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

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Abstract

This paper provides experimental evidence on the instrumental value of status signals in poor countries. I study the wealth-signaling value and associated financial benefits of obesity, a sign of status in many low-resource settings. My empirical strategy leverages two experiments that randomly assign obesity using weight-manipulated portraits. I provide three main results. First, residents of Kampala (Uganda) perceive obesity as a reliable proxy for wealth, against other traits such as beauty or health. Second, obesity facilitates access to credit. In a real-stake field experiment with 124 Kampala credit institutions, professional loan officers screen borrowers based on body mass. In an access-to-credit index based on loan officers' evaluations, going from normal weight to obese has an effect equivalent to increasing a borrower's earnings by 60%. Third, the obesity premium is mainly a response to asymmetric information and body mass matters because it serves as a proxy for wealth. To test for the wealth-signaling hypothesis, I vary the degree of asymmetric information over wealth: increasing the amount of borrowers' financial information available to the lenders lowers the obesity premium by two-thirds. While these results could be consistent with standard screening mechanisms, on both sides of the credit markets, people appear to place too much weight on obesity as a wealth signal —possibly distorting allocation of and demand for credit. Finally, obesity benefits in access to credit are commonly known and significantly overestimated —thus inefficiently raising the perceived cost of healthy behaviors.

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1 Introduction

In developing countries, screening costs are inefficiently high (Banerjee and Duflo, 2007). When acquiring reliable wealth information is costly, economic transactions may rely on status signals as imperfect proxies for wealth. Despite a literature on conspicuous consumption and status goods, we have little understanding of the instrumental benefits of status signals in market settings, and of the asymmetric information channel. Do status signals affect economic outcomes in poor countries? If so, to which extent is it an efficient response to an information extraction problem?

In this paper, I address these questions by studying experimentally how *obesity* affects credit-market outcomes in Kampala, the capital of Uganda. In poor countries, credit markets are characterized by large information asymmetries[1] and obesity can signal a person's status. Historically, prosperity has always meant having enough money to buy or own food. Today, this is still true in much of the developing world, where, unlike in richer countries, fat bodies are often positively perceived, there exists a market for weight-gain programs and rich people are more likely to be obese.[2]

While cars, clothes or watches may equally serve as a proxy for wealth, focusing on obesity as a signal of status is relevant because obesity is a global health challenge.[3] While a large literature focuses on the health and economic costs of obesity, to my knowledge, there is no experimental evidence on its benefit. Moreover, obesity is not an obvious determinant of lending decisions. First, a person's body mass cannot be seized, thus there is no collateral value through which it may affect access to credit. Second, obesity may not necessarily be a reliable proxy for wealth: while a person's obesity status is indeed a strong predictor of socio-economic status in Kampala, body mass is co-determined by many factors and has a genetic component.[4]

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

[2]Figure K.1 plots obesity prevalence by income quintile and country income level. Qualitative studies providing evidence of positive perception of fat bodies include: Anderson-Fye (2004) in Belize; Bosire et al. (2020) in South Africa; Chigbu et al. (2019) in Nigeria; Ettarh et al. (2013) in Nairobi, Kenya; Holdsworth et al. (2004) in urban Senegal; Popenoe (2012) among Arabs in Niger; Sobo (1994) in Jamaica. *Leblouh* or *gavage* describe the traditional practice, widespread among rich families in Kenya, Mauritania, Morocco, Niger, South Africa, or Uganda, of paying for daughters' weight-gain programs.

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

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

My empirical strategy leverages two complementary experiments, one involving borrowers and one professional loan officers. My design cross-randomizes body mass, using weight-manipulated images, and the degree of asymmetric information in which decisions are taken, to test for the mechanism. I ask three questions: (i) Is obesity is perceived as a reliable wealth signal? (ii) Does obesity facilitate access to credit, because it serves as a proxy for wealth? (iii) Are market outcomes shaped by correct or incorrect beliefs about the obesity wealth signal and its benefits?[5]

I begin by showing that obesity is perceived as a signal of wealth in a survey experiment with Kampala residents. To avoid experimenter demands, I ask respondents to rate portraits —randomly presented either in the obese or normal-weight version — along several dimensions. Obesity causally increases portraits' perceived wealth ratings, but has no effect on beauty, health, life expectancy, self-control or ability. Obesity is a strong wealth signal: obese individuals are perceived as rich as lean people owning a car. Obesity is also a relevant signal, providing information on top of other signals. When portraits are accompanied by other (noisy) wealth signals, e.g. place of residence or car ownership, the effect of obesity on wealth ratings is reduced, but remains significant.

Having established that obesity is perceived as a strong and reliable wealth signal, I test for obesity benefits in access to credit using a real-stake field experiment involving professional loan officers. Leveraging a cooperation with the Uganda Microfinance Regulatory Authority (UMRA), I recruit 254 loan officers from 124 formal and semi-formal financial institutions licensed to provide credit in Kampala. The participating institutions make up about one-fourth of the initial population of interest.[6] On the borrowers' side, I recruit a pool of 180 Kampala residents in need of a loan and collect their demographics, their financial characteristics.

In the experiment, loan officers review hypothetical borrowers' profiles during work hours and select those loan applications they would like to discuss in person.[7] Incentives

Index is 'heritable' and related to genetic similarities among twins.

[5]Previous research exploited weight-manipulated portraits to test for obesity *stigma* in high-income countries, with a focus on the beauty channel (see Neumark (2018) for a review). To my understanding, these works compared obese/manipulated portraits with not-obese/not-manipulated ones. For example, Rooth (2009) investigates *negative* obesity hiring discrimination in Sweden using an audit study. I test for *positive* obesity discrimination in a low-resource setting and create a higher and a lower body-mass version of each portrait (within-portrait variation, conditional on manipulation).

[6]The population of interest are 476 formal and semi-formal financial institutions, active in the Greater Kampala Area and offering cash loans between USD 250 to USD 2'000 (UGX 1 m to UGX 7 m). These selection criteria excludes commercial banks, which normally lend higher amounts. Participation means allowing 1 to 3 of their loan officers to take a survey during work hours. The median employee is 4.

[7]In this setting, loan officers deal with borrowers in person. Therefore, a correspondance study as in Bertrand and Mullainathan (2004) is not feasible.

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

The design pinpoints the relationship between obesity, asymmetric information and access to credit by cross-randomizing borrowers' body mass and financial information in the hypothetical loan profiles. Along the obesity dimension, each profile is associated to (1) an obese or (2) a normal-weight borrower by including a manipulated portrait as the identifier (portraits are standard identifiers in financial documents in Uganda). Along the wealth information dimension, I exogenously vary the borrowers' wealth information included in the profiles, and evaluate three information environments: (1) no financial information, (2) positive financial information, or (3) negative financial information. The financial information is self-reported and includes occupation, collateral and earnings. In total, loan officers make 6,445 evaluations and in 4,419 times out of 6,445 the borrower profile includes financial information.

My results show that loan officers screen borrowers based on body mass and in turn, obese borrowers are granted easier access to credit. When a given application includes a borrower's portrait in its obese version (vs. the normal weight), loan officers perceive the borrower as more creditworthy and financially able, and declare themselves more likely to approve the loan application. Finally, loan officers are also more likely to request the referral of obese borrowers.[9] These effects are large —equivalent to a 60% increase in a borrower's monthly income —but aligned with loan officers' explicit beliefs on returns to obesity in access to credit.[10]

Asymmetric information drives obesity benefits: providing loan officers' with borrowers' self-reported financial information reduces the premium by two-thirds (a result significant at the 5% level). Unresolved asymmetric information probably explains the residual obesity premium. Likely the unresolved asymmetric information stems from the

[8]My application differs from Kessler et al. (2019) on two aspects. First, the setting and the focus. To my knowledge, mine is the first application which (i) looks at credit markets, (ii) in the context of a low-resource setting, and (iii) tests for body-mass discrimination. Second, the design differs: I allow respondents to ask for referrals (that is, I include a real choice outcome) and I test for the driver of discrimination, asymmetric information.

[9]Given the incentive structure, the latter is a real-choice outcome.

[10]Improved access to credit is not confounded by the interest rate charged. Interestingly, I find that loan officers do not resort to screening using interest rate.

self-reported nature of the information. In fact, loan officers rate self-reported wealth information as not very reliable. In principle, taste-based discrimination could also explain the residual effect of obesity —e.g. a beauty premium as in Mobius and Rosenblat (2006). However, the results of the first experiment, where obese portraits were not perceived differently along any outcome except wealth, suggest this is not the case. Moreover, the obesity premium persists within same-sex loan officer/borrower pairs and is not driven by homophily. I interpret these results as consistent with statistical discrimination.

The two experiments are similar in structure but have different strengths. The credit experiment tests for financial benefits - with professional loan officers facing incentives as close as possible to real-life screening decisions- and tests for the asymmetric information channel. The beliefs experiment looks at the general population and measures a broad set of beliefs, suggesting implications beyond credit markets and contributing to exclude alternative narratives. Exploiting manipulated portraits avoids ethical concerns associated with randomly assigning calories consumption; the Incentivized Resume Rating allows me to reach a population of experts dealing with borrowers in person. These advantages come with a main limitation: by definition, weight-manipulated portraits imply that loan profiles are hypothetical. This makes it more challenging to test for biased beliefs, as I cannot test for heterogenous loan performance by body mass;[11] or to explore borrowers' responses. In a statistical discrimination framework, however, the results' implications crucially rest on people's accurate or inaccurate perception of the signal and the benefits. In the last part of the paper, I combine a simple model, additional tests, and experimental variation to further explore this aspect.

I begin by investigating whether people hold accurate beliefs on obesity benefits in credit markets. I replicate the credit experiment with the general population asking respondents to guess loan officers' evaluations of the hypothetical loan profiles (incentivized second order beliefs). I find evidence of biased beliefs: lay people are aware but significantly overestimate obesity premium in access to credit. Then, I move on to investigating whether people hold accurate beliefs on obesity as a proxy of earnings. On the borrowers' side, I elicit laypeople's incentivized beliefs on the earnings distribution by body mass in Kampala. On the loan officers side, I estimate a revealed-preferences measure of their beliefs. My starting point is that obesity premium can be decomposed into a direct —i.e., taste-based discrimination (Becker, 1956) —and an indirect component —i.e., statistical discrimination (Arrow et al., 1973; Phelps, 1972), based on loan officers' beliefs of the earnings distribution by body mass. Exploiting the experimental

[11]Because of the limited data the financial institutions collect, I cannot follow up on the matches.

cross-randomization of body mass and earnings, I infer loan officers' beliefs about the average earnings difference between obese and normal-weight borrowers and compare the distribution with the population value.[12] As a benchmark, I collect complementary survey data to estimate the conditional earnings distribution by body mass in Kampala. In Kampala, obese people earn around USD 80/month more than normal weight people. According to my data, both laypeople and loan officers similarly overestimate the statistic by a factor of 5.[13] In sum, the beliefs results show that on both sides of the credit markets, people place too much weight on obesity as a signal of wealth, and that, on top of this, borrowers overestimate returns to obesity in access to credit.

The evidence of obesity benefits and signal overestimation suggests that screening based on body mass is not necessarily efficient for credit markets and has relevant implications for health policy. In terms of credit allocation, both dispersion and overestimation may lead to distortions relative to a full wealth information framework. In particular, 1) demand for credit may be too low among poor people and 2) the credit allocation may favor obese borrowers too much.[14] In terms of health consequences, the results suggests an inefficient trade-off between weight gain health costs and financial benefits and more generally, sizable incentives to gain weight in poor countries. In fact, a preliminary information-provision pilot suggests that informing about benefits overestimation can increase willingness to pay for nutritional advice. Moreover, obesity benefits can directly affect obesity prevention policies, such as sugar or fat taxes. Building on Allcott et al. (2019), I show that accounting for obesity monetary benefits reduces the optimal sugar tax when soda consumption is not regressive.

This paper makes three contributions. First, it provides field-experimental evidence on the instrumental benefits of status signals relevant financial transactions in a low-resource setting. As noted in (Bursztyn and Jensen, 2017), the discussion on the hedonistic or instrumental nature of social concern is open. To my knowledge, the experimental evidence on tangible rewards generated by social signals is limited to social interactions (Bursztyn et al., 2020; Nelissen and Meijers, 2011). Most field experiments testing for

[12] My approach is conceptually close but in practice distinct to Bohren et al. (2019). They propose either (i) eliciting agents beliefs, implying a large increase in survey time, or (ii) providing information about group characteristics. Based on discussions with partner micro-finance institutions, collecting statistics on loan performance by body mass appeared practically nonviable.

[13] These results are consistent with a model of representativeness stereotyping (Bordalo et al., 2016) where obesity is a *representative* trait of rich people in Uganda, but also maybe in line with people having inaccurate reference population.

[14] Any conclusive statement on the effects of body mass screening on credit market efficiency hinges on the distribution of returns to capital by borrowers' body mass. To my knowledge there are no studies focusing on the heterogeneity in returns to capital by body mass.

social image concerns do not investigate the benefits reaped from signaling (Bursztyn et al., 2017b, 2019; Chandrasekhar et al., 2018; DellaVigna et al., 2016; Karing, 2018; Perez-Truglia and Cruces, 2017). A closely related paper is Bursztyn et al. (2017a), which provides experimental evidence of demand for status by looking at demand for platinum credit cards. My results on awareness of status signals' benefits suggests that financial returns may be driving demand for status, and explain the puzzling evidence on large expenditures in celebrations among the poor (Banerjee and Duflo, 2007; Bloch et al., 2004; Rao, 2001).[15] If benefits are overestimated, as my results suggest, investing in status may lead to welfare losses. Second, the paper sheds light on the driver of status signals' benefits —asymmetric information. To my knowledge, this is the first paper to randomize borrowers' financial information and test how the degree of asymmetric information affects professional lending decisions. [16] I identify a mechanism related but distinct from Fisman et al. (2017), as my design allows me to reject pure trust or homophily. The paper also relates to Cole et al. (2015) examining the role of loan officers effort and risk assessment in lending decisions (verifying borrowers' information is effortful) and Giné et al. (2012) studying the consequences of improving verification technologies in credit markets in Malawi. Finally, the paper links to a literature on bias in consumer lending (Agier and Szafarz, 2010; Berkovec et al., 1994; Corsi and De Angelis, 2017; Dobbie et al., 2018; Duarte et al., 2012; Labie et al., 2015; Pope and Sydnor, 2011; Ravina et al., 2008), and on agents' cognitive biases in processing non-quantitative information (Campbell et al., 2019; Cyert et al., 1963). Third, the paper provides the first piece of causal evidence on the socio-economic benefits of obesity in poor countries, adding to our understanding of obesity.[17]

The paper is structured as follows. Section 2 describes the obesity randomization and beliefs experiment. Section 3 describes the credit experiment. In Section 4, I test for loan officers' beliefs accuracy. In Section 5, I present experimental evidence obesity benefits awareness and discuss health implications. Section 6 discusses external validity, policy implications and concludes.

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

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

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

2 Beliefs Experiment

In this section, I describe an experiment showing that obesity is perceived as a strong and reliable signal of wealth in Kampala, Uganda. I begin by describing how I randomize body mass using manipulated portraits. Then, I describe sample selection, beliefs experiment design and results.

2.1 Identifying the Ceteris-Paribus Effect of Obesity

Identifying the causal effect of obesity is challenging. Observational analysis are problematic because body mass realizations are endogenous to individuals' preferences and constraints.[18] Experimentally testing for the effect of body mass is also complex because randomizing body mass is an experimental setting poses both feasibility and ethical constraints. In this paper, I circumvent these problems by randomly assign body mass using manipulated pictures.

I exploit thin/fat manipulated portraits of real Kampala residents (within-portrait). To build the manipulated pictures, I cooperate with two photographers. I begin by collecting a set of 30 original portraits of Kampala residents with Ugandan nationality. The 30 individuals are recruited via focus groups (previous consent), and are 15 women and 15 men. Their characteristics vary according to body mass, age, ethnicity, religion, occupation and income. Notice that the heterogeneity in characteristics matters for external validity reasons, but do not matter for internal validity because of the within-portrait obesity randomization.[19] To the set of 30 Kampala residents pictures (black race), I add 4 white race computer generated portraits [20] The final set is composed of 68 manipulated portraits (see: Fig. K.3). The original portraits are discarded and never shown to the respondents, which are instead randomly assigned to see either the thinner or the fatter version. Comparing across manipulated portraits allows me to identify the effect of *changes* in body mass, ceteris paribus.

One may worry that obese portraits may be perceived as something rare, or un-

[18] In Uganda and in Kampala the correlation between obesity and wealth is positive (see Appendix Fig. 1). Accordingly, obesity and overweight appear to be socially valorized (Ngaruiya et al., 2017).

[19] In Uganda, obesity and age have a hump-shaped correlation (Uganda DHS 2016). Thus, since manipulated portraits may differ by perceived age, the portraits are always presented to the respondents paired with the correct age information.

[20] An algorithm trained on thousands of pictures of human faces can build new faces from scratch. For an example, see: https://thispersondoesnotexist.com. For the black-race portraits, I resort to real individuals because I try to make the assessment as realistic as possible. For white-race portraits, I prefer to use fictitious portraits to abstract from place of residence.

common. For example, if obesity rates in Kampala were extremely low. This is not the case. Uganda, is a typical example of a developing country where obesity rates are rising fast. Kampala, the capital city, has the highest rates in the country. According to the Uganda Demographic and Health Survey (2016), the share of overweight and obese women ($BMI > 25$) in Kampala was 41%, against a 5.3% underweight ($BMI < 18.5$). For men, the share of overweight and obese was nearly 22%, against a 4.4% underweight.

To assign a meaningful interpretation to the body mass variation across portraits, I ask a set of Ugandan raters to assign to each picture its corresponding Body-Mass Index (BMI) value using the Body Size Scale for Assessing Body Weight Perception in African Populations (Cohen et al., 2015). Averaging the ratings at the portrait level, I link each portrait to a BMI value using the correspondence table (Fig. K.4). Figure K.5 plots the manipulated pictures BMI distribution. The average BMI of the higher body mass portraits is 37 (class II obesity), while for the lower body mass versions is 23 (normal weight). Thus, by randomly assigning the manipulated portraits, I can identify the effect of obesity relatively to normal weight. The fact that the average BMI of the lower body mass portraits is normal weight is reassuring in that results are unlikely to be driven by unnaturally thin portraits.

2.2 Sample Selection

Respondents are Kampala residents. The area of residence includes the districts of Kampala, Mukono and Wakiso, which build for the largest population share of the Greater Kampala Area. To provide variation in socio-economic status among respondents, I exploit wards of residence, the smallest Ugandan census unit. I classify the wards according to a Poverty Index I build from the Ugandan Census Data, then I stratify the sample according to ward of residence by selecting wards within the first, third and fifth quintile of the Poverty Index (I describe the stratification process and the index in detail in Appendix A). Field officers walked around each selected ward and enrolled respondents until the required number was reached. Within each ward, the sample was stratified by gender and age group. To qualify for study participation, individuals needed to provide written consent. Respondents are compensated with a small fee (USD 1) for their time. At the end of the survey, field officers measured the height and weight of each respondent, and communicated the measurements. Many respondents choose to participate in the study precisely to receive such measurements.[21]

[21] The survey was implemented in cooperation with IGREC Uganda. The survey was described as part of a study in partnership with the University of Zurich focusing on how appearance affects individuals'

The final sample, which I refer to as the *laypeople* sample, includes 511 respondents. The characteristics are summarized in Table 1. The sample mean monthly personal income (self-reported) is broadly aligned, but slightly larger than corresponding Ugandan census value for Kampala because I oversample wealthier neighborhoods.[22] The sample median age (35 years old) is higher than the Ugandan median age (15.9 years old) because I select only people aged 20+. Respondents, which are not stratified based on body mass, are average overweight (BMI 25.66). This data point is aligned with the data from the Uganda DHS 2016.

2.3 Design and Outcomes

In what follows I describe outcomes and design of the Beliefs Experiment. I exploit a survey experiment to test whether obesity is perceived as a reliable wealth signal, and how the obesity signal compares and interacts with other wealth signals.

Respondents are shown 4 portraits and have to rate them in terms of wealth (pre-registered primary outcome) and beauty, health, longevity, self-control, and ability to get things done (pre-registered secondary outcomes). Having respondents rate multiple portraits improves power and allows to have respondent fixed effects.

I exploit a 2x3 design, as outlined in Fig. K.6. Along the first dimension, I randomize body mass by showing each portrait either in its *obese* or its *not obese* version. This approach reduces potential experimenter demands by never actively referring to body mass, and allows me to identify the causal effect of obesity on ratings. Along the second dimension, respondents either learn the portrayed individual's age only (*no signals* arm), or learn the age and receive an additional wealth signal (*wealth signals* arm). The signal type (wealthy or poor) is randomized within subject: for each portrait the respondent learns either that the person owns a car (wealthy type) or that the person lives in a slum (poor type). The portraits are introduced using the sentence: *"Imagine you just met this person for the first time in Kampala..."*. Each portrait is rated twice: the first time, according to the respondent's own beliefs (first-order beliefs); the second time, guessing other respondents' beliefs (second-order beliefs).[23]

perception in Uganda. After the beliefs experiment, the survey included a credit section (described in Section 5), a nutritional knowledge survey and demographic section.

[22] Oversampling wealthier neighborhoods allowed me test whether obesity benefits are only perceived by relatively poor, lower educated individuals.

[23] 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)."*

First-order beliefs, the main outcome of interest, cannot be incentivized. Second-order beliefs are incentivized with the most frequent answer of other respondents. Comparing first-order beliefs and second-order beliefs is interesting for two reasons. First, it helps to understand whether that the information structure is compatible with signaling; second, respondents may be more truthful in the second-order beliefs either because of the monetary incentives, or because of any stigma associated with certain ratings patterns.

2.4 Results

The average ratings by obesity and wealth signal treatment are displayed in Fig. 2 and K.8. The main statistics of interest is the difference in the wealth rating between *obese* and *not obese* portraits. Overall the results show that obese portraits are perceived as wealthier.

Table 2 presents the equivalent regression results, including respondent and portrayed individual fixed effects.[24] I start by looking at first-order beliefs. Obese portraits are systematically rated as wealthier as compared to their normal weight counterpart (0.70 s.d). Yet, obese individuals are not perceived neither more beautiful nor healthier; they do not have a different perceived life expectancy or self-control, nor are better at getting things done. The second-order beliefs are broadly consistent with the first-order beliefs: the effect of obesity on wealth in the second order beliefs is comparable with the first-order beliefs' one (0.73 s.d.). Although respondents expect small effects of obesity on secondary outcomes, the effect on wealth beliefs is more than twice as large and statistically different. In sum, according to both measures, respondents systematically and primarily associate obesity with wealth.

A natural question to ask is how does the wealth signaling power of obesity compare with other signals. To address this question, I exploit the wealth signals variation across treatment arms. Naturally, providing more wealth signals, either positive (*car ownership*) or negative (*slum residence*), reduces the weight placed on the obesity signal by around 30% (significant at 10%). Table 2 shows that the interaction coefficient is negative and statistically significant. Thus, the results suggest that obesity provides additional information beyond the other (noisy) signals of wealth. Finally, I benchmark the wealth signaling power of obesity against car ownership.[25] I exploit the

Survey tools are in Appendix J.

[24]The details of the regressions analysis are presented in Appendix A.

[25]In Uganda cars are relatively expensive and uncommon: according to the WHO there are 40 reg-

cross-randomization of negative and positive wealth signals for respondents within the "wealth signal" treatment. *obese* portraits assigned to the "lives in slum" signal are rated on average as wealthy as *lean* portraits assigned to the "car ownership" signal (Fig. 2, Panel A).[26]

2.5 Discussion

The beliefs experiment provides shows that obesity is perceived as a strong and reliable wealth signal in Kampala. The obesity signal is general and salient (without any experimenter prompt, respondents associate obesity with wealth); there seems to be no stigma attached to exploiting obesity as a wealth signal (first and second-order beliefs are aligned); the obesity signal is strong and reliable, and provides additional information relative to other information (car ownership, residence); obesity is not associated to other characteristics rather than wealth. The results suggest that people routinely place substantial weight on obesity when they need to build their expectations on others' wealth. These results have some limitations. The experiment measures the beliefs of the general population. Professionals may be wary of exploiting informal technologies and may behave differently in economic interactions. Thus, it is not obvious that the beliefs updating process translates into economic benefits. In the next section, I move to investigating an obesity premium in access to credit working with a population of experts (loan officers) and test explicitly for the asymmetric information channel.

3 Credit Experiment

In this section, I exploit a real stakes field experiment to test whether obesity leads to easier access to credit in Kampala and whether the obesity premium is driven by asymmetric information.

3.1 Credit Markets in Kampala, Uganda

The Ugandan credit and banking system is characterized by a challenging informational framework. For example, only 20% of Ugandan land was registered in 2017 and although Uganda developed its credit reporting system in recent years, the majority of consumers

istered motor vehicles per 1'000 inhabitants. In the US there are 838 *cars* per 1'000 inhabitants, in Switzerland 716.

