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

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Abstract

I study the economic value of obesity—a seemingly inconsequential but unhealthy status symbol in poor countries. Randomizing decision-makers in Kampala, Uganda to view weight-manipulated portraits, I make four findings. First, obesity is perceived as a reliable signal of wealth rather than beauty and health. Second, being obese facilitates access to credit: in a real-stakes experiment involving loan officers, the obesity premium is comparable to raising borrower self-reported earnings by 60%. Third, asymmetric information drives this premium, which drops significantly when more financial information is provided. Fourth, obesity benefits and wealth-signaling value are commonly overestimated, raising the cost of healthy behaviors.

Keywords: Obesity, status, asymmetric information.
JEL classifications: I10, O10, Z13.

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1 Introduction

Conspicuous consumption, that is, consumption that signals a person's status, is normally defined as wasteful (Veblen, 1899). Recent experimental evidence confirms that people pay extra to acquire status goods (Bursztyn et al., 2017a). Among the poor, spending to signal status comes at the cost of basic human capital investment (Banerjee and Duflo, 2007). Despite the long-standing literature on conspicuous consumption and its costs (Frank, 1985; Bagwell and Bernheim, 1996; Charles et al., 2009; Moav and Neeman, 2010; Heffetz, 2011), very little is known about the benefits of status signals, particularly in market settings (Bursztyn and Jensen, 2017).

In this paper, I provide novel evidence on the economic benefits of status signals in a developing country setting and investigate the underlying mechanism. In markets characterized by pervasive asymmetric information, like credit markets in developing countries, status may lead to benefits because transactions rely on appearance to proxy for wealth or earnings. In support of this hypothesis, I test experimentally for the wealth-signaling value and the credit market benefits of obesity in the urban area of Kampala, the capital of Uganda.

Being fat is a sign of status in most poor countries.[1] Historically, prosperity has always meant having enough money to buy or own food. This is still true in the developing world, where, unlike in richer countries, fat bodies are often positively perceived and rich people are more likely to be overweight and obese, as shown in Figure 1.[2] Cars, clothes, or watches are other plausible status signals. Focusing on obesity allows for a cleaner analysis, because body mass has no confounding collateral value. Moreover, obesity is a costly sign of status from a health perspective.[3]

[1]In this paper, I use the word *fat(ter)* as opposed to *high(er) body mass*. This is meant to support the body-positivity movement effort to de-stigmatize the word *fat* and promote the concept of health at any size (Lupton, 2018).

[2]Qualitative studies showing 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 Senegal; Popenoe (2012) in Niger; and Sobo (1994) in Jamaica.

[3]Obesity is a *potential* signal in the definition of Spence (1973). First, while people cannot fully control their body size, a person's weight is manipulable and individual behavior can affect body mass at the margin. In a review of the literature, Yang et al. (2007) report that between 16% to 85% of body mass index (BMI) is heritable. Second, in Uganda, the signaling cost—the marginal cost of weight gain—is higher for poor versus rich people (single-crossing property). As in most low-income countries, poor people have limited access to calorie-dense food or motorized transportation and are more likely to engage in manual labor. Consistent with a separating equilibrium, BMI (kg/m^2) is the strongest predictor of socio-economic status among observable demographics such as age, gender, marriage status, and pregnancy status in Uganda (2016 DHS data, R^2 comparison in bivariate regressions with relative wealth index as dependent variable).

Obesity is a global health challenge. Developing countries count for the largest share of the obese and overweight population and the highest associated mortality risk (Shekar and Popkin, 2020). Obesity benefits may work as an incentive to gain weight (or prevent weight loss) at the margin. Independent of whether people strategically manipulate their weight, a test beyond the scope of this paper, obesity benefits change the opportunity cost of healthy behaviors and influence the design of obesity prevention policies.

To test for obesity benefits, I focus on credit markets. Theory shows that credit market failures create inefficiencies both at the micro and macro level, and access to credit is a major channel to lift people out of poverty. Credit markets are also characterized by widespread monitoring and screening problems, as first discussed in Stiglitz and Weiss (1981). These issues, especially severe in developing countries, make credit markets an ideal setting to test also for the asymmetric information channel.[4]

My empirical strategy leverages two complementary experiments (beliefs experiment and credit experiment) involving the general population and professional loan officers. To estimate the causal effect of obesity, I build 30 weight-manipulated portraits pairs of Kampala residents and assign decision-makers to see the thinner or fatter version of each original portraits. Thinner portraits are perceived on average as normal weight, while fatter portraits as obese. Thus, the average treatment effect captures the causal effect of obesity relative to normal weight.[5] To identify the mechanism, I cross-randomize obesity with the degree of asymmetric information in which decisions are taken.

The first result shows that Kampala residents perceive obesity as a signal of wealth but not of other traits that are commonly believed to be associated with obesity. In my first experiment, I ask 511 Kampala residents to rate randomly selected weight-manipulated portraits along several characteristics, including wealth. Obese portraits are rated as systematically wealthier than the normal-weight counterpart (0.69 standard deviations, p-value $= 0.00$). I find that obesity has no effect on perceived beauty, health, life expectancy, self-control, ability, and trustworthiness. Obesity is a strong wealth signal: obese individuals are perceived as being as wealthy as thin people who own a car. It is also a relevant signal. Being obese also provides information on top of other status signs: when portraits are accompanied by place of residence or asset

[4]Lacking technological advancements, such as credit risk models, loan officers in developing countries and especially in urban areas face both moral hazard and adverse selection problems (Karlan and Zinman, 2009). Research suggests that loan officers in poor countries often screen for rich borrowers either because of imperfect information (Banerjee, 2003) or higher returns to capital (De Mel et al., 2008).

[5]Original portraits are not deployed in the experiment. Including only manipulated portraits allows me to hold the manipulation's effect constant in the analysis.

ownership, the effect of obesity on wealth ratings is not significantly reduced (–0.19 standard deviations, p-value = 0.13).

Having established that obesity is perceived as a strong and reliable wealth signal, the second result shows that being obese leads to credit market benefits in Kampala. Working with 146 licensed financial institutions, I recruit 238 professional loan officers to take part in a real-stakes experiment to improve borrower/lender matching in Kampala.[6] I also collect demographic and financial characteristics on 187 prospective borrowers.

In the real-stakes experiment (henceforth credit experiment), loan officers review 30 hypothetical borrower profiles during work hours and select borrowers they would like to meet to discuss a loan application. The experiment's design identifies the relationship between obesity, asymmetric information, and access to credit by cross-randomizing borrower body mass and financial information. Portraits are standard personal identifiers in Uganda. Along the obesity dimension, each borrower profile is randomly assigned to a portrait, displayed in its thinner or fatter version. Along the information dimension, each profile is randomly assigned to display self-reported financial information (occupation, collateral, and earnings) or not. In total, loan officers evaluate 6,645 profiles, of which 4,566 include financial information.

Incentives are as close as possible to real life. Loan officers know that the profiles they evaluate are not real but are informed that at the end of the study, they will be referred to real prospective borrowers whose characteristics are similar to those they select in the experiment. Loan officers value good referrals—they either face a performance pay or are self-employed—and thus have incentives to select good borrowers. This incentive structure follows closely the Incentivized Resume Rating (IRR) recently developed by Kessler et al. (2019).[7]

Loan officers screen borrowers based on body mass in real-stakes lending decisions, leading obese borrowers to have easier access to credit. When a profile includes a borrower portrait in the obese version (versus the normal weight), loan officers perceive the borrower as more creditworthy (0.18 standard deviations, p-value = 0.00), more finan-

[6]The institutions are about 30% of all formal financial institutions active in the Greater Kampala Metropolitan Area, which deal with the general public and offer a standard type of loan: collateralized cash loans between \$250 and \$2'000, with a six-month term to maturity.

[7]Loan applications in Kampala are dealt in person, not allowing for an audit study as in Bertrand and Mullainathan (2004). The IRR, developed to test for discrimination in hiring in the US, allows me to elicit loan officers' preferences in an incentive-compatible manner. The application differs from Kessler et al. (2019) on several aspects. First, this is the first application (a) to credit markets, (b) in a developing country, and (c) testing for body mass discrimination. Second, for the design, I include a real choice outcome and test for the mechanism driving discrimination.

cially able (0.15 standard deviations, p-value = 0.00), and more likely to be approved (0.2 standard deviations, p-value = 0.00). Better credit ratings translate into easier access to credit: loan officers are more likely to request the referral of obese borrowers, which, given the incentive structure, is a real choice outcome (3 percentage points, p-value = 0.05). Across all outcomes, the obesity premium is large, equivalent to the effect of a 60% increase in borrower self-reported income in the experiment.

Moving to the mechanism, the third result shows that asymmetric information drives the obesity premium. The obesity premium is increasing in the amount of borrower financial information: when loan officers receive borrower self-reported profits, collateral, and occupation, the obesity premium drops by two-thirds (a result significant at the 5% level). The effect does not depend on the timing of financial information provision and is inconsistent with inattention.[8] The residual effect of obesity does not appear to be explained by taste, for example, a beauty premium, as in Mobius and Rosenblat (2006). In the first experiment obese portraits were not perceived differently along any outcome except wealth. The obesity premium in access to credit does not depend on loan officers' body mass (no homophily) and is as strong in same-sex borrower/lender pairs (no beauty premium). The residual premium is likely explained by unresolved asymmetric information due to the financial information provided being unverified or incomplete. In particular, loan officers perceive borrower self-reported information as "not very reliable" and rate obese borrowers' information as significantly more reliable. In summary, loan officers' behavior appears mainly consistent with statistical discrimination.

The evidence supports the claim that obesity matters beyond the experimental setting. First, body mass is not mentioned explicitly—limiting concerns of experimenter demands. Second, loan officers have real stakes, and third, they face realistic information sets, mimicking relevant stages of the loan application process. The obesity premium is strongest when loan officers learn demographics and loan profile information, namely what loan officers normally know when deciding which borrowers to meet (first screening). Obesity is still a factor when loan officers learn about the self-reported financial information normally shared during the first meeting (second screening). Consistent with obesity leading to benefits in real life, about 90% of the loan officers in the credit experiment explicitly state that an obese person is more likely to be considered for a

[8]Agents may mechanically pay less attention to all baseline traits when more financial information is available. This explanation appears inconsistent with the data: the sign of the interaction effect of financial information with baseline characteristics depends on the trait, as shown in Appendix Table H.5. For example, financial information leads officers to pay more attention to the requested loan amount (a characteristic always included at baseline).

loan relative to a normal-weight person.

In the final part of the paper, I test for the accuracy of people's beliefs. First, I test for awareness of obesity benefits in credit markets among the general population. I replicate the credit experiment with Kampala residents: respondents see the borrower profiles and guess loan officers' evaluations (incentivized).[9] I find that people are aware of the obesity premium but overestimate it by more than two times.

I then investigate the perception of the obesity wealth-signaling value. For the general population, I elicit Kampala residents' beliefs on the conditional earnings distribution by body mass in the city (N = 124). I find that people overestimate the average income difference between obese and non-obese people by about three times. Only about 12% of respondents hold beliefs within a 95% confidence interval from the population average. For loan officers, I estimate the corresponding beliefs from the credit experiment choices, using a revealed preference approach guided by a simple framework. Loan officers' beliefs are only slightly more accurate: about 17% hold accurate beliefs.[10]

The analysis shows that people commonly hold inaccurate beliefs on both obesity benefits and the wealth-signaling value in a way that overestimates the importance of obesity. Overestimating obesity benefits implies an inefficient trade-off between obesity health costs and misperceived socio-economic benefits. This may inefficiently raise the perceived cost of healthy behaviors and the incentives to gain weight.[11] Misperception of the obesity signal suggests that body mass screenings have ambiguous implications for market efficiency. Using body mass information may reduce the cost of credit, but inaccurate beliefs may lead to distortions relative to a full information framework. The nature of the experiment, based on hypothetical profiles, does not allow me to test for whether obese borrowers have better returns to capital and verify the overall efficiency effect of body mass screening. Since loan officers respond to additional information, however, cheap access to verified financial information may improve market efficiency.

This paper makes three main contributions. First, it provides novel experimental evidence on the economic value of status indicators in a low-resource setting. Most literature on social signaling does not investigate the benefits (DellaVigna et al., 2016; Perez-Truglia and Cruces, 2017; Chandrasekhar et al., 2018; Karing, 2018; Bursztyn et

[9]These are the same Kampala residents interviewed in the beliefs experiment.

[10]The benchmark is the conditional income distribution by body mass in the beliefs experiment sample. To my knowledge, there is no publicly available and representative dataset including BMI, earnings, and prospective borrower status for Kampala.

[11]In an open-ended survey question asking why people gain weight, about 70% of 124 Kampala residents mention either desire to signal status, prestige, or wealth as the first reason.

al., 2019). The experimental evidence on tangible rewards generated by social signals is limited to social interactions (Nelissen and Meijers, 2011; Bursztyn et al., 2017b). Closely related is Bursztyn et al. (2017a), who provides experimental evidence of demand for status in Indonesia. Economic benefits may be driving, at least partially, demand for status and help explain phenomena like large expenditures in celebrations among the ultra poor (Banerjee and Duflo, 2007).[12]

Second, the paper contributes to the literature on the credit market consequences of asymmetric information in poor countries. 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 in poor countries. Different from other experimental studies testing for the effect of reducing asymmetric information on credit market outcomes (e.g., Giné et al., 2012), my focus is loan officers' discriminatory behavior. Because of this focus, the paper also relates to the literature on discrimination (Bertrand and Duflo, 2017 and Neumark, 2018). There is a large literature on bias in consumer lending (Berkovec et al., 1994; Labie et al., 2015; Dobbie et al., 2018); Pope and Sydnor (2011) and Ravina et al. (2008) test for appearance discrimination in credit markets. Their setting is peer-to-peer lending in the United States, they look at negative discrimination, and identify different mechanisms (trust or beauty bias).

Finally, this paper adds to the literature on obesity by providing the first experimental evidence of the socio-economic benefits of obesity in poor countries, adding to our understanding of the global obesity epidemic. Most of the obesity literature focuses on investigating the causes and costs, in high-income countries (Finkelstein et al., 2009; Cawley, 2004; Cawley and Meyerhoefer, 2012). In the development context, Rosenzweig and Zhang (2019) studies the effects of education on healthy behaviors, including obesity, using twin data from rural China. Correcting beliefs about weight gain benefits may increase the uptake of healthy behaviors in poor countries.[13]

2 Beliefs Experiment: Obesity as a Signal of Wealth

I first design the beliefs experiment to test (1) whether obesity is perceived as a salient signal of wealth, against other traits, and (2) to what extent obesity is a relevant signal

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

[13] As obesity benefits imply rewards from extra calories, my findings add to the puzzle of calorie under-investment in poor settings (Subramanian and Deaton, 1996; Schofield, 2014; Atkin, 2016).

when compared to other common status indicators.[14]

2.1 Beliefs Experiment

Sample selection Respondents live in the districts of Kampala, Mukono, and Wakiso, the three largest districts in terms of population size of the Greater Kampala Metropolitan Area (National Population and Housing Census 2014). They are at least 18 years old and provide written consent. I stratify the sample by age, gender, and socio-economic status.[15] Ex-ante, obesity perception may depend on these three characteristics: the association between scarcity and positive perception of fat bodies is common; the anthropology literature describes obesity as a sign of fertility (Popenoe, 2012); and younger people, likely more exposed to Western media, may have changed their perception of body mass (La Ferrara et al., 2012).

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

The final sample includes 511 Kampala residents. Table 1 summarizes the sample characteristics. Field officers walked around the districts and enrolled respondents quasi-randomly until they reached the required number by strata. Because of the stratification, the sample is 50% male but is slightly richer and older than the Kampala average (National Population and Housing Census 2014). Respondents are heterogeneous in terms of personal income, occupation, age, and measured body mass. On average, respondents are overweight (BMI 25.66). This data point is aligned with the Uganda DHS 2016, pointing at the rising overweight and obesity risk in urban Africa.

Identifying the Causal Effect of Body Mass Body mass realizations are endogenous to preferences and constraints. Experimentally varying body mass, for example, by randomly assigning subject's caloric intake poses significant ethical concerns. Thus, in

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

[15] To proxy for socio-economic status, I use wards of residence (smallest Ugandan census unit). I rank and stratify the wards according to a poverty index based on dwelling characteristics, access to credit, and food security. The procedure is detailed in Appendix B.1.

this paper, I identify the causal effect of body mass using weight-manipulated portraits. I randomly assign decision-makers to see the thinner or fatter version of an original portrait. Comparing manipulated portraits, as opposed to comparing an original portrait with a fatter portrait, allows me to identify the effect of body mass changes holding the manipulation constant.[16]

After discarding the originals, the weight-manipulated portraits set is composed of 34 portrait pairs, each made of the thinner and fatter version of the same portrait. The original portraits are of 30 Kampala residents, plus 4 white race individuals, and half are men and half women. On average, Kampala residents perceive thinner portraits as normal weight and fatter portraits as obese. Thus, the average treatment effect I capture is the effect of obesity relative to normal weight.[17]

Design In this experiment, respondents see and rate a sequence of four portraits randomly selected from the weight-manipulated portraits set. The design cross-randomizes obesity with the amount of status signals available in a 2x3 design (Appendix Figure G.4). Along the first dimension, each portrait is shown either in the thinner or fatter version, allowing me to capture the causal effect of obesity, conditional on respondent and portrait pair fixed effects. Along the second dimension, respondents are assigned to one of two treatment arms. In the one-signal arm, respondents face one potential wealth signal (obesity). In the multiple-signal arm, they receive a second wealth signal: either the person owns a car (rich type) or lives in a slum (poor type). In either case, respondents learn the age of the portrayed individuals.

