6: Obesity Premium by Borrowers' Gender

	(1) Referral Request	(2) Approval Likelihood	(3) Financial Ability	(4) Credit-worthiness	(5) Access to Credit
Obese=1	0.004	0.007	0.050	-0.059	0.020
	(0.048)	(0.054)	(0.053)	(0.049)	(0.048)
Gender: Male=1	-0.203*	-0.458***	-0.472***	-0.534***	-0.199*
	(0.106)	(0.111)	(0.112)	(0.101)	(0.106)
Obese=1 × Gender: Male=1	0.065	0.115	0.096	0.226***	0.072
	(0.077)	(0.084)	(0.080)	(0.078)	(0.077)
Observations	2201	2180	2157	2170	2149

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. P-values are clustered at the loan officer level. *Meeting Request* is a dummy taking value 1 when the LO chooses to be referred an applicant similar to the hypothetical one. *Approve* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). *Access to Credit* is an index of access to credit based on the main outcomes. *Obese* is a dummy taking value one if the application included the high-body-mass version of the original picture. *Gender: Male* is a dummy taking value 1 if the borrower is a men. Regressions include loan officer fixed effects and control for occupation, collateral, reason for loan and loan application profile. The heterogeneity analyisis by gender was pre-registered.

Table J.7: Correlation of Loan Officers' Characteristics with Obesity Premium

	Approval Probability			Referral Request		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Below Median	Above Median	Diff	Below Median	Above Median	Diff
Age	31.030	31.567	0.537	30.788	31.640	0.852
	(6.733)	(7.625)	(1.039)	(6.865)	(7.363)	(1.050)
Gender: Male	0.582	0.612	0.030	0.624	0.577	-0.047
	(0.495)	(0.489)	(0.064)	(0.487)	(0.496)	(0.065)
Family Size	3.513	3.405	-0.107	3.354	3.537	0.183
	(2.166)	(2.110)	(0.279)	(2.007)	(2.227)	(0.282)
Highest Education Level	4.656	4.707	0.051	4.663	4.693	0.030
	(0.898)	(0.855)	(0.114)	(0.898)	(0.862)	(0.115)
Experience (Years)	2.566	2.819	0.253	2.723	2.664	-0.059
	(2.889)	(2.685)	(0.362)	(2.853)	(2.750)	(0.366)
Salary: Under 500,000	0.327	0.305	-0.022	0.284	0.339	0.055
	(0.471)	(0.463)	(0.064)	(0.454)	(0.475)	(0.065)
Salary: 500,000 to 1 ml	0.402	0.400	-0.002	0.443	0.371	-0.072
	(0.493)	(0.492)	(0.068)	(0.500)	(0.485)	(0.068)
Salary: 1 to 1.5 ml	0.206	0.238	0.032	0.193	0.242	0.049
	(0.406)	(0.428)	(0.057)	(0.397)	(0.430)	(0.058)
Salary: 1.5 to 2 ml	0.028	0.057	0.029	0.068	0.024	-0.044
	(0.166)	(0.233)	(0.028)	(0.254)	(0.154)	(0.028)
Salary: Over 2 ml	0.037	0.000	-0.037**	0.011	0.024	0.013
	(0.191)	(0.000)	(0.019)	(0.107)	(0.154)	(0.019)
BMI	24.604	24.133	-0.472	24.784	24.073	-0.711
	(4.368)	(4.882)	(0.600)	(4.391)	(4.778)	(0.606)
Self Employed	0.148	0.154	0.006	0.158	0.145	-0.013
	(0.356)	(0.362)	(0.046)	(0.367)	(0.353)	(0.047)
Performance pay	0.885	0.932	0.046	0.911	0.906	-0.005
	(0.320)	(0.253)	(0.037)	(0.286)	(0.293)	(0.038)
Borrowers Met, Daily	7.754	8.509	0.755	7.812	8.350	0.538
	(7.715)	(9.382)	(1.111)	(7.042)	(9.542)	(1.124)
Borrowers Approved, Daily	4.033	4.526	0.493	4.208	4.321	0.113
	(4.279)	(4.821)	(0.590)	(4.350)	(4.704)	(0.598)
Employees per Branch	6.512	7.530	1.018	6.340	7.500	1.160
	(6.830)	(7.848)	(0.956)	(6.730)	(7.755)	(0.967)
Financial Knowledge	1.238	1.241	0.004	1.208	1.263	0.055
	(0.464)	(0.468)	(0.060)	(0.432)	(0.489)	(0.061)
Days/week verify info	2.204	2.433	0.229	2.220	2.389	0.170
	(1.499)	(1.406)	(0.208)	(1.540)	(1.392)	(0.211)
Stress of verifying (1-5)	2.673	2.670	-0.003	2.512	2.788	0.275*
	(1.043)	(0.976)	(0.145)	(0.997)	(1.004)	(0.145)
Observations	122	117	239	101	138	239