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

are still not included in that system. In this context, credit costs are so high to limit access to formal credit to the majority of the population. Indeed, the main source of credit for the general population, on top of family members, are semi formal and informal financial institutions. [27]

Loan officers decisions are a crucial step of the lending process. The process normally begins with an in-person meeting between a loan officer and a borrower, which describes type of and reason for the loan, and provides self-reported information on relevant characteristics.[28] Based on the information provided, loan officers decide whether or not to engage in the effortful and time-consuming task of verifying the borrower's information. Once the verification process is concluded, in some cases loan officers have full discretionality on loan approval, in others their choice is about recommending the applicant to the final stage of the loan approval process (credit committee evaluation). Because their decisions are crucial, most loan officers face incentives to put effort in their work. The relevant performance metric varies across institutions. In general, performance is measured in terms of either quality or quantity of borrowers secured (or both). In some institutions the bonuses are formalized, in other they may take the form of in-kind bonuses in the form of collateral acquired from insolvent borrowers. In sum, the level of heterogeneity across and within institutions is very high, both in terms of characteristics, discretionality and incentives. The common traits are two. First, loan officers are responsible for the first (and often the sole) screening of borrowers. Second, loan officers are paid, at least to some extent, based on their performance.

[27] Uganda financial institutions are classified in four Tiers. Tier 1 institutions - commercial banks (25 institutions) - are what is commonly defined as formal credit institutions. Semi formal institutions (Tier 2) are credit institutions not authorized to establish checking accounts or trade in foreign currency (4 institutions). Informal financial institutions include the remaining two tiers. Tier 3 includes the 5 institutions referred to as Microfinance Deposit-Taking Institutions (MDI). Tier 4 is a residual category that includes all other forms of lenders, including all MFIs that did not transform into MDIs. Tier 4 institutions are heterogeneous: moneylenders, companies, NGOs, or savings and credit cooperatives (SACCOs). The Uganda Microfinance Regulatory Authority (UMRA) encourages Tier 3 and Tier 4 to register to the official registrar. In Fall 2019, at the time of which the field work for this paper was conducted, the official UMRA registrar recorded 708 moneylenders and 127 registered microfinance institutions (including MDIs, excluding SACCOs) in the Greater Kampala. For a description of the Ugandan credit market see: Duggan (2016); Nilsson (2017); Sebudde et al. (2017).

[28] To understand the process of accessing credit in Uganda, in August 2019 I implemented informational site visits of randomly selected financial institution, two for each Tier. In each site visit, I informally interviewed the branch manager with the help of an IPA field manager.

3.2 Loan Officers' Recruitment, Sample Characteristics and Incentives

My population of interest are loan officers working at registered formal and semi-formal financial institutions in Kampala, except commercial banks.

I obtain from the Ugandan Microfinance Regulatory Authority (UMRA) the list of all financial institutions active in Uganda and registered to their official registrar as of October 2019 (this list includes Tier 3 and Tier 4 institutions). To get at the final population of interest, I restrict the sample to all institutions active in the Greater Kampala Area. Then, I include in the list of the 5 credit institutions (Tier 2) institutions active in the Greater Kampala Area. Many institutions have only one branch. When institutions have multiple branches, I randomly select only up to 4 branches and treat them as independent institutions. Finally, I exclude institutions visited during piloting activities. The final list includes 447 institutions.

I implement the field experiment in October 2019, in partnership with IPA Uganda. All institutions in the list are visited by IPA field officers, which introduce themselves as employees of IPA Uganda, a research institution cooperating with the University of Zurich. Upon the site visit, field officers evaluates the institution's eligibility based on two criteria: institutions have to offer loans from UGX 1 million to UGX 7 million, and deal with the general public. For example, the latter requirement excludes institutions providing credit only to university employees or government workers. If an institution is determined eligible, the field officer introduces the study - the stated aim is to improve matching between borrowers and lenders in Uganda - and elicits consents to participate from the institution.

The final sample includes 124 institutions and 254 loan officers. Within each institution, a maximum of three employees are interviewed. Since many institutions are small (the median employees number is 4), this choices makes sure that the sample is balanced across institutions. To participate to the study, a loan officer has to deal with borrowers in person and provide a signed consent. The stated study aim is improving the matching between lenders and borrowers in Uganda, by investigating borrowers' characteristics which are most relevant to the loan officers. Before eliciting consent, loan officers learn that the survey consists in reviewing hypothetical applicants and that, based on their answers in the hypothetical evaluation, they will be matched with real Kampala residents in need of a loan with characteristics which match their preferences. The matching will be implemented at a later stage of the experiment. by providing the borrowers with the financial institution (or loan officer) more likely to meet them to discuss a loan application. As mentioned above, loan officers are paid based on performance and thus, value good referrals.

The incentives appear to work. Although respondents receive a small airtime compensation for their time (USD 1), anecdotal evidence suggests the prospect of referrals' prospect is the main reason why both financial institutions and loan officers take part in the study. Accordingly, respondents were engaged in the exercises and took time to explain their reasonings in the comments. The average survey duration is 2 hours (working time). Moreover, 82% of the loan officers opts in to receive referrals in their name, as opposed to generically refer the borrowers to their institution.

Table 3 describes the institutions in the sample. The participating institutions is broadly representative of the financial institutions tiers active in Kampala. To compensate for the exclusion of commercial banks, I over-samples formal institutions relative to semi-formal ones.[29] Most institutions offer both personal and business loans. The size of institutions, measured terms of branches, shows large variance: the average number of branches per institution is 8, but the median is 1. The cost of credit is high, in line with the Ugandan average (average monthly interest rate 12%).

Table 4 describes the respondents' characteristics. For simplicity, throughout the paper, I refer to the respondents as loan officers. However, the occupation set is more diverse. 63% of respondents define themselves as loan officers; 13% own the business and 9% declare to be the manager. The sample is roughly balanced in terms of gender (60% are men). Loan officers are more educated than the average Uganda: 67% hold a Bachelor degree. Accordingly, the median monthly salary ranges between USD 135 to USD 270, way above median monthly wage in Kampala (UGX 300'000, or ca. USD 80). The median loan officer has worked at most two years at that institution.

Concerning loan officers' activities: 74% of loan officers can directly approve loan applications. Some loan officers have such discretion only for given loan types or borrowers characteristics. Around 80% of the loan officers are in charge of verify borrowers' information. The verification process takes between 2 to 3 days per week on average and includes multiple visits to the borrowers' home or business (96% of the respondents), verifying collateral (95%), talking to the neighbors, family members and employees (75%) as well as requiring formal documents (92%). Finally, loan officers have discretion on the interest rate charged in 60% of the cases.

As mentioned above, business owners and loan officers care about the referrals, be-

[29]In the actual population non-deposit deposit taking microfinance institutions account for the 1%, deposit-taking microfinance account for the 0.12% and credit institutions account for the 0.15%.

cause good clients can affect their earnings prospects. The micro-finance environment in Kampala is indeed characterized by many institutions competing for high quality borrowers. Hence, both financial business owners and employed loan officers have incentives to exert effort and be truthful in evaluating the loan applications. Owners' choices may affect their profits. Most loan officers receive some form of performance pay.[30] Consistent with the presence of high personal stakes, most loan officers choose to have their name and contact information in the referral, against the option of referring the borrower to the institution.

Referrals To match loan officers to real borrowers I refer to a pool of 180 real prospective borrowers living in Kampala, which I obtain by selecting all respondents which declare to be in need of a loan from the laypeople sample. Following the approach of Kessler et al. (2019), to implement the referrals I match loan officers and borrowers on observables using a machine-learning algorithm. I train a *Random Forest Classifier* on the experimental data, which predicts the likelihood that a given loan officer would request the referral of a borrower, given the observables. I then apply the Random Forest Classifier to real prospective borrowers data. For each borrower and loan officer pair, the algorithm predicts a likelihood of referral. For each borrower, I select the best match (the highest likelihood).[31] A natural question is whether the referred obese borrowers are more likely to be approved, and down the line, whether they indeed happen to be more creditworthy or likely to repay. Answering these questions is unfeasible in this setting, because of the institutions heterogeneity and because data on loan applications or borrowers' performance are often not digitized or collected in a systematic or comparable fashion. These questions are better suited to future research exploiting different methodology and data (e.g., an observational study exploiting administrative data from one, larger financial institution).

3.3 Credit Experiment Design

In the credit experiment, loan officers evaluate 30 (hypothetical) loan applications each, to be matched with real borrowers according to their preferences. The hypothetical loan applications include several information and a picture from the set of manipulated

[30]As shown in Appendix Fig. K.11, the performance pay implementation vary across institutions and may depend on performance of portfolio (30%), sales volume (30%), revenue generated by self or bank on the whole (10%). For 18% of the loan officers, performance pay takes the form of yearly or quarterly bonuses if the person has done well or met a specific target.

[31]Appendix C presents details on the referrals' implementation.

pictures. Later in the text, I describe how I build the hypothetical applications. In what follows, I describe the comparative statics of interest.

To pin down the relationship between obesity, asymmetric information and access to credit, I exploit a 2x3 design (Fig. 3). Along the first dimension, I vary body mass of the borrowers by randomly assigning the portrait to be either the *obese* or the *not obese* version. This randomization technique works neatly because in Uganda it is standard to use portraits as identifier in financial documents. Along the second dimension, I randomly assign asymmetric information between borrowers and lenders by randomly varying the amount and quality of borrowers' self-reported information in the application. Loan applications are randomly assigned to include or not financial information (extensive margin). The financial information is randomly assigned to be positive or negative financial information (intensive margin) and includes self-reported monthly revenues, monthly profits, collateral and occupation. This is a realistic information environment because when evaluating a loan application for the first time, loan officers would not have access to verified information.[32]

All the information is cross-randomized across applications. Within each arm, applications are presented in random order. The information treatments' order was not randomized: the first 10 applications never include financial information; the last 20 applications include borrowers' self-reported wealth information (occupation, collateral and monthly earnings). This choice clearified to the loan officers that the type of information included or not included in the profiles was a design choice, rather than a borrowers' strategic decision.[33]

A main concern is that loan officers may evaluate applications differently in the experiment, as compared to a real-life scenario. I take several steps to mitigate this concern. First, I make sure that the hypothetical applications are realistic. Second, the survey is presented as an independent research study in partnership with the University of Zurich and the cooperation with the Uganda Micro Finance Regulatory Authority is never mentioned. Finally, loan officers' choices are incentive compatible and the out-

[32] Within the financial information arm, the applications are divided into two sub-treatment arms of 10 applications each. The difference is whether the additional information is provided endogenously (loan officers' opts in to see more information) or exogenously. The comparison between sub-treatments allows to understand at which point in the decision making process the discrimination bites. For example, loan officers may prefer to avoid to see the information of applicants which they perceive as less creditworthy ex-ante. While the extra information was provided for free to the loan officers, the price of the information is loan officers' time. The results show that loan officers opt in to receive more information about the applicants in 99% of the cases. In the analysis, I pool the two sub-treatments.

[33] In Appendix B I present evidence that the results are not driven by the order.

comes include a real choice, that is the choice of being matched with a similar borrower.

3.3.1 Building Hypothetical Loan Applications

I build hypothetical loan application by cross-randomizing information about typical loan profiles, as collected directly from loan officers. Each application includes information on age, picture, loan profile and reason for loan. All applications also included blurred name and passport information, as well as nationality (Ugandan).

In addition, applications randomly assigned to the second treatment arm include self-reported wealth information, that is occupation, monthly revenues, monthly profits and collateral.[34]

Following the procedure detailed in Appendix B and summarized in Table 5, I build 30 hypothetical borrower profiles. I assign each profile to a weight-manipulated portrait, so that for each profile there exist two counterfactual borrower profiles, one assigned to the *obese* and one to the *not-obese* version of the same portrait, for a total of 60 applications. Figure 4 shows the example of one application without wealth information. To avoid experimenter demands, I make sure that each loan officer never sees the same application twice: that is, for each application, the loan officer is assigned to see either the *not obese* or an *obese* version.

I take several steps to ensure that the hypothetical applications are realistic. First, the applications' template is based on real financial document (Fig. K.10). Second, all borrowers' characteristics including typical female occupations, typical male occupations, typical collateral used and common loan profiles are obtained from focus groups with loan officers. Third, each manipulated picture included in a loan application is selected from the pool of 60 manipulated pictures of Kampala residents, as detailed in Section 3. A last concern is that since the information is cross-randomized, the combination may result in an unrealistic profile. To ensure that all the randomly created combinations are reasonable, the final set of 60 loan applications produced after the randomization is vetted by real loan officers.

[34]The wealth information is delivered by adding, at the bottom of the application, the following sentence: *"This applicant is self employed and runs a [occupation type] in Kampala. The applicant claims that the business is going well. Last month, the business revenues amounted to [revenues amount]. The profits were [profits amount]. The applicant could provide a [collateral type] as collateral. Please notice that the information on revenues, profits and collateral are self reported by the applicant, and have not yet been verified."*

3.3.2 Outcomes

I elicit four primary outcomes as a measure of access to credit. On one hand, I elicit three measures of beliefs: approval likelihood, borrowers' creditworthiness and financial ability. On the other hand, I elicit a real-choice outcome: the binary choice of being referred to a borrower with similar characteristics. I additionally elicit two secondary outcomes: interest rate conditional on approval (when loan officers can charge discretionary interest rates) and, if the application includes self-reported financial information, reliability of the financial information. The questions are elicited in the following order: Approval Likelihood, Creditworthiness, Interest Rate (if applicable), Financial Ability, Reliability (if applicable), Referral. The number, wording and scale of the questions were pre-registered.[35]

4 Credit Experiment Results

In this section, I outline the results of the credit experiment. I begin by showing in Table 6 that the obesity randomization worked: applications associated with *Obese* and *Not Obese* borrowers are balanced across applicants' characteristics. Then, I move on to investigate how obesity affects credit.

Obesity and access to credit The main statistic of interest is the difference in access to credit between *Obese* and *Not Obese* borrowers. Fig. 5 plots the average ratings by body mass of the borrowers, residualized to control for application and loan officer fixed effects. The results show that on average obese borrowers are rated as more likely to have their loan application approved, they are perceived more creditworthy and financially able, and they are more likely to be requested for a referral (real-choice outcome). That is, obese borrowers have easier access to credit. To precisely quantify

[35] Approval Likelihood: *Based on your first impression, how likely would you be to approve this loan application? (1-5, not at all likely - extremely likely)*; Interest Rate: *If you had to approve this loan application, which interest rate would you charge? (Standard, Higher, Lower, Not applicable)*; Creditworthiness: *"Creditworthiness describes how likely a person is to repay a financial obligation according to the terms of the agreement." Based on your first impression, how would you rate the person's creditworthiness? (1-5, not at all likely - extremely likely)*; Financial Ability: *Based on your first impression, how likely do you think this person would be to put the loan money to productive use? (1-5, not at all likely - extremely likely)*; Info Reliability: *How reliable do you think the information provided by the applicant is? (1-5, not at all reliable - extremely reliable, not applicable if no additional info.)*; Referral: *Based on your first impression, would you like us to refer you a similar applicant to meet and discuss his/her loan application? (yes/no)*

the obesity premium in access to credit, I move to a regression framework. I exploit the following regression model:

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

where i indexes the application, j the loan officer and k is the outcome. Y_{ij}^{k} is the rating in terms of outcome k of loan application i by loan officer j. $Obese_{ij}$ is a dummy for application i being associated with the *Obese* version of a portrait when evaluated by loan officer j. δ_i are application fixed effects, and γ_j are loan officers fixed effects. Standard errors are clustered at the loan officer level.

The coefficient of interest, β_1, the effect of obesity by controlling for application (e.g. portrayed individual) fixed-effects and loan officers' fixed effects. That is, the average gain in access to credit when an application is associated to an obese portrait, relative to a counterfactual application including the same borrower portrait, in a not-obese version. Throughout the paper I refer to β_1 as the obesity premium in access to credit.

Table 7 (Panel A) summarizes the results. For ease of comparability, all outcome variables (including dummies) are standardized. The results confirm that obese borrowers have easier access to credit. Obese applicants face lower barriers to credit from the very beginning of the loan application process, being 0.05 s.d. more likely to be asked for a referral (Column 1). This is equivalent to a 2% age points increase in the probability of being requested for a referral relative to the average likelihood (74%). Obese borrowers have higher expected approval likelihood (Column 2), they are rated more financially able (Column 3) and creditworthy (Column 4). To prevent concerns related to multiple hypothesis testing, I build a PCA index of all the relevant access to credit variables (*Access to Credit*). In a regression where the index is the dependent variable, I find that the obesity premium is strong and significant (Column 5). Interestingly, obese borrowers do not suffer penalties in the interest rate charged (Column 3). In fact, loan officers appear not to screen based on interest rate at this stage. In sum, these results show that obesity facilitates access to credit in this setting.

Obesity premium monetary benchmark The credit experiment design allows me to get a monetary benchmark to the obesity premium, by exploiting the cross-randomized self-reported monthly profits in the loan applications. Across all outcomes, the obesity premium is comparable to an increase of 60% in monthly income, i.e. about UGX 1 million (USD 250).[36] Using a back-of-the-envelope calculation, I estimate that monetary value of obesity in the experiment is equivalent to an expected monetary gain of UGX 360'000, larger than the median monthly earnings in Kampala.[37] These results confirm that being obese leads to sizable financial benefits.

Obesity premium and asymmetric information My hypothesis is that loan officers screen borrowers' based on body mass as a response to asymmetric information over wealth and thus obese borrowers have easier access to credit because they are perceived as wealthier. This interpretation is aligned with the beliefs experiment results showing that obesity is perceived mainly as a wealth signal among the general population. However, loan officers may have different preferences from the general population (Palacios-Huerta and Volij, 2008), or there may be other characteristics to which obesity is associated with.

To understand to which extent the premium is a response to asymmetric information, I design the credit experiment to directly test for the effect of asymmetric information on the obesity premium by varying whether loan applications included self-reported borrowers' wealth information.[38] If obesity leads to monetary benefits *because* because loan officers screen borrowers based on body mass in the presence of asymmetric information, the obesity premium should be higher, the higher the asymmetric information. Vice versa, reducing asymmetric information about wealth should reduce the premium. To test for this mechanism, I estimate the following regression model:

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

As in the pooled regression specification, equation (1), i indexes the application, j the loan officer and k is the outcome. Y_{ij}^{k} is the rating in terms of outcome k of loan application i by loan officer j. $Obese_{ij}$ is a dummy for whether application i is associated with an *Obese* manipulated portrait when evaluated by loan officer j. δ_i are application fixed effects, and γ_j are loan officer fixed effects. Standard errors are clustered at the loan

[36] Appendix table L.10 plots the effect of self-reported monthly income on access to credit.

[37] I assume that an applicant is accepted if the loan officer states that he/she will be *likely, very likely or extremely likely* to approve the application. An obese applicant is 5 p.p. more likely to be approved and on average an accepted loan applicant receives UGX 7.2 millions.

[38] As described in the design section, my design, on top of varying the amount of information, varied if wealth information was revealed endogenously (choice of the loan officer) or exogenously. However, since loan officers hardly ever opted out of receiving additional information (potentially because of the low information cost), I pool both sub treatments in the analysis. Since this choice was not pre-registered, in Appendix B I report the analysis as initially planned. The results are qualitatively unaffected.

officer level. The new component is $FinancialInfo_{ij}$, a dummy for whether application i included self-reported financial information, when evaluated by loan officer j.

The coefficients of interest are θ_1, the obesity premium in the absence of self-reported wealth information and θ_3, the effect of reducing asymmetric information on the obesity premium. In particular, if asymmetric information was driving the obesity premium one would expect to have $\theta_3 < 0$.

The results, summarized in Table 7 (Panel B), show that the obesity premium is mainly driven by asymmetric information and drops by two-thirds when more the borrower profile includes self-reported financial information on the borrower. The coefficient θ_1 is positive, statistically significant and larger than the equivalent coefficient in the pooled regression (0.22 s.d against 0.1 s.d). Instead, across all outcomes, the interaction between obesity and financial information (θ_3) is negative and in most cases, statistically significant (p-value range: 0.002-0.371). In sum, providing self-reported information on profits, revenues, collateral and occupation significantly reduces the obesity premium. To see this more clearly, look at the effects in the PCA index regression (Column 6): providing self-reported financial information reduces the obesity premium by nearly 70% (p-value: 0.002).

Notably, obesity appears to still matter on top of self-reported financial information. The residual obesity premium is probably driven by unresolved asymmetric information, and mainly due to the financial information being self-reported and unverified. In line with this interpretation, Appendix Table L.4 shows that, on average, loan officers do not trust applicants' self-reported financial information: the average reliability rating is 1.98, on a scale from 1 to 5. Interestingly, the very same self-reported information is perceived as more reliable when associated to an obese borrower. That is, as the self-reported information is perceived as unreliable, loan officers do not fully disregard the obesity wealth signal. Accordingly, obese borrowers' self-reported financial information is perceived as more reliable. This is in line with statistical discrimination, because the financial information included in the borrowers' profiles describes on average richer individuals than the Kampala average. Naturally, unresolved asymmetric information may also be the result of lacking information in the applications (for example, information on guarantors or reference letters). Finally, taste-based discrimination (e.g. a beauty premium) may be also explaining the residual obesity premium. However, this is unlikely considering the results of the first experiment, as well as that the residual premium persists when looking at same-sex borrowers pairs.

4.1 Additional Results

How does obesity interact with other wealth signals? Is the relationship between body mass and credit linear? Is the obesity premium homogeneous across loan officers? In this section, I present evidence to address these three questions.

Interaction between obesity and other wealth signals Jointly, high-type signals may boost, or substitute each other. Taking a perspective similar to Börgers et al. (2013), I define two signals as complement if there is a premium in access to credit for displaying both signals. Instead, I define two signals as substitutes if there are decreasing returns in access to credit to acquiring the second signal, conditional on possessing already the other signal. My design allows me to test for this interaction by exploiting the fact that, in the Wealth Information treatment, some applications were randomly assigned to a low Debt-to-Income ratio (rich type) and some to a high Debt-to-Income ratio (poor type). It is important to notice that applications with high Debt-to-Income ratio may still be eligible for credit. To explore the interaction between wealth signals, I estimate the following model:

$$Y_{ij}^{k} = \lambda_0 + \lambda_1 Obese_{ij} + \lambda_2 LowDTI_i + \lambda_3 Obese_{ij} \cdot LowDTI_i + \delta_i + \gamma_j + u_{ij}, \quad (3)$$

Here, $LowDTI_i i$ is a dummy variable for the borrowers Debt-to-Income ratio being between 30% and 45%, as opposed to being between 90% and 105%. In the regression model, λ_3 is the coefficient of interest. In particular, the sign of λ_3 can suggest whether obesity and other wealth signals are substitute or complement: a positive sign implies that the signals are complement; a negative sign suggests that obesity substitutes other signals. The regression includes only those applications including additional wealth information.

Results, summarized in Table 8, suggest that the obesity premium is equivalent among wealthy and poor borrowers: the coefficient of income is negative but very small and not statistically significant. This result suggests that body mass neither complements or substitutes other wealth signals. This pattern is consistent with the survey experiment results, where the car ownership and the obesity signal appeared to be accounted for independently by the respondents.

Effect of body mass on access to credit: continuous measure When I estimate the obesity premium, I compare borrowers whose BMI in portrait is above and below the WHO obesity threshold of $BMI = 30$. However, it is interesting to explore non linearities in the effect of body mass. To do so, I exploit a continuous measure of body mass: the Body-Mass Index associated with each manipulated portrait by a set of Ugandan raters. I estimate the following regression model:

$$Y_{ij}^{k} = \phi_0 + \phi_1 f(BMI_{ij}) + X_i + \delta_i + \gamma_j + u_{ij}, \quad (4)$$

where $f(BMI_{ij})$ is a second-order polynomial in the manipulated pictures' BMI, X_i are all characteristics included in the applications, δ_i are application and γ_j are loan officer fixed effects.

Fig. 6 plots the results. One may have expected a hump-shaped correlation between body mass and access to credit, where extremely obese borrower suffer from penalties. Instead, financial benefits are linearly increasing in BMI, peaking at extreme obese levels. This suggests that, in this context, marginal benefits from gain are nearly constant.

Loan officers' obesity premium distribution: The baseline results provide an estimate of the average treatment effect of obesity on access to premium, *across* loan officers. In the experiment, each loan officer evaluates multiple applications. Thus, it is possible to estimate the distribution of obesity premium across loan officers. Fig. 7 plots the obesity premium distribution and shows that it is very heterogeneous across loan officers. In Table 9, I explore the determinants of such heterogeneity. For each measure of access to credit, I split the sample according to the loan officers' median obesity premium and compare loan officers whose obesity premium is above and below median across all characteristics I collect. First, reassuringly, the obesity premium is not increasing in loan officers' BMI, rejecting the homophily hypothesis, nor with experience. In general, older loan officers and loan officers from smaller institutions have higher obesity premia. Interestingly, across outcomes and in line with the notion that the obesity information is valuable when screening costs are high, the obesity premium is larger, the larger the cost of information verification. Along both measures of financial information verification effort I collect —(i) days/week spent in the verification process and (ii) perceived effort of the verification) —loan officers self-reporting higher effort favor obese borrowers more.

All in all, the results are aligned with the interpretation according to which loan officers screen borrowers based on body mass, when verification costs are high. Yet, the large heterogeneity hints at a biased credit provision. If loan officers were all accurately statistically discriminating, we would expect a relatively homogeneous obesity premium across loan officers. In the next section, I investigate the heterogeneity determinants by linking my results to standard models of discrimination.