Outcomes Respondents rate each portrait along six characteristics presented in random order: wealth, beauty, health, longevity, self-control, ability to get things done, and trustworthiness. Wealth is the pre-registered primary outcome. The secondary outcomes were chosen based on qualities that are anecdotally and positively associated with obesity in poor countries (health, beauty, life expectancy) and those associated with body mass stigma in high-income countries (self-control, ability). Trustworthiness is a potential determinant of credit outcomes (Duarte et al., 2012).[18]

[16]Other papers use weight-manipulated portraits to test for negative discrimination by obesity in high-income settings (see Bertrand and Duflo, 2017 and Neumark, 2018 for a review). However, these compared a fatter (manipulated) version of a portrait with the original (non-manipulated) portrait.

[17]The portraits are displayed in Appendix Figure G.1. Appendix A provides more information on the weight-manipulation portraits.

[18]All secondary outcomes were pre-registered except for trustworthiness, which was added during the experiment.

First-order beliefs—the primary outcome of interest—cannot be incentivized. Because I elicit many characteristics, it is unlikely that respondents guess the experimental hypothesis. Yet, lack of monetary incentives may still raise concerns. First, people may not take the evaluation seriously. To limit this issue, I elicit an incentivized measure of beliefs as a secondary outcome: beliefs on the most frequent rating given by other respondents (beliefs about others' beliefs).[19] More generally, people's attention may be unnaturally drawn to body mass. To reduce this concern, I include a second salient and visible wealth signal: about one out of four rated portraits is of white people.[20]

2.2 Obesity Is Perceived as a Signal of Wealth

Figure 2 plots the average wealth ratings by portraits' obesity status and other wealth signals. The wealth-rating difference between obese and non-obese portraits is positive and statistically significant across outcomes and treatment arms. Obesity appears to be a strong wealth signal. To see this, I benchmark the effect of obesity against the effect of car ownership, another common wealth signal.[21] As shown in Figure 2, the effect of car ownership in the multiple-signal arm is not statistically different from the obesity effect in the single-arm (test p-value = 0.4397).

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

$$Y_{ij}^k = \beta_0 + \beta_1 Obese_{ij} + \beta_1 MultipleSignals_j + \alpha_i + \gamma_j + u_{ij}. \tag{1}$$

Y_{ij}^k is the rating with respect to outcome k of portrait i by respondent j. $Obese_{ij}$ is a dummy variable for portrait i being displayed to respondent j in the obese version. $MultipleSignals_j$ is a dummy variable for whether respondent j was assigned to the multiple-signal arm. α_i are portrait pair fixed effects, and γ_j are respondent fixed effects.

[19] The portraits are introduced by the following 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 and the second time to guess 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)." Second-order beliefs are incentivized using the most frequent ratings in a pilot data. Details on the survey tools are in Appendix H.

[20] White race portraits are excluded from the analysis.

[21] 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 716 in Switzerland. The experimental text does not specify a model, but field officers were trained to report average car models if prompted by respondents' clarifying questions.

Standard errors are clustered at the respondent level.

Table 2 summarizes the analysis. Figure **??** plots β_1, the preferred estimate of the obesity wealth-signaling value. This coefficient captures the effect of obesity on wealth ratings, controlling for portrait-specific characteristics and respondent rating leniency thanks to the fixed effects. The results show that the same portrait in its obese version is rated 0.7 standard deviations (p-value 0.000) wealthier as compared to its non-obese counterpart (Table 2, Panel A). Instead, obese portraits are not perceived as more beautiful, healthier, or more likely to live a long life.[22] Obesity is also not associated with trust, the ability to get things done, or self-control (ability to resist temptation). Thus, people routinely use body size to update their beliefs on peoples' wealth but not on other traits.[23] The large wealth-signaling value of obesity does not systematically vary by the portrayed person's age or gender (Appendix Table H.2, Columns 1 and 2).

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

3 Credit Experiment: Obesity and Market Benefits

To understand whether being obese matters in economic interactions and to understand the mechanism behind this, I focus on credit markets. Credit markets are an economically relevant and high-stakes market: distortions in credit screening can lead to inefficiencies both at the micro and macro level, and access to credit is a major

[22]The results on health are noteworthy given that the same respondents seem to be aware of the health costs of obesity (mortality risk) in a survey questionnaire at the end of the beliefs experiment. Thus, explicit and implicit beliefs on the health costs of obesity do not appear to be aligned. There are two possible explanations for this: either health risks are known but not salient or respondents perceive a positive correlation between health and wealth.

[23]Beliefs about others' beliefs are broadly consistent with first-order beliefs: Table 2, Panel B shows that the effect of obesity on wealth ratings is twice as large and statistically different from the effect on any other outcome.

channel to lift people out of poverty. Additionally, credit markets are characterized by asymmetric information problems. These problems in poor countries are emphasized by structural monitoring and screening challenges, making the asymmetric information channel particularly relevant to investigate.[24]

Uganda's credit market is relatively similar to the one described in Karlan and Zinman (2009). Loan officers face both adverse selection and moral hazard, and similar to other low-income countries, officers tend to favor anecdotally rich borrowers.[25] Loan applications are normally dealt in person, with loan officers choosing which borrowers they want to meet. Based on the information provided in the first meeting, they decide whether to engage in a verification procedure and often also make the final approval decision. While most loans are collateralized, verifying borrower information is a key and costly procedure in terms of loan officers' time and effort. In fact, easy-to-access and reliable information on a borrower financial situation or collateral value and property titles is lacking. For example, only 20% of Ugandan land titles—a common collateral—was registered in 2017. Although there exists a formal credit score system, the majority of consumers were not included as of 2019. Given their key role in the loan application process, most loan officers are paid based on performance and thus have incentives to select the best borrowers.

3.1 Credit Experiment

In what follows, I describe the credit experiment, a real-stakes field experiment involving professional loan officers employed in formal Kampala credit institutions to test for obesity benefits in credit markets.

Institutions and loan officers sample I obtained the listing of the universe of financial institutions *licensed* to provide credit from the Ugandan Microfinance Regulatory Authority (UMRA) or from the Bank of Uganda. Institutions providing credit in Uganda are many and very heterogeneous.[26] When the field work for this paper was conducted,

[24]See Karlan and Morduch (2010) for a review of the literature on accessing financial services in poor countries.

[25]Banerjee (2003) derives a theoretical framework to explain why asymmetric information leads loan officers to favor rich borrowers. More recently, De Mel et al. (2008) show experimentally that rich borrowers have also better returns to capital.

[26]Financial institutions legally allowed to provide credit are classified in four tiers. Tier 1 institutions are commercial banks. Tier 2 institutions are credit institutions not authorized to establish checking accounts or trade in foreign currency. Tier 3 institutions are microfinance deposit-taking institutions (MDI). Tier 4 institutions are a residual category including all other forms of lending (moneylenders,

the listing included 25 commercial banks, 5 credit institutions, 4 microfinance deposit-taking institutions, 127 microfinance institutions, and 708 licensed moneylenders. I focus on licensed institutions in Greater Kampala, which are open to the general population and offer a standard set of loans: individual and collateralized cash loans between $250 and $2500 with a six-month term to maturity.[27] The population of interest counts 447 institutions.[28]

Field officers visited each of the 447 institutions, confirmed eligibility, and asked for management consent to participate in a study (in partnership with the University of Zurich) aimed at improving matching between borrowers and lenders in Kampala.[29] Although institutions must actively consent to participate, external validity concerns related to sample selection are minimal. The sample involves more than one-third of the original population (146 out of 447 institutions). Moreover, the participating institutions are broadly representative of the types of institutions providing personal loans in Kampala (Table 3). Most institutions offer both personal and business loans. The size is heterogeneous, although, as in general in Uganda, the majority are small (median number of employees is 4). The cost of credit is high but in line with the Ugandan monthly interest rate in 2019 (10%–12%).[30]

The final sample includes 238 professional loan officers, whose characteristics are summarized in Table 4. To improve on sample representativeness, 1 to 3 loan officers per institution are interviewed. There are two requirements for participation: dealing directly with borrowers and providing written consent. I refer to the respondents as loan officers, but their occupations are more diverse: 63% self-identify as loan officers, 13% own the business, 9% say they are the manager, and the residual percentage holds institution-specific appointments. Forty percent are women and about 70% hold a bachelor's degree. The monthly salary ranges between $135 and $270, above the median

companies, NGOs, or savings and credit cooperatives. For a description of the Ugandan credit market, see Duggan (2016), Nilsson (2017), and Sebudde et al. (2017).

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

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

[29] The experiment was implemented in partnership with Innovation for Poverty Action Uganda. The study description is accurate because at the end of the experiment, loan officers are matched with real prospective borrowers, which reduces experimenter demands concerns by not mentioning body mass.

[30] Unfortunately, running a survey that also includes non-participating institutions, to compare the participating and non-participating institutions, was unfeasible due to budget and logistic constraints.

monthly wage in Kampala ($80 in the National Population and Housing Census 2014). Looking at the tasks loan officers perform, the data confirm respondents' key role in the lending process: 74% directly approve loan applications, and 80% verify borrower information. Loan officers spend, on average, about half of their working week verifying borrower information: they travel to interview prospective borrower neighbors, family members, and employees and verify collateral property and value. According to the loan officers, what matters most in getting a loan is good collateral (average rating of 2.92, on a scale from 1 to 3), followed by income, guarantor, occupation, nationality, and age.

Borrower Sample and Hypothetical Profiles On the borrower side, I collect information on 187 prospective borrowers.[31] Combining prospective borrower data and information from loan officer focus groups, I build 30 hypothetical borrower profiles.[32] Each profile is cross-randomized to a name (blurred), passport number (blurred), age, nationality (all Ugandans), loan information (reason, amount, time to maturity), and self-reported financial information (loan profile, reason for loan, occupation, monthly revenues, monthly profits, and collateral). For each profile, I also randomly assign a portrait—a standard identifier in financial documents in Uganda. Portraits are randomly selected from the set of weight-manipulated portraits of Kampala residents described in Section 2. Because there is a thinner and a fatter version for each picture, in total I have 30 identical profiles pairs that differ only in the borrower's body mass.

The resulting profiles (see, e.g., Appendix Figure G.6) are realistic. The layout is based on financial documents from two Ugandan commercial banks (Appendix Figure G.7). Borrower information comes from real borrowers and professional loan officers. To avoid unrealistic combinations of cross-randomized information, the final set of loan profiles is vetted by loan officers from pilot institutions.

Flow and incentives In Kampala, loan applications are dealt in person, making a correspondence study (as notably in Bertrand and Mullainathan, 2004) not feasible. In this experiment, I ask loan officers to evaluate 30 borrowers profiles, knowing that these are hypothetical, and choose the borrowers they would like to meet with to discuss a loan application. Loan officers' incentives are as close as possible to a real-life lending

[31] To identify prospective borrowers, at the end of the beliefs experiment, I collect information on the respondent's credit history and need for a loan. Conditional on needing loan, I elicit the reason for borrowing, type, and amount of loan needed. I also elicit consent to be included in a study that aims to improve matching borrowers and lenders in Kampala.

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

decision. Even if the exercise occurs during work hours, monetary rewards are minimal ($3 fee). Instead, the main incentives offered to loan officers are real borrower referrals. Loan officers know that based on their choices in the hypothetical exercise, at the end of the study, they will be referred to real prospective borrowers (from the 187 prospective borrowers pool) whose characteristics match their preferences.[33] This incentive structure follows closely the IRR recently developed by Kessler et al. (2019) to test for discrimination in hiring without deception and is incentive compatible in this setting.[34]

Loan officers care about referrals because good borrowers have lower expected verification costs. Moreover, good clients can improve their earnings prospects. Credit markets in Kampala are characterized by many institutions competing for few high-quality borrowers (cherry-picking market), and who the owner approves for a loan may affect their profits. Most employed loan officers face a form of performance pay.[35] Consistent with the presence of high stakes, loan officers spent, on average, two hours of their working time on the evaluation exercise and ask for a direct referral (versus referral to the institution) more than 80% of the times.

Design To pin down the relationship between obesity, access to credit, and asymmetric information, the design cross-randomizes borrower obesity status and the degree of asymmetric information between borrowers and lenders. Along the first dimension, I vary borrower body mass by randomly assigning each loan officer to a loan application associated with the obese or non-obese version of the same borrower portrait. Along

[33] To implement the referrals, I provide borrowers with the name and contact information of the loan officer who would be most likely to meet them to discuss a loan application. The matching is based on observable characteristics. I train a simple machine learning algorithm (*Random Forest Classifier*) on the experimental data to identify borrower characteristics that give the highest referral request probability for each loan officer. I then apply the algorithm to the 187 prospective borrower dataset and select the best match. The procedure is detailed in Appendix C.3. Notably, following Kessler et al. (2019), the algorithm does not match on borrower gender and body mass. While this may be seen as mildly deceptive, loan officers' preferences are taken into account, and in practice a perfect match would never be possible. This choice was a response to the ethical concern of avoiding biased credit outcomes.

[34] 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.

[35] 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 has met a specific target.

the second dimension, I vary whether the profile displays the borrower self-reported financial information. For each loan officer, of the 30 profiles evaluated in total, the first 10 randomly selected profiles display the borrower demographics and loan application information (reason, amount, time to maturity). The last 20 randomly selected profiles also display self-reported monthly revenues, monthly profits, collateral, and occupation information.[36] This design allows me to control for loan officer and borrower profile fixed effects.[37] Out of realism, the borrowers profiles are such that their reported financial information gives them a non-zero chance to get a loan: a truly bad candidate would be unlikely to apply for loan and truthfully disclose their information. However, borrowers are still randomly assigned to have a relatively low or high debt-to-income ratio (DTI). Thus, the resulting experimental design is a 2x3 design (Appendix Figure G.5).

Table 5 summarizes the realized borrower profiles characteristics by the obesity status of the displayed borrower portrait. The statistics confirm that the obese and non-obese borrower profiles are nearly identical except for body mass: the difference is 14 BMI points and is statistically different from zero. Obese and non-obese borrowers have the same average profits and collateral, suggesting that the cross-randomization with financial information worked well. Profiles differ according to the average likelihood of selling clothes or owning a jewelry shop as an occupation. These differences are driven by the small number of profiles within each obesity-gender-occupation cell, due to some of the occupations being gender specific. This is not a concern because the main results rely on profile fixed effects.

Outcomes Loan officers evaluate each profile according to four primary outcomes: three belief measures (approval likelihood, borrower creditworthiness, and financial ability) and the binary choice of asking to meet with a borrower with similar characteristics. Given the incentive structure, the latter is a real choice outcome: choosing to meet a hypothetical borrower increases the likelihood that the loan officer is referred to a real

[36]When financial information is provided, I also vary whether loan officers can opt in to see more information (10 to 20) or the information is presented by default (20 to 30). Ex-ante, this allowed me to test whether there was discrimination in the request for information. In practice, however, the additional information cost is minimal (forgone time), and loan officers always opt in to receive more information about the applicants in 99% of the cases. Thus, in the main analysis, I pool the two sub-treatments.

[37]The order of treatment arms was not randomized, which helped clarify to loan officers that whether respondents provided or did not provide financial information was a design choice rather than strategic decisions of the borrower. Supporting the claim that the treatment arms' order is not confounding the results, Appendix C.4 shows there are no order effects, neither at baseline nor in interaction with body mass.

borrower with those characteristics. I also elicit two pre-registered secondary outcomes: interest rate charged conditional on approval and, when profiles include self-reported financial information, beliefs on the reliability of the self-reported financial information.[38]

3.2 Obesity Premium in Access to Credit

The main statistic of interest is the average ratings difference between obese and non-obese borrowers, all else equal. Figure 3 plots the average credit ratings by borrower obesity status (binary) and the predicted credit ratings by BMI (continuos). The left-hand side (LHS) of the graphs shows that across all main outcomes, obese borrowers have better credit ratings and these ratings translate into better access to credit because obese borrower profiles are also more frequently asked for a referral (real choice outcome). It also shows that the obesity premium is strongest in the absence of financial information, but obesity still matters when self-reported information on income, collateral and occupation is provided. The right-hand side (RHS) shows that the credit market benefits of weight gain are linearly increasing in body mass: benefits of weight gain start when individuals are overweight and loan officers do not penalize extreme BMI values, those above and beyond 40 BMI points (obesity of degree II).[39]

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

$$Y_{ij}^k = \beta_0 + \beta_1 Obese_{ij} + \beta_2 FinancialInfo_{ij} + \beta_3 FinancialInfo_{ij} \cdot Obese_{ij} + \delta_i + \gamma_j + u_{ij}. \quad (2)$$

Y_{ij}^k describes outcome k's rating of profile i by loan officer j and $Obese_{ij}$ is a dummy variable for loan profile i being associated with the obese version of a borrower portrait when evaluated by loan officer j. $FinancialInfo$ indicates whether profile i included self-reported information on collateral, occupation, revenues, and profits when shown to loan officer j. δ_i are profile fixed effects, and γ_j are loan officer fixed effects. I cluster standard errors at the loan officer level and standardize all outcome variables, including the referral request dummy, for comparability. The coefficient β_1 captures the preferred measure of the obesity premium in access to credit. This is the premium charged by loan officers when they do not have access to borrower financial information, as common

[38]The order is the following: approval likelihood, creditworthiness, interest rate (if applicable), financial ability, reliability (if applicable), and referral request. The wording is in Appendix C.1.

[39]The results are equivalent when estimating a model controlling for all observable characteristics, including a second-order polynomial in the portraits' BMI to allow for non-linearity.

when loan officers choose whom to meet among borrowers in waiting room.[40]

Table 6 summarizes the regression results. The obesity coefficient is positive and statistically significant across all outcomes. When associated with obese portraits, the same loan profile has a higher expected approval likelihood of 0.19 standard deviations (p-value = 0.00, Column 1). Consistent with the notion that loan officers perceive obese borrowers as better borrowers, obese borrowers are rated more financially able (0.18 standard deviations, p-value = 0.00, Column 2) and creditworthy (0.15 standard deviations, p-value = 0.00, Column 3). Most notably, obese borrowers actually have easier access to credit: profiles including the obese version of a portrait are more likely to be asked for a referral by 0.07 standard deviations (p-value = 0.05, Column 4).[41] In terms of the odds of getting past the first screening stage, the chances that a loan officer asks an obese borrower for a meeting are 3 percentage points higher relative to an average likelihood of 70.5% among normal-weight borrowers (4.25%).[42]

The estimated obesity premium in access to credit is large. To see this, 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 mean (about \$270–\$300 more).[43]

The obesity premium is comparable among rich- and poor-looking borrowers, again suggesting that obesity and other signals are accounted for independently; that is, obesity and good self-reported financial information are not substitutes.[44] Finally, as shown in Appendix Table H.9, the obesity premium size is not systematically correlated with any observable institution or loan officer characteristic. There is some mild evidence that richer loan officers are less likely to rely on obesity, while loan officers who self-report higher stress or time to verifying borrower information appear to rely more on obesity.