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. Column (1) and (2) refer to loan officers with standardized bias below the median. Column (2) and (4) refer to loan officers with standardized bias above than the median. Column (3) and (6) report the difference and the associated standard error between the groups. Similar results are obtained when using the 75th percentile as cutoff.

Table J.8: Obesity Premium in Lay People's Guesses Of Loan Officers' Ratings

	(1) Share Meeting	(2) Approval Likelihood	(3) Worth Applying
Obese	0.140***	0.477***	0.172***
	(0.015)	(0.051)	(0.026)
Observations	2044	2044	2044
Actual Loan Officers' Bias	Yes	Yes	No
Mean Control			0.515
compare	0.0782	0.0491	

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. Standard errors are clustered at the respondent level. Beliefs experiment sample: N=511. The experiment flow is such that respondents complete the Beliefs Experiment first, then they complete the Credit Experiment Replication. Each respondent evaluates 4 hypothetical loan applications, knowing that these applicaitons have been previously rated by a group of loan officers currently employed in financial institutions in Kampala. No applications in Credit Experiment Replication includes self-reported wealth information. Respondent's answers for Col (1) and Col (2) are incentivized with the loan officers' correct answers. *Share Referrals* is the respondent's prediction of how many out of 10 loan officers would explicitely request the referral of the applicant (standardized). *Approval Likelihood* is the respondent's prediction of the loan officers' expected likelihood of approving the application on a 1-5 scale (standardized). *Worth Applying* is a dummy taking value one if the respondent believes it is worth applying to a given loan for an applicant with the observed characteristics.

Table J.10: AUC: Models Comparison

	Model	AUC Train	Accuracy Test	AUC Test
1	Logistic: Baseline	0.50	0.77	0.50
2	Logistic: All variables	0.52	0.49	0.53
3	Penalized Logistic (LASSO)	0.83	0.82	0.84
4	Random Forest	0.85	0.84	0.86
5	Boosted Trees	0.85	0.85	0.87
6	Support Vector Machine	0.82	0.82	0.84

Table J.9: Image Ratings by BMI - Rural Malawi

	Dependent variable:				
	Credit	Dating	Authority	Wealth	Beauty
	(1)	(2)	(3)	(4)	(5)
High BM Picture	0.482*	0.179	0.204	1.612***	0.489
	(0.283)	(0.319)	(0.417)	(0.409)	(0.401)
Observations	241	241	241	241	241
R^2	0.012	0.006	0.002	0.064	0.008
Adjusted R^2	0.004	-0.002	-0.007	0.056	-0.001
Residual Std. Error	2.186	2.469	3.220	3.161	3.101

Notes: * p< 0.1, ** p< 0.05, ** p<0.01. Small scale experiment in rural Malawi, involving 241 women, to investigate external validity on a rural, poorer sample. In this setting, I exploited a similar paradigm as in Experiment 1. The main differences are that each woman rates one picture. I only included 2 pictures, 1 men and 1 woman, for a total of 4 photo morphed pictures. The outcomes measured are women s beliefs on what other think about the portrayed individuals and were elicited using the wording: How many out of 10 individuals would..: 1) lend money; 2) go on a date; 3) listen to a monition; 4) rate the individual as wealthy; 5) rate the individual as attractive. Answers are not incentivized.

Table J.11: Most common reason for gaining and for losing weight in Kampala (open questions).

Why do people want to gain weight?	**Why do people want to lose weight?**
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. [...]	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 normal 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
Feeling to appear healthy	To look rich and show that they doing well financially
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

Note: The table reports the answers to a phone survey administered to 39 Kampala residents by IGREC field officers. The questions wording were: "In Kampala, what are the most common reasons why normal weight people may want to gain weight or put effort to gain weight? Please answer with your best guess." and "In Kampala, what are the most common reasons why overweight people may want to lose weight or put effort to lose weight? Please answer with your best guess."