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Abstract: Income inequality and obesity are both widespread socioeconomic issues, particularly salient in middle-income countries. This article seeks to detect the relationship between local income inequality and excess weight in Mexico, using robust municipal income inequality measures generated through small area estimation method and instrumental variable multilevel estimations. Our results emphasize a negative impact of municipal income inequality on individual bodyweight, especially for women. We also explore the potential channels through which income inequality may decrease bodyweight. Three-stage least squares estimations highlight that the social capital pathway, the public policy pathway and the psychological pathway help to explain the negative effect of inequality on excess weight. Our results are fairly robust to alternative inequality measures and nutritional indicators.

Keywords: Mexico; income inequality; obesity; instrumental variables.

1. Introduction

In the last decades, both within-country income inequality and obesity rates have alarmingly increased worldwide, especially in developing countries (NCD-Risk Factor Collaboration, 2016; Alvaredo et al., 2018). Surprisingly, the potential link between these two issues remains poorly researched.

It is well-known that poverty has a harmful impact on lifestyles, nutrition and health (Currie, 2009). However, because humans are social beings, absolute income and material deprivation are insufficient to predict health and nutritional outcomes (Wagstaff and van Doorslaer, 2000). The latter may also be affected by the distribution of income within society. Theoretically, income inequality creates a social environment that potentially affects health in several dimensions. The existing literature finds convincing damaging effects of income inequality on both mental and physical health, including psychological disorders, life expectancy reduction, and premature death (Pickett and Wilkinson, 2015).

The rare studies that analyze the role of income inequality on the alarming rise of worldwide obesity exhibit confusing results. Comparing 21 rich countries, Pickett et al. (2005) report a positive association between income inequality and obesity. However, the inclusion of extreme cases such as the US and Japan shows a misleading positive link: while the US have the highest levels of inequality and obesity among rich countries, Japan has the lowest levels in both phenomena. Likewise, Su et al. (2012) find that, in OECD countries, the positive association between income inequality and obesity rate disappears when extreme cases are excluded from the sample.

In addition to these cross-country studies, the literature focusing on the US context provides mixed evidence on the relationship between state/county income inequality and individual bodyweight outcomes. While some studies report a negative link (Bjornstrom, 2011; Fan et al., 2016), others conclude on a positive one (Diez-Roux et al., 2000; Robert and Reither, 2004) or on the absence of a significant association (Chang and Christakis, 2005; Mobley et al., 2006). Furthermore, three limitations could bias the estimates from previous studies. First, most of existing studies are based on self-reported anthropometric data (namely height and weight) which is problematic since inequality-based psychosocial troubles potentially infer own body perception (Fan et al., 2016). Indeed, individuals living in unequal societies might overstate their weight. Second, previous studies primarily use multilevel models that do not address potential endogeneity issues linked to reverse causality and omitted variables (Pickett and Wilkinson, 2015). Third, although each study is highly informative on the relationship between inequality and obesity, potential pathways underlying this relationship have not been studied.

This study fills the literature gap by analyzing the nutritional impacts of municipal income inequality using objective anthropometric measurements and an endogeneity-correction methodology. Another input of the study is its original focus on a middle-income country where the link between local income inequality and obesity is unclear and potentially different from the US and other rich countries, due to specific institutional settings and socio-cultural factors (Karlsson et al., 2010). Nonetheless, country-specific studies focusing on developing countries demonstrate that provincial income inequality correlates with poorer self-rated health in Argentina (Maio et al., 2012), China (Pei and Rodriguez, 2006) and India (Rajan et al., 2013), and with lower life expectancy in Brazil (Rasella et al., 2013). To our knowledge, only Larrea and Kawachi (2005) focus on the nutritional consequences of inequality in the case of developing countries. They identify a positive link between provincial income inequality and childhood stunting in Ecuador, suggesting that income inequality threatens food security among vulnerable households. Finally, it should be noted that the literature examining the health consequences of inequality in developing countries only measures income inequality at a relatively aggregated scale (i.e. at the provincial level), thus ignoring the influence of more local social mechanisms.

In this study, we focus on the relationship between municipal income inequality and adult bodyweight in Mexico. Several reasons justify our choice. First, Mexico exhibits a very high level of income inequality with the fourth highest Gini index of 0.46 among OECD members in 2016 (OECD, 2019). Second, overweight and obesity have rapidly increased and are now predominant: one-third of Mexican adults are obese and two-thirds are overweight (NCD-Risk Factor Collaboration, 2016).