[40] Another approach is to estimate the obesity premium on the pooled information treatment arms. The results are qualitatively and quantitatively unaffected. In the pooled analysis the coefficients are harder to interpret because there is no obvious link to a specific information environment.

[41] Loan officers do not seem to screen using interest rates: while about half of the loan officers can charge discretionary interest rates, only 5% actually choose to do so at this stage.

[42] The results are robust to a randomization inference exercise (Appendix Figure G.8).

[43] Since self-reported profits are randomized, I simply test whether β_1 is statistically different from $Y^k_{ij} = \delta_0 + \delta_1 Profits_i + \gamma_j + u_{ij}$. I use Stata's *suest* and *test*. The test's p-value is 0.58.

[44] Taking a perspective similar to Börgers et al. (2013), I define two signals as complements (substitutes) if there is an obesity premium (penalty) in access to credit for displaying both good signals jointly, relative to possessing only one. Appendix Table H.10 summarizes the results of the analysis where I test the interaction between obesity status and a relatively good or low DTI, conditional on the profile including financial information. The interaction coefficient is very small and not statistically different from zero.

3.3 Mechanism behind the Obesity Premium

So far I found that obesity is perceived as a signal of wealth and that obesity leads to market benefits. My hypothesis is that the obesity premium is a response to an information extraction problem: loan officers screen by body mass because in low-income countries, where credit markets favor rich borrowers and asymmetric information is pervasive, obesity is perceived as a reliable signal that a borrower is rich (*statistical discrimination*). From a theoretical perspective, a competing explanation is that loan officers are not profit maximizing and prefer obese borrowers for a reason which is unrelated to the obesity wealth signal (*taste-based discrimination*). While the beliefs experiment results do not highlight a beauty or trust premium associated with obesity, loan officers may have preferences that are different from the general population (Palacios-Huerta and Volij, 2008). Moreover, the premium may be also driven by factors not measured in the beliefs experiment, like homophily.

Ex-ante, the two explanations are not mutually exclusive. Statistical and taste-based discrimination may both contribute to the obesity premium. To identify the relative importance of each model, I vary the degree of asymmetric information between loan officers and borrowers in the experiment. In a statistical discrimination framework, loan officers are profit-maximizing agents and asymmetric information drives the obesity premium: the more information there is available on a borrower's financial situation, the less loan officers rely on the obesity signal. In a taste-based discrimination model, loan officers' obesity bias should not be affected by the amount of financial information available.[45]

To test for this mechanism, I look at the interaction of obesity and financial information in Equation (2). First, the self-reported financial information provided reduces the degree of asymmetric information between borrowers and lenders. Profiles that include self-reported financial information overall have easier access to credit: β_2 is positive and statistically significant across all outcomes. This confirms that loan officers consider the financial information provided and actually reduces the degree of asymmetric information. Second, providing additional financial information indeed substantially and

[45] A limitation of this design is that it cannot tease out true and apparent statistical discrimination; that is, it does not allow me to identify the discriminator's animus. Imagine that loan officers have a taste for obese borrowers but having more financial information available makes it harder for them to justify their bias (to other people or themselves): they would respond to information provision by reducing their bias, and the outcome would be indistinguishable from "true" statistical discrimination. In this setting, this is not very concerning because the obesity premium is not stigmatized; however, if one were to apply a similar design to another discrimination context (e.g., gender or race discrimination), this limitation may be more relevant.

significantly reduces the obesity premium: the interaction between obesity and financial information (β_3) is negative and always statistically significant (except for referral request, negative but not statistically significant). Overall, the obesity premium drops by nearly two-thirds when loan officers evaluate profiles that include self-reported financial information.[46] For example, focusing on approval likelihood, providing self-reported financial information reduces the obesity premium by nearly 70% (p-value = 0.041).

Thus, most of the obesity premium appears driven by asymmetric information, implying that loan officers' behavior is not consistent with a pure taste-based discrimination model.[47] From a theoretical perspective, both residual asymmetric information and taste-based discrimination (e.g., a beauty premium) could explain the residual obesity premium. While the financial information provided solves part of the asymmetric information between borrowers and loan officers, loan officers likely face residual asymmetric information. First, the information is self-reported. Consistent with this interpretation, on average, loan officers do not fully trust borrower self-reported financial information. The self-reported information, on average, is perceived as not very reliable.[48] Notably, the same self-reported information is perceived as more reliable when associated to an obese borrower.

Second, loan officers normally also base their decisions on other information, not included in the profiles, such as the existence of a guarantor. To the contrary, I find no empirical evidence in support of taste-based discrimination. The results of the first experiment do not provide evidence in support of any beauty, health, or trustworthiness premium. In the credit experiment, the obesity premium is stronger for men and persists in same-sex borrower/lender pairs (Appendix Table H.8). Moreover, premium size is not systematically correlated with loan officers' body mass (Appendix Table H.9). I interpret

[46] As mentioned in credit experiment design description, in the experiment I also vary the timing in which the financial information is provided: either all the information at the same time or portrait and demographics first, followed by financial information. The effect of information provision is slightly larger when the financial information is shown simultaneously with the portrait (Appendix Table H.6). This suggests that loan officers may stick to their first impression of the borrower when making lending decisions, making the obesity premium even more consequential in real life.

[47] Inattention is an alternative explanation for the results. When additional financial information is provided, loan officers may pay mechanically less attention to all the baseline characteristics including borrower body mass. The ideal experiment would have added a third treatment arm providing non-financial information, but doing this was not feasible due to budgetary and logistical constraints. As an alternative robustness check in Appendix Table H.5, I present a set of regressions and test for the effect of self-reported financial information on the cross-randomized characteristics included in the baseline borrower profiles. Contrary to what we would expect if the results were mechanically driven by inattention, the interaction term's sign is not systematically negative.

[48] The average reliability rating is 1.98 on a scale from 1 to 5 (Appendix Table H.7).

these results as consistent with loan officers engaging in statistical discrimination.

3.4 Discussion and External Validity

The credit experiment establishes that obese borrowers, all else equal, have easier access to credit. Loan officers prefer obese borrowers because they perceive them to have ex-ante higher verification probability based on the body mass signal—aligned to the predictions of an attention discrimination model for a cherry-picking market (Bartoš et al., 2016). Loan officers' behavior appear to be a response to an information extraction problem: the stronger the asymmetric information, the more they rely on obesity, a visible status signal. Moreover, there is no evidence of homophily, nor of a beauty, trust, or health premium. Thus, loan officers' behavior is mostly consistent with statistical discrimination.

There are two main reasons that suggest obesity matters in real-life credit market settings, although the design, based on hypothetical profiles and weight-manipulated portraits, does not allow me to investigate borrowers' actual approval rates and loan performance. First, the amount of information loan officers face in the experiments is as close as possible to the information set they face in real life, in two main screening stages. The baseline information (demographics, loan profile, appearance) is the information loan officers have when they choose which prospective borrowers to meet with, among those in their waiting room (first screening). The self-reported information is the information borrowers normally share during the first in-person meeting, when loan officers choose whether or not to embark in the effortful procedure of verifying borrower collateral and financial standing. Consistent with these being routine decisions, loan officers do not struggle in evaluating borrowers and choosing whom to meet based on the information provided in the experiment. Second, and most notably, loan officers explicitly state the existence of an obesity premium in credit markets in Kampala: at the end of the experiment, in an open-ended question, about 90% of the loan officers state that an obese borrower is more likely to get a loan as compared to a normal-weight borrower (Figure 4). Thus, the evidence suggests obesity matters at key stages of the loan application process.

The results are drawn from the Ugandan setting, but I expect obesity status to lead to socio-economic benefits in countries that are at a similar stage of the nutritional transition, that is, where obesity is a status symbol (Figure 1, Panel B) and is characterized by pervasive asymmetric information problems. Most low-income countries fit this profile. Indeed, when replicating the beliefs experiment with 241 women in rural Malawi, I find similar results: obese people are perceived as wealthier and more creditworthy but not more beautiful or healthier (Appendix Table H.11).[49]

4 Beliefs Accuracy

The previous sections show that obesity benefits in Kampala credit markets appear to be the result of statistical discrimination, whereby agents rely on obesity as a signal of wealth and earnings when asymmetric information is pervasive. In a statistical discrimination environment, implications depend on whether people's beliefs about returns to obesity and the obesity signaling value are accurate. Is the general population aware of obesity benefits in credit markets? If so, do they happen to over or underestimate the premium? Do people, and loan officers among them, inaccurately estimate the wealth-signaling value of obesity? In what follows, I use additional survey evidence, experimental variation, and a simple model to answer these questions.

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

Loan officers are aware of the obesity premium in credit markets, but the general population might not be. I start by testing experimentally whether people are aware of the credit market benefits of obesity and if they hold accurate beliefs on the size of the obesity premium.

Design and outcomes I replicate the credit experiment with a sample of Kampala residents (laypeople).[50] In the replication, the field officer describes the study I ran with professional loan officers and the experimental design except for the obesity manipulation and the results. Laypeople must guess loan officers' ratings. I elicit two main incentivized outcomes: (i) the number of loan officers who requested the referral of a similar applicant (0 to 10) and (ii) the most common loan officers' approval likelihood rating (1 to 5). I also ask them to state if they would or would not recommend a borrower with similar characteristics to apply for that loan based on their assessment of loan officers' interest (not incentivized).

[49] The same experiment in a small-scale Amazon MTurk pilot with US workers gives opposite and smaller effect size magnitudes (Appendix E.2).

[50] Respondents are part of the beliefs experiment sample. In the same session, respondents first answer the beliefs experiment section and then the credit experiment replication section. By design, respondents will see different portraits in both sections.

The respondents are shown four loan profiles randomly selected from the 30 hypothetical loan profile pairs, either in the obese or non-obese version. For simplicity, I focus on loan profiles at baseline (no financial information). This design allows me to elicit incentivized second-order beliefs on the obesity premium and to test for misperception since loan officers' ratings in the original credit experiment can be matched one-to-one with laypeople's guesses. Relative to direct beliefs elicitation, this design is more conservative because it does not need body mass or obesity to be mentioned to the respondents, reducing concerns of experimenter demands.

Results Figure 5 summarizes the results. The key comparative static is how borrower obesity status affects laypeople's guesses of (i) loan officers' most frequent approval likelihood rating (approval likelihood) and (ii) share of loan officers asking for a referral (referral request). I estimate this effect using an obesity dummy in a regression model including respondent and borrower fixed effect, equivalent to Equation (2). The analysis provides two results. First, laypeople are aware of obesity benefits in credit markets. Laypeople rightly guess that the very same borrower profile, when associated to an *obese* portrait, had a higher approval likelihood rating and was more often requested for a referral by the loan officers.

Second, laypeople largely and systematically overestimate the obesity premium in credit markets. Looking at the approval likelihood outcome, on average, the obesity premium is overestimated by a factor of two. Overestimation is four times larger among overweight respondents and in general, it is even stronger for the referral request outcome. Overestimation of obesity benefits likely directly affects people's decisions. For example, in the experiment laypeople are systematically more likely to recommend obese borrowers to apply for loans, suggesting potential distortions for credit demand.

4.2 (Mis-)Perception of Obesity Wealth-Signaling Value

As a second step, I investigate the misperception of obesity's wealth-signaling value and test whether people form accurate beliefs on a person's financial situation based on the observed body mass. In a survey experiment with 124 Kampala residents, I elicit incentivized first-order beliefs on the conditional earnings distribution by body mass in Kampala.[51] I use the figurative Body Size Scale for African Populations designed and validated in Cohen et al. (2015) and incentivize respondents' answers with survey

[51]Due to COVID-19 restrictions, the survey was partly run online and partly on the phone. The belief accuracy sample is described in Appendix D.1 and Appendix Table H.12.

data on monthly earnings and body mass that were originally collected for the beliefs experiment sample.[52]

Laypeople's belief distribution is displayed in Figure 6, Panel A, and it is very heterogeneous. According to the body mass and income data for Kampala residents, on average, an obese person earns about \$63 more per month as compared to a normal-weight person. Only 11% of respondents hold accurate beliefs (within a 95% confidence interval). Respondents also overestimate the difference to be about \$200, nearly three times as large. Similar to the misperception of benefits, the extent of the overestimation is about four times larger among overweight and obese respondents relative to normal-weight ones. These estimates are robust to the exclusion of outliers, and the comparison is based on the equivalent BMI support.

These results show that the general population holds inaccurate beliefs on the wealth-signaling value of obesity. Similar to the overestimation of obesity benefits, people also place too much *weight* on obesity as a signal of wealth. Overestimation of the wealth-signaling value of obesity may distort economic transactions, such as lending decisions. If loan officers misperceive the wealth-signaling value of obesity and base their decisions on body mass when verified wealth information is unavailable, this may induce a biased credit provision relative to a full information framework. At the same time, there may be reasons to believe that experts—loan officers in this case—may have a more accurate perception of the signal relative to the general population, either because of their training or their stakes. If beliefs are accurate, since obesity is a relatively cheap signal from a loan officers' perspective, body mass screening may even have positive implications for credit markets efficiency.

I can exploit the credit experiment to provide insights on whether loan officers hold more accurate beliefs than the general population,[53] which I do by estimating their beliefs on the conditional earnings distribution by body mass from their choices in the

[52]For each of the 511 respondents in the beliefs experiment, I measure height and weight using a weight scale and a height board. Moreover, I also ask about self-reported monthly earnings. This is not a representative sample; the benefits are that earnings are an intuitive measure of socio-economic status and BMI is precisely measured. To my knowledge, no publicly available data exist on the conditional earnings distribution by body mass in Kampala. The DHS data wealth variable is a relative and asset-based wealth index, therefore is not an intuitive measure to guess.

[53]This is conceptually close to testing for inaccurate statistical discrimination as defined in Bohren et al. (2019). Notably, their definition is outcome based. In my setting there are two outcomes: a final outcome (credit performance) and an intermediate outcome (wealth or earnings). Since I do not have data on credit performance by BMI, I focus on earnings. Under the assumption that obese borrowers do not have sizably better returns to capital, one can argue that loan officers are likely to engage in inaccurate statistical discrimination if they hold inaccurate beliefs on the wealth signal.

credit experiment, using a revealed preferences approach.[54] Intuitively, the total obesity premium in the absence of financial information about a borrower can be decomposed into a taste-based and statistical discrimination component—of which either could be zero ex-ante. The taste-based component is a preference parameter. The statistical discrimination component is a function of loan officers' beliefs on the importance of earnings for creditworthiness and beliefs on the conditional distribution of earnings by body mass (obesity wealth-signaling value).

The goal of this analysis is to isolate beliefs on the obesity wealth-signaling value from the total obesity premium. Under a linear separability assumption, the credit experiment design allows me to estimate these beliefs residually.[55] First, I compare the obesity premium in creditworthiness across information treatment arms to net out the taste-based component, by assumption independent from the amount of information provided. This step identifies the statistical discrimination component from the total obesity premium.[56] Second, exploiting the cross-randomization of (self-reported) earnings in the loan profiles, I estimate loan officers' beliefs on the importance of earnings for creditworthiness. This step allows me to back out residually an estimate of loan officers' beliefs of the obesity wealth-signaling value from the statistical discrimination component. Because each loan officer evaluates multiple profiles, I estimate beliefs at the loan officer level. Because of how the credit experiment data are constructed, the summary statistics that capture the wealth-signaling value of obesity is the average monthly income difference between obese and non-obese borrowers.

This approach has two main limitations. First, it is data intensive because it is based on few evaluations per loan officer. To improve on this aspect, I estimate the beliefs only for the 167 loan officers who evaluate the full set of 30 profiles. To further account for outliers, I winsorize the top and bottom 1% of the data. Second, since the measure of earnings in the profiles is self-reported, this leads to measurement error in the estimated beliefs on the effect of earnings on creditworthiness. Notably, loan officers perceive obese borrower information as more reliable, so measurement error correlates with obesity. To minimize bias, I focus on loan profiles whose financial information was rated as above-average reliable by the loan officers, for a total of 3,716 evaluations or

[54] Appendix D.2 details the estimation procedure and the simple theoretical framework that grounds it.

[55] Linear separability means that creditworthiness is linearly separable in obesity and financial information. I can test for this assumption in the data and find support for it because obesity and other wealth signals neither complement nor substitute each other significantly.

[56] This means I do not have to worry about other observable or unobservable borrower characteristics associated with obesity (partner's income, collateral) to bias the belief's estimates.

about 55% percent of the original sample.

Loan officers' estimated beliefs distribution on the obesity wealth-signaling value is plotted in Figure 6, Panel B and appears to be very dispersed. To test for beliefs accuracy, I compare beliefs with my data on the actual monthly income difference between obese and non-obese prospective borrowers in Kampala.[57] About 17% of the loan officers hold beliefs within a 5% confidence interval from the true average difference in the full population, $22 (about 13% when comparing it to the average difference among prospective borrowers, $63). Taken together, the results suggest that although loan officers have slightly more accurate beliefs as compared to the general population, the wealth-signaling value of obesity is prevalently misperceived even by loan officers. In summary, signal misperceptions are widespread among laypeople and professionals alike.

4.3 Discussion and Implications for Policy

The results show that people are aware of the obesity benefits and the positive correlation between wealth and body mass. However, people commonly overestimate significantly the importance of obesity, both in terms of benefits and the wealth-signaling value.