5 (Positive) obesity discrimination: theory and evidence

The credit experiment results show that obesity causally affects credit provision. Loan officers screen borrowers based on their body mass, and thus obese people have easier access to credit. However, if loan officers' beliefs on the body mass and income distribution are inaccurate, exploiting obesity as a second-best wealth verification technology may distort credit provision.

The evidence on obesity premium heterogeneity suggests that credit provision may be distorted but it is not a conclusive test. In fact, the reduced form analysis does not allow me to pin down the source of heterogeneity. On one hand, loan officers' may have inaccurate beliefs about the income distribution by body mass and thus, credit provision may be distorted. On the other hand, loan officers' beliefs on what obesity signals in terms of borrowers' income may be on average accurate, thus one could say that exploiting obesity as a proxy for income would improve overall efficiency. In this case, the observed heterogeneity may be due to heterogeneous beliefs on the direct link between obesity and creditworthiness, for which there is no obvious prior.[39]

To explore loan officers' beliefs accuracy, it is useful to look at the credit experiment results through the lenses of a simple theoretical framework.[40] Assume that a loan officer chooses whether or not to meet a borrower based on the borrowers' creditworthiness. In a perfect information environment, I assume that the loan officer's creditworthiness evaluation depends on demographics, obesity status, income and an unobservable normally distributed error component u_{ij}.[41] Let j denote the loan officer and i the borrower, then:

[39] This direct link may be arguably zero, however if one factors in raised mortality it may be also zero. Moreover, if some loan officers think that obesity proxies health, or longevity, this may be even positive.

[40] In Appendix D I present a micro-foundation for this framework.

[41] This framework makes strong simplifying assumptions. For example, the applications include other financial characteristics which the loan officers could take into account on top of income. However, since this information is cross-randomized and I can always control for it, the simplification does not compromise the generality of the model.

$$C_{ij} = \alpha_j \mathbb{1}(BMI_i \geq 30) + \eta_j Y_i + \mathbf{X}_i \beta_j + u_{ij}, \tag{5}$$

However, in real life as in my experiment, the borrower's true income is unobservable. Thus loan officers' officers form beliefs about Y_i, and the evaluation function becomes:

$$C_{ij} = \alpha_j \mathbb{1}(BMI_i \geq 30) + \gamma_j E(Y_i | \mathbb{1}(BMI_i \geq 30), \mathbf{X}_i) + \mathbf{X}_i \beta_j + v_{ij}, \tag{6}$$

From the perspective of the experimenter, loan officers' beliefs about the borrowers' income are a latent variable. Thus, exploiting the omitted variable bias formula, the observed (measured) obesity premium can be decomposed into a direct effect and an indirect effect, mediated by loan officers' beliefs the income distribution given body mass:

$$\alpha_j = \delta_j + \gamma_j \Big(E_j(Y_i | BMI_i \geq 30, X_i) - E_j(Y_i | BMI_i < 30, X_i) \Big) = \delta_j + \gamma_j \phi_j, \tag{7}$$

where δ_j, can be interpreted as taste-based discrimination (Becker, 1956), $\gamma_j \phi_j$, can be intepreted as statistical discrimination (Arrow et al., 1973; Phelps, 1972) and ϕ_j is j's estimate of the average difference in monthly income between obese and not obese borrowers.

This framework provides a simple test for loan officers' beliefs accuracy. In fact, one could estimate loan officers' expectation of the average income difference between obese and not obese borrowers (ϕ_j) and compare it with the average income difference between obese and not-obese individuals in Kampala (that is, the equivalent population statistic). If loan officers' expectations differ from the truth, then this would suggest inaccurate statistical discrimination.[42]

My credit experiment design allows to estimate loan officers' expectations ϕ_j by exploiting the cross-randomization of body mass and self-reported income information in the loan applications. This requires to assume the functional form of loan officers income beliefs. Let W be a dummy for an application including self-reported income information, I assume that loan officers form their expectations as follows:

$$E_j(Y_i | BMI_i, \mathbf{X}_i, \tilde{Y}_i) = (1 - W)(\mathbb{1}(BMI_i \geq 30) + X_i) + W(\lambda \tilde{Y}_i)), \tag{8}$$

that is, when no income signal is available, loan officers form their beliefs about

[42] This definition is borrowed from (Bohren et al., 2019), to distinguish it from the standard statistical discrimination, which assumes rational expectations

borrowers income based on observables, while when self-reported income is available, expected borrowers' income is a only a function of self-reported income. In other words, I assume that body mass does not affect income beliefs when self-reported income is available. There are reasons to believe this is unlikely to hold in my data, for example because loan officers perceive obese borrowers' self-reported income as more reliable. In particular, λ, the parameter controlling to which extent loan officers' rely on the self-reported information, may be increasing in body mass. To deal with these concerns, in my estimation I consider only applications whose income information is perceived as reliable or very reliable. That is, I assume $\lambda = 1$ (loan officers' fully trust the income information provided). I later discuss relaxing this assumption.

Plugging equation (8) into (6), the loan officer evaluation function translates into the following system of equation:

$$\begin{cases} C_{ij} = \alpha_j \mathbb{1}(BMI_i \geq 30) + X_i\beta_j + u_{ij}, & \text{if } W = 0 \\ C_{ij} = \delta_j \mathbb{1}(BMI_i \geq 30) + \tilde{Y}_i\gamma_j + X_i\beta_j + v_{ij}, & \text{if } W = 1, \end{cases} \tag{9}$$

The credit experiment design allows me to estimate both equations separately for each loan officer and thus, to estimate α_j, δ_j and γ_j. In particular, 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 expectation distribution (phi_j), according to the obesity premium decomposition in equation (7).

The estimate loan officers' expectations distribution is plotted in Figure 8.[43] The red line represents the equivalent population statistics: according to my own survey data, obese people in Kampala earn on average USD 80/month more as compared to normal weight one.[44]

[43]As mentioned above, for the $\lambda = 1$ assumption credible, I build these estimates from the set of loan applications whose financial information is perceived as above average reliable.

[44]The statistic is based on the *laypeople* sample, for which I record respondents' body mass (measured using a scale and a height board) and self-reported monthly income. The upside of my data is that self-reported personal monthly income makes the results easier to interpret. In contrast, the other publicly available representative survey collecting both body mass and financial information - the Uganda DHS - records income by way of a household level, asset-based and standardized wealth index which is not straightforward to interpret. The downside of my own data is that my sample is not designed to be representative. However, drawing from different neighborhoods gets at a reasonable income variation. In fact, the income distribution which emerges from my data is very similar to the Uganda DHS one. Standardizing the income measures in both data I find that the conditional distribution of income given body mass is 0.04 s.d. in my data and 0.03 s.d in the Uganda DHS 2016 (Kampala region).

According to the analysis, on average loan officers overestimate the true population income difference between obese and not-obese individuals. Within the trustworthy-information sample the implied average beliefs is as high as USD 900. However, the sample average hides a large heterogeneity, with around 10% of loan officers underestimating this value by more than 5 times.[45]

This analysis has clear limitations. First, it stems from the functional form of equation (8), and in particular, on the assumption that body mass does not affect income beliefs, when self-reported income is available. While this is a strong assumption, this is likely to hold at least for the sample whose self-reported income is rated as very reliable. Moreover, I note that it still allows BMI to affect other financial beliefs (e.g. partners' income), and this would be captured in δ_j. To the contrary, in the full sample, loan officers are likely to discount the information provided by the borrowers (that is, $\lambda < 1$) and potentially this may correlate with body mass. In line with the presence of attenuation bias, in Appendix Figure K.17 I show that replicating the estimate on the full set of applications renders an estimated distribution more compressed around zero. Second, it assumes that the population average is representative of borrowers income distribution by body mass, while these two values may differ on average.

5.1 Obesity wealth signal perception among borrowers (laypeople)

The revealed preference approach outlined above suggests that loan officers appear to overestimate the correlation between obesity and earnings, that is: they place too much *weight* to obesity as a signal of wealth. How do loan officers' beliefs compare to laypeople perception? To answer this question I directly elicit laypeople incentivized beliefs on the correlation between body mass and earnings.I exploit the figurative Body Size Scale for African Populations (Cohen et al., 2015) and I incentivize beliefs using the actual body mass and earnings distribution, as it emerges from my own survey data. The results —displayed in Table 11 —provide two main insights. First, laypeople also appear to overestimate the correlation between earnings and obesity. Second, the degree of overestimation is comparable, on average, to the loan officers' overestimation as it emerges from the revealed preference beliefs. These results suggest that the tendency to put too much weight on obesity as a wealth signal is general in the population and therefore, that it may have implications beyond inefficiencies in credit supply.

[45]The estimates are based on a sample of 88 loan officers obtained by focusing on loan officers with no missing loan applications evaluated (30 observation per loan officer, and excluding loan applications which perceived below-average reliable).

6 Perception of Obesity Benefits

Thus far the paper has focused on testing for the economic benefits of obesity, identifying the drivers and exploring implications in terms of credit allocation by looking at perception of the obesity wealth *signal*. In this section, I focus on testing for awareness of obesity benefits and misperceptions. Since obesity financial benefits may change the opportunity cost of unhealthy behaviors and affecting demand for credit, understanding whether laypeople are aware of obesity benefits, and whether their beliefs are on average accurate is highly policy relevant.

Investigating obesity benefits awareness can be challenging because quantifying obesity benefits is challenging in itself. The credit experiment provides a good opportunity to overcome this challenge by creating a controlled environment where the effect of obesity can be causally identified and measured. To investigate lay people's awareness of obesity benefits, I replicate the credit experiment with the sample of over 511 Kampala residents from the Beliefs experiment.[46] Respondents are informed about the previous credit experiment (not about the results). Then, they see 4 randomly selected applications from the credit experiment and guess the loan officers' evaluation (incentivized second-order beliefs). Differently from the credit experiment, here focusing on the drivers of premium is not relevant and thus the applications do not include financial information. This design minimizes experimenter demands because obesity or body mass are never mentioned to the respondents, and the applications vary according to many characteristics. I elicit three outcomes. First, the number of loan officers which asked for the referral of a similar applicant, on a scale from 0 to 10; second, the most common loan officer approval likelihood rating on a scale from 1 to 5 and third, whether they would recommend to a similar borrower to apply for that loan, based on their assessment of the loan officers' interest in the candidate. The latter question is not incentivized.

The results, summarized in Fig. 9 (dark grey columns), show that lay people are aware of obesity benefits in access to credit. In the replication, lay people guess that more loan officers requested the referral of obese applicants, all else equal, and that the corresponding approval likelihood rating was higher. Notably, respondents are also 17 percentage points more likely to recommend to obese applicants to apply for that loan, suggesting that obesity benefits may have implications also for the demand for credit. Interestingly, comparing the average loan officers' obesity bias with the lay people's pre-

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

dictions shows that lay people overestimate the obesity premium in credit by a factor of 2 and in particular, overweight respondents overestimate such premium by a factor of 8. Similarly, the results of a survey experiment exploiting hypothetical investment scenarios show that lay people are generally aware of obesity costs in Uganda and that perceived costs are mildly larger for overweight individuals.[47] In sum, the results on awareness of obesity costs and benefits in Uganda, joint with the evidence of overestimation in obesity financial benefits suggest the presence of an inefficient trade-off between obesity health costs and perceived financial benefits.

7 Conclusion and Policy Implications

This paper shows that in developing countries asymmetric information problems generate screening mechanisms that reward successful but unhealthy wealth displays. In doing so, the paper provides the first piece of experimental evidence the benefits of obesity in accessing credit in a low-resources setting. The rationale for obesity benefits is that obese individuals are perceived as wealthier. In fact, I show that benefits are driven by asymmetric information. Looking at implications for credit provision, while loan officers appear to engage in statistical discrimination, many hold inaccurate beliefs about the conditional distribution of income given body mass and credit provision appears to favor obese borrowers to an inefficient extent. Investigating health implications, benefits of obesity appear to be commonly known and obesity perception correlates with body mass. Exploratory evidence from a small scale pilot suggests that correcting (downwards) obesity benefits beliefs may increase willingness to engage in healthy behaviors.

External Validity The results are unlikely to be driven by the experimental settings. The experiment involves real loan officers, facing incentive as close as possible to those they face in real life. The design is such that the information environments faced by the loan officers in the experiments are realistic and mirror specific moments in the loan officer/prospective borrower relation. At the same time, the obesity wealth signal and the benefits are also perceived by the general population and thus, are not a specific result of loan officers' training. All in all, the evidence suggests that obesity is likely to exploited as a signal of wealth in context where 1) asymmetric information over wealth is pervasive; 2) obesity is a status signal. These two conditions apply to most low-income

[47] Survey tools and more details on the survey implementation are in Appendix G. The results are summarized in Fig.K.15.

countries at a stage of the nutritional transition comparable to Uganda. In fact, a beliefs experiment with more than 300 women in rural Malawi confirm that obese individuals are perceived as wealthier and more creditworthy beyond the specific Ugandan context (see Appendix H). More generally, the asymmetric information mechanism I test for may apply to other status signals (in contexts where the body mass signal is not relevant) and other economic interactions where asymmetric information over wealth is pervasive.

Policy implications The analysis leads to a number of policy relevant considerations. First, the results emphasize the importance of fostering cheaper wealth verification technologies in developing countries. Interestingly, reducing asymmetric information problems in market settings may have implications beyond markets efficiency and may have benefits in terms of obesity prevention. In fact, obesity financial benefits can work as an incentive to gain weight (or not to lose weight). The evidence of overestimation suggests an inefficient trade-off between obesity financial benefits and health costs. Do obesity financial benefits actually affect body mass realizations? Qualitative evidence on markets for weight-gain products in low-resource setting suggests this may actually be the case. I design a simple information provision experiment to test whether informing about the true benefits of obesity affects willingness to engage in healthy behaviors (paying for nutritional advice).[48] Exploratory results suggest that informing about obesity benefits overestimation can indeed increase willingness to pay for nutritional advice (Fig. 10). The trade-off between obesity health costs and financial benefits also matters for the design of obesity prevetion policies, for example the calibration of sugar-sweetened beverages (SSB) taxes. Building on the optimal sin taxation framework of Allcott et al. (2019), I estimate that accounting for the indirect monetary benefits of SSB consumption significantly reduces the optimal SSB tax.[49] Finally, the results suggest that extra calories consumption is indirectly conspicuous. Food consumption may also be directly conspicuous if certain foods, such as fast foods, signal high socio-economic status. Investigating to which extent conspicuous food consumption contributes to rising obesity rates in low-income countries is an interesting avenue for future research.

[48]The information experiment details are outlined in Appendix E.

[49]The estimate is based on survey data on sugar beverages consumption, body mass, nutritional knowledge and prices in Uganda, as well as data from Allcott et al. (2019). I account only for financial benefits of obesity in access to credit, within a partial equilibrium approach. I model the benefits as a subsidy to SSB consumption. The calibration, detailed in Appendix F, suggest a reduction of 15% relative to the tax in the absence of monetary benefits.

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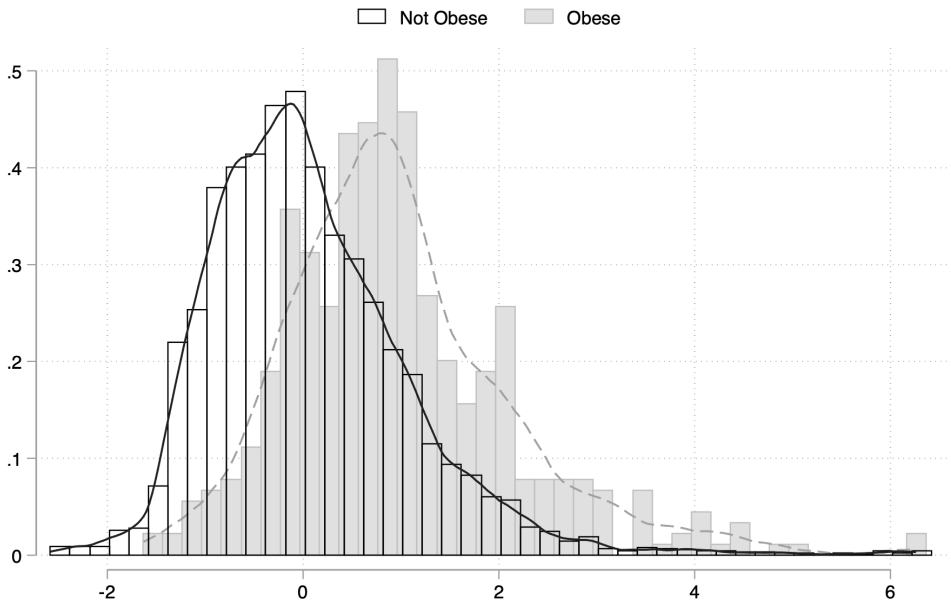
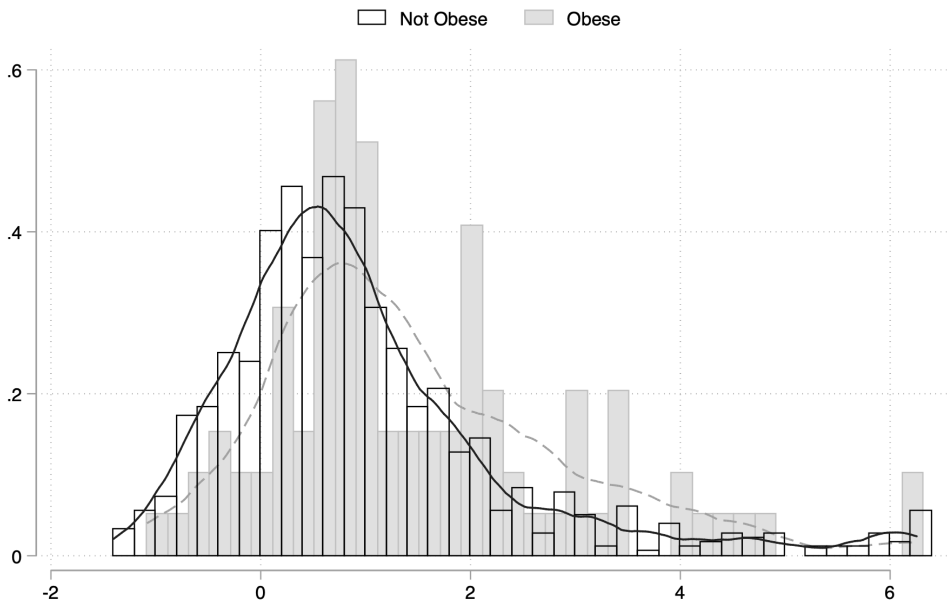
8 Figures

Figure 1: Wealth Distribution by Body Mass in Uganda, and in the Kampala Region.

(a) Uganda

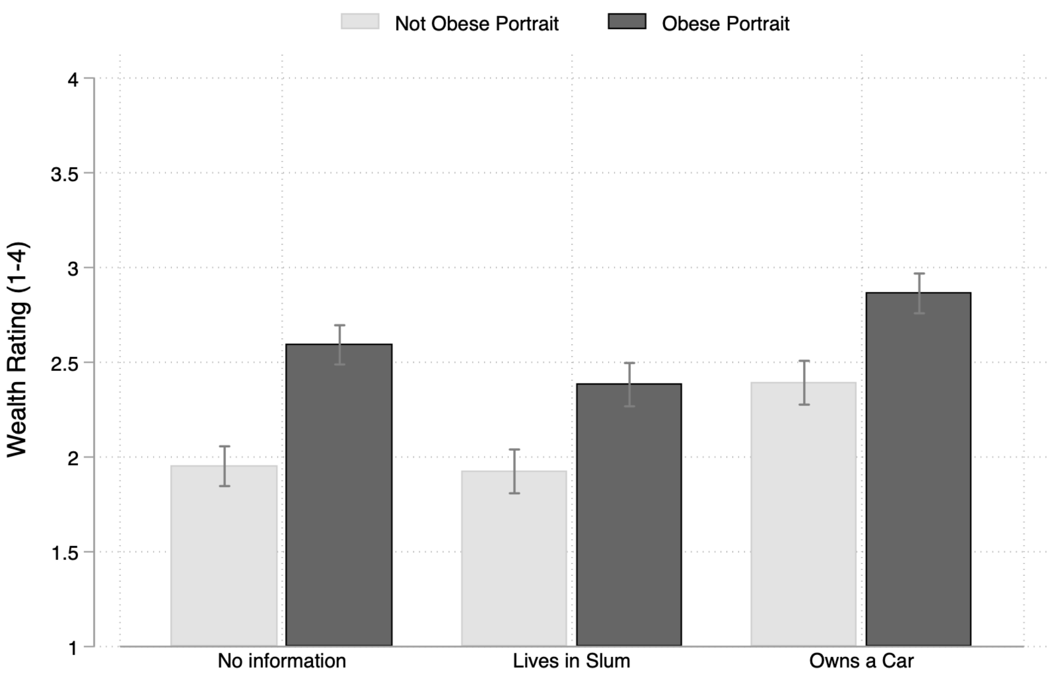


(b) Kampala Region



Note: Panel (a) plots the Ugandan wealth distribution by obesity status. Panel (b) plots the equivalent distribution for the Kampala region. Body-Mass Index and Wealth Index (urban-rural adjusted) from the Uganda DHS 2016. Obesity status is defined as a body-mass index (BMI) greater or equal than 30 (WHO definition).

Figure 2: Wealth Ratings by Obesity Status and Other Wealth Information (Beliefs Experiment)



Note: The graph plots portraits' wealth ratings (first-order beliefs) from the Beliefs Experiment. Respondents are 511 Kampala residents, rating 4 portraits each. The graph restricts to black-race portraits for a total of 1699 observations. Portraits were randomly selected from the manipulated portraits set, and shown in the obese or the not-obese version. All portraits were accompanied by age information. Additionally, 60% of the respondents were shown portraits associated to a second wealth signal: car ownership (wealthy type, 30%), or residence in a Kampala slum (poor type, 30%). Ratings were elicited on a scale from 1 (not at all) to 4 (very). *Wealth* is the primary outcome of the experiment (pre-registered). The experiment also elicited *Beauty*, *Health*, *Life Expectancy*, *Self-Control* and *Ability to get things done* ratings (pre-registered secondary outcomes). The outcomes were elicited in random order. Table 2 shows the results of the secondary outcomes results. I find that obese portraits are not rated differently in terms of any other outcome except wealth.

Figure 3: Credit Experiment Design

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

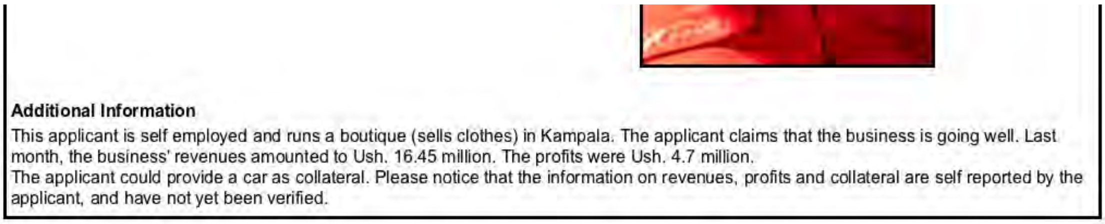
Note: The table outlines the Credit Experiment design. Loan officers evaluate 30 hypothetical loan applications each. All applications include a portrait, demographics and loan profile information: reason for loan, type of loan, place of residence, nationality, date of birth. For each application, the loan officer is randomly assigned to the version associated either with the obese or the not-obese version of the same borrower. This randomization allows me to test for the obesity premium in access to credit. In addition, the last 20 applications evaluated included self-reported financial information (self-reported financial information on borrower's revenues, profits, collateral and occupation). Profits information was randomly assigned to produce a relatively high or low Debt-To-Income ratio.

Figure 4: Hypothetical Loan Application Example

(a) Not Obese Applicant

(b) Obese Applicant

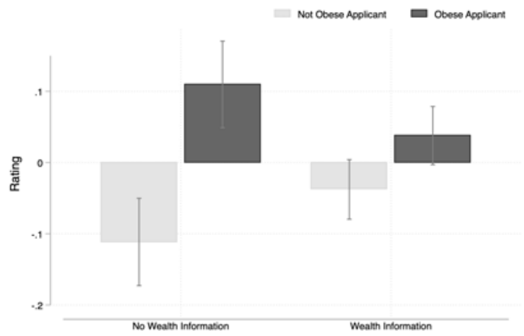
(c) Self-Reported Financial Information



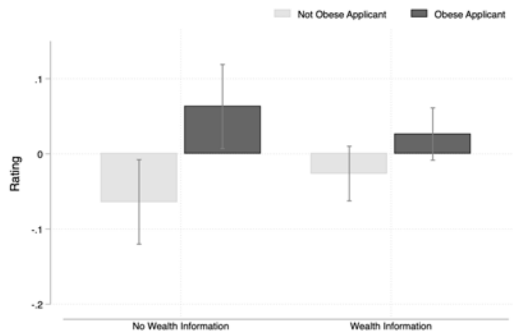
Note: The figure presents one of the hypothetical borrowers profiles created for the Credit Experiment. Panel (a) presents the not obese version; panel (b) the obese version; panel (c) displays on the additional self-reported financial information.