Our empirical investigation is based on the construction of an original database that merges municipality-level data from various sources and individual-level data from the 2016 Mexican Health and Nutrition Survey (*Encuesta Nacional de Salud y Nutricion*, ENSANUT*)*. To measure income inequality, we rely on small area estimation (SAE) and combine data from the 2015 inter-census survey (*Encuesta Intercensal*, EIC) and the 2016 National Survey of Household Income and Expenditure (*Encuesta Nacional de Ingresos y Gastos de Hogares*, ENIGH) to construct measures of income inequality that are representative at the municipal-level. Using this original dataset, we implement multilevel estimations to identify the link between municipal income inequality and individual nutritional outcomes. To limit potential reverse causality bias and the presence of unobserved heterogeneity, we also run a two-stage estimation model based on instrumental variables (IV), besides controlling for a comprehensive set of municipal and individual characteristics. The IV design uses meteorological data as instruments for municipal income inequality (i.e. yearly average amount of precipitation, temperature and altitude). We also investigate potential gender heterogeneity. Finally, we explore pathways through which municipal income inequality can affect individual nutritional outcomes, using three-stage least square estimations (3SLS).

Surprisingly, our results show that municipal income inequality has a negative effect on adult bodyweight. This negative effect of inequality on individual weight is primarily driven by the results for women. Further investigations about potential pathways suggest that this counter-intuitive effect particularly transits through the low levels of social capital and the deficit in public infrastructures associated with high municipal inequality. For instance, individuals living in unequal municipalities are less likely to have social and outdoor entertainments, including activities related to weight gain such as outdoor food and beverage intakes, and have lower access to public services such as piped water, increasing the risk of infectious diseases related to weight loss in addition to increase daily physical activity for fetching water. Moreover, we also detect a notable importance of the psychological pathway since income inequality tends to favor weight loss (or impede weight gain) through a poorer quality of sleep. These results point out the necessity for public policies aiming at reducing inequalities to be accompanied by nutritional policies and awareness campaigns.

The rest of the article structures as follows. In section 2, we illustrate the conceptual framework. In sections 3 and 4, we respectively describe the database and the empirical strategy. In section 5, we present the results. Finally, section 6 concludes and provides policy recommendations.

2. Literature review and conceptual framework

An extensive literature analyzes the impact of income inequality on health, considering both cross-country and country-specific studies (Pickett and Wilkinson, 2015). Three pathways are consensually mentioned in order to explain how an unequal income distribution may influence health outcomes, especially mental and physical illness (Kawachi and Kennedy, 1999; Subramanian and Kawachi, 2004): (i) a psychological pathway (i.e. in unequal societies, the feeling of isolation and vulnerability increases and individuals are more often subject to mental illness such as chronic stress and depression); (ii) a social capital pathway (i.e. as unequal societies are prone to market-oriented policies and individualism, the structurally low levels of social cohesion, civic involvement, reciprocity and trust may affect health outcomes in several ways); (iii) a public policy pathway (i.e. public revenues from taxation being generally low in unequal areas, income inequality might interact with health through a reduction of local investments in human capital and public facilities).

Globally, empirical studies show that income inequality has negative impacts on health outcomes. In contrast, there is no consensus in the literature about its effects on nutritional outcomes. In fact, the nutritional impacts of income inequality might be different to those observed on other health outcomes insofar as the effects of each pathway are highly ambiguous.

First, individual psychological disorders induced by relative position in society might increase obesity risk. In Mexico, Esposito et al. (2020) find that relative wealth deprivation predicts higher BMI and obesity risk. Pickett et al. (2005) suggest that, by decreasing mental well-being, income inequality reduces the desire for physical exercise, outdoor social interactions and eating healthy. They also mention the potential physiological effects of chronic stress and depression such as snacking, overeating and risky non-food consumptions such as drinking alcohol and narcotic intake, which potentially lead to weight gain (Brunner et al., 2007). However, the nutritional effects of stress and depression are ambiguous in the epidemiological literature since they can result in weight loss in some circumstances. In fact, food intake disorders associated with stress and depression depend on baseline bodyweight and eating status (dieter vs. non-dieter). Kivimäki et al. (2006) and de Wit et al. (2009) find that both stress and depression induce weight gain among already overweight subjects, but weight loss for initially thin individuals. Moreover, one's relative position in society may generate envy and social comparisons. As shown by Bjornstrom (2011) and Fan et al. (2016)

in the US context, the higher proportion of affluent and healthy residents in unequal localities, compared to localities where income is more homogenously distributed, can provide role models for mainstream social norms and health-related behaviors, therefore improving the nutritional outcomes of the poorest.