One theoretical implication of misperception of the obesity wealth-signaling value is a rejection of standard statistical discrimination, which assumes rational expectations, in favor of *inaccurate* statistical discrimination (discrimination that stems from incorrect beliefs about the group distributions of the relevant outcome Bohren et al., 2019). This is straightforward to see when looking at laypeople's beliefs on the conditional income distribution by obesity status.[58] When looking at loan officers' beliefs, talking about inaccurate statistical discrimination is more complex. There are two outcomes on which loan officers form beliefs: an intermediate outcome, the borrower financial situation (for simplicity, earnings) and a final outcome, loan performance or returns to capital. Since there is no data on credit outcome data by body mass in Kampala, this paper cannot say whether loan officers final choices are biased: most loan officers hold inaccurate beliefs on obese borrowers' wealth, whether this translates into inaccurate statistical discrimination

[57]Loan officers' beliefs should be based on the sub-population of borrowers rather than the full population. In the beliefs experiment survey, on top of measuring BMI and eliciting self-reported earnings, I also ask whether respondents need a loan. Doing this allows me to estimate the conditional earnings distribution by body mass among prospective borrowers. I find that obesity is a less strong signal of high earnings among this subsample: on average, an obese prospective borrower earns $22 per month more as compared to a normal-weight one.

[58]In fact, eliciting beliefs about the group distribution is the first way to identify inaccurate statistical discrimination suggested by Bohren et al. (2019).

depends on loan officers' beliefs about the importance of earnings for creditworthiness and the actual loan performance of obese relative to normal-weight borrowers.

Bias and heuristics may be one reason why people hold systematically inaccurate beliefs (Fiske, 1998). Overestimation of the obesity premium and wealth-signaling value is consistent with a stereotyping model as in Bordalo et al. (2016), where obese people are representative of rich people in Kampala. Another explanation for inaccurate beliefs could be lack of information. Lacking credit scores or bank statements, loan officers may just not have enough precise information to build accurate beliefs. Learning could mitigate inaccurate beliefs, but the literature, summarized in Bohren et al. (2019), suggests this is often not the case. For example, there may be limited feedback, leading to learning traps, or agents may face trade-offs between maximizing cost effectiveness and learning about the true distribution of an outcome across groups.

In terms of policy, the evidence of misperception leads to considerations for credit markets efficiency and health policy. Concerning credit markets efficiency and financial inclusion, the results suggest that screening by body mass has ambiguous implications. Screening by body mass may reduce the cost of credit, while biased beliefs may lead to an inefficient credit allocation relative to a full information framework. This paper cannot quantify the overall efficiency effect. However, since loan officers in the experiment respond to information, providing access to cheap and more accurate financial information may be a way to improve credit markets efficiency. Concerning health policy, the trade-off between costs and benefits of obesity affects obesity prevention. First, the trade-off affects the calibration of existing policies in poor countries. Building on the optimal sin tax framework of Allcott et al. (2019), I show in Appendix F that accounting for the monetary benefits of soda consumption (through weight gain) significantly reduces the optimal sugar tax in Uganda.[59] Second, people's awareness and overestimation of the trade-off suggests that obesity benefits can work as an incentive to gain weight and inefficiently raise the perceived costs of healthy behaviors. In line with this hypothesis, respondents in an open-ended questionnaire stated that showing off wealth and prestige was the main reason why people gain weight in Kampala (Appendix Figure G.10).

5 Conclusion

Exploiting the random assignment of weight-manipulated portraits, this paper shows that obesity is perceived as a strong and reliable wealth signal in urban Kampala. Being

[59] I show this in a partial equilibrium framework.

obese substantially increases people's chances of accessing credit because professional loan officers screen borrowers by body mass in real-stakes lending decisions characterized by pervasive asymmetric information. Loan officers' behavior appears consistent with statistical discrimination; however, screening by body mass is not necessarily efficient. While body mass positively correlates with wealth and earnings in Kampala, people (including loan officers) hold inaccurate beliefs on the signal and its benefits and overestimate the importance of obesity.

I interpret the results as showing, for the first time, that seemingly irrelevant status signals, like obesity, have sizable market benefits and to identify the mechanism for which this is true. Costly status signals work as reliable and ready-to-access wealth signals in contexts where asymmetric information is pervasive. This evidence provides a rationale behind phenomena like large expenditures on festivals and celebrations among the poor.

The paper also provides novel experimental evidence on the benefits of obesity in a low-income country setting. Obesity benefits are sizable, encompass both social and monetary returns, and are commonly overestimated. While my evidence comes from a specific market (credit), anecdotally obese people enjoy preferential treatment in many other daily interactions—including shopping, transportation, or the marriage market. One major implication of obesity benefits and their overestimation is the inefficient trade-off between the perceived socio-economic benefits and the health costs of obesity. The existence of this trade-off changes the incentives to gain weight and to engage in healthy behaviors, adding to our understanding of the global obesity epidemic. Quantifying to what extent obesity benefits contribute to the obesity epidemic in poor countries may provide interesting avenues for future research.

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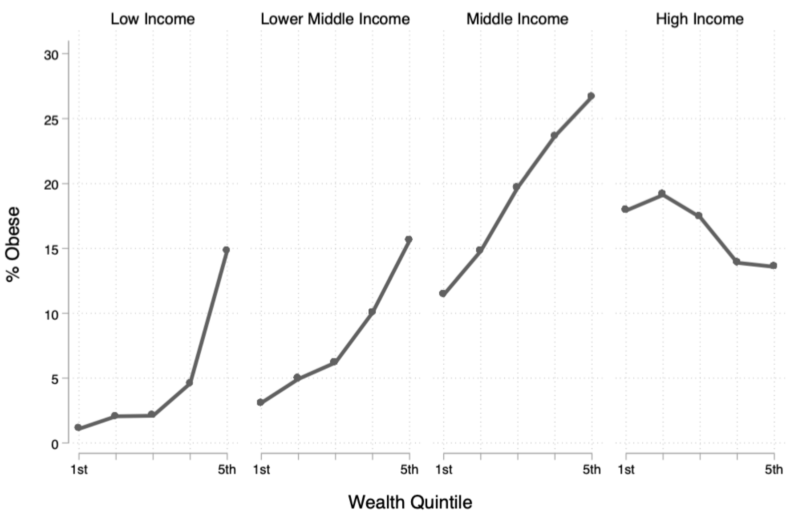
Figures

Figure 1: Obesity Prevalence by Wealth Quintile

(a) Low- and lower-middle-income countries

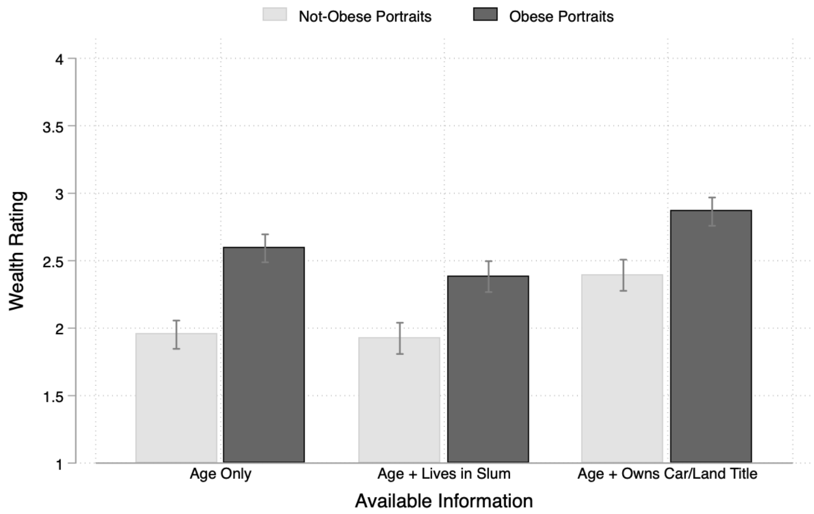
(b) By country income level



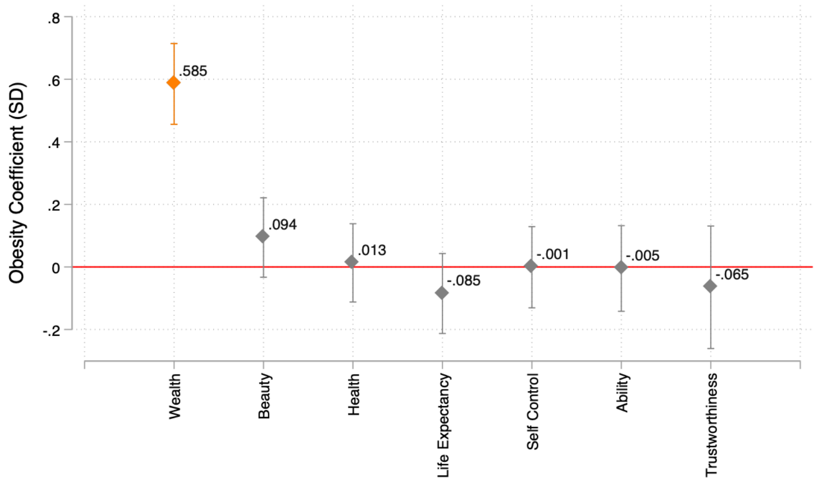
Note: Panel A plots data from the most recent DHS wave as of 2019 (2010–2016) for low- and lower-middle-income countries: Armenia, Bangladesh, Benin, Bolivia, Burkina Faso, Burundi, Cambodia, Cameroon, Comoros, DRC Congo, Ethiopia, Gambia, Ghana, Guinea, Haiti, India, Ivory Coast, Kenya, Kyrgyzstan, Liberia, Lesotho, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Tajikistan, Tanzania, Timor-Leste, Togo, Uganda, Uzbekistan, Zambia, and Zimbabwe. The red line is the quintile level average. Obesity is defined as a body mass index (BMI) greater than or equal to 30 (WHO definition). Panel B aggregates at the country income level and includes DHS data of middle-income countries, Eurostat, and CDC data.

Figure 2: Beliefs Experiment Results

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



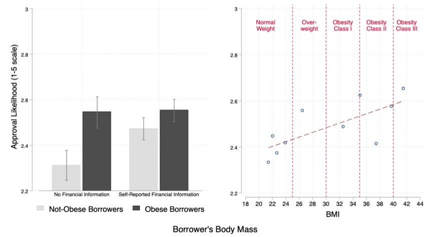
(b) Effect of Obesity Status on Portrait Ratings



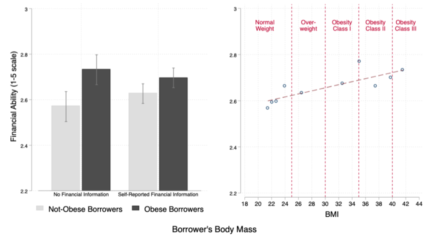
Note: The figure plots the main results of the beliefs experiment. A total of 511 respondents rate three to four black-race portraits each, for a total of 1,699 observations. Wealth ratings are the pre-registered primary outcome. Portraits were randomly selected from the weight-manipulated portraits set. About two-thirds of the respondents receive additional wealth signals about the respondents, either asset ownership (rich type) or place of residence (poor type). Panel (a) plots the raw wealth ratings data, by portrayed person obesity status and other information. Panel (b) plots the obesity coefficient from a regression including portrait pair and respondent fixed effects. The regression includes all the evaluations, with and without additional wealth information. The bars are 95% confidence intervals. All outcomes are standardized, and standard errors are clustered at the respondent level.

Figure 3: Obesity Premium in Access to Credit

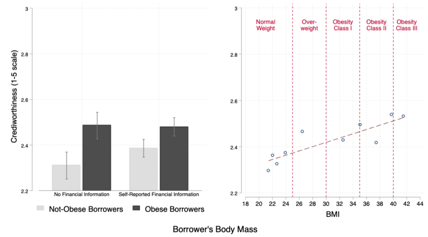
(a) Approval Likelihood



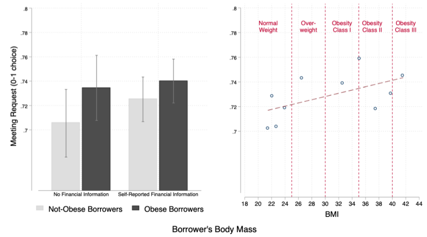
(b) Financial Ability



(c) Creditworthiness

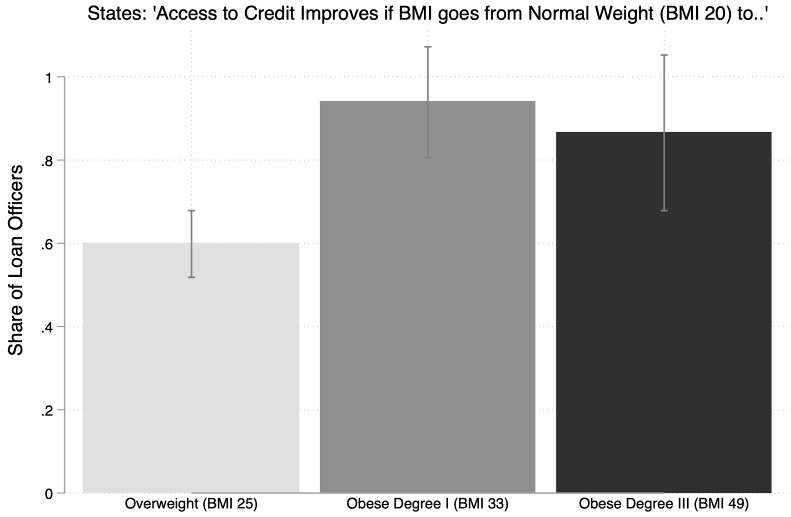


(d) Referral Request



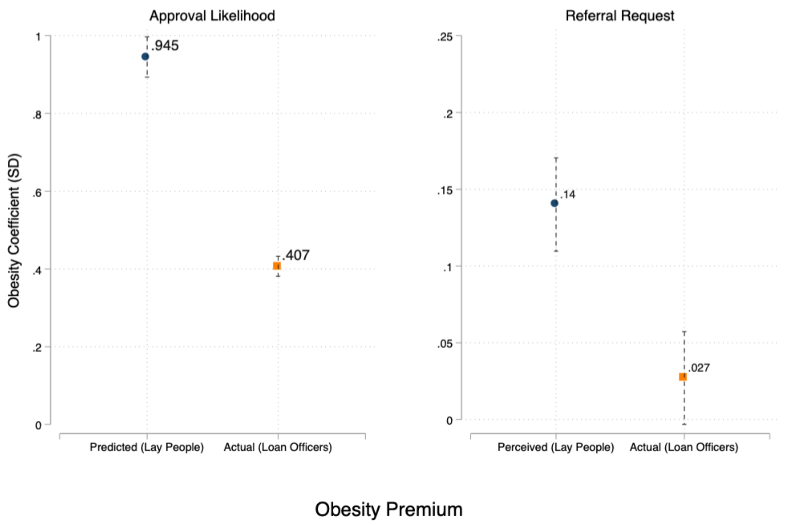
Note: The graphs summarize the main results from the credit experiment. Respondents are 238 loan officers engaging in 6,645 borrower profile evaluations. Each profile is evaluated along four primary outcomes (in this order): likelihood of approval (approval likelihood), probability of repayment (creditworthiness), ability to put money to productive use (financial ability), and referral request, that is, the choice of meeting a borrower with similar characteristics. Ratings are on a scale from one to five (not at all to very), and referral request is a real choice outcome (no/yes). The left-hand side (LHS) graphs plot the raw data by borrower obesity status and degree of asymmetric information. The bars are 95% confidence intervals. The right-hand side (RHS) graphs plot the binned scatterplot of a continuous measure of body mass (BMI, kg/m2) using Stata's *binscatter*. The number of bins specified is 10. Both dependent and independent variables are residualized on individual borrower profile and loan officer dummies.

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



Note: The graph plots loan officers explicit beliefs on returns to BMI in access to credit. At the end of the credit experiment, loan officers are shown three body-size silhouettes (overweight, obese of degree I, and obese of degree III) in pair comparisons and state which silhouette in each pair has a higher likelihood of getting a loan. The silhouettes' comparisons are 1) normal weight and overweight, 2) overweight and obese degree I, and 3) obese of degree I and obese of degree III. The graph plots the cumulative points relative to normal weight.