Figure 5: Obesity Premium in Access to Credit

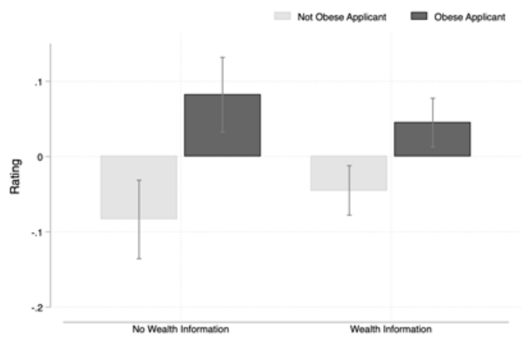
(a) Approval Likelihood



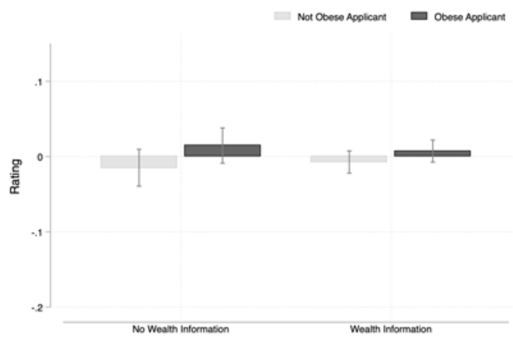
(b) Financial Ability



(c) Creditworthiness



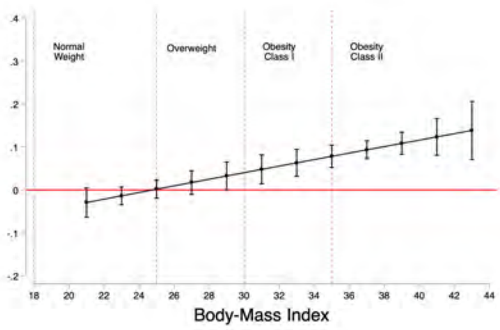
(d) Referral Request



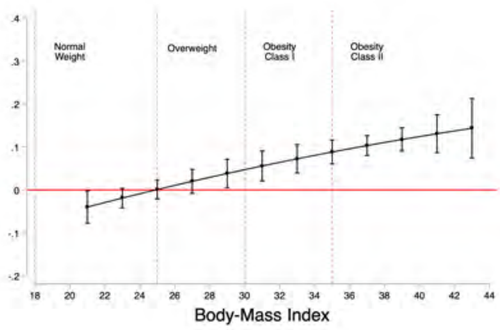
Note: The graph displays the results from the Credit Experiment. Respondents are 254 loan officers, making a total of 6,445 borrowers' profiles evaluations. In 2,026 evaluations, the profiles did not include any financial information on the borrower. In 4,419 evaluations, the profiles included self-reported information on revenues, profits, occupation and collateral. Within information treatment, the profiles were stratified by borrowers' obesity status. Loan officers evaluated the applications along 4 primary outcomes (in this order): likelihood of approval (*Approval Likelihood*), probability of repayment (*Creditworthiness*, ability to put money to productive use (*Finacial Ability*) and *Referral Request*, the choice of being referred to an applicant with similar characteristics. *Referral Request* is a real choice outcome. All evaluations are elicited on a scale from 1 to 5, except *Referral Request* (0-1 dummy, no/yes). In the graph, the outcomes are residualized to control for loan officer, and application fixed effects. The vertical bars indicate the 95% confidence intervals.

Figure 6: Access To Credit by Body Mass (Continuous Measure)

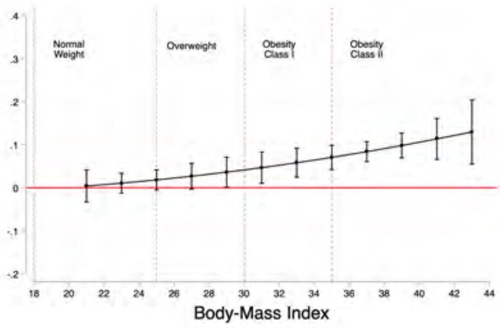
(a) Approval Likelihood



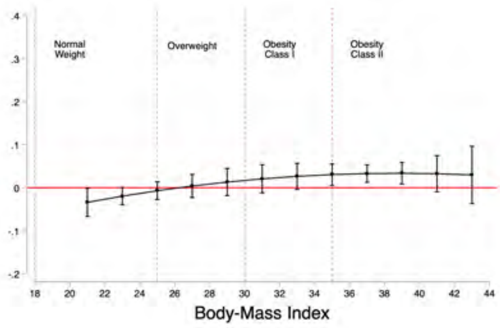
(b) Creditworthiness



(c) Financial Ability



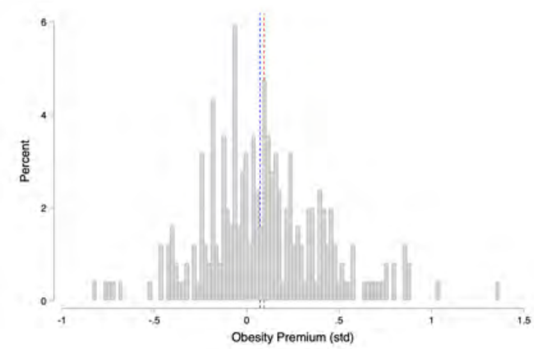
(d) Referral Request



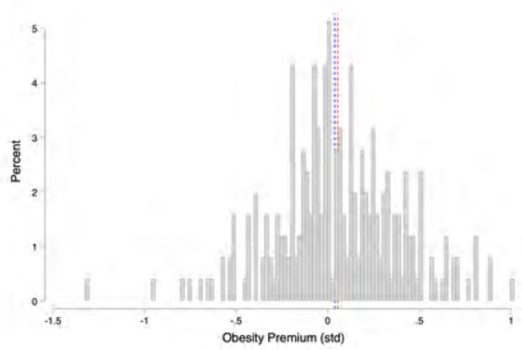
Note: The figure plots the predicted access to credit associated to a given body mass (BMI, kg/m2) using Stata's *marginsplot*. Each regression model includes a double polynomial in BMI, application and loan officers fixed effects. Standard errors are clustered at the loan officer level. The portraits' BMI support is between 21.09 and 43.57 BMI points.

Figure 7: Loan Officers' Obesity Premium Distribution

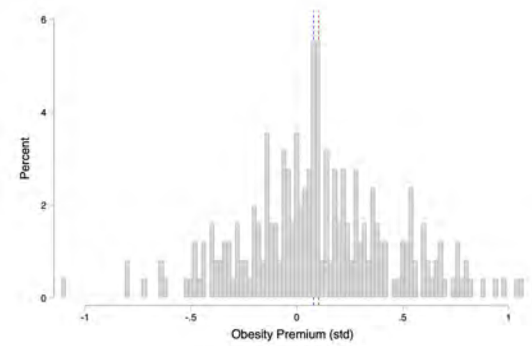
(a) Approval Likelihood



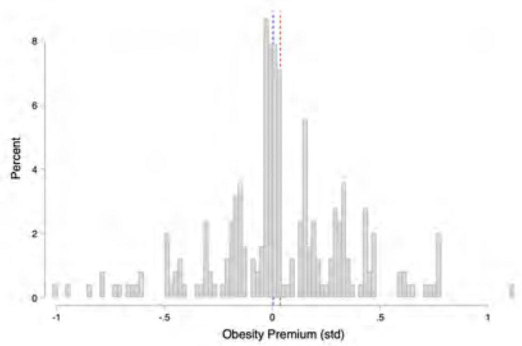
(b) Financial Ability



(c) Creditworthiness

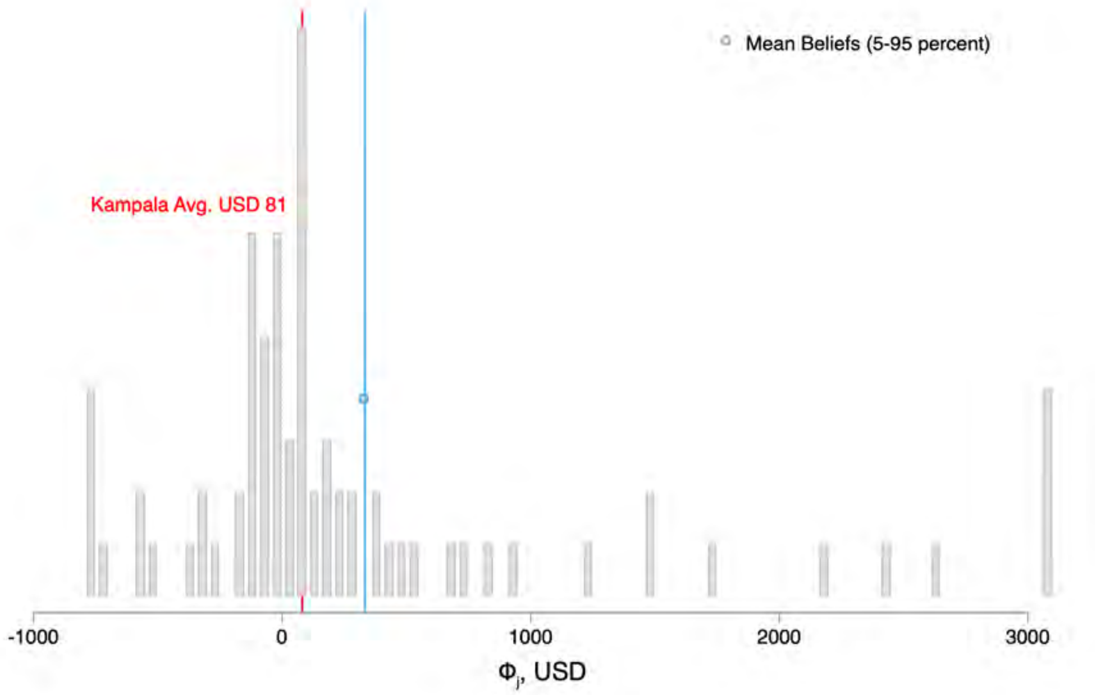


(d) Referral Request



Note: The graph plots the loan officers' obesity premium distribution for each Credit Experiment primary outcome. Each data point in the distribution is the obesity premium associated to a given loan officer, from a regression including an interaction between the obesity dummy and the loan officer ID, the obesity dummy and loan officer, borrower profile and information treatment fixed effects. The dashed red line indicates the distribution's mean, the blue dashed line the median. The results show that the obesity premium is heterogeneous across loan officers.

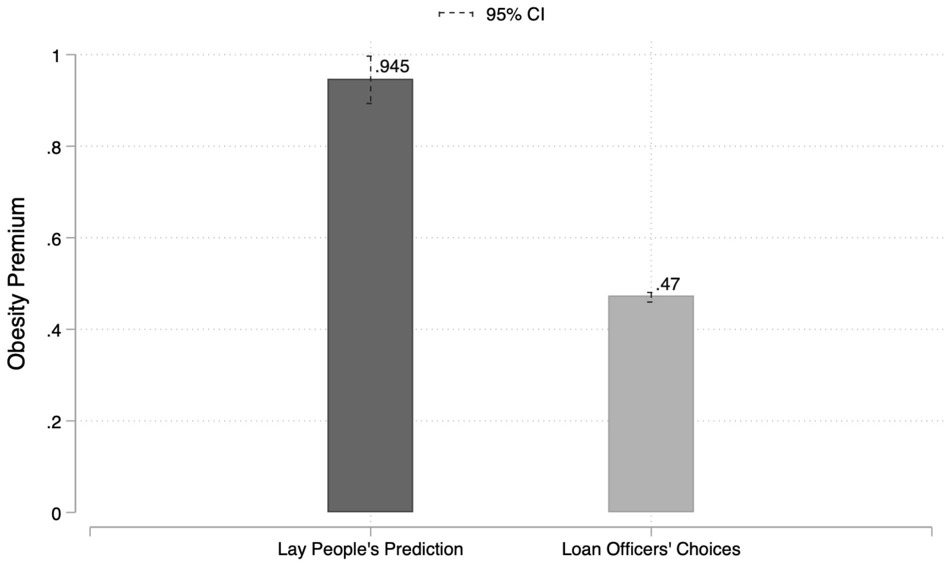
Figure 8: Monthly Income Difference Between Obese and Not-Obese Kampala Residents: Estimated Loan Officers' Beliefs Distribution



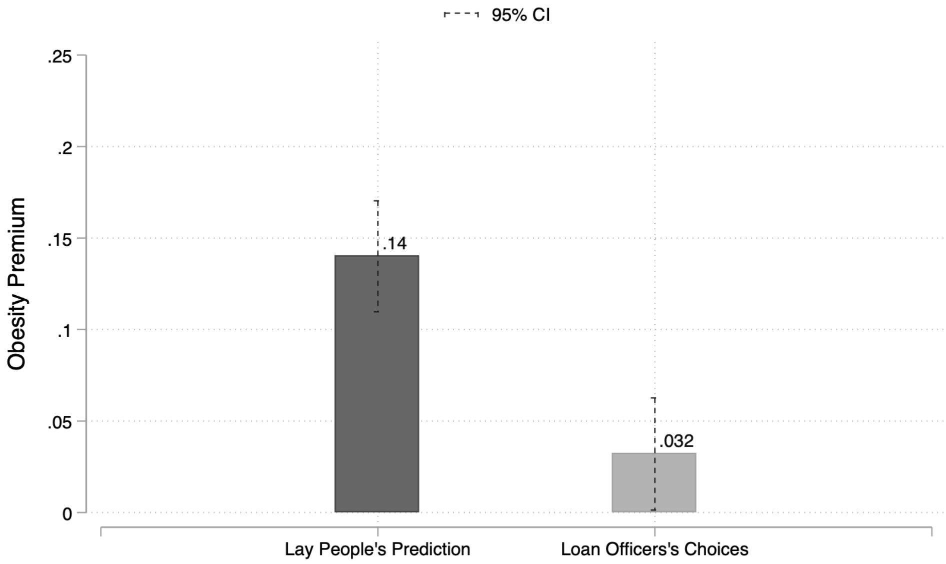
Note: The graph plots the estimated loan officers' beliefs distribution about the average difference in monthly income between obese and not obese borrowers (ϕ_j) in USD. To estimate the beliefs, I focus on applications whose information is perceived above median reliable (N=4,260). The red line indicates the average monthly income difference between obese and not obese Kampala residents (own survey data). The light blue line indicates the mean beliefs (excluding outliers below 5th and above 95th percentile). Appendix Fig. K.17 plots the equivalent distribution, but estimated on the full set of loan applications (that is, including those whose information is rated as below average reliable). As expected, the distribution is less dispersed, in line with the presence of attenuation bias due to loan officers' anticipating reporting error in self-reported income, but still heterogeneous.

Figure 9: Lay People's Obesity-Premium Predictions vs Actual Obesity Premium

(a) Most Frequent Approval Likelihood Rating (1-5)

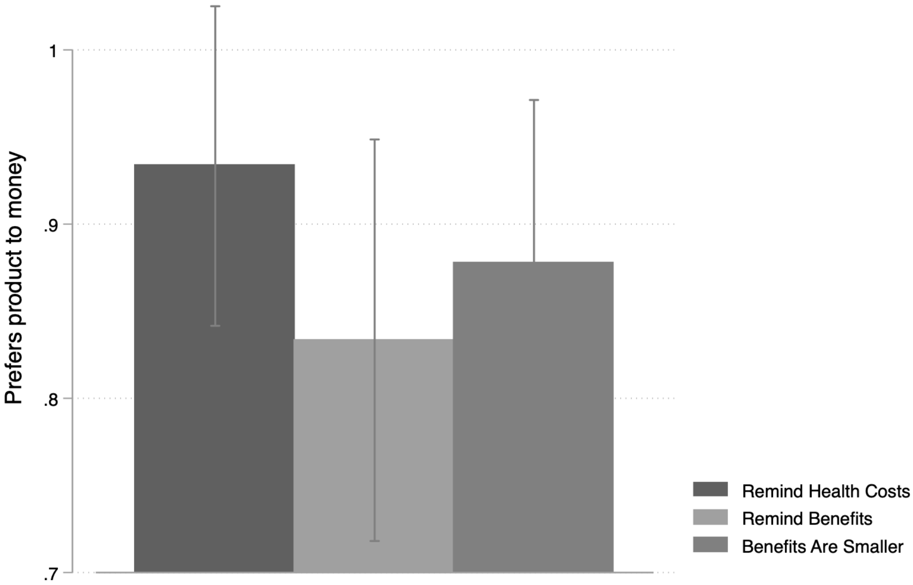


(b) Share of Referral Requests



Note: The graph compares the predicted obesity premium by lay people (Credit Experiment replication), to the actual obesity premium measured in the loan officers' Credit Experiment. In the Credit Experiment replication, 511 Kampala residents are shown randomly selected loan applications from the credit experiment (no financial information) 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*). Both second-order beliefs are incentivized. The predicted obesity premium is the coefficient of the *Obese applicant* dummy on each outcome, in a regression including respondent and applications fixed effects. The loan officers' choices are the equivalent statistics from the original Credit Experiment (no financial information applications).

Figure 10: Obesity Benefits Salience and Willingness to Pay for Nutritional Help.



Note: Data from a small scale pilot with 49 Kampala residents. In a first stage of the pilot, respondents are assigned to one of three information treatments: 1) a recent medicine study finds that health costs from weight gain start with mild overweight; 2) a study in Kampala finds there are status and monetary benefits from being overweight; 3) a study finds there are status and monetary benefits from being overweight in Kampala, but these benefits are much smaller than what the normal people think. In a second stage of the pilot, respondents are randomly offered to purchase either nutritional advice or nutritional supplements. I elicit willingness to pay (WTP) with BDM procedure (N=121).

9 Tables

Table 1: Beliefs Experiment Sample: Descriptive Statistics

	(1) Mean	(2) Sd	(3) Median	(4) P25	(5) P75	(6) Min	(7) Max
District: Kampala	0.63	0.48	1.00	0.00	1.00	0.00	1.00
Wakiso	0.34	0.47	0.00	0.00	1.00	0.00	1.00
Mukono	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Age	37.47	13.20	35.00	26.00	46.00	20.00	95.00
Body-Mass Index (kg/m2)	25.66	5.28	24.61	21.83	28.39	15.43	46.87
Gender: Male	0.50	0.50	1.00	0.00	1.00	0.00	1.00
Education: Primary	0.40	0.49	0.00	0.00	1.00	0.00	1.00
O Level	0.31	0.46	0.00	0.00	1.00	0.00	1.00
A Level	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Certificate	0.06	0.23	0.00	0.00	0.00	0.00	1.00
Diploma	0.06	0.25	0.00	0.00	0.00	0.00	1.00
Bachelor	0.06	0.24	0.00	0.00	0.00	0.00	1.00
Master/PhD	0.00	0.06	0.00	0.00	0.00	0.00	1.00
Personal Income, UGX m.	0.47	0.74	0.25	0.10	0.50	0.00	6.00
Household Income, UGX m.	0.70	1.04	0.35	0.15	0.75	0.00	7.00
Marital Status: Single	0.28	0.45	0.00	0.00	1.00	0.00	1.00
Married	0.41	0.49	0.00	0.00	1.00	0.00	1.00
As married	0.13	0.34	0.00	0.00	0.00	0.00	1.00
Separated	0.10	0.31	0.00	0.00	0.00	0.00	1.00
Divorced	0.02	0.15	0.00	0.00	0.00	0.00	1.00
Widowed	0.05	0.22	0.00	0.00	0.00	0.00	1.00

Notes: The table displays summary statistics for the 511 Kampala residents participating to the *Beliefs Experiment*. Information is self-reported with the exception of BMI. Field officers took anthropometric measurements of each respondent using a heigh board and a scale previous consent.

Table 2: Portraits' Perceived Characteristics by Obesity Status

	(1) Wealth	(2) Beauty	(3) Health	(4) Life Expectancy	(5) Self Control	(6) Ability
Panel (a): First-Order Beliefs						
Obese Portrait	0.699***	0.113	0.005	-0.072	0.052	0.039
	(0.093)	(0.098)	(0.106)	(0.095)	(0.099)	(0.112)
Obese Portrait x Wealth Info	-0.190	-0.032	0.014	-0.022	-0.089	-0.074
	(0.125)	(0.129)	(0.133)	(0.131)	(0.131)	(0.143)
Wealth Info	0.677***	-0.234	-0.008	0.076	0.215	0.086
	(0.239)	(0.273)	(0.250)	(0.245)	(0.283)	(0.292)
Panel (b): Beliefs about Others' Beliefs						
Obese Portrait	0.731***	0.320***	0.227**	0.154	0.171	0.102
	(0.094)	(0.098)	(0.109)	(0.111)	(0.108)	(0.109)
Obese Portrait x Wealth Info	-0.110	-0.081	0.007	-0.028	0.039	0.044
	(0.124)	(0.125)	(0.137)	(0.138)	(0.136)	(0.140)
Wealth Info	0.406*	-0.370	0.178	0.055	-0.043	0.134
	(0.232)	(0.249)	(0.243)	(0.242)	(0.215)	(0.262)
Obs.	1699	1699	1699	1699	1699	1699

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. All regressions include respondent and portrayed individual fixed effects, moreover I control for the order in which the portrait was rated. Standard errors are clustered at the respondent level. Each portrait is rated according to 6 characteristics: wealth (pre-registered primary outcome), beauty, health, life-expectancy, self control and ability. Ratings are elicited on a scale from 1 to 4, and then standardized. First, for all outcomes, respondents first rate the portrait according to their own beliefs. Then, they rate the portrait according to their best guess the most frequent answer of other respondent (incentivized second-order beliefs). Panel (a) displays the first order beliefs, while panel (b) the second order beliefs. *Obese Portrait* is a dummy for when the portrait is randomly selected in the higher-body mass version, as opposed to be selected in the lower-body mass one. *Wealth Info* is a dummy for whether a respondent was assigned to the *additional information* treatment arm. In this arm, portraits were accompanied by either residence information (lives in slum) or car ownership information. This additional information was randomly assigned within-subject.

Table 3: Financial Institutions: Descriptive Statistics

	(1) Mean	(2) SD	(3) Median	(4) P25	(5) P75	(6) Min	(7) Max
District: Kampala	0.80	0.40	1.00	1.00	1.00	0.00	1.00
Wakiso	0.17	0.38	0.00	0.00	0.00	0.00	1.00
Mukono	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Type: Credit Instititution	0.01	0.09	0.00	0.00	0.00	0.00	1.00
Micro-Finance Institution	0.22	0.41	0.00	0.00	0.00	0.00	1.00
Non-Deposit Taking MFI	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Moneylenders	0.73	0.44	1.00	0.00	1.00	0.00	1.00
Size: Number of Branches	3.85	8.22	1.00	1.00	2.00	0.00	58.00
Employees in Branch	6.02	6.45	4.00	3.00	6.00	0.00	50.00
Offers: Personal Loans	0.90	0.30	1.00	1.00	1.00	0.00	1.00
Business Loans	0.97	0.18	1.00	1.00	1.00	0.00	1.00
Interest Rate: UGX 1m, 6 months	12.07	7.36	10.00	5.00	20.00	2.00	40.00
UGX 5m, 6 months	12.07	7.41	10.00	5.00	15.00	2.00	40.00
UGX 7m, 6 months	11.39	6.97	10.00	5.00	15.00	2.00	40.00

Notes: The table reports descriptives statistics for the 124 financial institutions participating in the experiment. All participating institutions are registered and licensed either at Bank of Uganda (formal, Tier 1 and Tier 2), or at the Uganda Micro-Finance Regulatory Authority (semi-formal, Tier 3 and Tier 4). In particular, different institution types are associated with the tiered-structure as follows. Credit Institutions are Tier 2; Non-Deposit Taking MFI are Tier 3; Micro-Finance institutions and Moneylenders are Tier 4. Tier 1 institutions (Commercial Banks) are not included in the sample. Tier 2 and Tier 3 (i.e., formal) financial institutions are purposefully over-sampled with respect to the true distribution of financial institutions in Kampala, to increase representation of formal credit institutions: in my sample Tier 2 are the 1 percent, while in Kampala they represent the 0.1 percent of all financial institutions. Kampala, Mukono and Wakiso districts are the three districts accounting for the largest share of the Greater Metropolitan Kampala Area (population). *Number of Branches* is the total number of branches of the institutions; *Employees per Branch* reports the number of employees at the visited branch.