Second, the loss of social capital induced by income inequality is expected to have ambiguous effects on bodyweight. On the one hand, lower trust and cohesiveness in society may reduce the occurrence of outdoor entertainment and physical activity (Broyles et al., 2011), which is a potential risk factor for weight gain. On the other hand, it might also induce a reduction of outings with friends and family, associated with junk food and beverage intakes, as well as outdoor non-food intakes associated with weight gain such as drinking alcohol (Leyden, 2003). Furthermore, the lack of trust, reciprocity and transfers characterizing unequal societies can increase the risk of transitory food insecurity and infectious diseases when shocks occur and may lead to important individual weight loss (Hadley et al., 2007).

Third, the nutritional impacts of the policy pathway are even more ambiguous. For instance, a lower availability of health services, social safety nets or sanitation-related infrastructures (e.g. drinkable water taps, drainage systems) intensifies household vulnerability to economic and demographic shocks, increasing the risks of nutritional deprivations and infectious diseases related to weight loss (e.g. diarrhea, cholera, intestinal worms) (Gundry et al., 2004). Similarly, lower collective investments in public transportation may increase walking time to work and overall physical activity. In contrast, lower investments in urban amenities such as parks, street pathways and public lighting may decrease the occurrence of out-of-work outdoor physical activity, thus increasing body-mass (Feng et al., 2010). However, Leyden (2003) finds a positive association between neighborhood walkability, social capital and outdoor social activities such as restaurant and pub attendance. This means that living in unequal areas, where public investments in pedestrian amenities are low, might protect residents against risky outdoor consumptions and related weight gain.

3. Data

3.1. Nutrition variables

Our data for the measurement of nutritional outcomes come from the Mexican Health and Nutrition Survey (ENSANUT), a nationally representative household survey coordinated by the National Public Health Institute (*Instituto Nacional de Salud Pública*, INPS). In this article, we use the 2016 mid-stage (*medio camino*) survey (ENSANUT-MC 2016). In line with the existing literature analyzing adult bodyweight indicators in Mexico (e.g. Levasseur, 2019), we restrict our sample to adults aged from 18 to 65 (pregnant women excluded), accounting for more than 6,000 observations. As explained by Elia (2001), older individuals are subject to several metabolic changes and are not physically comparable to working-age adults. Among the 2,457 Mexican municipalities, only 214 municipalities are covered by the ENSANUT-MC 2016 survey. However, the sampling procedure ensures the inclusion of municipalities with different sizes and socio-demographic characteristics in order to reflect the diversity of all Mexican municipalities and guarantee representativeness. Appendix S2 in Supplementary Materials presents descriptive evidence supporting the representativeness of the restricted sample. While Figure S2.1 suggests a quasi-normal distribution of observations across the 214 municipalities, Figure S2.2 shows that the 214 selected municipalities are representative of the distribution of municipality sizes in Mexico. Finally, for several variables of interest, Figure S2.3 displays similar distributions in both samples.

Our main nutritional measure is the body mass index (BMI) defined as the weight (in kilograms) divided by the square of the height (in meters). The extreme values (below 15kg/m² and above 50kg/m²) have been excluded. It should be noted that in the ENSANUT surveys, weight and height are measured with an objective procedure (using stadiometers and weighting machines) by trained health professionals. Based on the BMI, we also identify clinical bodyweight categories using the WHO cut-offs that are officially approved in Mexico: underweight for BMI<18.5kg/m²; normal weight for BMI between 18.5 and 25kg/m², overweight for BMI between 25 and 30kg/m² and obesity for BMI>30kg/m². Lastly, a robustness test uses waist circumference (in centimeters) as an alternative nutritional measure.

(Insert Figure 1 and Table 1)

Figure 1 presents the distribution of BMI for women and men respectively and Table 1 reports the proportion of population within each BMI clinical categories. As expected, there is a large diffusion of overweight and obesity within the Mexican society since approximately 70% of adults from our sample are overweight or obese. In contrast, underweight has become residual. In terms of gender, these results point out that there is a much higher prevalence of obesity among women (about 41% for women against 28.5% for men) while men are more concerned with overweight (41.5% for men against 37% for women).