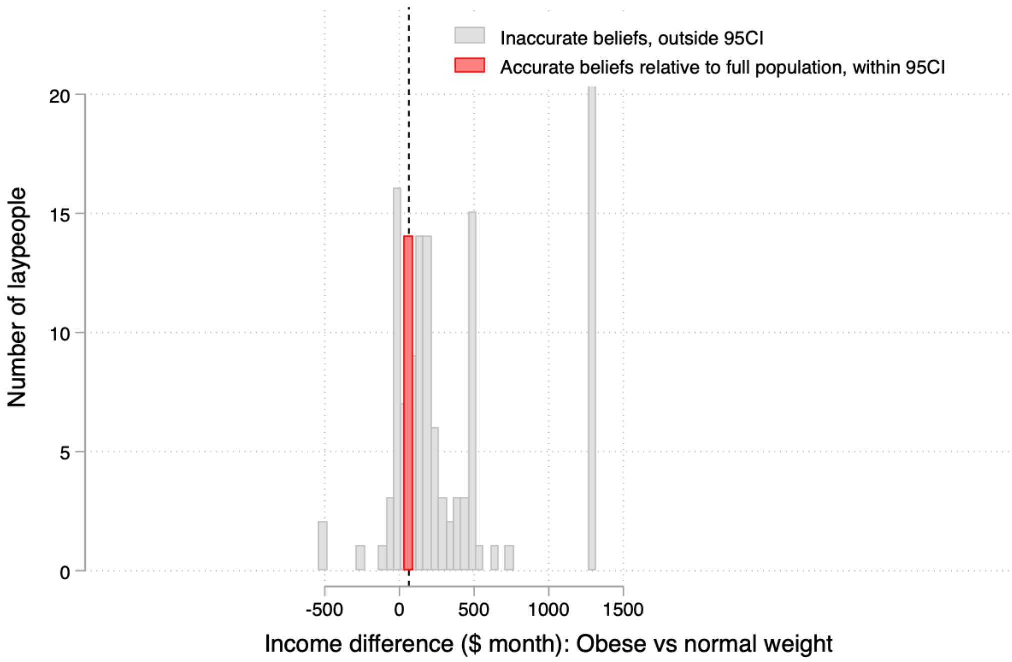
Figure 5: Perceived (Laypeople) vs. Actual (Loan Officers) Premium in Credit Markets



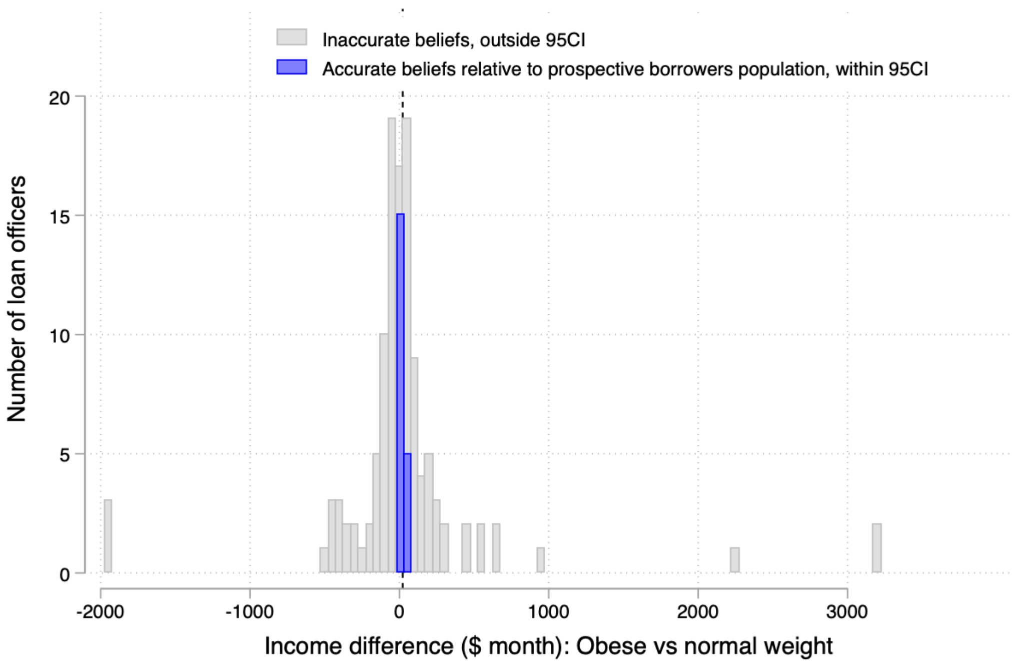
Note: The figure compares laypeople's perceived obesity premium with the actual obesity premium. The perceived premium comes from an incentivized experiment with 511 Kampala residents. Respondents are shown randomly selected borrower profiles and guess (1) loan officers' most frequent approval likelihood rating and (2) the share of loan officers asking to be referred to a borrower with similar characteristics (referral request). The perceived premium (dots) is the effect of obesity laypeople evaluations (conditional on layperson and profile fixed effects). The actual premium (squares) is the equivalent coefficient estimated on loan officers' evaluations in the credit experiment. Laypeople overestimate the obesity premium in approval likelihood and referral request by more than two and four times, respectively.

Figure 6: Beliefs Accuracy: Obesity as a Signal of Earnings

(a) Laypeople's Beliefs Distribution



(b) Loan Officers' Revealed Preference Beliefs Distribution



Note: The histograms plot beliefs about the monthly income difference between obese and non-obese individuals among laypeople (Panel A) and loan officers (Panel B). In Panel A respondents are 124 Kampala residents, quasi-randomly selected. Beliefs are elicited by asking them to guess the monthly income of a randomly selected normal weight and an obese Kampala resident using the Body Size Scale for African Populations and taking the difference. Answers are incentivized using the self-reported income of a randomly selected respondent in the beliefs experiment sample. In Panel B I estimate a revealed preference measure of loan officers' beliefs from their choices in the credit experiment. For 167 loan officers, I estimate beliefs on the average income difference between obese and non-obese borrowers and plot the distribution.

Tables

Table 1: Belief Experiment Sample: Summary Statistics

VARIABLES	(1) mean	(2) sd	(3) p50	(4) min	(5) max
District of Residence: 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
Gender: Male	1.50	0.50	1.00	1.00	2.00
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
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, USD Month	126.34	200.84	67.50	0.00	1,620.00
Household Income, USD Month	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 in the beliefs experiment. The sample is stratified by gender, age group, and SES (using ward of residence as a proxy). Information is self-reported except for weight and height, which are measured by the field officer at the end of the survey using a height board and a scale.

Table 2: Portrait 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: The table summarizes the main results from the beliefs experiment. All regressions include respondent and portrayed individual fixed effects. Standard errors are clustered at the respondent level, and outcome variables are standardized. For each portrait and outcome, respondents first rated the portrait according to their own beliefs and then according to their best guess of the most frequent answer of other respondents (incentivized second-order beliefs). Wealth is the pre-registered primary outcome. Health, beauty, self-control, ability, and life expectancy are pre-registered secondary outcomes. Trustworthiness was not preregistered and only elicited to 30% of the sample. *Obese* is a dummy for the weight-manipulated portrait being in shown in the fatter version. *Additional Wealth Signal* is a dummy taking a value of 1 when the respondent learns a second wealth signal on top of body mass, either place of residence (slum, poor type) or asset ownership (car or land title, rich type).

Table 3: Financial Institutions Sample: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	mean	sd	p50	min	max
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
Credit Institutions	0.02	0.13	0.00	0.00	1.00
Non-deposit-taking MFI	0.11	0.32	0.00	0.00	1.00
Microfinance Institution (MFI)	0.30	0.46	0.00	0.00	1.00
Licensed Moneylenders)	0.57	0.50	1.00	0.00	1.00
Number of Branches	6.06	18.14	1.00	0.00	160.00
Employees per Branch	6.76	6.63	4.00	0.00	50.00
Interest Rate: UGX 1 mln/ USD 300	11.78	7.43	10.00	1.50	40.00
UGX 5 mln/ USD 1.5k	11.73	7.60	10.00	1.50	40.00
UGX 7 mln/ USD 2k	11.20	7.31	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 in the Credit Experiment. The institution type relates to the Ugandan banking tiered structure as follows. Credit Institutions are tier 2, Non-Deposit-Taking Microfinance Institutions are tier 3, and Micro-Finance Institutions and Moneylenders are tier 4. The institutions sampled are representative of all tiers except for tier 1: Commercial Banks are not included in the sample because they lend, on average, larger amounts. The participating institutions are about 30% of the initial population of interest and 15% of all institutions active in Uganda in 2019. The population of interest are institutions that provide credit to the general population and offer standard loans (between 1 million to 7 million Ugandan shillings (USD 300–2000) and with a six-month term to maturity.

Table 4: Loan Officers Sample: Summary Statistics

VARIABLES	(1) mean	(2) sd	(3) p50	(4) min	(5) max
Age	31.27	7.22	30.00	16.00	69.00
Gender: Male	0.60	0.49	1.00	0.00	1.00
BMI	24.31	4.61	23.40	16.16	43.57
Education (Years)	15.38	1.79	16.00	6.00	18.00
Family Size	3.47	2.15	3.00	0.00	12.00
Salary: Under UGX 500k	0.32	0.47	0.00	0.00	1.00
UGX 500k to 1 mln	0.39	0.49	0.00	0.00	1.00
UGX 1 to 1.5 mln	0.22	0.42	0.00	0.00	1.00
UGX 1.5 to 2 mln	0.04	0.20	0.00	0.00	1.00
over UGX 2 mln	0.02	0.12	0.00	0.00	1.00
Role: Loan Officer	0.62	0.48	1.00	0.00	1.00
Owner	0.14	0.35	0.00	0.00	1.00
Manager	0.10	0.30	0.00	0.00	1.00
Performance pay or self-employed	0.90	0.30	1.00	0.00	1.00
Experience (Years)	2.67	2.78	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
provide product information	0.95	0.21	1.00	0.00	1.00
review personal information	0.95	0.21	1.00	0.00	1.00
review financial information	0.91	0.29	1.00	0.00	1.00
refer borrowers to next step	0.80	0.40	1.00	0.00	1.00
recruit new borrowers	0.75	0.43	1.00	0.00	1.00
approve borrowers	0.74	0.44	1.00	0.00	1.00
collect credit	0.68	0.47	1.00	0.00	1.00
verify financial information	0.82	0.38	1.00	0.00	1.00
Days/week to verify information	2.34	1.46	2.00	0.00	5.00
Matters for Loan: Age	2.13	0.67	2.00	1.00	3.00
Appearance	1.31	0.50	1.00	1.00	3.00
Collateral	2.92	0.29	3.00	1.00	3.00
Education	1.22	0.45	1.00	1.00	3.00
Gender	1.26	0.57	1.00	1.00	3.00
Guarantor	2.79	0.46	3.00	1.00	3.00
Income	2.92	0.33	3.00	1.00	3.00
Nationality	2.15	0.82	2.00	1.00	3.00
Occupation	2.76	0.49	3.00	1.00	3.00
Borrowers Met, Daily	8.03	8.56	5.00	1.00	60.00
Borrowers Approved, Daily	4.27	4.59	3.00	0.00	30.00

Notes: The table reports descriptive statistics for the 238 loan officers participating in the credit experiment. All information is self-reported, except BMI is noted by enumerator using the Body Size Scale for Assessing Body Weight Perception in African Populations (Cohen et al., 2013). An easy way to convert UGX into USD is to multiply by 0.0003.

Table 5: Borrower Profile Covariates

	Non-Obese		Obese		P-value of Difference		
	Mean	SD	Mean	SD	Diff	Standard	RI
Profile BMI value	23.34	1.93	37.30	3.40	13.958	0.00	0.00
Profile age	36.53	9.35	36.89	9.58	0.354	0.21	0.14
Profile sex (male)	0.50	0.50	0.50	0.50	0.003	0.54	0.83
Profile Collateral: Car	0.33	0.47	0.33	0.47	0.002	0.77	0.87
Land Title	0.50	0.50	0.50	0.50	-0.006	0.19	0.63
Motorcycle	0.17	0.37	0.17	0.38	0.004	0.39	0.65
Occupation: Agri Shop	0.10	0.30	0.10	0.30	0.003	0.57	0.72
Sells Clothes	0.19	0.39	0.21	0.41	0.020	0.06	0.04
Diary Project	0.10	0.30	0.10	0.30	-0.001	0.91	0.91
Hardware Store	0.10	0.30	0.10	0.31	0.007	0.12	0.34
Jewelry Shop	0.11	0.31	0.09	0.29	-0.016	0.03	0.03
Retail and Mobile Money	0.21	0.41	0.19	0.40	-0.012	0.05	0.22
Phone and Movies Shop	0.10	0.30	0.10	0.30	0.001	0.84	0.91
Poultry and Eggs	0.10	0.30	0.10	0.30	-0.001	0.79	0.87
Profile revenues UGX ml	5.91	4.81	5.83	4.77	-0.078	0.17	0.53
Profile profits UGX ml	1.69	1.37	1.67	1.36	-0.022	0.17	0.53
Profile order in arm	5.51	2.84	5.50	2.90	-0.010	0.72	0.91
Profile Loan Reason: Business	0.20	0.40	0.20	0.40	-0.006	0.33	0.54
Home improvement	0.24	0.42	0.23	0.42	-0.004	0.38	0.70
Purchase animal	0.17	0.37	0.17	0.38	0.004	0.39	0.65
Purchase asset	0.17	0.37	0.17	0.37	0.002	0.66	0.81
Purchase land	0.23	0.42	0.23	0.42	0.004	0.39	0.70
Loan Amount: UGX 1 mln	0.33	0.47	0.34	0.47	0.006	0.32	0.60
UGX 5 mln	0.34	0.47	0.33	0.47	-0.011	0.07	0.32
UGX 7 mln	0.33	0.47	0.33	0.47	0.005	0.45	0.67
Observations	6,645						

Notes: The Obese (Non-Obese) column indicates if a borrower's profile displayed the thinner or fatter weight-manipulated portrait. The P-value of Difference column reports the difference, the standard p-value, and the randomization inference p-value based on 5,000 replications. BMI 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 is averaged at the portrait level. All the profiles' information is cross-randomized, following the procedure described in Table H.3.

Table 6: Obesity Premium in Access to Credit

	(1) Approval Likelihood	(2) Financial Ability	(3) Credit-worthiness	(4) Referral Request
By Financial Information Treatments				
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	6,645	6,645	6,645	6,645
Pooled Financial Information Treatments				
Obese	0.110	0.123	0.093	0.045
	(0.019)	(0.021)	(0.022)	(0.019)
Observations	6,645	6,645	6,645	6,645

Notes: All regressions include borrower profile and loan officer fixed effects. Standard errors are clustered at the loan officer level. All outcomes are standardized and elicited in the order they are displayed in the table (from left to right). Approval Likelihood is the perceived likelihood of approving the application (1–5 scale). Creditworthiness is the perceived creditworthiness (i.e., likelihood of paying back) of the applicant (1–5 scale). Financial ability is the perceived ability of the applicant to put money to productive use (1–5 scale). Referral Request is a dummy taking a value of one when the loan officer chooses to meet with a similar applicant (real choice outcome). Obese is a dummy taking a value of one if the application included the high body mass version of the original picture. Self-Reported Financial Info is a dummy taking a value of one if the application was randomly assigned to include self-reported financial information when shown to a given loan officer.

Part

Appendix

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A Weight-Manipulated Portraits

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

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

On average, thinner portraits are perceived as normal weight, while fatter portraits as obese. To quantify the body mass variation across thinner and fatter portraits, I elicit the portraits' perceived Body-Mass Index (BMI) among 10 independent raters (Kampala residents).[60] To rate portrait's perceived BMI, raters compare each portrait to the figurative Body Size Scale for African Populations developed and validated in Cohen et al. (2015). The portraits' perceived BMI ranges from 20 to 44 points. Importantly, none of the thinner portraits is perceived to be underweight ($BMI < 18.5$), and all fatter portraits are perceived to be obese ($BMI \geq 30$).[61] Thus, my experimental average treatment effect is the effect of obesity relatively to normal weight —captured in the data by a dummy taking value 1 if the portrait is shown in the obese version.

[60]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 meters. While the BMI has flaws, for example it does not take into account muscle mass or bone density, it is still the most common body mass measure used by health institutions, including the World Health Organization.

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

B Beliefs Experiment

B.1 Respondents' Wards of Residence

The wards are selected at random from the list of all wards in the districts of Kampala, Mukono and Wakiso (Greater Kampala). The selection is stratified by quintiles of a poverty index at the ward level, which I use to proxy for socio-economic status for the respondents. I build this ward-level poverty-index from Ugandan Census data. From the universe of wards in Greater Kampala, I drop one industrial area, the two richest neighborhoods (Kololo and Muyenga), and the wards counting less than 2% of the 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). I define poverty-index quintiles and I randomly select 10 wards from each of the first, third and fifth quintile. The list of selected wards and their characteristics is in Appendix Table H.1.

C Credit Experiment

C.1 Outcomes' Wording

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

C.2 Hypothetical Borrower Profiles

Using information from loan officers focus groups and data from 187 real prospective borrowers in Kampala, I build 30 hypothetical profiles. To cross-randomize the information in the applications I use Python *numpy.random* and the *itertools.cycle* functions. Each profile includes a set of borrower characteristics and the borrower portrait, selected from the weight-manipulated portraits set (black race only). I stratify the information randomization by body mass, and as the signaling power of body mass might differ for men and women, by gender. The procedure is as follows. First, the hypothetical borrower body mass and gender are randomly assigned (male/female; thin/fat). Then:

- **Portrait:** Each portrait is randomly selected from the set of 30 black-race original portraits, conditional on gender.
- **Loan profile and reason for loan:** There are three different loan profiles: UGX 1 million ($ 250), UGX 5 million ($ 1,350), UGX 7 million ($ 2'000). Reason for the loan was either business or personal. All loan profiles have a 6-month term to maturity. Loans could be personal or for business. Business was left generic, while the reasons for personal loans included: home improvements, purchase of land, purchase of an animal and purchase of an asset (e.g., a fridge or car). Loan profile and reason for loan randomization is stratified by gender and body mass of the borrower.
- **Name, Passport ID, Nationality and Place of Residence:** Name and passport ID are included to increase realism, but are blurred. Nationality is always Ugandan, as most 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. All applications include a date of birth, where the year of birth is the actual year of birth of the portrayed individual, while month and day are randomly selected. This information was not randomized.
- **Occupation:** The information was randomized conditional on gender of the applicant. 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. The set of occupations was vetted in focus groups with loan officers. All the hypothetical loan applicants are self-employed because employees normally have a line of credit with their employer.

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

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

The financial information is displayed at the bottom of the loan profile, using the sentence: *"This applicant is self employed and runs a [occupation type] in Kampala. The applicant claims that the business is going well. Last month, the business revenues amounted to [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. "*

C.3 Implementation of Borrower Referrals

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

To implement the procedure I use R and my code mostly relies on *Tidymodels*.[62]

Introduction to the machine learning problem The problem of matching new borrowers with loan officers based on loan officer's preferences is a supervised machine learning algorithm problem. Supervised machine learning revolves around the problem of predicting out-of-sample y from in-sample x. One needs to predict loan officers' preferences for new borrowers (out-of-sample) based on the preferences they expressed on hypothetical borrowers in the credit experiment (in-sample). Since my measure of loan officers' preferences is the binary choice of requesting or not to meet with the hypothetical borrower, I train a supervised *classification* algorithm.

To implement this matching, in short, I train a set of competing classification models on the experimental data and select the optimal model to identify loan officer's preferences. Then, I apply it to the new database of real prospective borrowers to predict which borrowers which loan officers would be more likely to get a meeting with a given loan officer. 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 in Spring 2020. Depending on loan officers' stated choice, I refer the borrower either to the institution, to a specific loan officer.