Table 4: Loan Officers: Descriptive Statistics

VARIABLES	(1) mean	(2) sd	(3) p50	(4) p25	(5) p75	(6) min	(7) max
Age	31.28	7.03	30.00	26.00	35.00	16.00	69.00
Sex: Male	0.61	0.49	1.00	0.00	1.00	0.00	1.00
Education: Primary	0.02	0.12	0.00	0.00	0.00	0.00	1.00
0 Level	0.02	0.14	0.00	0.00	0.00	0.00	1.00
A Level	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Diploma	0.18	0.38	0.00	0.00	0.00	0.00	1.00
Bachelor	0.67	0.47	1.00	0.00	1.00	0.00	1.00
Master or Higher	0.07	0.26	0.00	0.00	0.00	0.00	1.00
Body-Mass Index	24.32	4.57	23.40	21.75	25.54	16.16	43.57
Family Members	3.49	2.13	3.00	2.00	5.00	0.00	12.00
Experience (Years)	2.62	2.72	2.00	1.00	3.00	0.00	11.00
Fin. Knowledge: Self-reported	1.24	0.46	1.00	1.00	1.00	1.00	3.00
Score	1.96	0.28	2.00	2.00	2.00	0.00	2.00
Discretionary Interest Rate	0.57	0.50	1.00	0.00	1.00	0.00	1.00
Monthly Wage UGX: Under 500,000	0.29	0.45	0.00	0.00	1.00	0.00	1.00
500,000 to 1 m	0.37	0.48	0.00	0.00	1.00	0.00	1.00
1 to 1.5 m	0.24	0.43	0.00	0.00	0.00	0.00	1.00
1.5 to 2 m	0.07	0.25	0.00	0.00	0.00	0.00	1.00
Over 2 m	0.03	0.17	0.00	0.00	0.00	0.00	1.00
Any Performance Pay	0.70	0.46	1.00	0.00	1.00	0.00	1.00
Role: Owner	0.14	0.35	0.00	0.00	0.00	0.00	1.00
Manager	0.09	0.29	0.00	0.00	0.00	0.00	1.00
Task: Approve Borrowers	0.74	0.44	1.00	0.00	1.00	0.00	1.00
Verify Information	0.83	0.38	1.00	1.00	1.00	0.00	1.00
Days/Week Verifying Info	2.34	1.46	2.00	1.00	3.00	0.00	5.00
Borrowers: In Office Daily	8.19	8.49	5.00	3.00	10.00	1.00	60.00
Met Daily	4.31	4.52	3.00	2.00	5.00	0.00	30.00

Notes: The table reports descriptive statistics for the 254 loan officers participating to the credit experiment. *BMI* is noted by enumerator using the Body Size Scale for Assessing Body Weight Perception in African Populations (Cohen et al., 2013). *Financial Knowledge Score* is the average number of correct answers to two financial mathematics questions. *Discretionary Interest Rate* is a dummy taking value one if the loan officer has any discretion in setting the interest rate. *Any Performance Pay* is a dummy taking value one if pay is linked in any way to his/her performance.

Table 5: Hypothetical Loan Applications Content

Information	Randomization	Conditionality	Options
Body mass	Randomized		*high* *low*
Gender	Stratified by BM		*male* *female*
Picture	Stratified by BM	women men	*pic n1 to n15* *pic n16 to n30*
Loan Profile	Stratified by BM and gender		*Ush 1 million (ca $270)* *Ush 5 million (ca $1,400)* *Ush 7 million (ca $1,900)*
Reason for loan	Stratified by BM and gender		*business* *home improvement* *purchase of animal* *purchase of land* *purchase of asset*
Date of Birth	Not randomized	Based on picture's age	
Residence	Not randomized		*Kampala*
Nationality	Not randomized		*Ugandan*
Occupation	Stratified by BM	women	*retail shop and mobile money* *boutique (sells clothes)* *jewelry shop* *agri produce and drug shop* *hardware store*
		men	*retail and mobile money shop* *phone acc. and movies shop* *poultry and eggs business* *boutique (sells clothes)* *diary project*
Income	Stratified by BM and gender		*high* *low*
Monthly Profits		low Debt-To-Income Ratio	*DTI = [30, 35, 37, 40]*
Revenues = 3.5 Profits	Not randomized	high Debt-To-Income Ratio	*DTI = [90, 95, 97, 1.05]*
Collateral	Strat. by BM and gender	Ush 7 or 5 million	*car* *land title*
		Ush 1 million	*motorcycle* *land title*

Notes: The table describes the information included in the hypothetical loan application and the corresponding cross-randomization rules. The content information are of typical loan profiles and are obtained from focus groups with multiple loan officers.

Table 6: Application Characteristics: Covariates Balance

	Not Obese		Obese		P-value of Difference		
	Mean	SD	Mean	SD	Diff	Standard	RI
Body-Mass Index	23.33	1.92	37.30	3.40	13.965	0.00	0.00
Age	36.48	9.35	36.87	9.61	0.388	0.17	0.11
Sex: Male	0.50	0.50	0.50	0.50	0.005	0.31	0.69
Collateral: Car	0.33	0.47	0.33	0.47	0.003	0.73	0.85
Land Title	0.50	0.50	0.50	0.50	-0.004	0.54	0.80
Motorcycle	0.17	0.37	0.17	0.37	0.001	0.88	0.93
Occupation: Agri Shop	0.10	0.30	0.10	0.31	0.002	0.69	0.81
Sells Clothes	0.19	0.40	0.20	0.40	0.010	0.48	0.43
Diary Project	0.10	0.30	0.10	0.30	-0.001	0.84	0.84
Hardware Store	0.10	0.30	0.10	0.30	0.002	0.67	0.79
Jewelry Shop	0.10	0.30	0.09	0.29	-0.012	0.22	0.20
Mobile Money	0.21	0.41	0.20	0.40	-0.004	0.66	0.77
Phone Shop	0.09	0.29	0.10	0.30	0.003	0.63	0.76
Poultry/ Eggs	0.10	0.30	0.10	0.30	0.000	0.99	0.99
Loan Reason: Business	0.21	0.41	0.21	0.41	-0.006	0.33	0.54
Home Improv.	0.23	0.42	0.23	0.42	-0.004	0.60	0.81
Purchase Animal	0.17	0.37	0.17	0.38	0.006	0.32	0.62
Purchase Asset	0.17	0.37	0.17	0.37	0.002	0.78	0.88
Purchase Land	0.22	0.42	0.23	0.42	0.002	0.57	0.80
Revenues (UGX m)	5.84	4.77	5.81	4.75	-0.028	0.84	0.92
Profits (UGX m)	1.67	1.36	1.66	1.36	-0.008	0.84	0.92
Portrait ID (1-30)	15.53	8.69	15.55	8.69	0.019	0.96	0.97
Profile: UGX 1 m, 6 months	0.33	0.47	0.34	0.47	0.007	0.33	0.59
UGX 5 m, 6 months	0.34	0.47	0.33	0.47	-0.011	0.08	0.34
UGX 7 m, 6 months	0.33	0.47	0.34	0.47	0.004	0.45	0.66
Observations	6,445						

Notes: The *Obese* (*Not-Obese*) column indicates the applications which were randomly assigned to the higher (lower) body mass manipulated portrait. The *P-Value of Difference* column reports the difference, the standard p-value and the randomization inference p-value based on 5'000 replications. BMI of the pictures is evaluated by 10 third-party Ugandan raters using the Body Size Scale for Assessing Body Weight Perception in African Populations (Cohen et al. 2013) and averaged at the portrait level. The content of the applications is randomly assigned as described in Table 5.

Table 7: Obesity Premium in Access to Credit

	(1) Referral Request	(2) Approval Likelihood	(3) Financial Ability	(4) Credit-worthiness	(5) Access to Credit Index	(6) Interest Rate
Panel A: Pooled Information Treatments						
Obese Applicant	0.045**	0.106***	0.120***	0.073***	0.107***	0.030
	(0.019)	(0.020)	(0.022)	(0.023)	(0.020)	(0.023)
Observations	6445	6445	6445	6445	6445	3175
Panel B: By Wealth Information						
Obese Applicant	0.070**	0.195***	0.176***	0.123***	0.196***	0.065*
	(0.035)	(0.036)	(0.038)	(0.040)	(0.036)	(0.038)
Obese Applicant × Financial Info	-0.036	-0.129***	-0.082*	-0.073	-0.130***	-0.050
	(0.040)	(0.041)	(0.042)	(0.046)	(0.041)	(0.050)
Financial Info	0.039	0.171***	0.133***	0.118***	0.171***	0.026
	(0.052)	(0.043)	(0.043)	(0.045)	(0.043)	(0.025)
Observations	6445	6445	6445	6445	6445	3175

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. The first 4 columns display the primary outcomes. *Referral Request* the standardized value of a dummy taking value 1 when the loan officer chooses the meet with a similar applicant (real choice outcome). *Approval Likelihood* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). *Access to Credit* is a PCA index based on the primary outcomes. *Interest rate* is a preregistered secondary outcome, and is the probability of assigning an interest rate higher than the standard one (standardized). The question is only applicable to loan officers which have interest rate discretionality for a given loan profile. *Obese Applicant* is a dummy taking value one if the application included a higher body-mass manipulated portrait higher body-mass manipulated portrait when evaluated by a given loan officer. *Financial Info* is a dummy taking value one if the application was randomly assigned to include self-reported wealth information. All regressions include applications (portrait), loan officer, and information treatment fixed effects. Standard errors are clustered at the loan officer level.

Table 8: Obesity Premium in Access to Credit by Borrowers' Debt-To-Income Ratio (Self Reported)

	(1) Referral Request	(2) Approval Likelihood	(3) Financial Ability	(4) Credit-worthiness	(5) Access to Credit Index	(6) Interest Rate
Obese Applicant	0.054*	0.077***	0.113***	0.071**	0.077***	-0.006
	(0.028)	(0.028)	(0.033)	(0.035)	(0.028)	(0.043)
Low DTI	0.241**	0.626***	0.451***	0.324***	0.629***	0.008
	(0.113)	(0.125)	(0.105)	(0.113)	(0.126)	(0.151)
Obese Applicant × Low DTI	-0.044	-0.024	-0.040	-0.044	-0.024	0.043
	(0.037)	(0.044)	(0.045)	(0.051)	(0.044)	(0.069)
Observations	4419	4419	4419	4419	4419	2217

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. The table displays the interaction between two borrowers' creditworthiness signals: obesity and self-reported debt-to-income ratio. The first 4 columns display the primary outcomes. *Referral Request* the standardized value of a dummy taking value 1 when the loan officer chooses the meet with a similar applicant (real choice outcome). *Approval Likelihood* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). *Access to Credit Index* is a PCA index based on the primary outcomes. *Interest rate* is a preregistered secondary outcome, and is the probability of assigning an interest rate higher than the standard one (standardized). The question is only applicable to loan officers which have interest rate discretionality for a given loan profile. *Obese Applicant* is a dummy taking value one if the application included a higher body-mass manipulated portrait. *Low Debt-To-Income* is a dummy for the application being randomly assigned to a Debt-To-Income ratio between 30 % and 40%, against having a Debt-To-Income ratio between 90% and 105%. In focus groups, loan officers reported to approve also borrowers with such high DTIs. *Low Debt-To-Income* and *Obese applicant* are cross randomized. The sample includes applications reporting additional financial information. Regressions includes loan officer fixed effects and application fixed effects. Standard errors are clustered at the loan officer level.

Table 9: Obesity Premium Correlation with Loan Officers and Institutions Characteristics

Variable	Difference Above/Below Median Obesity Premium							
	Meeting Request		Approval Likelihood		Credit-worthiness		Financial Ability	
Age	-0.17	(1.77)	1.39	(1.76)	2.88	(1.76)	-0.44	(1.77)
Sex: Male	0.02	(0.06)	0.06	(0.06)	-0.02	(0.06)	-0.02	(0.06)
Body-Mass Index	-0.26	(0.57)	-0.27	(0.57)	-0.73	(0.57)	0.02	(0.57)
Education (Years)	-0.11	(0.30)	-0.06	(0.30)	0.36	(0.30)	0.24	(0.30)
Experience (Years)	0.61*	(0.34)	0.38	(0.34)	0.30	(0.34)	-0.03	(0.34)
Family Members	0.00	(0.27)	-0.12	(0.27)	-0.35	(0.27)	-0.40	(0.27)
Fin. Knowledge	0.13**	(0.06)	0.06	(0.06)	0.08	(0.06)	0.08	(0.06)
Role: Owner	-0.04	(0.04)	0.01	(0.04)	-0.07	(0.04)	-0.09**	(0.04)
Wage	-0.06	(0.13)	-0.14	(0.13)	-0.16	(0.13)	-0.06	(0.13)
Task: Approve Borrowers	0.01	(0.05)	0.01	(0.05)	-0.01	(0.05)	0.01	(0.05)
Verify Information	0.04	(0.05)	0.04	(0.05)	0.01	(0.05)	0.01	(0.05)
Days/Week Verifying Info	0.33	(0.20)	0.57***	(0.20)	0.43**	(0.20)	0.32	(0.20)
Verify Challenge	0.36***	(0.14)	0.05	(0.14)	-0.02	(0.14)	0.10	(0.14)
Type: Credit Instititutions	0.03**	(0.02)	0.02	(0.02)	0.03**	(0.02)	0.00	(0.02)
MFI	-0.06	(0.06)	0.04	(0.06)	0.04	(0.06)	0.01	(0.06)
NDT MFI	0.01	(0.04)	0.04	(0.04)	-0.04	(0.04)	0.02	(0.04)
Moneylenders	0.02	(0.06)	-0.09	(0.06)	-0.03	(0.06)	-0.03	(0.06)
Pay: Sales volume	0.10*	(0.06)	-0.06	(0.06)	0.06	(0.06)	0.01	(0.06)
Portfolio performance	0.02	(0.03)	0.00	(0.03)	0.00	(0.03)	0.05*	(0.03)
Product sales	0.00	(0.06)	-0.03	(0.06)	0.08	(0.06)	-0.03	(0.06)
Bank revenues	-0.02	(0.04)	-0.01	(0.04)	-0.06	(0.04)	0.01	(0.04)
Bonus if done well	-0.06	(0.05)	0.01	(0.05)	-0.01	(0.05)	0.01	(0.05)
Size: Number of Branches	-7.77	(7.38)	-4.86	(7.39)	-7.83	(7.38)	-11.05	(7.37)
Employees per Branch	-1.21	(1.14)	0.68	(1.14)	-1.12	(1.14)	0.97	(1.14)
Observations	254		254		254		254	

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. For each relevant credit experiment outcome, I split the sample according to the median obesity premium. Each table column plots the standardized difference and the associated standard error in the characteristics between the two groups. Comparable results are obtained when using the 75th percentile as cutoff.

Table 10: Lay People Incentivized Second-Order Beliefs Of Loan Officers' Ratings

	(1) Share Referral	(2) Approval Likelihood	(3) Worth Applying
Obese Applicant	0.140***	0.475***	0.171***
	(0.015)	(0.051)	(0.026)
Observations	2044	2044	2044
Std. Outcome	Yes	Yes	No
Mean Control			0.515
Actual Obesity Premium	0.070	0.195	

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. The table displays the results from the laypeople replication of the Credit Experiment. Respondents are the 511 Kampala residents (Beliefs Experiment sample). First all respondents complete the Beliefs Experiment. In a second stage, they complete the Credit Experiment Replication. The replication protocol works as follows: respondents are informed about the loan officers' Credit Experiment (not about the results). Then, each respondent is asked to evaluate 4 hypothetical loan applications from the credit experiment (no financial information). For each application, the respondent guesses: 1) how many loan officers wanted to be referred to a similar applicant (*Share Referrals*, Col 1); 2) the most frequent approval likelihood rating on a scale from 1 to 5 (*Approval Likelihood*, Col 2); 3) *Worth Applying* is a dummy for the respondent recommending that a similar applicant apply for that loan. The first two answers are incentivized with the loan officers' true evaluations (Actual Obesity Premium). Regression includes respondent and borrower profile fixed effects. Standard errors are clustered at the respondent level.

Table 11: Obesity signal perception among Kampala residents (laypeople)

Kampala Monthly Income Distribution by Body Mass

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

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

Appendix

A Beliefs Experiment

A.1 Wards Selection

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

A.2 Regression Analysis

A.2.1 Main analysis

The coefficient of interest is β_1 in the following specification:

$$Y_{ij}^k = \beta_0 + \beta_1 HighBM_{ij} + \alpha_i + \gamma_j + u_{ij}, \tag{10}$$

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

A.2.2 Interaction with other wealth signals

In this Appendix I investigate how the wealth signaling power of obesity interacts with other wealth signals. I exploit the fact that, in 60% of the cases, respondents, learn additional wealth signals about the portrayed individual: either car ownership (wealthy type) or residence in a slum (poor type). Thus, I estimate the following regression specification:

$$Y_{ij}^k = \beta_0 + \beta_1 Obese_{ij} \cdot Car_{ij} + \beta_2 Obese_{ij} + \beta_3 Car_{ij} + \alpha_i + \gamma_j + v_{ij}, \tag{11}$$

where Car_i is a dummy for the portrayed individual being described as owning a car. The excluded category the portrayed individual is described as living in a slum. Results are summarized in Table L.2. Car ownership and obesity do not seem to be neither complement nor substitute signals - in the sense of Börgers et al. (2013). In fact, the interaction term is not statistically significant and is close to zero.

A.2.3 Heterogeneity by portrait's race

In this Appendix, I investigate heterogeneity in the effect of body mass by race of the portrayed individual. Understanding whether the wealth-signaling value of obesity varies by race is not a core question of this analysis. However, including white race portraits is relevant for two reasons: first, it reduces experimenter demand effects because it introduces another salient aspect which distinguishes the portraits; second, being white in Uganda is a major wealth signal and therefore, looking at the interaction between whiteness and obesity can additionally inform on signals' interactions.

In total, there are 4 pairs of weight-manipulated white race portraits (two men and two women). Among the four portraits shown to the respondents, one is always of white race. Out of 2,029 portrait evaluations, 330 time the respondents evaluate a white race portrait. These portraits' evaluations are not included in the main results regressions.

To test for heterogeneity by portraits' race, I exploit the following regression model:

$$Y_{ij} = \beta_0 + \beta_1 HighBM_{ij} \cdot White_i + \beta_2 HighBM_{ij} + \beta_3 White_i + \gamma_j + u_{ij}, \tag{12}$$

Results are summarized in Table L.3. First, as expected, white race portraits are rated on average as wealthier than black race portraits. Second, the effect of obesity on wealth ratings is also present for white race portraits, but smaller in magnitude (the interaction term coefficient β_1 is negative and statistically significant).

A.3 Correlation between survey experimental outcomes

Figure K.9 displays the correlation matrix of all the outcomes of the beliefs experiment. The analysis of correlation across outcomes, within beliefs set, provides additional evidence supporting the idea that obesity signals wealth. In fact, beliefs about wealth do not strongly correlate with any other beliefs (neither in the first-order beliefs, nor in the beliefs about others. Reassuringly, on the other hand, portraits which are perceived as more beautiful are also perceived as healthier. This also suggests that beliefs were not simply stated at random. The analysis of the correlation across beliefs provides additional concerning data quality. Only beliefs about others' beliefs were incentivized. Yet the correlation matrix shows that first- and second order beliefs within outcome correlate strongly within each outcome. This suggests that although the first-order beliefs were not incentivized, they are a reliable measure of beliefs.

B Credit Experiment

B.1 Building hypothetical loan applications

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

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

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

- **BMI, gender and age:** The information about gender and BMI is conveyed using a picture. For each application, a picture is selected from the set of 30 passport-style pictures of individuals living in Kampala described in Section 3. In each application, the picture is selected conditional on gender and body mass (randomly assigned). Body mass of the applicant is selected between high and low BMI. If high BMI (low BMI) is selected, then the picture included in the application will be the high BMI (low BMI) photo-morphed version of that picture. As far as age information is concerned, all applications include a date of birth, where the year of birth is the actual year of birth of the portrayed individual, while month and day are randomly selected.
- **Loan profile and reason for loan** There are three different loan profiles: UGX 1 million (USD 270), UGX 5 million (USD 1,350), UGX 7 million (USD 1,900). [50] The chosen repayment time was of 6 months for all loan profiles. The reason for the loan was randomly assigned to be either business or personal. Business was left open, while for personal loans the choice set included home improvements, purchase of land, purchase of an animal and purchase of an asset (for example, a fridge or car). Both loan profile and reason for loan were stratified by gender and body mass (high/low).
- **Name, Passport ID, Nationality and Place of Residence** The information on name, passport ID, nationality and place of residence is not randomized. Name and passport ID are included to increase realism, but are blurred. Nationality is always Ugandan, as most loan officers would not issue loans to non-Ugandan citizens. Place of Residence is always Kampala, as most loan officers would be skeptical about issuing a loan to people living in another city.

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

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

- **Occupation:** All the hypothetical loan applicants are self-employed. This is because most employed individuals would have a direct and more convenient credit line with their employer. This choice hardly limits the external validity of the results because the share of self-employed work in Uganda, as in many other low income countries, is much larger than the employed one. For example, self-employed individuals as percent of total employment in Uganda were 85. 30% in 2017 according to estimates of the International Labour Organization. The occupations included in the applications have been vetted in focus groups and are assigned conditional on gender. Female-typical occupations include owning a retail and mobile money shop, owning a boutique, owning a jewelry shop, owning an agricultural produce and drug shop, owning a hardware store. Male-typical occupations include: owning a retail shop and mobile money business, owning a phone accessories and movies shop, selling clothes (owning a boutique), running a poultry and eggs business, running a dairy project.
- **Monthly Income:** Because applicants are self-employed, income information is provided in the form of last month's self-reported revenues and profits. Each application is randomly assigned to be high or low income. Then, profits and revenues are randomly assigned conditional on the income realization and the loan profile. For each loan profile, I compute the monthly repayment rate based on the average interest rate in Kampala. Then, I determine monthly profits according to the formula $MonthlyRepayment = X \cdot MonthlyProfits$. If the application is a high income application, X is randomly selected between [0.3; 0.35; 0.37; 0.4]; if the application is a low income application, X is randomly selected between [0.9; 0.95; 0.97; 1-05]. [51]
- **Collateral:** Collateral is assigned conditional on loan profile. For loan profiles of UGX 1 million, the choice is between motorcycle and land title. For loans of UGX 5 million or above, the choice is either car or land title.

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

B.2 Robustness Checks

B.2.1 Randomization inference

The credit experiment results are consistent, large and therefore unlikely to have occurred by chance. In this section, I demonstrate this with a simulation exercise following Athey and

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

Imbens (2017) and Young (2019), who recommend randomization-based statistical inference for significance tests. This approach calculates the likelihood of obtaining the observed treatment effects by random chance, where the randomness comes from assignment of a fixed number of units (in our case, high schools) to treatment, rather than from random sampling from a population.

I focus on the main results: the benefits in access to credit in the pooled analysis. Using the experimental data, I re-assign the applications' obesity status using the same procedure used in the original randomization and I estimate treatment effects based on this reassignment. I repeat this procedure 10,000 times to generate a distribution of potential treatment effects that could be due to baseline differences of applications and loan officers' when they are combined together. For each outcome, I calculate the share of the 10,000 simulated treatment-control differences that is larger in absolute value than the difference observed in the actual random assignment discussed throughout the paper. This proportion represents the randomization-based p-value. The results are summarized in Figure K.12, where I plot the distribution of treatment effects from the 10,000 iterations for a selection of outcomes. The dashed vertical line in each graph plots the actual treatment effect. The analysis confirms that findings cannot be explained by random differences between the loan officers and applications including a portrait in its obese version.

B.2.2 Beauty bias

In principle, the obesity premium could be a beauty premium. Beauty bias can lead to strong distortions as shown in Mobius and Rosenblat (2006). If obese individuals are perceived as more beautiful, that may explain why loan officers are more lenient towards them. Both the beliefs experiment results, showing that laypeople do not perceive obese borrowers as more beautiful, and the fact that the obesity premium is mostly driven by asymmetric information suggest this is unlikely.

In this appendix, I further show that although some loan officers perceive higher body mass portraits as more beautiful, this is fully a cross-gender effect and thus cannot explain the obesity premium. At the end of the loan applications evaluation, one photo-morphed portrait was randomly selected out of the 60 photo-morphed portraits set. Loan officers were then asked to rate the portrayed individual in terms of wealth, health, beauty, life expectancy and self-control (first-order beliefs, not incentivized). Table L.6 summarizes the results. Male loan officers appear to perceive female obese portraits as more attractive. This result is less reliable than the beliefs experiment, because it does not include rater fixed effects. To confirm that the beauty effect does not drive the obesity premium, in Table L.7 I restrict the sample to male loan officers evaluating male borrowers. The results are qualitatively unaffected.

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

In the credit experiment, the information treatment order is not randomized. The reason is that, during pilot activities, loan officers appeared confused when asked to evaluate first applications including financial information, followed by applications with no financial information. However, one may be worried that the lack of randomization may bias the results. In this appendix, I look into how the moment in which an application was presented to loan officers (within a given arm) affects the results. The idea is that if evaluating an application has spillovers on future evaluations, this should happen both within and across arms. To test for this hypothesis, I generate a dummy variable which indicates whether a given application was displayed in the first half (n. 1 to n. 5 included) or in the second half (n. 6 to n. 10 included). I use this dummy to investigate heterogeneity in the effect of body mass by order in which the applications were presented. Table L.8 summarizes the results: the effect of body mass on access to credit is equivalent in applications in the first half and applications in the second half of each arm.

B.3 Additional Results

B.3.1 Variation in timing of financial information provision

In this appendix, I investigate how variation in the moment in which financial information is revealed to the loan officers affects bias. As described in the main text, the credit experiments randomly varies amount and quality of the borrowers' financial information in the applications. Within the financial information arm, the design also varied whether receiving the extra information was a loan officers' choice or was exogenous provided. In practice, in half of the applications, loan officers' were asked whether they wanted to learn additional information on the applicant; for the remaining half, they were shown the financial information right away. The results show that 99% of loan officers always chose to learn additional information. Thus, loan officers do not exploit their opportunity to choose whether to receive additional information to hide discrimination. Because there is basically no difference in selection between the two sub-arm, in the main analysis I pool all the data. Yet, this variation can be exploited to understand the effect of timing of information provision on the effect of body mass. In fact, when the information was provided exogenously, all the information was provided at once; instead, when loan officers had the choice, they first saw the baseline information, and then the financial information. The results in Table L.9 show that the interaction coefficient is negative but insignificant. This result may be policy relevant because they suggest that presenting all the information at once may reduce body mass discrimination; however, given the small effect size, further research is needed to make more conclusive claims.