3.2. Inequality variables

From a methodological perspective, analyzing the spatial distribution of intra-municipal inequality raises some important issues. Ideally, census data should be privileged to measure inequality at the municipal level, to the extent that doing so ensures representativeness at the municipal scale. However, censuses are not suited for the measurement of income inequality because of the absence of income data collection. Household surveys are better suited in this regard but fail to be representative at a disaggregated level, such as municipalities. This is the reason why, in line with the pioneering work of Elbers et al. (ELL) (2003), we apply small area estimation (SAE) techniques. The main objective of SAE is to combine census and survey data in order to simulate representative inequality measures at a spatially disaggregated level. In this study, we provide our own SAE estimates based on the combination of the 2015 inter-census survey (EIC) and the 2016 National Survey of Household Income and Expenditure (ENIGH) implemented by the National Institute of Statistics and Geography (*Instituto Nacional de Estadística y Geografía*, INEGI).

Despite many recent refinements in SAE methods, we adopt the standard approach developed by ELL because of its multiple applications in poverty and inequality analysis. This procedure relies on a welfare model estimated from the household survey to impute income to households in the census. The model includes income predictors that are common to both data sources and comparable across them. The methodology and its implementation are extensively described in the online Supplementary Material S1. From these SAE simulations, we generate our main measures of income inequality, calculated at the municipal level. We mainly use the Gini index but have also calculated the generalized entropy indices to test the robustness of our results.

We enrich the analysis using alternative measures describing the income distribution at the municipal scale. Interestingly, the National Council for the Evaluation of Social Development Policy (*Consejo Nacional de Evaluación de la Política de Desarrollo Social*, CONEVAL) has also proposed estimates of the municipal Gini index based on the 2015 EIC survey and on a different SAE methodology (i.e. the empirical best predictor methodology assuming heteroscedasticity) (CONEVAL, 2017). We use it as an alternative measure of municipal income inequality. Another measure calculated by CONEVAL for 2015 is also considered to account for the municipal-level income distribution: the extreme income poverty rate.

For these different inequality measures, Figure S2.3 reported in Supplementary Materials exhibits comparable distributions between the restricted sample of 214 municipalities and the whole set of municipalities, even though the restricted sample seems to be slightly more unequal when our own estimates of the Gini index are considered (average Gini respectively equal to 0.420 and 0.393).

3.3. Control variables

In the regression analysis, we consider control variables that are determinants of bodyweight in accordance with the empirical literature on the topic (e.g. Robert and Reither, 2004; Fan et al., 2016). First, we include individual covariates available in the ENSANUT-MC 2016 survey: age, squared age, gender, ethnicity (indigenous language spoken), working status (yes or no), education (tertiary education), and migration (at least one household member lives abroad). We also include the household’s socioeconomic status. In the survey, the socioeconomic status is a multidimensional index constructed through principal components analysis and combining variables describing housing and living conditions: floor, wall and roof materials, number of bedrooms, water source, number of automobiles, number of domestic appliances, and number of electric appliances (Morales-Ruán et al., 2018). Quintiles of socioeconomic status are used as controls in the regression analysis.

Second, to account for the influence of the living environment on nutrition, we include municipal-level predictors collected from different sources. From INEGI datasets, we account for demography with municipal population density and control for the exposure to violence with the 2015 homicide rate per 100,000 inhabitants. From CONEVAL, we use a composite index of deprivation which measures the percentage of population who are deprived in at least three dimensions among six dimensions (educational lag, lack of access to health services, lack of access to social security, housing with inadequate quality or insufficient space, lack of basic housing services and lack of access to food) (CONEVAL, 2014). From the 2015 EIC survey, we calculate a proxy for migration prevalence defined as the proportion of household heads living in a different municipality in 2010. We control for municipal economic development by taking into account SAE estimates of the households' average annual income per capita and its square.

3.4. Variables accounting for potential pathways

As explained previously, three pathways may explain the bodyweight effect of income inequality: the social capital, psychological and policy pathways. To account for these transmission channels, we select three variables in the ENSANUT survey. For the social capital pathway, we consider adults' eating away from home practices. Given the strong diffusion of fast-food culture in Mexico, we suggest that accounting for fast-food attendance may be a relevant way to capture the importance of socialization behaviors (Long and Vargas, 2005). The variable is defined as the number of times per week an adult consumes fast-food or snacks (at least 100 grams). For the psychological pathway, we consider sleep quality that is often used as a mediator of psychological stress. For instance, Hill et al. (2009) find that neighborhood disorder increases psychological distress through a poorer sleep quality. More precisely, our variable measures the bad quality of sleep on a 5-point Likert scale from "very good" to "very bad". For the policy pathway, although only limited information is available in the ENSANUT survey, we use a proxy for the quality of infrastructure based on water accessibility. This variable is defined as the number of days per week water is accessible for the adult's household. In case of limited accessibility, the quality of water provision can be viewed as of poor quality.