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

Machine learning algorithms search automatically for the variables, and interactions among them, who best predict the outcome of interest. One must decide how to select, encode and transform the underlying variables before they are fed to the machine learning algorithm. I include all loan officers and firm characteristics recorded in the credit

[62] Code available upon request.

experiment. Concerning the borrower characteristics, I include all the characteristics in the profile except: 1) gender and body mass, because of ethical reasons 2) occupation, which was elicited as an open question to the new borrowers. Including the occupation information requires making some assumptions on how to code the self-reported occupations of the prospective borrowers, which does not seem worthwhile considering that algorithm performance are quite good even in the absence of occupation information. The preferences data includes:

- Loan officers: age, body mass, gender, education, self-reported financial knowledge, financial knowledge score, experience, role (dummies for manager or owner), employed/self-employed status, monthly income, family members, activities performed, perceived stress of the verification procedure, dummies for factors influencing loan 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.

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

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

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

The data on real prospective borrowers comes from a subsample of the Beliefs Experiment respondents. These are 187 individuals from the 511 respondents in the Beliefs Experiment which stated to be in need of a loan and agreed to be contacted with information on where to apply for a loan. The data includes: age, monthly income, collateral, requested loan amount, requested loan type, requested loan reason, place of residence, nationality.

Setup and Pre-Processing I split the preferences database in a training set and a test data set, stratifying over the outcome variable. This is because "Meeting Request" classes in the preferences database are unbalanced: 76% - class 1 (wants to meet); 24% class 0 (do not want to 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 the 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, borrower 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.

Training Process and Model Selection The training set is used to tune the hyper parameters 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 is be assessed on the test data. Before 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 resulted in the highest AUC in the first tuning step. Appendix Table H.14 shows the estimated models and their respective performance. 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, require more careful tuning and are prone to overfitting. Given the limited test data available, I chose to rely on the simpler Random Forest model. The preferred Random Forest model is run with the ranger engine, 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), uses numeric scores for all ordered categorical variables, and reduces the number of levels of variables by grouping infrequent categories into a new "Other" category. I fit the Random Forest model with optimal parameters a last time to the entire available data.

Matching and Referrals To match borrowers and lenders, I merge the borrowers data with the preferences data. Then, I apply the trained model to the merged database to predict a Meeting Request probability for each borrower-loan officers pair. The result of the classification exercise, the probability score, is a variable, between 0 and 1, indicating the probability that a given loan officer would want to meet that applicant. Finally, I select those matches 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.

C.4 Robustness Checks: No Evidence of Order Effects

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

At the same time, one may worry that lack of treatment randomization could bias the results, if evaluating an application has spillovers on future evaluations (e.g., if people get tired). To investigate whether this is a relevant concern, I test whether applications presented later to loan officers (within a given arm) are rated systematically differently. I generate a dummy variable which indicates whether a given application was displayed in the first half (1-5) or in the second half (6 -10) and test for the heterogeneity by order at baseline, and in the effect of body mass in a regression including both loan officer and information treatment fixed effects. Appendix Table H.4 summarizes the results: there is no evidence of order effects, and most notably, there is no significant interaction of order with body mass.

C.5 Robustness Checks: Randomization Inference

The credit experiment results are consistent, large and therefore unlikely to have occurred by chance. In this section, I demonstrate this with a simulation exercise following Athey and Imbens (2017) 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 officer's when they are combined together. For each outcome, I calculate the share of the 10,000 simulated treatment-control differences that is larger in absolute value than the difference observed in the actual random assignment discussed throughout the paper. This proportion represents the randomization-based p-value. The results are summarized in Figure G.8, where I plot the distribution of treatment effects from the 10,000 iterations for a selection of outcomes. The dashed vertical line in each graph plots the actual treatment effect. The analysis confirms that findings cannot be explained by random differences between the loan officers and applications including a portrait in its obese version.

D Perception of Obesity Benefits and Wealth-Signaling Value

D.1 Lay people sample

In Spring 2021 I ran two additional surveys, one phone survey with 75 respondents and one online survey with 49 respondents. These surveys were not pre-registered. Sample selection was random from a sample of Kampala residents which provided their phone numbers to IGREC and agreed to take part to phone and online surveys in the future. Respondents had to provide consent and received a small compensation for filling up the survey.

The main aim of the two surveys was to elicit incentivized first-order beliefs on the earnings distribution by body-mass. To analyze these data, I pool the online and samples. The summary statistics for the pooled 124 respondents are in Appendix Table H.12.

In the phone survey, I also elicited willingness to pay for nutritional advice and respondent's beliefs on reasons for weight gain in Kampala. Thus, the data plotted in Figure G.10 comes from the online subsample of this sample.

D.2 Estimation of Loan Officers Beliefs on Obesity Wealth Signaling Value

Theoretical framework I focus on loan officers' evaluation of a borrower profitability. When financial information is available, I assume that perceived profitability depends on demographics, obesity status, income, and an unobservable normally-distributed error component u_{ij}.[63]

Formally, consider a loan officer j who evaluates borrower i's repayment probability of borrower 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 to meet borrower i, $v_{ij} = 1$, if $\pi_{ij} > t$ where $t = 0$ for simplicity;

(A2) loan office j cannot observe borrower i income Y_i and form beliefs about Y_i based on BMI_i and X_i linearly.

(A3) π_{ij} depends on body mass (BMI_i), self-reported income ($\tilde{Y}_i$) and other observable non-financial characteristics (X_i);

(A4) α_i is linearly separable in the observable and unobservable characteristics, and $\tilde{Y}_i$ is a linear separable in Y_i.

Assumptions (1) is because loan officers have financial incentives to select borrowers who are profitable. Assumption (2) means that there is asymmetric information. Assumption 3 allows for discrimination by body mass. Assumption 4 simplifies the framework. Linear separability assumptions are supported by the data: obesity and other signals appear to be neither complements nor substitutes.

I define loan officer j expectations of borrower i profitability as:

$$\pi_{ij}(\alpha_i, Y_i; BMI_i; \mathbf{X_i}; R_i; t_i) = p_{ij}(\alpha_i, Y_i; BMI_i)R_i - t_i \tag{3}$$

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:

$$\begin{aligned} p_{ij} &= E_j(\alpha_i|\tilde{Y}_i, BMI_i, X_i) = E_j(\beta_i Y_i + \gamma_i BMI_i + \theta_i X_i + u_i|\tilde{Y}_i, BMI_i, X_i)) = \\ &= \int_k (\beta_i Y_i + \gamma_i BMI_i + \theta_i X_i + u_i|\tilde{Y}_i, BMI_i, X_i)) \cdot g_j(Y_{ik}|\tilde{Y}_i, BMI_i, X_i)), \end{aligned} \tag{4}$$

[63] This framework makes strong simplifying assumptions theoretically (the loan officers likely exploit other measures of wealth, on top of income). This is because in the experiment all the available financial information is cross-randomized, thus the simplification does not compromise the reliability of the estimation procedure.

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.

The framework describe above guides the estimation of loan officer's beliefs on the conditional income distribution by body mass. Under A1-A4, plus the simplifying assumption that loan officers care about obesity status rather than BMI, Equation (5) can be rewritten as:

$$p_{ij} = \delta_j \mathbb{1}(BMI_i \geq 30) + \gamma_j E(Y_i|\mathbb{1}(BMI_i \geq 30), \tilde{Y}_i, \mathbf{X}_i) + \mathbf{X}_i\beta_j + u_{ij}, \tag{5}$$

where $BMI_i \geq 30$ is a dummy measure of obesity, Y_i is true income (unobservable), $\tilde{Y}_i$ is self-reported income, $\mathbf{X}_i$ are other observables.

In this framework, positive body-mass discrimination, $\frac{dpi_{ij}}{dBMI_i} > 0$, can be decomposed as follows:

$$\alpha_j = \delta_j + \gamma_j \bigg(E_j(Y_i|BMI_i \geq 30, X_i) - E_j(Y_i|BMI_i < 30, X_i) \bigg) = \delta_j + \gamma_j \phi_j, \tag{6}$$

where δ_j is the direct effect of obesity on creditworthiness, γ_j, is the effect of perceived earnings on perceived creditworthiness and ϕ_j is j's estimate of the average difference in monthly income between obese and not obese borrowers. Another way to obtain this decomposition is using the omitted variable bias formula. This is because from the perspective of the experimenter loan officers' beliefs about borrower income are a latent variable.

Thus, the observed obesity premium can be decomposed into a direct effect and an indirect effect, mediated by loan officer beliefs the income distribution given body mass. This means that this framework produces a summary statistic for loan officer beliefs on the wealth signaling value of obesity: ϕ_j, loan officer's 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 whether loan officers hold accurate or inaccurate beliefs on the wealth-signaling value of obesity.

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

$$E_j(Y_i|BMI_i, \mathbf{X}_i, \tilde{Y}_i) = (1 - W_i)(\mathbb{1}(BMI_i \geq 30) + X_i) + W_i(\lambda\tilde{Y}_i)), \tag{7}$$

That is, when no income signal is available, loan officers form their beliefs about borrower income based on demographics, while when self-reported income is available, loan officers mainly rely on self-reported 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 but strong, because loan officers may rely on the self-reported information (λ) depending on body mass (loan officers perceive obese borrower self-reported income as more reliable). To respond to this concern, I focus the estimation on applications whose self-reported income is rated as above average reliable, and assume that loan officers fully trust the self-reported income provided ($\lambda = 1$).

Under this additional functional form assumption, I estimate α_j, δ_j and γ_j as follows. Plugging equation (7) into equation (5) I obtain:

$$\begin{cases} C_{ij} = \alpha_j \mathbb{1}(BMI_i \geq 30) + X_i\beta_j + u_{ij}, & \text{if } W = 0 \\ C_{ij} = \delta_j \mathbb{1}(BMI_i \geq 30) + \tilde{Y}_i\gamma_j + X_i\beta_j + v_{ij}, & \text{if } W = 1, \end{cases} \tag{8}$$

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 (6).

Strengths and Limitations The framework provides an intuitive revealed-preference measure of loan officers' beliefs on the wealth-signaling value of obesity among borrowers. This can be seen as more reliable, as opposed to directly eliciting beliefs on the conditional earnings distribution which may be more prone to experimenter demands. This analysis is also cost-effective, because it does not affect survey time. Finally, because of the residual estimation approach and thanks to the cross-randomization of obesity and earnings, the framework does not require to make any assumption on the existence of taste-based discrimination.

The analysis has three main limitations. First, it is data intensive because it requires to estimate one parameter for each loan officers, based on a maximum of 30 evaluations. To limit noise, I focus on loan officers which evaluate all 30 applications, about 60% of loan officers which are responsible for 75% of the evaluations. Second, there is measurement error in my measure of earnings because it income is self-reported and this may correlate with body mass. To reduce bias due to measurement error, I focus on profiles whose self-reported earnings information was rated above average reliable. The final sample includes 167 loan officers, for a total of 3,716 evaluations. Finally, the results rest on an assumption of linear separability between the effect of body mass and self-reported income. This assumption 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.

E External Validity

E.1 Beliefs Experiment Replication 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).

To investigate the external validity of these findings 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 H.11). Comparatively with the Ugandan sample, the Malawi one is substantially poorer and less educated. These results, combined with the extensive qualitative literature showing evidence of positive perception of fat bodies across developing countries and in the past in Europe or the USA, suggests that obesity is perceived as a signal of wealth in poor countries in general.

E.2 Beliefs Experiment Replication on Amazon MTurk (USA)

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

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

Respondents rate portraits in terms of 9 characteristics. 7 traits (wealth, beauty, health, life expectancy, self control, ability, trustworthiness) are the very same as in the original Beliefs Experiment. The remaining two allow me to measure obesity premium or penalty in credit markets: creditworthiness and willingness to lend money. All responses are on a scale from 1 to 4, as in the original experiment. The results are displayed in Appendix Figure G.9. Obese portraits are associated with worse ratings along all outcomes. The difference in ratings however is not statistically different from zero, except for beauty. The effects are also in smaller in magnitude as compared to the Ugandan experiment.

I interpret these results as suggestive that obesity is stigmatized in the US context, but it is not exploited as a wealth signal as in poor countries, likely because of lower asymmetric information problems.

F Sugar-Beverages Tax and Weight-Gain Monetary Benefits

Building on Allcott et al. (2019), henceforth ALT, I describe how accounting for the obesity benefits can affect the calibration of obesity prevention policies by focusing on the optimal sugar-beverages tax example.

ALT develops a theoretical framework for optimal sin taxes and exploits it to estimate the optimal soda tax in the US. The strength of this framework is that it delivers empirically implementable sufficient statistics formulas for the optimal commodity tax which can be estimated in a wide variety of empirical applications. To estimate how accounting for obesity benefits would affect the optimal sugar tax (beverages) in the Ugandan context, I proceed in two steps: (1) I exploit equation (9) 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:

$$t \approx \frac{\bar{\gamma}(1+\sigma) + e - \frac{p}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)] + A)}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)] + A)} \tag{9}$$

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

In Equation (9), $\bar{\gamma}$ 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.

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

Thus, the equation for the optimal tax for Uganda simplifies to:

$$t_{uga} \approx \frac{\bar{\gamma} - \frac{p}{\bar{s}\bar{\zeta}^c}(Cov[g(z); s(z)])}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}(Cov[g(z); s(z)])}. \tag{10}$$

How do obesity benefits enter the optimal sugar-beverages tax? My results show there exists two types of benefits. Social benefits: sugary beverages consumption increases people's BMI and higher BMI individuals are perceived as wealthier. Financial benefits: obese people have easier access to credit or other monetary returns.

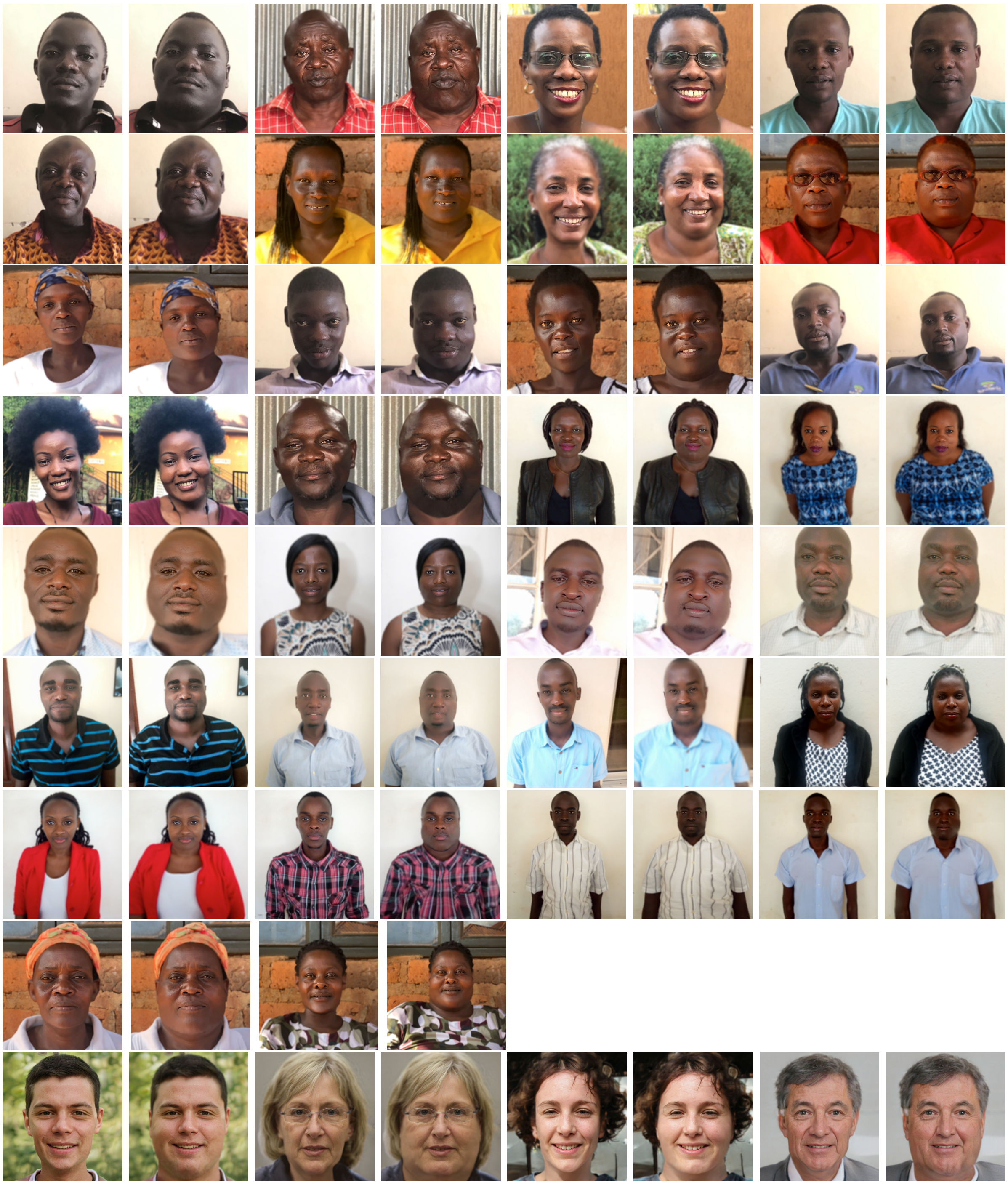
Social benefits enter the utility function and are captured in the elasticity of sugar-beverages consumption in Equation (10). As far as monetary benefits are concerned, this is equivalent to a subsidy in sugar-beverages consumption equal to the expected returns per unit consumed ($p' = p - E(b)$). The optimal sugar-beverages tax accounting for financial benefits is:

$$t^b_{uga} \approx \frac{\bar{\gamma} - \frac{(p-E(b))}{\bar{s}\bar{\zeta}^c}(Cov[g(z);s(z)])}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}(Cov[g(z);s(z)])}. \tag{11}$$

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

G Appendix Figures

Figure G.1: Weight-Manipulated Portraits



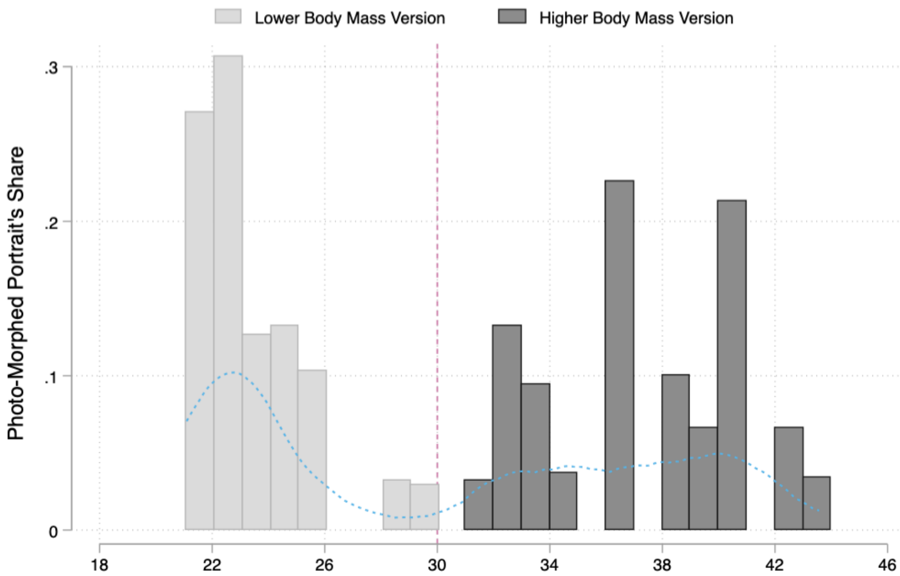
Note: The figure displays the 34 manipulated portraits exploited in the analysis. The original portraits (not displayed) have been manually manipulated by two photo-morphing expert to create the thinner and the fatter versions. The black-race originals portraits are of Kampala residents. The white-race original portraits are computer generated.