C Real borrowers' referrals

In the credit experiment, I incentivize loan officers' evaluation of the hypothetical loan application by referring them to real borrowers' referrals which match their preferences, as they emerged from the hypothetical evaluation exercise. In this appendix, I describe how I implement the referrals. The matching is based on observable characteristics and is obtained using a machine learning algorithm. To implement the procedure I use R and my code mostly relies on *Tidymodels*.[52]

C.1 Introduction to the machine learning problem

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

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

C.2 Data description

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

Machine learning searches automatically for the variables, and interactions among them, who best predict the outcome of interest. Practically, then, one must decide how to select, encode

[52]Code available upon request.

and transform the underlying variables before they are fed to the machine learning algorithm.

First, I select all loan officers and firm characteristics recorded in the credit experiment. Concerning the applicants characteristics, I select all the characteristics for which there exists a counterpart in the new borrowers' data.[53]

The final database includes:

- Loan officers characteristics: age, gender, BMI, education, self-reported financial knowledge, financial knowledge score, experience, role (dummies for manager or owner), employed/self-employed status, monthly income, family members, activities performed, perceived stress of the verification procedure, dummies for factors influencing loan officers choices (age, gender, income, nationality, appearance, education, guarantor, collateral, occupation), number of applicants met daily, number of applicants approved daily, dummies for actions implemented to verify the applicants, performance pay and relevance of the performance pay.
- Firm characteristics: institution name, tier, district, organization size, interest rate for 1 million, 5 million and 7 million loan, loan types offered
- Applicant's characteristics: age, monthly profits, loan reason (business, personal), loan amount. [54]

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

C.3 Setup and pre-processing

I split the Credit Experiment data in a training set and a test data set, stratifying over the outcome variable). This has to do with the fact that most times, loan officers want to meet the client and hence classes in the training database are unbalanced: 76% - class 1 (meet); 24% class 0 (do not meet). The test sample contains 20% of the observations. After selecting the relevant variables, I convert to ordered factors the education, financial knowledge, loan amount and the stress variable. I convert all string variables and numerical dummies to factor variables. After this initial pre-processing, each model has its unique pre-processing steps. In *Tidymodels*, these steps are defined in the respective recipe. In most models, I include polynomials of degree 3 for continuous variables (loan officers' and applicants' age, loan officers' body mass, borrowers' profits). I standardize all predictors and remove those with no variation. When necessary (for

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

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

example, in the Lasso), I create dummies for all non continuous predictors and impute all missing values with a nearest neighbor procedure.

C.4 Training process and model selection

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

The performance of the preferred model on unseen data will be assessed on the test data. Before doing that, I tune the algorithm parameters on the train data. I use 5-fold cross validation and a two-step procedure to find the optimal parameter: first, I use a semi-random set of parameter values for the first grid. In a second step, based on the results from this first grid, I used Bayes optimization to estimate additional models around the parameter combinations that resulted in the highest AUC in the first tuning step. Table L.11 shows the estimated models and their respective performance. I select the model with the highest AUC on the test data as my preferred model. The models with the highest test AUC are the Gradient Boosting classifier (extreme gradient boosting) followed very closely by a Random Forest classifier. Gradient Boosting models are more complex objects, require more careful tuning and are prone to overfitting. Since I have a limited set of test data available, I prefer to rely on the Random Forest model. The preferred Random Forest model is run with the ranger engine, includes polynomial variables for age and BMI of the loan officer,as well as age and profits of the applicants. It also imputes missing data using nearest neighbors (3 neighbors). It uses numeric scores for all ordered categorical variables, and reduces the number of levels of variables by grouping infrequent categories into a new "Other" category.

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

C.5 Matching and referrals

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

D Credit Discrimination Model

In this appendix, I describe the credit discrimination model which provides the micro-foundation to my theoretical framework. Formally, consider a loan officer j who evaluates borrower i's profitability π_{ij}, and chooses whether to undertake a costly verification action $v_{ij} \in 0, 1$ in order to learn about i's true repayment probability α_i. Assume: (A1) loan officer j chooses $v_{ij} = 1$ if $\pi_{ij} > 0$; (A2) there is asymmetric information about borrowers' income, Y_i; (A3) ij depends on body mass (BMI_ii), self-reported income ($\tilde{Y}_i$) and other observable characteristics (X_i); (A4) α_i is linear in the observable and unobservable characteristics, and $\tilde{Y}_i$ is a linear in Y_i. Assumptions A1 and A2 tie the model to the setting. Loan officers have financial incentives to select profitable borrowers; in their first meeting, loan officers cannot verify the self-reported borrowers information. Assumption A3 allows for discrimination by body mass. Assumption A4 simplifies the framework without loss of generality. I define loan officer j expected profitability of borrower i as:

$$\pi_{ij}(\alpha_i, Y_i; BMI_i; \mathbf{X_i}; R_i; t_i) = p_{ij} R_i - t_i \tag{13}$$

where pi_{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:

$$\begin{aligned} p_{ij} &= E_j(\alpha_i|\tilde{Y}_i, BMI_i, X_i) = E_j(\beta_i Y_i + \gamma_i BMI_i + \theta_i X_i + u_i|\tilde{Y}_i, BMI_i, X_i)) = \\ &= \int_k (\beta_i Y_i + \gamma_i BMI_i + \theta_i X_i + u_i|\tilde{Y}_i, BMI_i, X_i)) \cdot g_j(Y_{ik}|\tilde{Y}_i, BMI_i, X_i)), \end{aligned} \tag{14}$$

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

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

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

$$\frac{dp_{ij}}{dBMI_i} = \gamma_i + \beta_i \frac{\delta E_j(Y_i|\tilde{Y}_i, BMI_i, \mathbf{X_i})}{dBMI_i}, \tag{15}$$

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

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

E Obesity benefits and body mass realizations: information experiment pilot

Obesity benefits raise the opportunity cost of engaging in healthy behaviors. Building on the observed correlation between perceived obesity benefits and body mass, and in particular, on the results showing that obesity benefits are overestimated among laypeople, I design a simple information provision experiment to test whether informing about the true benefits of obesity affects willingness to engage in healthy behaviors. In what follows, I present this design and outline some preliminary results from piloting activities run in Spring 2020.[55]

The design is as follows. First, I elicit priors along a set of dimensions, including ideal body size, reasons to lose or gain weight in Kampala, obesity and income correlation, and the health costs of obesity. Then, I allocate respondents to one of three informational treatment arms: (T1) respondents learn that a study has found that obesity leads to sizable benefits in access to credit in Kampala; (T2) respondents learn that according to a recent study most people overestimate the benefits of obesity in terms of access to credit in Kampala; (T3) respondents learn that according to a recent study the costs of weight gain start with mild overweight.[56] Then, the study is over. As a thank you for their time, respondents can enter a lottery which

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

[56]The treatment wordings are in Appendix J.

gives them the opportunity to receive nutritional support (randomly assigned between nutritional supplements or nutritional advice) at a subsidized rate. If they win the lottery, they can either purchase the nutritional support or keep the won amount. I measure demand for willingness to pay to receive support using the Becker–DeGroot–Marschak procedure.

The aim of the design is to test whether informing about overestimation of obesity benefits increases willingness to engage in healthy behaviors, proxied by willingness to pay for nutritional support. My main comparison of interest is between T1 and T2. Relative to a pure control design, this approach allows me to control for the fact that, by providing information on obesity benefits overestimation, I implicitly confirm the presence of obesity benefits. The comparison between T2 and T3 allows to benchmark the effect against a standard obesity health costs treatment. Some steps in the design are aimed to limit experimenter demand concerns: first, I elicit some priors using open ended questions (e.g., reasons to lose or gain weight); second, the experiment is structured so that the information-provision and the willingness to pay for the products are presented as separate events; third, I do not explicitly ask for posterior beliefs. Instead, after providing the information, I ask respondents to rate how much they trust the results of the study.

Exploratory results, based on a sample of 40 respondents and 121 observations, are summarized in Fig. 10. Informing about obesity benefits overestimation increases willingness to pay for nutritional support. This effect is smaller in magnitude, when compared to the informing about obesity costs. The lowest willingness to pay is associated with confirmation of obesity benefits in access to credit. These results are preliminary and need to be taken with a grain of salt: the sample size is extremely small and the results are not statistically significant. Yet, the results are encouraging in that correcting beliefs about obesity benefits may indeed be successful at encouraging healthier behaviors. Larger scale implementation may investigate the complementarity of health costs and benefits messages.

F Sugar beverages tax in the presence of obesity benefits

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

ALT develops a theoretical framework for optimal sin taxes and exploits it to estimate the optimal soda tax in the US. The strength of this framework is that it delivers empirically implementable sufficient statistics formulas for the optimal commodity tax which can be estimated in a wide variety of empirical applications.

In this appendix, I exploit this sufficient-statistic approach to estimate how accounting for obesity benefits would affect the optimal sugar tax (beverages) in the Ugandan context. I proceed in two steps: (1) I exploit equation (16) 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:

$$t \approx \frac{\bar{\gamma}(1+\sigma) + e - \frac{p}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)] + A)}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)] + A)} \tag{16}$$

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

In equation (16), $\bar{\gamma}$ is the bias; σ is the redistributive effect of the corrective motive, e measures the externality from the sin good consumption, $g(z)$ are welfare weights, $T(z)$ is the income tax, $\bar{\zeta}^c$ is the compensated price elasticity, ζ_z the compensated elasticity of income relative to the marginal tax.

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

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

$$t_{uga} \approx \frac{\bar{\gamma} - \frac{p}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)])}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)])}. \tag{17}$$

How do obesity benefits enter equation (17)? My results show there exists two types of benefits:

1. Social benefits: sugary beverages consumption increases people's BMI and higher BMI individuals are perceived as wealthier. [57]
2. Financial benefits: obese borrowers have easier access to credit.

I assume that social benefits enter the utility function and in equation (17) they are captured in the elasticity of soda consumption. As far as monetary benefits are concerned, this is equivalent to a subsidy in soda's consumption equal to the expected returns per unit consumed ($p' = p - E(b)$). The equation for the optimal sugar beverages tax accounting for financial benefits can be written as:

$$t^b_{uga} \approx \frac{\bar{\gamma} - \frac{(p-E(b))}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)])}{1 + \frac{1}{\bar{s}\bar{\zeta}^c}((Cov[g(z); s(z)])}. \tag{18}$$

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

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

average: the larger the financial benefits, the higher the optimal tax. When $(Cov[g(z); s(z)]) < 0$, like in Uganda where rich people (lower welfare weights) consume more soda, the larger the financial benefits, the lower the optimal tax.

To understand whether accounting for obesity benefits can have sizable effects on the tax, I implement a simple calibration of the Ugandan optimal soda taxes, not accounting for obesity benefits (t_{uga}) and accounting for benefits (t^b_{uga}). In the levels, these calibrations should be taken with a grain of salt as the estimates are subject to severe data limitations. In short, the estimate of the soda tax is based on soda consumption data, data on preferences for sodas, soda prices, data to compute the welfare weights, and when accounting for obesity benefits, data on financial returns to soda consumption. My data limitations rely in soda consumption data and the welfare weights. For example, while ALT exploit soda purchase data (Nielsen Homescan Data), I only have self-reported soda consumption and income data from a non-representative survey of Kampala residents. This has two main consequences: first, I cannot estimate bias as in ALT, rather I can only build an average bias estimate; second, I cannot estimate the sugary beverages elasticity. My solution to this limitation is to exploit the corresponding ALT US value in lieu of the statistics which are unavailable for Uganda. This strong assumption mainly affects the level of benchmark in equation (17), while the goal of this estimation exercise is the effect of accounting for obesity benefits, that is the difference between equation (17) and equation (18).

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

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

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

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

G Explicit beliefs on obesity benefits and costs

G.1 Obesity benefits

In the paper, I elicit implicit beliefs about body mass and wealth or body mass and credit-worthiness. This choice limits experimenter demand, and would be the go-to in case of stigma concerns. However, at the end of each experimental protocol I also elicited explicit beliefs on obesity benefits. Comparing explicit beliefs with implicit ones can help understanding whether stigma effects are actually at play, and help to bound experimenter demands.

To elicit explicit beliefs I always referred to the Body Size Scale for African Populations. To elicit laypeople's explicit beliefs, I included four questions on obesity benefits in the job market, the dating market, the credit market and the probability of developing cardiovascular diseases at the end of the beliefs experiment survey. The questions exploited the wording: *"If someone had a figure like Silhouette X and increased to Silhouette Y, do you think he/she would be more or less likely to develop a cardiovascular disease. (Man: more/less/equally likely; Woman: more/less/equally likely)"* and the comparisons allowed for were normal weight to overweight; overweight to obese; obese of degree I to obese of degree II.

For what concerns loan officer explicit beliefs, I included two questions on explicit returns to obesity in access to credit. The wording was *"Imagine a person which looks like Silhouette X and a person which looks like Silhouette Y. Which person would be more likely to be considered for a loan?"*. The comparisons allowed for were normal weight to overweight; and from overweight to obese. In the loan officers' case, the answers were open ended and coded in a second step. This allowed loan officers to provide reasoning and motivations, as well as to state whether they thought body size was irrelevant to obtaining a loan.

Fig.K.13 summarizes the laypeople's explicit beliefs and Fig. K.14 summarizes the loan officers' explicit beliefs. Explicit beliefs are quite in line with the measured implicit beliefs, suggesting that body mass benefits are commonly known in Uganda and that screening based on body mass is not stigmatized in this setting. Similar patterns are observable among the laypeople's answers. While in general weight gain is positively perceived, benefits of obesity are strongest in the credit markets. Interestingly, in the explicit beliefs, laypeople appear to be aware of the health costs of obesity. These latter results are consistent with the other survey evidence, presented in the next section, suggesting that laypeople are aware of the health costs of weight gain and of unhealthy eating or lack of exercising.

G.2 Obesity costs

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

The Eating or Exercise scenarios vary along one of two dimensions: (i) the calorie intake of the individual from ages 30-65 (Eating), and (ii) the amount of exercise undertaken daily by the individual from ages 30-65 (Exercise). For calorie intake, I consider two levels: the healthy amount ("two traditional Ugandan meals per day", the modal calories intake) and the unhealthy amount ("three traditional Ugandan meals per day plus a snack"). I cannot refer to recommended calories intake because most people are not familiar with the concept of calories. Similarly for exercise, the healthy behavior is defined as 60 minutes of exercise every day, while the unhealthy one is 0 minutes of exercise. The results are summarized in Fig.K.15. Respondents understand the consequences of unhealthy behaviors related to overeating and lack of exercising. They also understand the BMI production function. For what concerns the scenario on exercising, the only one comparable to the results of Biroli et al. (2020), the effects of unhealthy behaviors are comparable in magnitude and if something slightly larger (overweight: 4,500 against 2,800; cardiovascular disease: 4,520 against 2,579), except for the mortality effect (0.300 against 1.477). The mortality effect is substantially lower because the average life expectancy in Uganda is below 65 years old.

H Beliefs Experiment in Malawi

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

I conduct a similar, smaller scale survey experiment with 241 women in rural Malawi. Differently from the Ugandan survey experiment, the Malawi one exploits only 2 portraits (1 men and 1 woman), for a total of 4 photo-morphed pictures. I elicit only second order beliefs (not incentivized). For each picture, the respondents are asked to guess how many out of 10 people would rate the individual as wealthy, would rate the individual as beautiful, would give credit to the individual, would go on a date with the person or would respect the individuals' admonitions.

Obese individuals are around 30 p.p. more likely to be perceived wealthy and slightly more likely to be perceived creditworthy. Similarly, the effects on other outcomes are not statistically significant (Table L.13). Comparatively with the Ugandan sample, the Malawi one is substantially poorer and less educated. These results, together with the set of qualitative and descriptive results discussed in introduction, suggest that the results have external validity for Sub Saharan Africa and more generally for low-resources settings.

I Beliefs Experiment on MTurk USA

In this section I describe the results of a not-preregistered, small-scale beliefs experiment implemented on Amazon MTurk in Spring 2020. I select respondents to be US resident. I recruit 37 respondents, each rating 3 portraits for a total of 111 observations. Each respondents rates each portrait both in terms of first-order and second-order beliefs. Answers are not incentivized. While this is a small sample, a similar sized pilot in Uganda had resulted in statistically significant results.

I elicit 9 outcomes per each portrait. 6 outcomes (wealth, beauty, health, life expectancy, self control, ability) are the very same as in the original Ugandan Beliefs experiment. I further elicit beliefs on trustworthiness, 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 Figure **??**. In general, not obese portraits are associated with more positive beliefs along all outcomes. However, there is no statistically different between the portraits in the obese and not obese version, except for beauty. The effects are also in smaller in magnitude as compared to the Ugandan experiment. The final relevant patterns is that results in the second-order beliefs are comparable, but systematically of a larger magnitude as compared to the first-order beliefs.

The results of this experiment have to be taken with caution considering the small sample size. However, a Ugandan pilot with only 30 respondents evaluating 3 portraits each had provided statistically significant outcomes. All in all, I interpret these results as suggestive that although obesity appears to be stigmatized in the US context, it is not exploited as a wealth signal as in the Ugandan context. Potentially, this has to do with the fact that in the US there is generally lower asymmetric information problems as compared to Uganda.

J Survey Tools

J.1 Information Provision Experiment

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

- Treatment 1: *People and families make decisions based on their environment or community. Many people in Kampala think that one person's body size affects the way people think of him or her. Recently IGREC, together with Elisa Macchi and the University of Zurich ran a study on this topic. The results showed that indeed this is true: Talking both with real loan officers and with normal people on the street, they learned that a person's weight matters for important decisions such as getting a loan or how wealthy the others think you are.*
- Treatment 2: *Several studies from the World Health Organization show that overweight and obesity are strongly associated with severe health conditions including heart disease, stroke, diabetes and high blood pressure. Many people think that obesity or high overweight start causing problems only when a person's weight is extremely high, for example when a person's body mass is like S9. This is not true. Doctors say that already a little bit of extra weight increases the chances of developing diabetes, heart disease and high blood pressure.*
- Control: *People and families make decisions based on their environment or community. Many people in Kampala think that one person's body size affects the way people think of him or her. Recently the results of a study of IGREC, together with Elisa Macchi and the University of Zurich showed that this is mostly only a belief. For example most people do not find overweight people neither more attractive, nor healthier, nor better at getting things done or more trustworthy. Also, people overestimate how easy it is for an obese person to get a loan. Once a loan officer learns self-reported information on a person's income, then weight does not matter much.*

Product description:

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

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

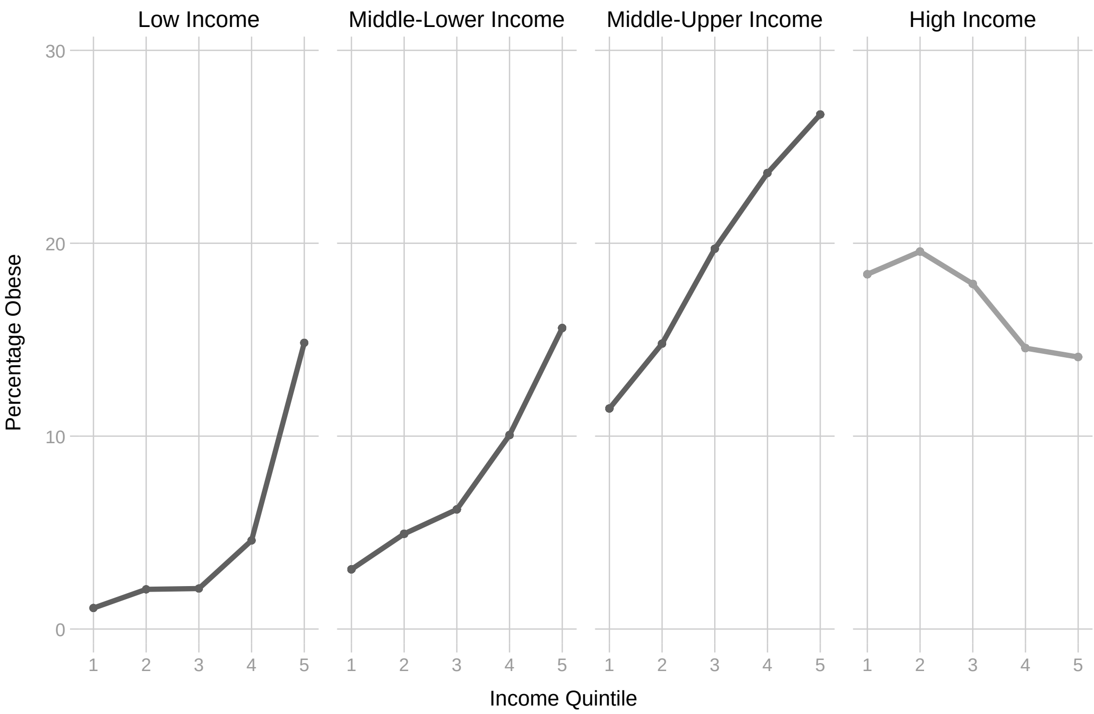
Willingness to pay (BDM) wording:

- *"Now we are going to give you the opportunity to enter a lottery in which you may earn between UGX 0 and UGX 7'000 that you will receive at the end of the lockdown. If you win in the lottery, you will have the possibility to either receive the lottery price in money*

money and be free to use it to spend it on whatever you want, or to purchase $product. $product has a market value of USD 20. You will not find out what amount you have earned in the lottery until the end of the interview. Before the lottery, For different amounts, I will ask you whether you would like to receive the full amount after the lockdown or receive a $product after the lockdown. At the end of the interview, the amount you have earned in the lottery will be revealed and you will receive your choice for that amount."