Descriptive statistics for the variables used in the study are reported in Table S3.1 in Supplementary Materials.

4. Methods

Two of the main methodological challenges of this study are to control for both the multilevel structure of the data (individuals nested within municipalities) and the endogeneity of our variable of interest (potential reverse causality and unobserved heterogeneity). Addressing clustering in the analysis of hierarchical data is fundamental to ensure the validity of the results. If not, standard errors will be underestimated, leading to an overstatement of the statistical significance of coefficients, especially for higher-level variables. To take the hierarchical structure of our data into account, we use a multilevel modelling approach, which generates statistically efficient estimates of regression coefficients, and provides unbiased standard errors, confidence intervals and significance tests.

Dealing with endogeneity is another important issue. Indeed, we suspect that our different measures of inequality may be endogenous. The first reason is potential reverse causality. By reducing the chance of educational and professional success, obesity could contribute to lowering income and then to increasing income inequality at the municipal level. Although we control for many potential determinants of bodyweight, endogeneity may also arise from omitted variables plausibly correlated with income inequality and weight gain (e.g. local politico-economic changes such as austerity reforms or local natural disasters). To limit endogeneity issues, we adopt a multilevel model combined with an instrumental variables (IV) strategy based on a control function approach. In the first stage, we regress our endogenous variable on all exogenous variables defined at the municipal level and the selected instruments.

$$INEQ_j = \alpha_0 + \alpha_1 X_j + \alpha_2 Z_j + \varepsilon_j \quad (1)$$

Equation (1) models inequality levels for each municipality j ($INEQ_j$). X_j is a vector of municipality-level exogenous variables and Z_j is a vector of instruments. ε_j are municipal residuals.

Then, we use a multilevel model to allow for clustering of adults' BMI by municipality (Equation 2). The BMI for individual i living in municipality j (BMI_{ij}) is regressed on the inequality index ($INEQ_j$) and the predicted residuals ($\hat{\varepsilon}_j$) obtained from the previous stage. In this specification, we add control variables at the individual (X_{ij}) and municipal (X_j) levels. e_{ij} and u_j refer to residuals fitted at the individual and municipal level, respectively. The error terms are assumed to be normally distributed.

$$BMI_{ij} = \alpha_0 + \alpha_1 X_{ij} + \alpha_2 X_j + \alpha_3 INEQ_j + \alpha_4 \hat{\varepsilon}_j + e_{ij} + u_j \quad (2)$$

This multilevel model allows the intercept to vary randomly across municipalities. As a result, the residual variance is decomposed into a between-municipality component (variance of the municipal-level residuals) and a within municipality component (variance of the individual-level residuals). The standard errors of the second-stage estimates are adjusted via bootstrapping (500 replications) to account for the two-step estimation and obtain robust standard errors.

Identifying relevant instrumental variables is challenging as they have to satisfy two requirements: (i) being good predictors of the endogenous variable even after controlling for the exogenous regressors and (ii) having no direct effect on BMI other than through its influence on the endogenous variable. This challenge is even more important when focusing on a spatially disaggregated level such as the municipality for which little information is available. Moreover, as argued by Schneider et al. (2018: 501), "scholars have yet to identify a convincing instrument for income inequality, and it seems unwise to rule out any investigation (…) on those grounds".

Following the pioneering work of Easterly (2007), and in particular its underlying intuition, we use meteorological and geographical data as instruments to tackle endogeneity. Sokoloff and Engerman (2000) have demonstrated that factor endowments in Latin American colonies historically contributed to the emergence of wealth, human capital, and political power inequalities, which are still deeply rooted nowadays. Because these countries had soil and climate which were well suited for cash crops such as sugarcane, cocoa and coffee, settlers established large plantations relying on intensive slave labor. The resulting distribution of land, income and human capital was highly unequal. Even if Mexico was not historically known for high-scale sugarcane production relying on slavery, factor endowments played an important role in shaping inequality in the Mexican society (Sokoloff and Engerman, 2000). At the time of colonization, Spanish authorities awarded property titles to the early settlers, allowing the implementation of large-scale agricultural exploitation and mines, concentrated in the hand of a local elite. This resulted in a highly unequal distribution of land and wealth. After the independence, inequalities persisted as the elite maintained its dominant status and power.