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

1.09	1.55	1.87	2.50	3.18	3.90	4.64	6.19	7.97	Endomorphy
9.93	10.00	10.76	18.91	19.74	24.89	30.83	36.53	36.96	Body Fat (%)
16.39	19.17	21.72	24.09	25.76	27.97	32.37	39.03	43.24	BMI

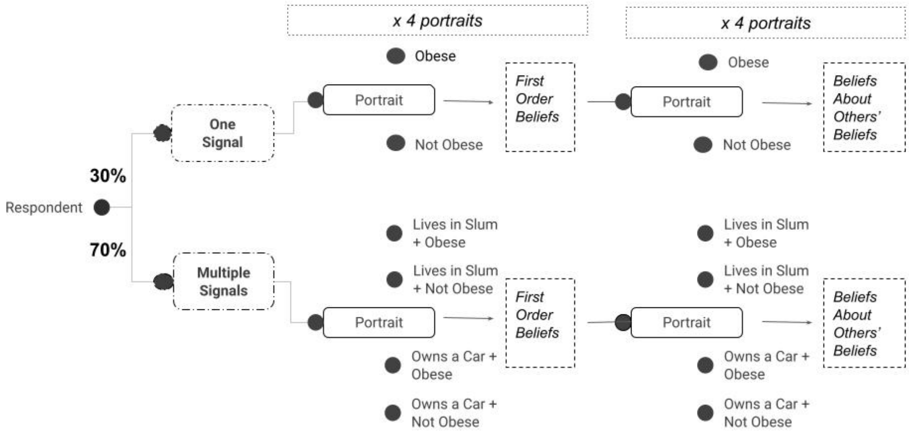
Note: 10 independent Ugandan raters match each weight-manipulated portrait using the Body Size Scale for African Populations developed and validated by Cohen et al. (2015). I averaged the ratings at the portrait level and compute the corresponding BMI using the conversion model.

Figure G.3: Perceived BMI of Weight-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 indicates the obesity cut-off, BMI = 30.

Figure G.4: Beliefs Experiment Design



Note: The graph summarizes the beliefs experiment design. Respondents rate four portraits each along with seven characteristics in random order. Portraits are selected from the 34 weight-manipulated portraits set and are randomly displayed in the obese or non-obese version. Body mass randomization is at the respondent portrait level. Respondents can be assigned either to the "One Signal" arm to see the portrait and learn only the individual's age. Respondents assigned to the "Multiple Signals" arm learn about asset ownership (car or land title, rich type) or place of residence (whether the person lives in a slum, poor type). The four portraits are first rated in terms of first-order beliefs (not incentivized) and later in terms of beliefs about others' beliefs (incentivized).

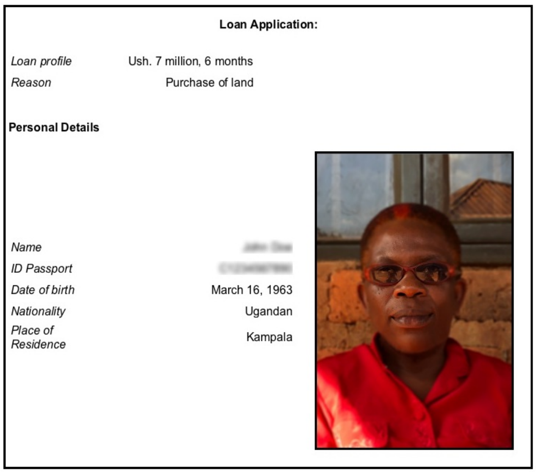
Figure G.5: Credit Experiment Design

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

Note: The figure outlines the credit experiment design. Loan officers evaluate 30 hypothetical borrowers profiles each. For each borrower, a loan officer is randomly assigned to see the portrait either in the non-obese or obese version. The borrower body mass information is cross-randomized with the amount of information provided. The first 10 applications display the borrower picture plus demographics and loan profile information: reason for loan, type of loan, and loan amount. The last 20 applications display self-reported revenues, profits, collateral, and occupation. Profit information was randomized to induce a high bad or low debt-to-income ratio (DTI).

Figure G.6: Example of Borrower Profile

(a) Non-Obese Borrower



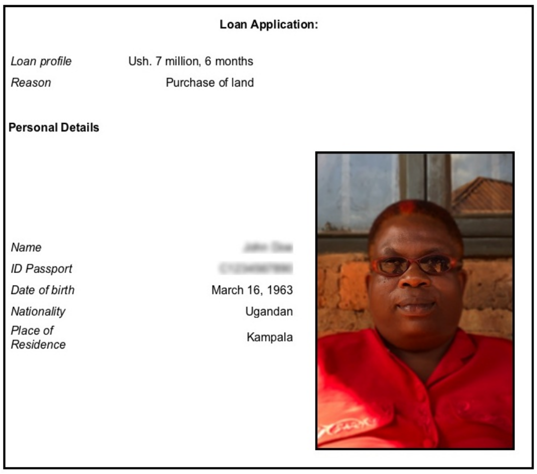
Loan Application:

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



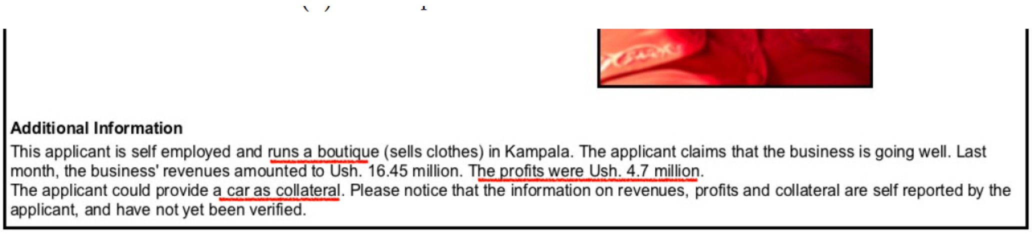
Loan Application:

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



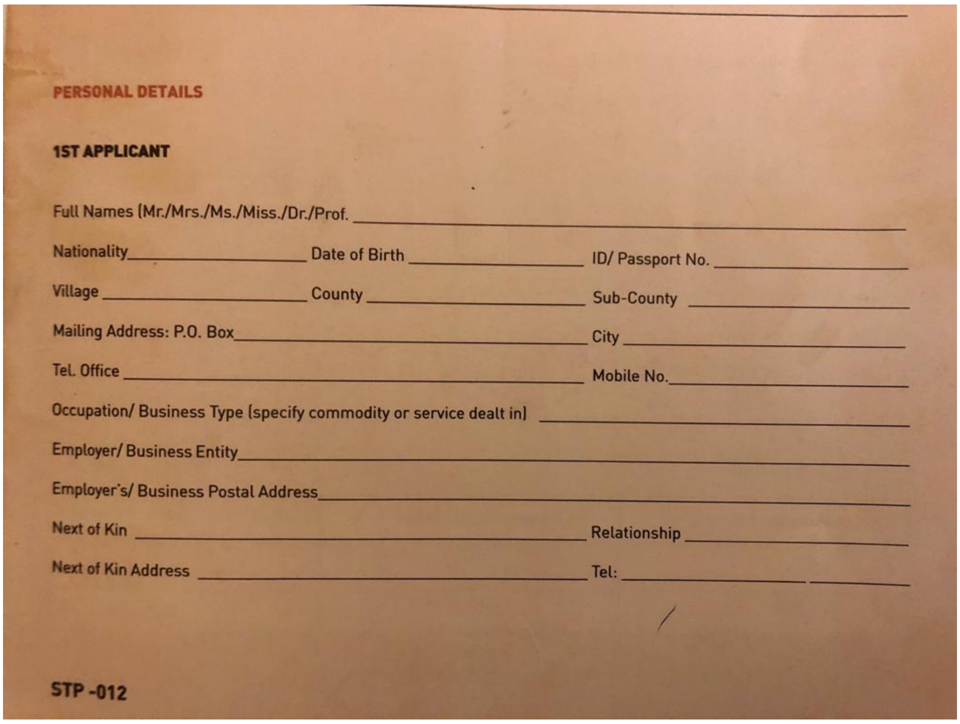
Additional Information

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 profiles. Panel (a) and (b) present the thinner and fatter version at baseline (no information). Panel (c) zooms on the same profile when including additional financial information. The displayed portrait and amount of information depends on treatment assignment (see Appendix Figure G.5).

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

Template A



PERSONAL DETAILS

1ST APPLICANT

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

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

Village ______ County ______ Sub-County ______

Mailing Address: P.O. Box ______ City ______

Tel. Office ______ Mobile No. ______

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

Employer/ Business Entity ______

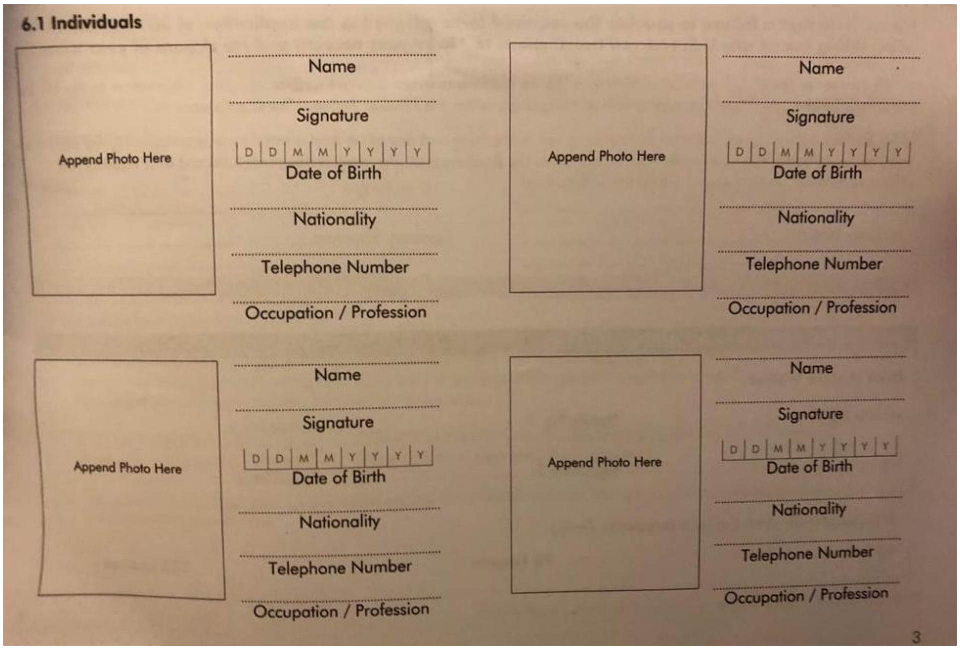
Employer's/ Business Postal Address ______

Next of Kin ______ Relationship ______

Next of Kin Address ______ Tel: ______

STP -012

Template B



6.1 Individuals

Append Photo Here

Name

Signature

D D M M Y Y Y Y

Date of Birth

Nationality

Telephone Number

Occupation / Profession

Append Photo Here

Name

Signature

D D M M Y Y Y Y

Date of Birth

Nationality

Telephone Number

Occupation / Profession

Append Photo Here

Name

Signature

D D M M Y Y Y Y

Date of Birth

Nationality

Telephone Number

Occupation / Profession

Append Photo Here

Name

Signature

D D M M Y Y Y Y

Date of Birth

Nationality

Telephone Number

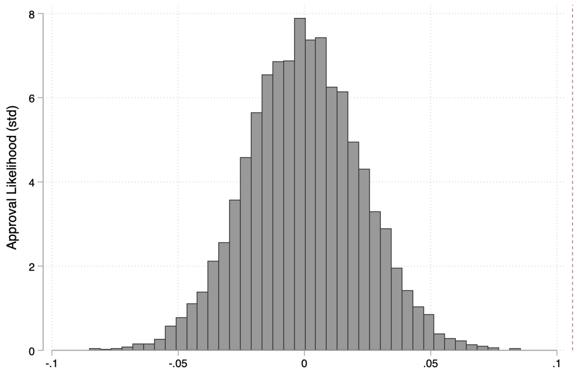
Occupation / Profession

3

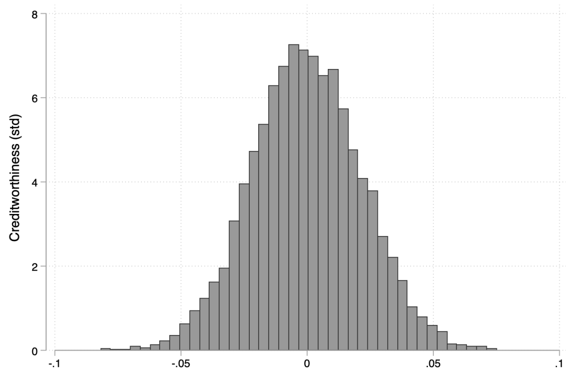
Note: Photos of financial applications from two major Ugandan commercial banks, used to design the hypothetical profiles. The applicant is always supposed to provide a picture, which in Template A is simply clipped to the application.

Figure G.8: Obesity Premium in Access to Credit: Randomization-Based Inference

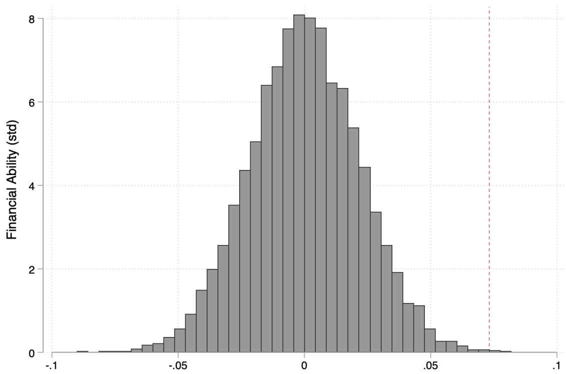
(a) Approval Likelihood (z)



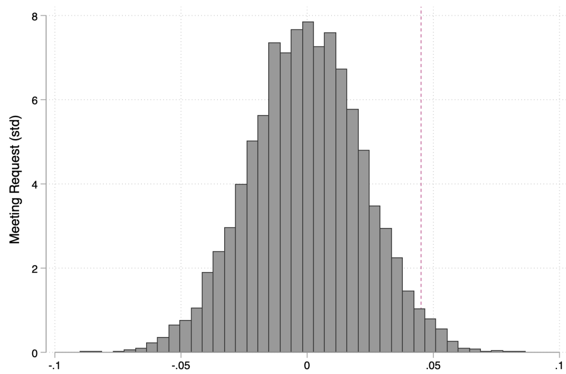
(b) Creditworthiness (z)



(c) Financial Ability (z)

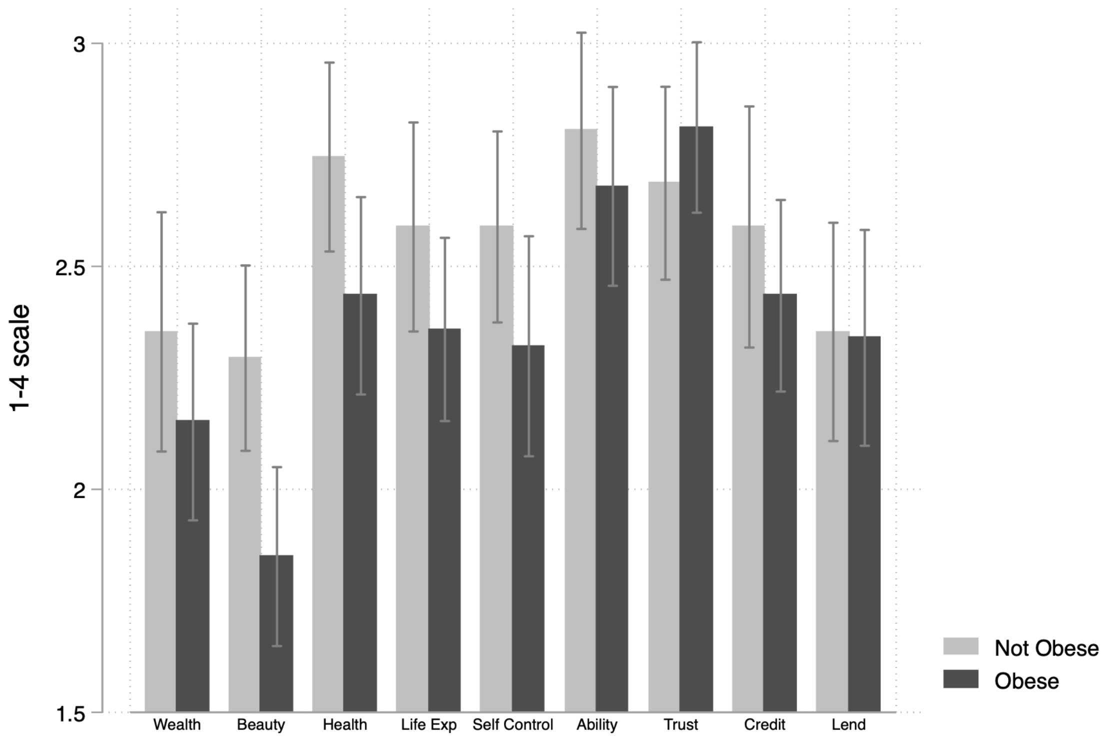


(d) Meeting Request (z)