K Appendix Figures

Figure K.1: Obesity Prevalence by Income Quintile and Country Income Level



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

Figure K.2: Greater Kampala Metropolitan Area (Schoebitz et al. , 2017)

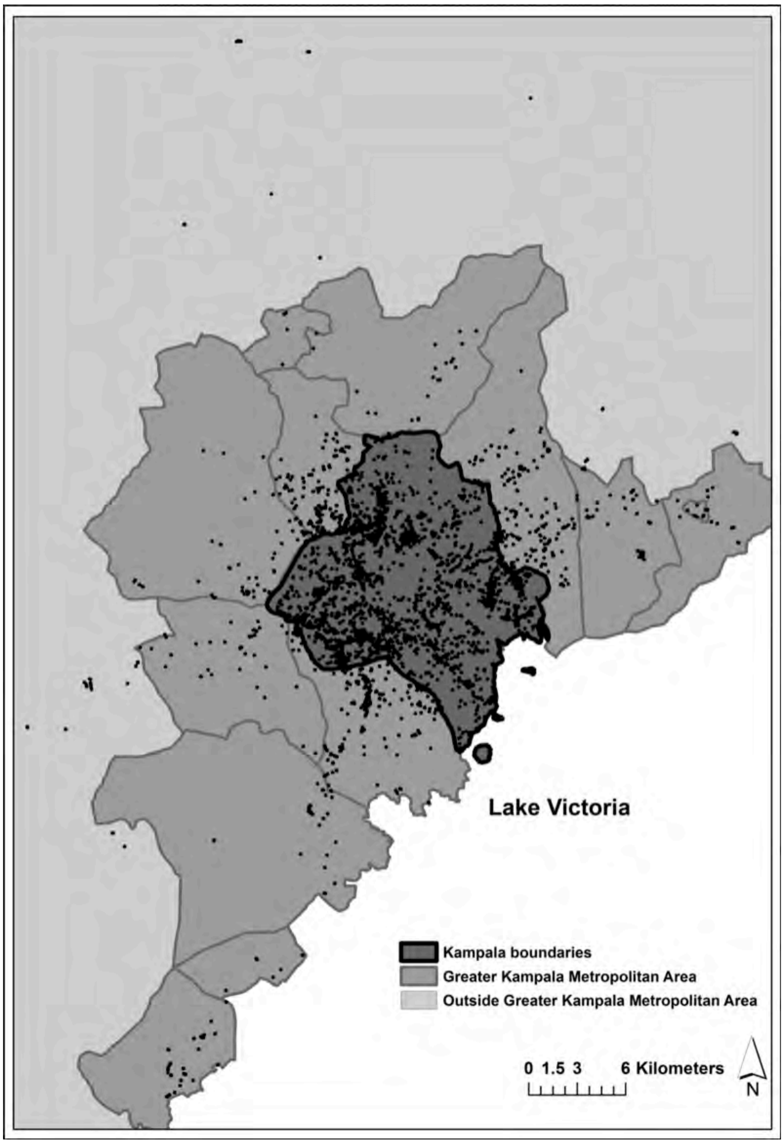
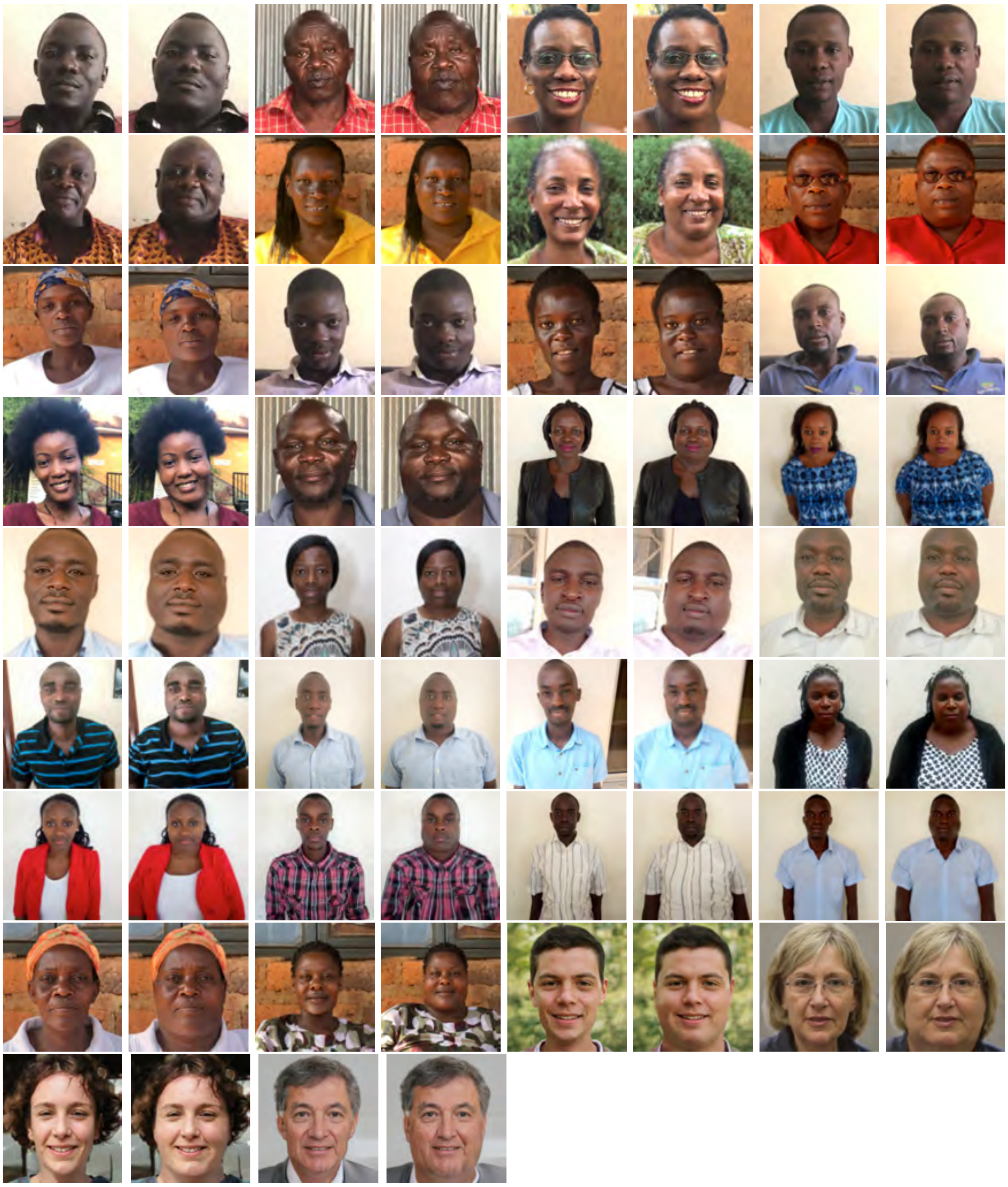


Figure K.3: Manipulated Portraits



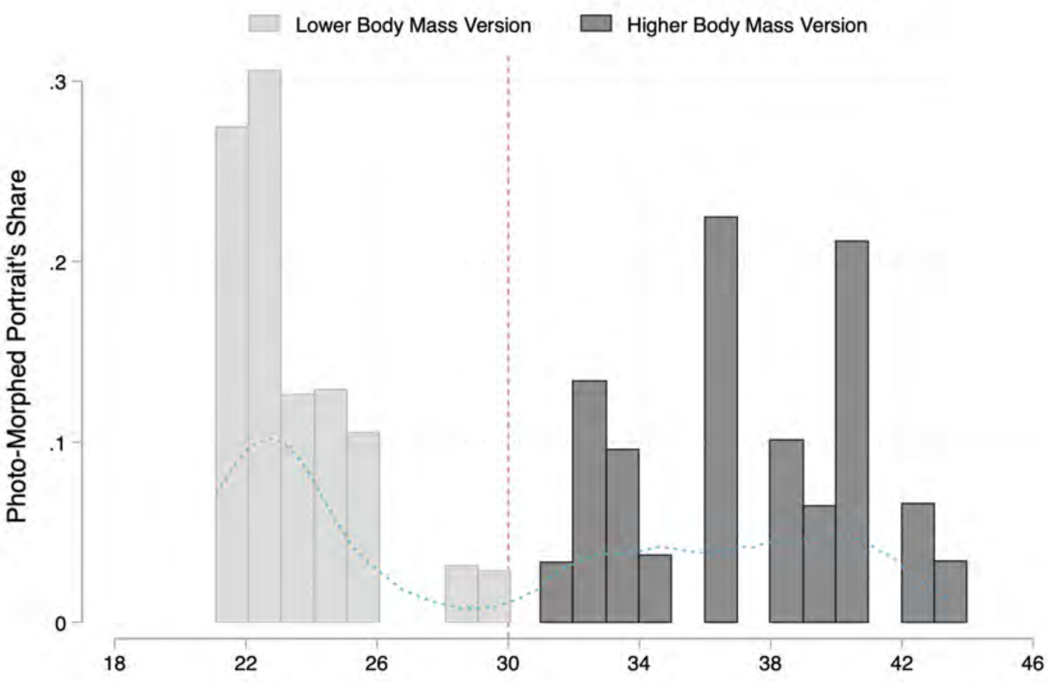
Note: The figure displays the 34 manipulated portraits exploited in the analysis. An original portrait (not displayed) has been manually manipulated by one of two independent experts, to create a lower body mass and a higher body mass version. The black race original portraits are of Kampala residents.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

Figure K.4: Linking Pictures to BMI using the Body Size Scale for Assessing Body Weight Perception in African Populations

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

Note: Portraits were matched to a BMI value with the help of 10 independent Ugandan raters. Each rater was shown the full set of pictures and the Body Size Scale shown above. The rates associated each picture to a silhouette. Then, I averaged the ratings across raters and associated a BMI to each picture using the conversion model described in Cohen et al. 2013.

Figure K.5: Manipulated Portraits: Body-Mass Index (BMI, kg/m2) Distribution



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

Figure K.6: Beliefs Experiment Structure

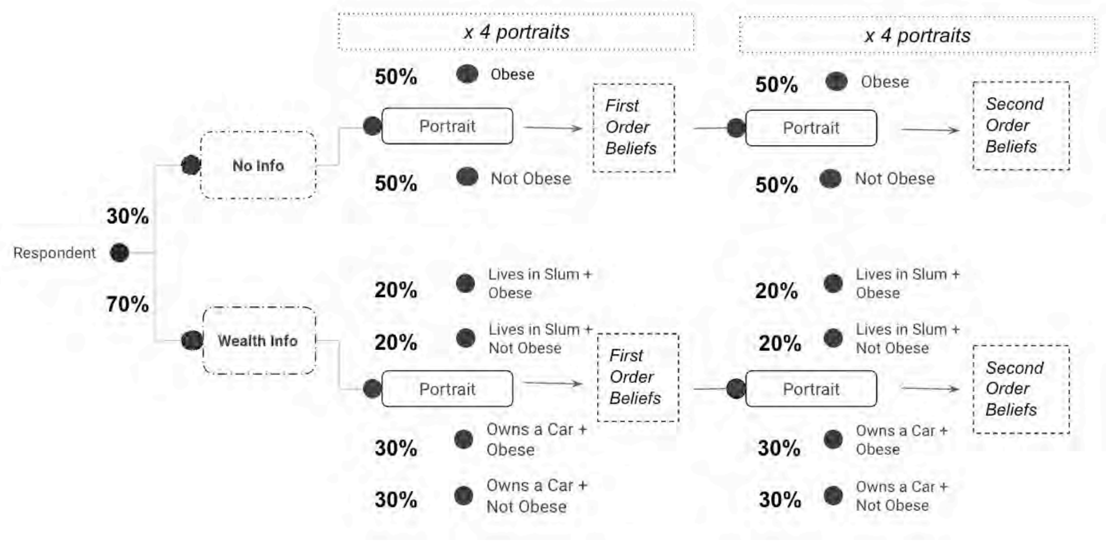


Figure K.7: Beliefs Experiment: Second Order Beliefs by Obesity Status and Wealth Information

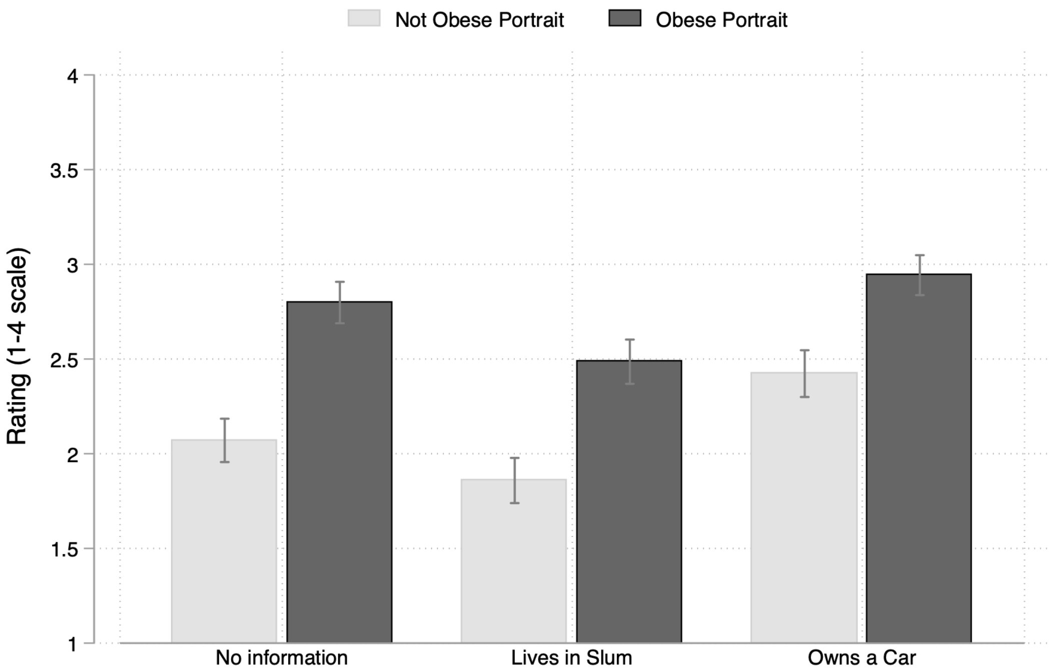


Figure K.8: Wealth

Note: The figure plots the second-order wealth beliefs from the beliefs experiment. Respondents rated several portraits' characteristics. These results include only portraits of black race, for a total of 1533 observations. In the "No Information" arm, each portrait was accompanied by age information. In the "Information" arm, portraits were associated to age information and another wealth signal: either car ownership (wealthy type), or residence in a Kampala slum (poor type). Second order beliefs are elicited using the wording: *"We showed this picture to other respondents from Kampala. Respondents learned [...]. How did other respondents rate this person's* $outcome*? Please provide your best guess of the most frequent answer on a scale from 1 to 4, where 1 is not at all ...and 4 is very ...".*

Figure K.9: Correlation between First Order Beliefs and Second Order Beliefs

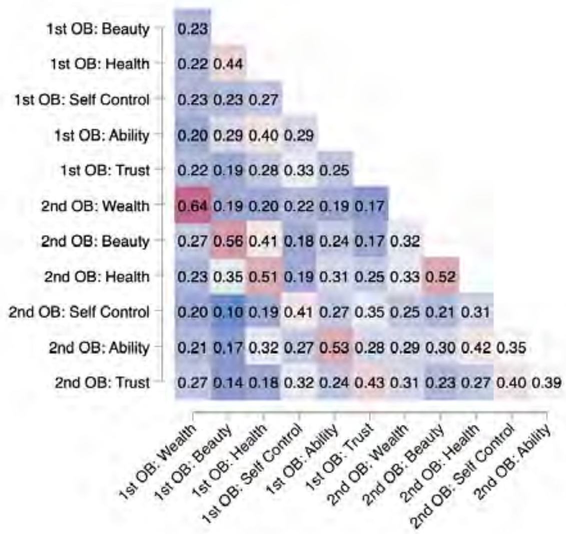
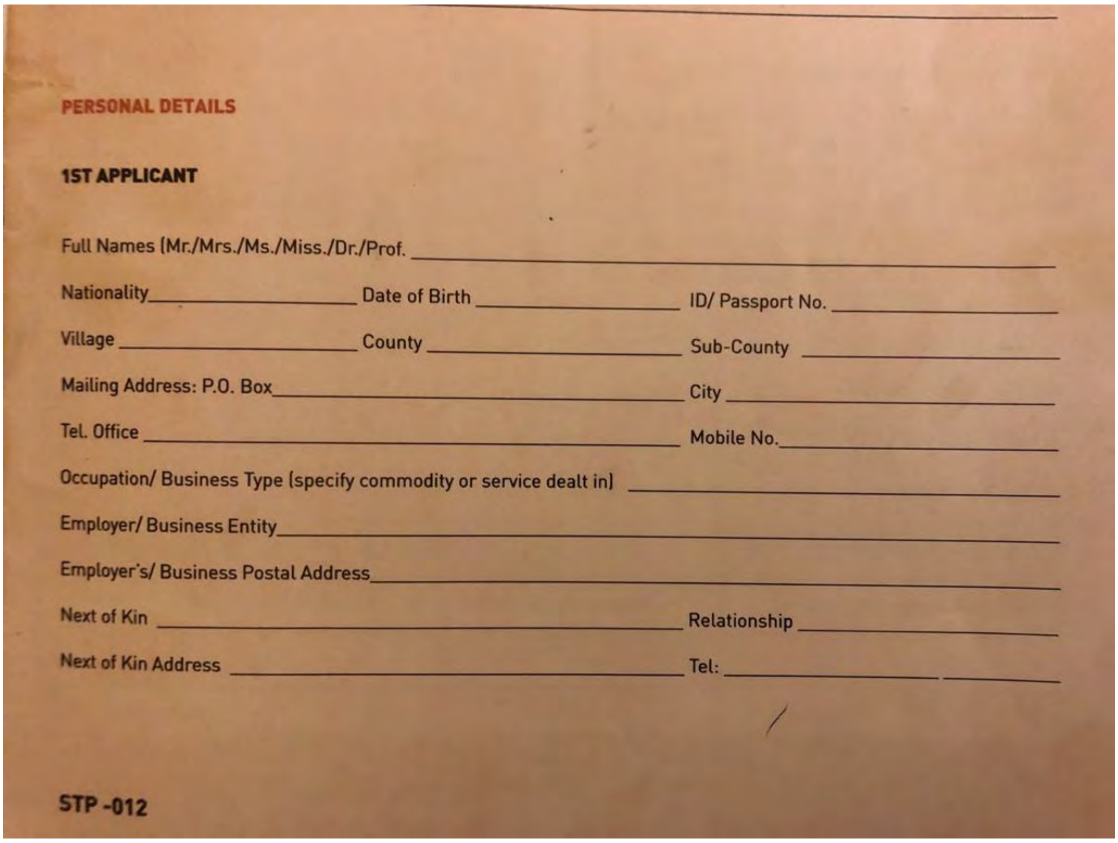


Figure K.10: Application Templates

Template A



PERSONAL DETAILS

1ST APPLICANT

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

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

Village ______ County ______ Sub-County ______

Mailing Address: P.O. Box ______ City ______

Tel. Office ______ Mobile No. ______

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

Employer/ Business Entity ______

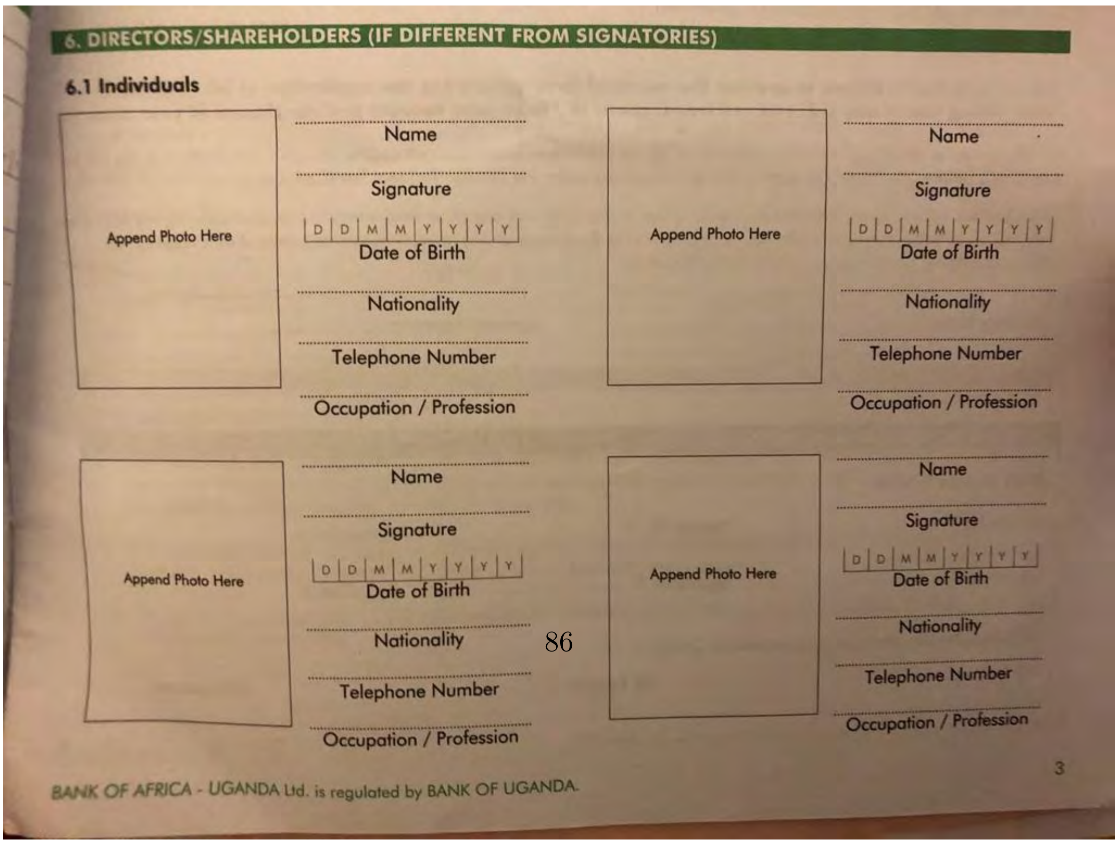
Employer's/ Business Postal Address ______

Next of Kin ______ Relationship ______

Next of Kin Address ______ Tel: ______

STP -012

Template B



6. DIRECTORS/SHAREHOLDERS (IF DIFFERENT FROM SIGNATORIES)

6.1 Individuals

Append Photo Here	Name Signature D D M M Y Y Y Y Date of Birth Nationality Telephone Number Occupation / Profession	Append Photo Here	Name Signature D D M M Y Y Y Y Date of Birth Nationality Telephone Number Occupation / Profession
Append Photo Here	Name Signature D D M M Y Y Y Y Date of Birth Nationality Telephone Number Occupation / Profession	Append Photo Here	Name Signature D D M M Y Y Y Y Date of Birth Nationality Telephone Number Occupation / Profession

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Figure K.11: Loan Officers' Performance Pay Types (excludes self-employed)

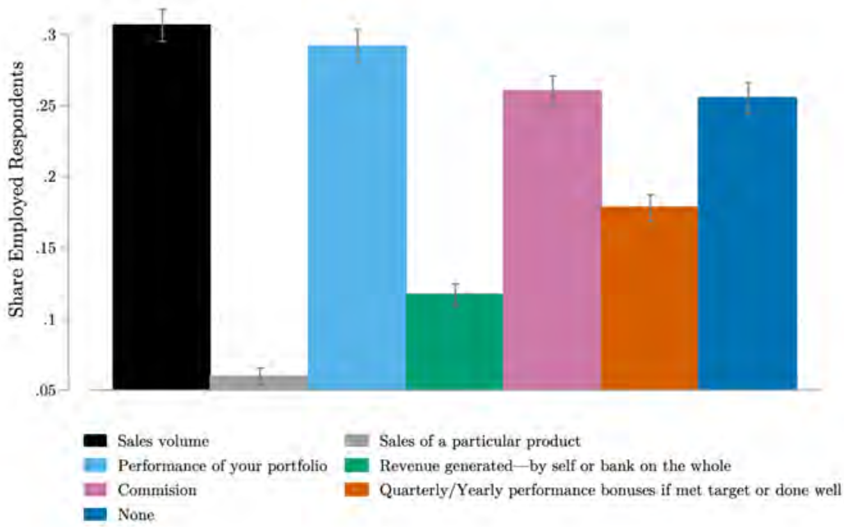
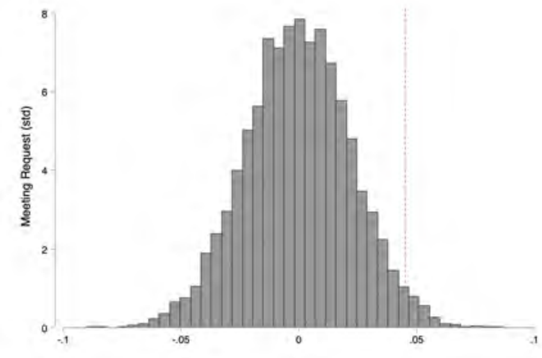
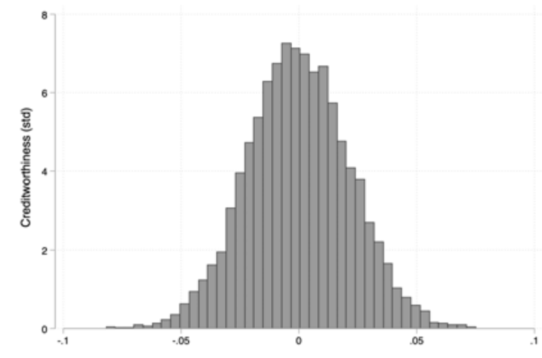


Figure K.12: Access to Credit by Applicants' BMI and Income Information



(a) Meeting Request (z)

(b) Approval Likelihood (z)



(c) Creditworthiness (z)

(d) Financial Ability

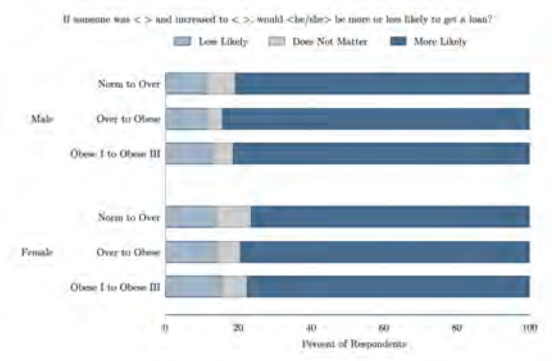
(e) Interest Rate (z)

(f) Reliability of Self-Reported Information

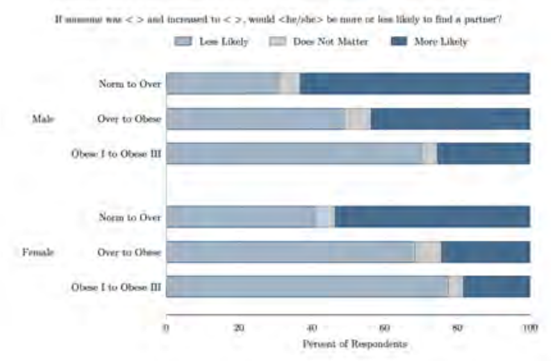
Note: Treatment effect distribution from 10,000 simulations.

Figure K.13: Laypeople explicit beliefs on the effects of body mass on credit, dating, health and job market opportunities.

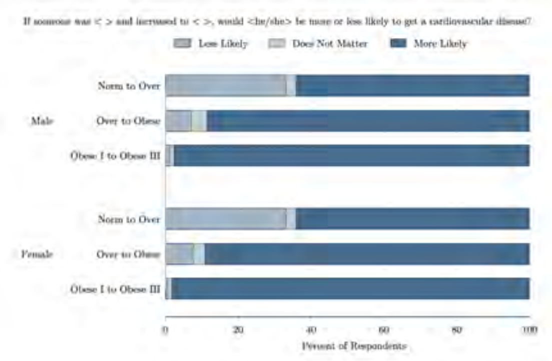
(a) Credit



(b) Dating



(c) Cardiovascular Disease



(d) Job Market

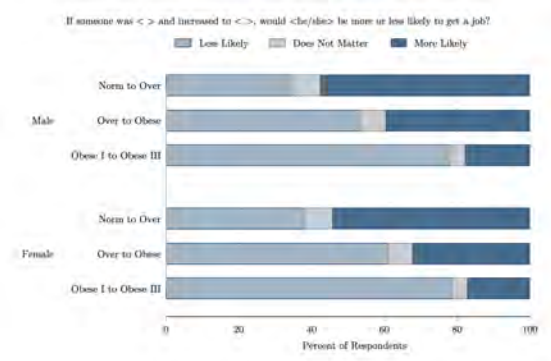
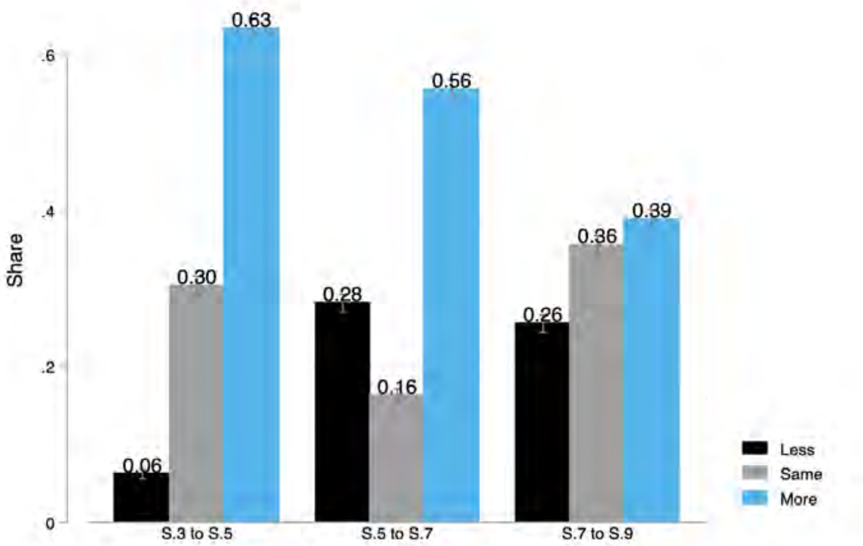
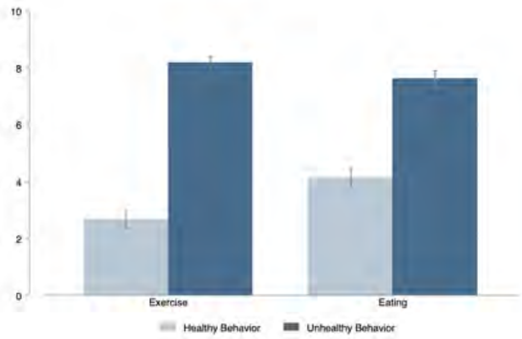


Figure K.14: Loan officers explicit beliefs about the effect of body mass on access to credit

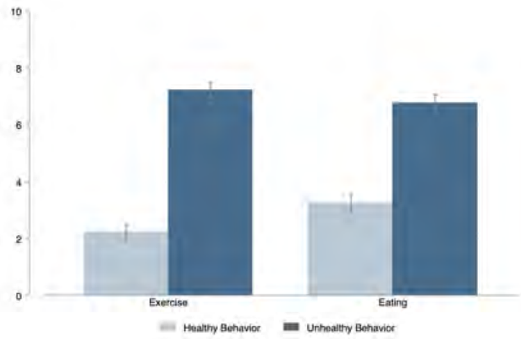


Note: Loan officers at the end of the credit experiment are shown the Body Size Scale for African Populations and asked for three silhouette jump (3 to 5, 5 to 7, 7 to 9) whether a person would be more, equally or less likely to be considered for a loan.

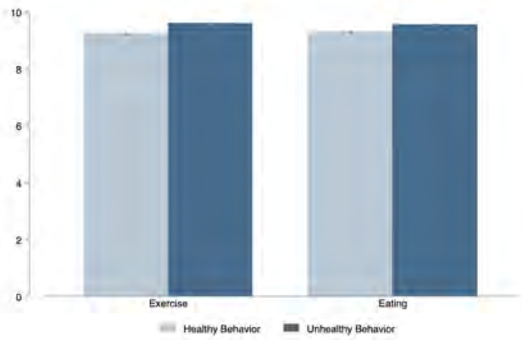
Figure K.15: Explicit beliefs about unhealthy behaviors health costs (overnutrition, lack of exercising)



(a) Overweight at age 65



(b) Cardiovascular disease at age 65

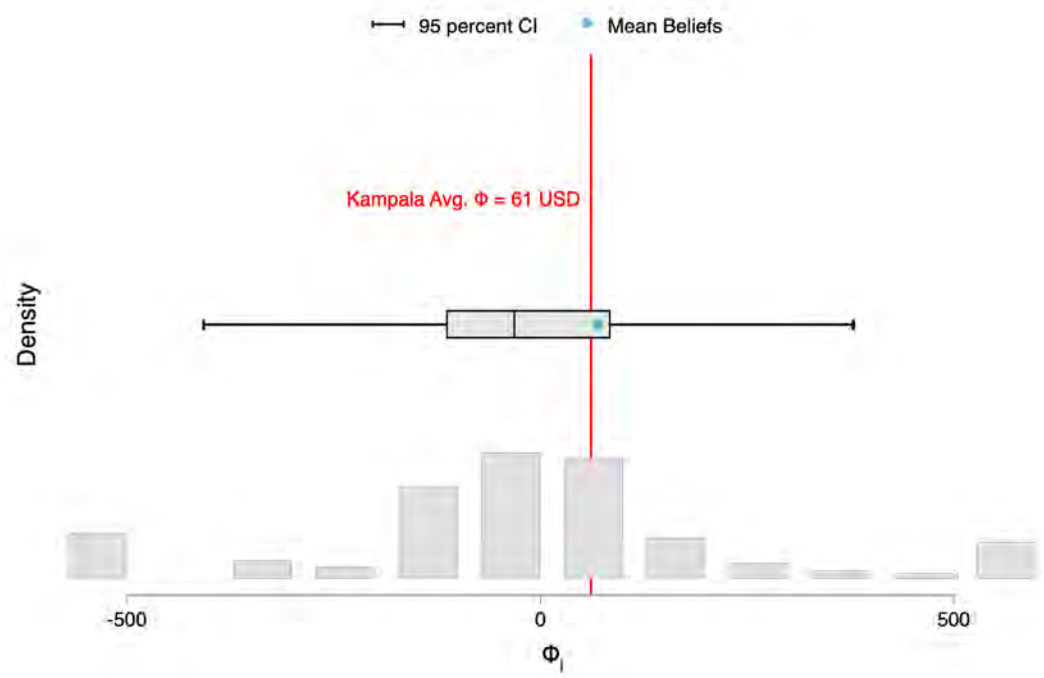


(c) Dead at age 65

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

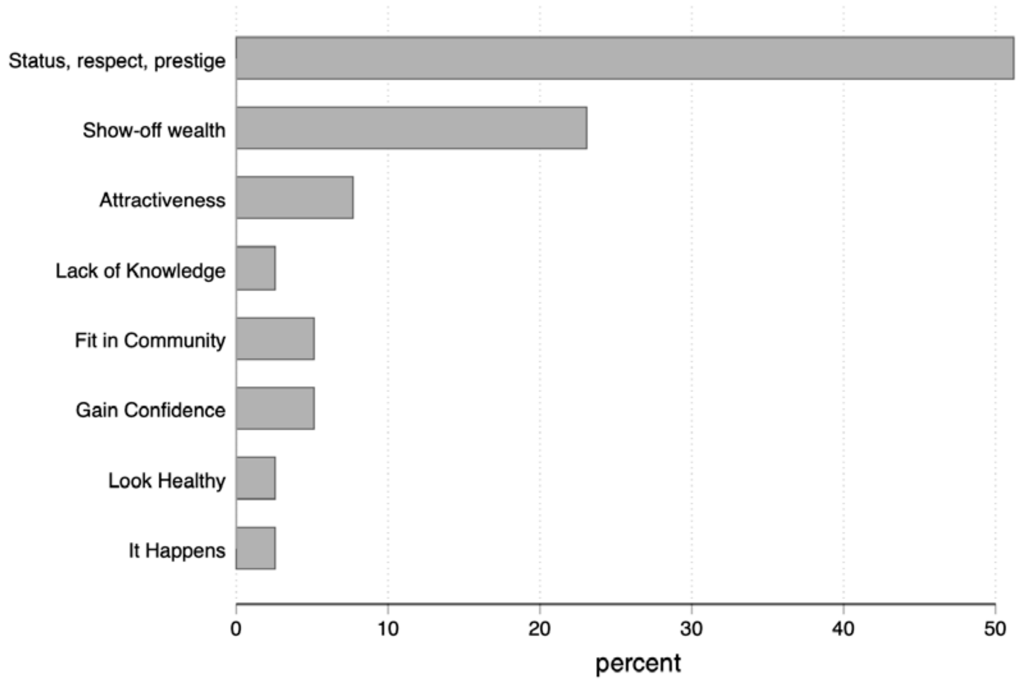
Figure K.16: Estimated loan officers' beliefs about the average income by obesity status.

Figure K.17: All applications:



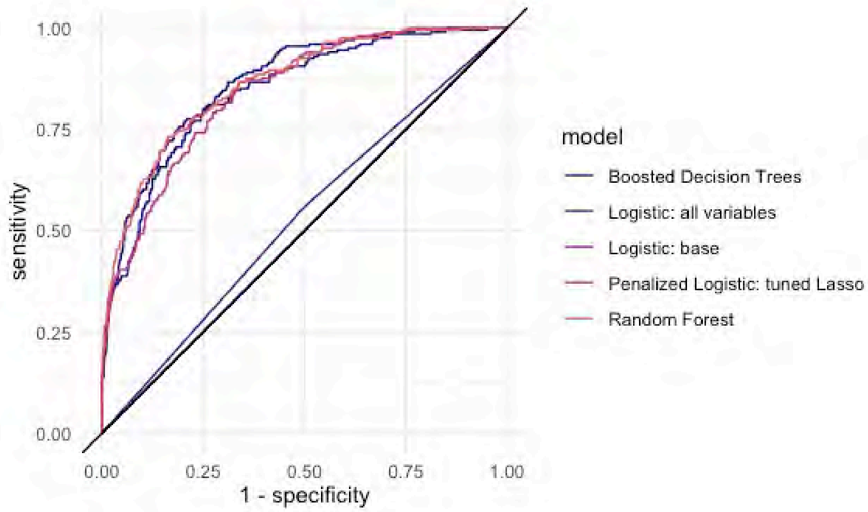
Note: The graph plots the implied loan officers' beliefs distribution about the wealth and obesity conditional correlation ϕ_j for all applications (N= 142). As expected, the distribution for trustworthy borrowers is less dispersed, suggesting that estimates may suffer from attenuation bias because of measurement error.

Figure K.18: "Why do normal weight people put effort to gain weight?" (open question)



Note: The figure categorizes the open-ended answers to the questions: "In Kampala, what are the most common reasons why normal weight people may want to gain weight or put effort to gain weight? Please answer with your best guess. " Respondents are 39 Kampala residents.

Figure K.19: ROC Curve Comparison



L Appendix Tables

Table L.1: Selected Wards (GKMA)

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

Table L.2: Survey experiment: body mass effect heterogeneity by car ownership.

	(1) Wealth	(2) Beauty	(3) Health	(4) Life Expectancy	(5) Self Control	(6) Ability
First Order Beliefs						
Obese Portrait	0.544***	0.155	0.030	-0.140	0.039	-0.102
	(0.114)	(0.124)	(0.121)	(0.123)	(0.117)	(0.120)
Owns A Car	0.870***	0.082	0.043	-0.020	0.227*	0.087
	(0.135)	(0.123)	(0.135)	(0.129)	(0.137)	(0.129)
Obese x Owns a Car	-0.059	-0.176	-0.047	0.091	-0.065	0.129
	(0.150)	(0.160)	(0.170)	(0.159)	(0.181)	(0.172)
Obs.	1023	1023	1023	1023	1023	1023
Resp. FE	Yes	Yes	Yes	Yes	Yes	Yes
Picture FE	No	No	No	No	No	No
Order FE	Yes	Yes	Yes	Yes	Yes	Yes
Second Order Beliefs						
Obese Portrait	0.647***	0.252**	0.206*	0.077	0.166	0.014
	(0.098)	(0.107)	(0.110)	(0.106)	(0.113)	(0.118)
Owns A Car	0.868***	0.031	0.044	-0.061	-0.039	-0.146
	(0.126)	(0.114)	(0.123)	(0.129)	(0.122)	(0.137)
Obese x Owns a Car	-0.118	-0.024	0.082	0.132	0.059	0.268*
	(0.142)	(0.149)	(0.153)	(0.149)	(0.157)	(0.161)
Obs.	1023	1023	1023	1023	1023	1023
Resp. FE	Yes	Yes	Yes	Yes	Yes	Yes
Picture FE	No	No	No	No	No	No
Order FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are clustered at the respondent level. Outcome variables are elicited on a scale from 1 to 4 and standardized. *Higher BM Portrait* is a dummy taking value one when the portrait rated is the high body mass version of the original portrait. Out of 2,029 total portraits ratings, 330 refer to white portraits. *Owns a Car* is a dummy taking value 1 if the portrayed individual was associated to owning a car. The excluded category is *Living in a Slum.*

Table L.3: Survey experiment: body mass effect heterogeneity by race of the portrayed individual .

	(1) Wealth	(2) Beauty	(3) Health	(4) Life Expectancy	(5) Self Control	(6) Ability
First Order Beliefs						
Obese Portrait	0.628***	0.110*	-0.011	-0.076	0.024	0.007
	(0.063)	(0.064)	(0.062)	(0.062)	(0.062)	(0.066)
White Race Portrait	0.758***	0.674***	0.348**	0.071	0.301**	0.285**
	(0.134)	(0.130)	(0.147)	(0.145)	(0.142)	(0.135)
Obese x White Race Portrait	-0.459***	-0.058	-0.008	0.030	-0.136	-0.084
	(0.137)	(0.135)	(0.151)	(0.145)	(0.152)	(0.146)
Obs.	2029	2029	2029	2029	2029	2029
Second Order Beliefs						
Obese Portrait	0.709***	0.310***	0.225***	0.131**	0.198***	0.128*
	(0.062)	(0.060)	(0.065)	(0.063)	(0.064)	(0.066)
White Race Portrait	1.001***	1.038***	0.859***	0.594***	0.544***	0.494***
	(0.134)	(0.132)	(0.134)	(0.131)	(0.136)	(0.128)
Obese x White Race Portrait	-0.639***	-0.238*	-0.231	-0.066	-0.289*	-0.293*
	(0.135)	(0.143)	(0.144)	(0.151)	(0.154)	(0.150)
Obs.	2029	2029	2029	2029	2029	2029

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are clustered at the respondent level. Outcome variables are elicited on a scale from 1 to 4 and standardized. Regressions include respondent and portrayed individual fixed effects. *Obese Portrait* is a dummy taking value one when the portrait rated is the high body mass version of the original portrait. Out of 2,029 total portraits ratings, 330 refer to white portraits.

Table L.4: Reliability of Self-Reported Wealth Information

	(1) Financial Information Reliability Rating	(2) Financial Information Reliability Rating (z)
Obese Applicant	0.045**	0.042**
	(0.019)	(0.017)
Constant	1.980***	-0.043
	(0.057)	(0.053)
Observations	4408	4408

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. All regressions include applications (portrait), loan officer, and information treatment fixed effects. Standard errors are clustered at the loan officer level. Reliability rating is on a scale from 1 (not at all reliable) to 5 (extremely reliable). The question is only applicable to applications which included wealth information. to loan officers which have interest rate discretionality for a given loan profile. In Column 1, the dependent variable is the reliability evaluation on 1-5 scale, Column 2, the dependent variable is the equivalent variable standardized. *Obese Applicant* is a dummy taking value one if the application included the high-body-mass version of the original picture.

Table L.5: Obesity Premium by Gender (Borrower)

	(1) Referral Request	(2) Approval Likelihood	(3) Financial Ability	(4) Credit-worthiness	(5) Access to Credit Index
Obese Borrower=1	-0.003	0.050*	0.092***	0.012	0.051*
	(0.026)	(0.028)	(0.028)	(0.029)	(0.028)
Male Borrower=1	-0.286**	-0.315***	-0.250**	-0.161	-0.317***
	(0.120)	(0.107)	(0.122)	(0.110)	(0.108)
Obese Borrower=1 × Male Borrower=1	0.096**	0.112**	0.056	0.124***	0.112**
	(0.043)	(0.044)	(0.043)	(0.044)	(0.044)
Observations	6445	6445	6445	6445	6445

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. P-values are clustered at the loan officer level. *Meeting Request* is a dummy taking value 1 when the loan officer chooses to be referred a borrower similar to the hypothetical one. *Approve* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). *Interest rate* is probability of assigning an interest rate larger than the standard one. The question is only applicable to loan officers which have interest rate discretionality for a given loan profile. Regressions includes loan officer fixed effects and control for occupation, collateral, reason for loan and loan application profile. This heterogeneity analyisis was pre-registered.

Table L.6: Images Ratings by BMI (Loan Officers)

	(1) Wealth	(2) Beauty	(3) Health	(4) Life Expectancy	(5) Self Control
All pictures:					
Image BMI: High	0.272**	0.330***	-0.003	0.226*	0.086
	(0.127)	(0.116)	(0.131)	(0.132)	(0.132)
Observations	254	254	254	254	254
Picture FE	Yes	Yes	Yes	Yes	Yes
Mean	Std.	Std.	Std.	Std.	Std.
By Pictures' Sex:					
Image BMI: Obese	0.221	0.289*	-0.067	0.143	0.104
	(0.177)	(0.173)	(0.164)	(0.169)	(0.187)
Image Sex: Male	-0.286	-0.331**	-0.233	-0.294*	-0.481***
	(0.176)	(0.165)	(0.165)	(0.177)	(0.177)
Male × Obese	0.234	0.019	0.136	0.168	-0.009
	(0.244)	(0.241)	(0.242)	(0.247)	(0.246)
Observations	254	254	254	254	254
Picture FE	No	No	No	No	No
Mean	Std.	Std.	Std.	Std.	Std.

Notes: * p< 0.1 , ** p< 0.05, *** p< 0.01. Regressions include picture fixed effect. *Wealth* is a standardized 1-5 rating of the applicant's wealth. *Attractiveness* is a standardized 1-5 rating of the applicant's attractiveness. *Health* is a standardized 1-5 rating of the the applicant's health status. *Life Expectancy* is a standardized 1-5 rating of the the applicant's life expectancy. *Self-control* is a standardized 1-5 rating of the the applicant's ability to resist to temptation. Panel B reports the heterogeneity by sex, as pre-registered.

Table L.7: Male Loan Officers Evaluating Male Borrowers

	(1) Referral Request	(2) Approval Likelihood	(3) Financial Ability	(4) Credit-worthiness	(5) Access to Credit Index
Obese Borrower	0.093**	0.200***	0.144***	0.139***	0.141***
	(0.044)	(0.043)	(0.048)	(0.046)	(0.047)
Observations	1948	1948	1948	1948	1948

Notes: * p<0.1, ** p< 0.05, *** p<0.01. P-values are clustered at the loan officer level. *Meeting* is a dummy taking value 1 when the LO chooses to be referred an applicant similar to the hypothetical one. *Approve* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). *Interest rate* is probability of assigning an interest rate larger than the standard one. The question is only applicable to loan officers which have interest rate discretionality for a given loan profile. Regressions include application fixed effects, loan officer fixed effects and fixed effects for the information included in the application (demographics only; demographics and wealth information). *Obese borrower* is a dummy taking value one if the application included the high-body-mass version of the original picture.

Table L.8: Heterogeneity by Application Order

	(1) Meeting Request	(2) Approval Likelihood	(3) Interest Rate	(4) Financial Ability	(5) Credit-worthiness
Obese Applicant	0.035	0.098***	0.066	0.113***	0.065**
	(0.030)	(0.032)	(0.046)	(0.034)	(0.031)
Second-Half	0.101	0.293***	0.126	0.284***	0.108
	(0.097)	(0.101)	(0.163)	(0.089)	(0.090)
Obese Applicant × Second-Half	0.021	0.017	-0.071	0.013	0.015
	(0.046)	(0.050)	(0.079)	(0.050)	(0.043)
Observations	6445	6445	3175	6445	6445

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. P-values are clustered at the loan officer level. *Meeting Request* the standardized value of a dummy taking value 1 when the loan officer chooses the meet with a similar applicant (referral). *Approval Likelihood* is the self-reported likelihood of approving the application (standardized). *Creditworthiness* is the perceived creditworthiness of the applicant (standardized). *Financial ability* is the perceived ability of the applicant to put money to good use (standardized). *Interest rate* is probability of assigning an interest rate larger than the standard one (standardized). The question is only applicable to loan officers which have interest rate discretionality for a given loan profile. Regressions include application, loan officer and information arm fixed effects (demographics only; demographics and wealth information). *High BM Application* is a dummy taking value one if the application included the high-body-mass version of the original picture. *Order* is a categorical variable indicating at which point of the sequence did

Table L.9: Obesity Premium by Wealth Information Timing

	(1) Meeting Request	(2) Approval Likelihood	(3) Interest Rate	(4) Financial Ability	(5) Credit-worthiness	(6) PCA Index	Info Reliability
Obese	0.054*	0.069**	0.081**	0.047	0.021	0.070**	0.041*
	(0.032)	(0.031)	(0.034)	(0.034)	(0.037)	(0.031)	(0.024)
Info Later	0.067*	0.004	-0.027	-0.043	-0.007	0.004	-0.000
	(0.036)	(0.039)	(0.036)	(0.034)	(0.035)	(0.039)	(0.025)
Obese $\times$ Info Later	-0.044	-0.009	0.024	0.005	-0.011	-0.010	0.001
	(0.042)	(0.045)	(0.046)	(0.044)	(0.048)	(0.045)	(0.031)
Observations	4419	4419	4419	4419	2217	4419	4408
Application FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Information FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Standardized	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table L.10: Obesity Premium by Borrower's Income

	(1) Referral Request	(2) Approval Likelihood	(3) Interest Rate	(4) Financial Ability	(5) Credit-worthiness	(6) PCA Index
Obese Applicant=1	0.069**	0.094***	0.046	0.126***	0.068*	0.094***
	(0.034)	(0.036)	(0.051)	(0.037)	(0.038)	(0.036)
Profits (UGX mil)	-0.043	0.139	-0.213	-0.036	0.194*	0.139
	(0.110)	(0.119)	(0.139)	(0.113)	(0.116)	(0.120)
Obese Applicant=1 × Profits (UGX mil)	-0.022	-0.018	-0.019	-0.020	-0.011	-0.018
	(0.015)	(0.017)	(0.019)	(0.017)	(0.017)	(0.017)
Observations	4419	4419	2217	4419	4419	4419

Notes: * p< 0.1, ** p< 0.05, *** p<0.01. P-values are clustered at the loan officer level. Regressions includes loan officer fixed effects and application fixed effects. The regression only applies to applications which included self-reported wealth information.

Table L.11: AUC: Models Comparison

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

Table L.12: Most common reason for gaining and for losing weight in Kampala (open questions).

Respondent Number	Why do people want to gain weight?	Why do people want to lose weight?
1	To be more respected and look presentable in the society.	To avoid diseases like pressure
2	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
3	So that they appear attractive and respected. Its common for unmarried people. [...]	Sexual pleasure. [...]
4	To look wealthy	To avoid diseases
5	To be respected in public	To easily do work without getting tired
6	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
7	Just like myself, they feel you can look cash but after gaining the weight you start battling to reduce it	To live healthier
8	In Kampala its commonly known that people with money	To look smarter though most times normal weight people don't want to lose weight.
	have the weight so even conmen and women find a better technique to gain weight	They only lose unwillingly due to conditions like stress.
9	Respect	To avoid diseases like pressure and other heart related diseases
10	Prestige. Fat people are respected even in terms of finances	To be more healthy
11	Financial-such other people should look at them as wealthy	To be more fit
12	Feeling to appear healthy	To look rich and show that they doing well financially
13	To look more representable and wealthy	To be healthy and lighter
14	Fat people are assumed to have money and are respected	Overweight is associated with diseases so most people do it to prevent easy attacks
15	Peer pressure fit in community	Be fit for some jobs
16	To be more respected	To be healthy and fit
17	They are ignorant	People may mistake n you to be wealth
18	It just happens as they Eat fatty foods and do not do exercise	Avoid sickness related to over weight
19	To gain respect	Avoid sickness associated with over weight
20	Earn more respect, self confidence	Fighting the attack of diseases and be more flexible
21	They want to be seen as different and attractive	To be more flexible and attractive
22	Get respect in community	Get rid of sickness associated with obesity
23	To look rich	Healthier
24	To gain more respect from people around them	To be more flexible, and to be in good shape
25	So that they can look good with some weight	To fight disease attack
26	To fit in community	Fit in community
27	So that they can respect them	To look more attractive
28	Gain more respect	Avoid diseases like pressure and diabetes
29	Fit in group	Fit in society pear pressure
30	Get more respect	Fear to sicknesses
31	To earn more respect	Fighting not to get diseases
32	To gain more respect	To be in shape and flexible
33	Due to Inferiority complex	Portability
34	So that they don't under rate them	To fight disease and look attractive
35	To earn more respect	They don't want to be attacked by diseases and be fit
36	To earn more respect	Fear of getting diseases
37	So that they can be more attractive	Not to get diseases
38	So that they can be respected	To be in good shape
39	Earn more respect, to gain some big status	They look more flexible

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

Table L.13: Image Ratings by BMI - Rural Malawi

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

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