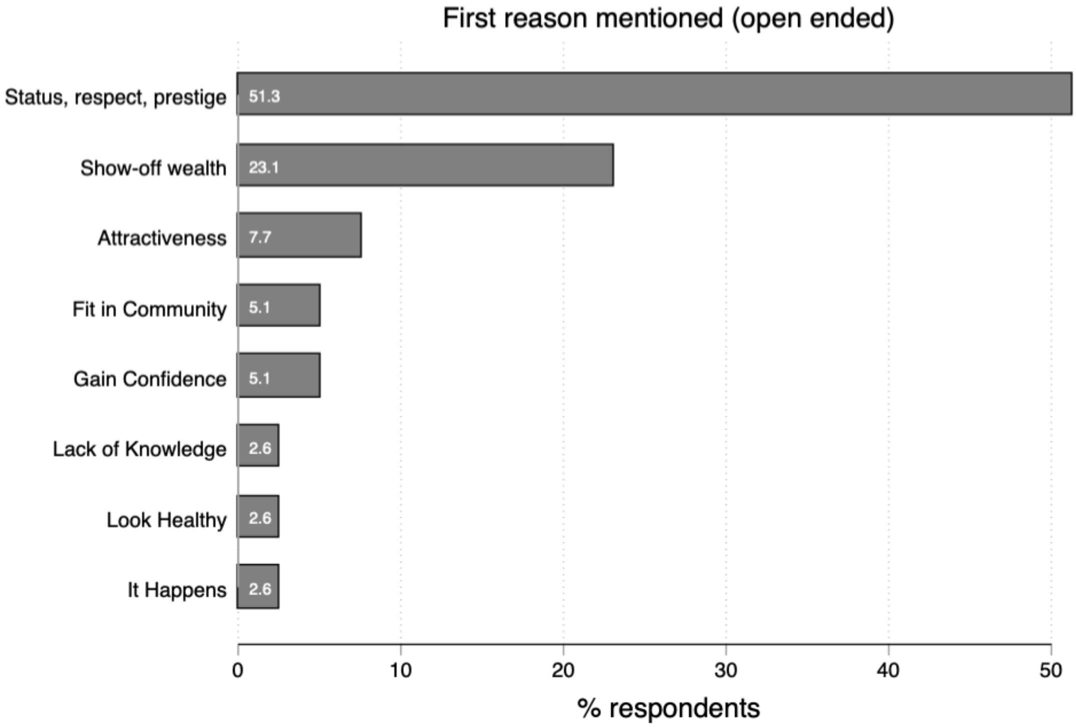
Note: Simulation exercise following Athey and Imbens (2017). Each simulated treatment effect comes from first randomly assigning profiles to "obese" treatment using the same randomization algorithm used for true assignment, then running a regression of the outcome on "obese" status, including controls for borrower profile and loan officers fixed effects. The red dashed bar is the actually estimated effect.

Figure G.9: Beliefs Experiment Replication: Amazon MTurk (USA)



Note: The figure plots first-order beliefs from a Beliefs Experiment on Amazon MTurk. The survey involves 37 respondents, for a total 111 portraits evaluations. This is a small sample but a similar sized pilot in Uganda had produced statistically significant results. Ratings are elicited on a 1-4 scale, using the same wording as in the original experiment. Portraits are randomly shown either in the obese or not obese version, stratified by race (black, white). The results show that people appear to engage in (negative) obesity discrimination. Second-order beliefs are aligned with first-order beliefs.

Figure G.10: Reasons for Weight Gain in Kampala



Note: The figure plots the distribution of reasons why Kampala residents think people want to gain weight. These categories based on the first answers to the open-ended question: "In Kampala, what are the most common reasons why normal weight people may want to (put effort to) gain weight? Please answer with your best guesses of the 3 main reasons. " Respondents are 49 Kampala residents which are randomly selected to be part of a phone survey. The open ended answers are tabulated in Appendix Table H.13. The sample is described in Appendix D.1.

H Appendix Tables

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

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

Notes: Wards visited to recruit respondents for the Beliefs Experiment. The selection procedure is described in Appendix B.1.

Table H.2: Obesity Wealth-Signaling Value: Heterogeneity by Portrait Person Gender, Age, and Asset Ownership

	(1) Wealth	(2) Wealth	(3) Wealth
Obese	0.600	0.548	0.546
	(0.088)	(0.230)	(0.112)
Male	0.070		
	(0.091)		
Obese × Male	0.042		
	(0.119)		
Age		0.011	
		(0.005)	
Obese × Age		0.002	
		(0.006)	
Owns Car/Land Title			0.867
			(0.134)
Obese × Owns Car/Land Title			-0.056
			(0.150)
Observations	1,699	1,699	1,023

Notes: The table summarizes the wealth-signaling value of obesity by gender, age, and asset ownership of the portrayed individuals. In column 3, the residual category is 'living in a slum' and portraits in the one-signal arm are excluded. All regressions include respondent and portrayed individual fixed effects. Standard errors are clustered at the respondent level. *Wealth* indicates standardized first-order beliefs on the portrayed person's wealth.

Table H.3: Hypothetical Borrower Profiles Content

Information	Randomization	Conditionality	Options
Body mass	Randomized		*high* *low*
Gender	Stratified by BM		*male* *female*
Picture	Stratified by BM	women men	*pic n1 to n15* *pic n16 to n30*
Loan Profile	Stratified by BM and gender		*Ush 1 million (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 summarizes the procedure to build hypothetical profiles. The content information comes from real prospective borrowers, and typical loan profiles from focus groups with loan officers.

Table H.4: Obesity Premium by Profiles' Rating Order

	(1) Approval Likelihood	(2) Financial Ability	(3) Credit-worthiness	(4) Meeting Request
Obese	0.095	0.103	0.076	0.037
	(0.032)	(0.034)	(0.032)	(0.029)
Second-Half	-0.005	-0.021	-0.023	-0.012
	(0.031)	(0.037)	(0.031)	(0.030)
Obese $\times$ Second-Half	0.032	0.045	0.037	0.013
	(0.053)	(0.053)	(0.045)	(0.047)
Observations	6,645	6,645	6,645	6,645

Notes: Regressions include loan-officer and information arm fixed effects. Standard-errors are clustered at the loan officer level. *Obese* is a dummy taking value one if 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 H.5: Robustness to Inattention: Effect of Profile Characteristics by Financial Information Provision

	(1) Approval Likelihood	(2) Approval Likelihood	(3) Approval Likelihood	(4) Approval Likelihood
Obese	0.199			
	(0.035)			
Self-Reported Financial Info	0.168	0.043	-0.027	-0.153
	(0.041)	(0.098)	(0.050)	(0.059)
Obese × Self-Reported Financial Info	-0.129			
	(0.039)			
Profile age		-0.035		
		(0.012)		
Self-Reported Financial Info × Profile 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				-0.027
				(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
	(0.066)	(0.448)	(0.068)	(0.062)
Observations	6,645	6,645	6,645	6,645

Notes: All regressions include borrower profile, and loan officer fixed effects. Standard errors are clustered at the loan officer level. The regressions' outcome is the Approval Likelihood, standardized. *Self-Reported Financial Info* is a dummy taking value one if the application was randomly assigned to include self-reported financial information. *Obese* is a dummy for the borrower profile being associate with a fatter weight-manipulated portrait. *Age* is a continuous variable indicating borrowers' age in years. *USh 5 million* or *USh 7 million* are dummies for loan amount. The residual category is *USh 1 million. Home improvements, purchase of land, of an asset, an animal* are dummies for the loan reason. The results show that financial information provision interacts differently with different information, rather than just reduce the importance of each characteristic for approval likelihood. This suggests that the reduction of obesity premium caused by financial information provision is not driven by inattention.

Table H.6: Obesity Premium by Timing of Financial Information Provision

	(1) Approval Likelihood	(2) Financial Ability	(3) Credit-worthiness	(4) Meeting Request
Obese	0.199	0.180	0.151	0.066
	(0.035)	(0.037)	(0.039)	(0.033)
Info Sequential	0.163	0.129	0.123	0.018
	(0.041)	(0.043)	(0.045)	(0.053)
Info Same Time	0.173	0.107	0.085	0.080
	(0.049)	(0.048)	(0.048)	(0.053)
Obese × Info Sequential	-0.116	-0.080	-0.084	-0.004
	(0.042)	(0.046)	(0.048)	(0.046)
Obese × Info Same Time	-0.143	-0.085	-0.084	-0.060
	(0.048)	(0.048)	(0.050)	(0.041)
Constant	-0.316	-0.325	-0.160	-0.156
	(0.065)	(0.060)	(0.066)	(0.069)
Observations	6,645	6,645	6,645	6,645

Notes: Regressions include borrower profile and loan officer fixed effects. Standard errors clustered at the loan officer level. The estimation focuses on profiles which displayed additional financial information. *Obese* is a dummy for the profile being associated with a fatter weight-manipulated portrait. *Info Same Time* is a dummy taking value one if the profile is immediately shown including financial information. The baseline category are profiles where picture and demographic information are not shown. 'Info sequential' indicates that baseline information is shown first, and then the financial information is provided. 'Info same time' indicates that all the information is provided at the same time. The effect of providing information does not systematically differ by timing of the information provision.

Table H.7: Perceived Reliability of Borrower Self-Reported Financial Information

	(1) Information reliability (1-5 scale)
Obese	0.047
	(0.018)
Constant	1.972
	(0.054)
Observations	4,438

Notes: The regression includes loan officer and borrower profile fixed effects. Standard errors are clustered at the loan officer level. The dependent variable is loan officers' reliability rating of the self-reported financial information. The outcome is only defined for loan profiles which included financial information. The scale is from 1 (not at all reliable) to 5 (extremely reliable). The results show that on average self-reported financial information is perceived as not very reliable, while obese borrowers' information is considered more reliable. This is consistent with a model of statistical discrimination because obese borrowers are on average richer and more likely to own collateral, as well as to have revenues and earnings which make applying for a loan reasonable.

Table H.8: Obesity Premium in Access to Credit: Men Rating Men

	(1) Approval Likelihood	(2) Financial Ability	(3) Credit-worthiness	(4) Referral Request
Obese	0.196	0.143	0.145	0.089
	(0.043)	(0.046)	(0.046)	(0.044)
Observations	1,977	1,977	1,977	1,977

Notes: Regressions include borrower profile fixed effects and loan officer fixed effects. Standard errors are clustered at the loan officer level. Sample restricted to male loan officers rating male borrowers profile. The results show that the obesity premium is as strong when restricting to same sex borrower/lender pairs (specifically, men rating men).

Table H.9: Obesity Premium Size by Loan Officer and Institution Characteristics

	Obesity Premium on Approval Probability			Obesity Premium on Referral Request		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Below Median	Above Median	Diff	Below Median	Above Median	Diff
Age	31.146	31.421	0.275	30.595	31.822	1.227
	(6.756)	(7.566)	(1.038)	(6.916)	(7.320)	(1.042)
Gender: Male	0.563	0.630	0.067	0.612	0.585	-0.026
	(0.498)	(0.485)	(0.064)	(0.490)	(0.495)	(0.064)
Family Size	3.474	3.445	-0.029	3.327	3.560	0.233
	(2.286)	(1.986)	(0.279)	(2.045)	(2.202)	(0.281)
Highest Education Level	4.613	4.748	0.134	4.680	4.681	0.002
	(0.940)	(0.805)	(0.113)	(0.795)	(0.936)	(0.115)
Experience (Years)	2.580	2.798	0.218	2.592	2.763	0.171
	(2.927)	(2.651)	(0.362)	(2.932)	(2.683)	(0.365)
Salary: Below USD 140	0.346	0.287	-0.059	0.360	0.285	-0.075
	(0.478)	(0.454)	(0.064)	(0.483)	(0.453)	(0.065)
Salary: USD 140 to 300	0.385	0.417	0.032	0.416	0.390	-0.025
	(0.489)	(0.495)	(0.068)	(0.496)	(0.490)	(0.069)
Salary: USD 300 to 420	0.192	0.250	0.058	0.146	0.276	0.130**
	(0.396)	(0.435)	(0.057)	(0.355)	(0.449)	(0.057)
Salary: USD 420 to 600	0.038	0.046	0.008	0.056	0.033	-0.024
	(0.193)	(0.211)	(0.028)	(0.232)	(0.178)	(0.028)
Salary: Over USD 600	0.038	0.000	-0.038**	0.022	0.016	-0.006
	(0.193)	(0.000)	(0.019)	(0.149)	(0.127)	(0.019)
BMI	24.651	24.098	-0.553	24.818	24.036	-0.782
	(4.456)	(4.785)	(0.599)	(4.713)	(4.539)	(0.604)
Self Employed	0.151	0.151	-0.000	0.165	0.141	-0.024
	(0.360)	(0.360)	(0.047)	(0.373)	(0.349)	(0.047)
Performance Pay	0.891	0.924	0.034	0.922	0.896	-0.026
	(0.313)	(0.266)	(0.038)	(0.269)	(0.306)	(0.038)
Borrowers Met, Daily	7.815	8.429	0.613	7.553	8.556	1.002
	(7.852)	(9.234)	(1.111)	(7.022)	(9.570)	(1.120)
Borrowers Approved, Daily	4.160	4.387	0.227	4.019	4.467	0.447
	(4.485)	(4.627)	(0.591)	(4.300)	(4.736)	(0.596)
Employees per Branch	6.500	7.517	1.017	6.755	7.201	0.447
	(6.788)	(7.860)	(0.956)	(7.001)	(7.618)	(0.967)
Interest Rate Charged	2.030	1.960	-0.071	2.025	1.974	-0.050
	(0.302)	(0.348)	(0.046)	(0.315)	(0.334)	(0.047)
Offers Business Loans	0.958	0.975	0.017	0.971	0.963	-0.008
	(0.201)	(0.157)	(0.023)	(0.169)	(0.190)	(0.024)
Financial Knowledge	1.252	1.227	-0.025	1.233	1.244	0.011
	(0.473)	(0.459)	(0.060)	(0.447)	(0.480)	(0.061)
Days/week verify information	2.143	2.495	0.352*	2.134	2.451	0.317
	(1.506)	(1.385)	(0.207)	(1.480)	(1.427)	(0.210)
Stress of verifying (1-5)	2.633	2.711	0.079	2.500	2.796	0.296**
	(1.049)	(0.968)	(0.145)	(0.984)	(1.010)	(0.145)
Observations	119	119	238	103	135	238

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. *Performance Pay* includes owners of the financial institution as a subcategory.

Table H.10: Obesity Premium by Borrower Type (Low versus High Debt-to-Income Ratio)

	(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 $\times$ 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: 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. 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 relatively low Debt to Income ratio (good type) versus a relatively high Debt to Income ratio. In my profiles, a relatively high DTI implies that a borrower is borderline approvable. The results show that the obesity premium is equally strong for relatively good vs relatively bad borrowers.

Table H.11: Main Results of Beliefs Experiment Replication in Malawi

	Credit	Dating	Authority	Wealth	Beauty
	(1)	(2)	(3)	(4)	(5)
Obese 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

Notes: Small scale experiment in rural Malawi to investigate external validity on a rural, poorer sample. Respondents are 241 women. In this setting, I exploited a paradigm comparable to the Beliefs Experiment. The main difference are a) women rate one picture each; b) the portraits are portrait drawings from Project Implicit. I use two pairs of fat/thin drawing portraits, 1 male and 1 female. The outcomes measured are second-order beliefs 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." The results show that also in rural Malawi obesity is perceived as a signal of wealth and ability to obtain credit, but it is not associated with beauty, or health.

Table H.12: Laypeople Sample (Belief Accuracy Analysis): Summary Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	mean	sd	p50	min	max
Gender: Female	0.61	0.49	1.00	0.00	1.00
Age: 18-24	0.25	0.43	0.00	0.00	1.00
Age: 25-34	0.49	0.50	0.00	0.00	1.00
Age: 35-44	0.18	0.38	0.00	0.00	1.00
Education: Primary School	0.02	0.13	0.00	0.00	1.00
Education: Secondary school	0.11	0.31	0.00	0.00	1.00
Education: Professional degree	0.65	0.48	1.00	0.00	1.00
Education: Some college	0.02	0.13	0.00	0.00	1.00
Education: 2-year degree	0.21	0.41	0.00	0.00	1.00
Personal Income: Average	0.28	0.45	0.00	0.00	1.00
Personal Income: Far Above Average	0.05	0.23	0.00	0.00	1.00
Personal Income: Far Below Average	0.11	0.31	0.00	0.00	1.00
Personal Income: Moderately Above Average	0.14	0.35	0.00	0.00	1.00
Personal Income: Moderately Below Average	0.07	0.26	0.00	0.00	1.00
Personal Income: Slightly Above Average	0.12	0.33	0.00	0.00	1.00
Personal Income: Slightly Below Average	0.23	0.42	0.00	0.00	1.00
Personal Income (Month, USD)	179.52	189.47	108.00	13.50	945.00

Notes: The table displays summary statistics for the 124 Kampala residents part of the belief accuracy survey. Because of Covid-19 the survey was run partly online ($N = 75$) and partly on the phone ($N = 49$).

Table H.13: Most Common Reason for Gaining and Losing Weight in Kampala (Open-Ended Question)

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 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."

Table H.14: Borrowers Referrals: Predictive 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