Following this theory, Easterly (2007) uses measures of agricultural endowments to instrument inequality. In particular, he relies on geographical and meteorological data (such as soil, rainfall, temperature and altitude) to predict the percentage of agricultural land suitable for growing wheat versus sugarcane in a country. Furthermore, he argues that despite being less precise than real production data, relying on meteorological measures ensures the exogeneity of the instruments. As explained by Easterly (2007: 756), “one confusion in the theoretical and empirical analysis of inequality is between what we could call structural inequality and market inequality”. The current high levels of inequality observed in Latin American countries are primarily linked to structural inequality with historical foundations (colonization, slavery and land distribution). The combination of agricultural and meteorological data is therefore well-suited to account for the structural component of inequality. Unfortunately, data on land suitability are not available at the scale of Mexican municipalities. We were however able to collect weather data for 967 weather stations all over the territory. The data comes from the National Water Commission (*Comisión Nacional del Agua*, CONAGUA). For every station over the 1951-2010 period, it includes the yearly average amount of precipitation, temperature and altitude. Every municipality centroid is then matched with the nearest weather station based on latitude and longitude coordinates. These meteorological data intend to reflect the land endowment of every municipality and thus their historical path of inequality (i.e. structural inequality). It is worth noting that relying on meteorological variables to instrument inequality has already been done in previous studies (e.g. Nepal et al., 2010; Ramcharan, 2010).

Finally, in order to explore the potential channels through which income inequality may affect bodyweight, we estimate a simultaneous equation model using three-stage least squares (3SLS). This model does not control for the hierarchical structure of the data but allows us to assess how the three potential pathways mediate the relationship between income inequality and nutrition. The use of 3SLS estimations to identify potential pathways is relatively common in the literature. Using a similar methodology as Seguino (2011) applied to our study context, the model structure can be expressed as follows, for a given pathway:

$$\begin{cases} INEQ_j = \alpha_0 + \alpha_1 X_j + \alpha_2 Z_j + \varepsilon_j \\ PATH_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_2 X_j + \beta_3 INEQ_j + v_{ij} \\ BMI_{ij} = \gamma_0 + \gamma_1 X_{ij} + \gamma_2 X_j + \gamma_3 PATH_{ij} + w_{ij} \end{cases} \quad (3)$$

The first equation is the instrumentation equation for the income inequality index, with vector Z_j being composed of the same instruments as in the multilevel modeling procedure. The second equation describes the effect of income inequality on the variable accounting for the considered pathway ($PATH_{ij}$). The third equation models the impact of the considered pathway on adults' BMI. Since we are interested in estimating the variation of BMI through variations in a given pathway imputable to municipal variations in structural income inequality, we voluntary exclude income inequality from the third equation, as it is commonly done in previous studies (e.g. Haveman et al., 1994; Seguino, 2011; Passarelli et al., 2018).

5. Results

5.1. Effect of municipal income inequality on bodyweight

(Insert Table 2)

To determine the impact of municipal-level inequality on bodyweight while controlling for the endogenous nature of this relationship, we instrument the municipal-level Gini index with municipal-level temperature, rainfall and altitude variables using a control function approach. The first-stage regression of the IV approach (Table S3.2 in Supplementary Materials) shows positive and significant coefficients for these three instruments, suggesting that meteorological and altitude variations strongly affected farming specialties across Mexican municipalities in the past and then positively influenced local income inequality. Note that the R-squared and F-statistics on excluded instruments are both high, which confirms the strength and relevance of these instruments. Table 2 shows the results of our IV multilevel estimations on the continuous BMI variable and on binary weight thresholds (i.e. underweight, overweight and obesity) for the whole sample and gender subsamples. Sargan-Hansen overidentification tests indicate that there is no correlation between the instruments and the error terms, suggesting that the instruments do not violate the exogeneity condition.

Table S3.3 in Supplementary Materials presents the complete results (including control variables) and also reports multilevel estimations without instrumentation. Broadly speaking, the control variables have the expected associations with bodyweight. Most of individual-level control factors are significant and exhibit effects that are fully in line with the literature analysing the determinants of obesity in Mexico (e.g. Levasseur, 2015). Moreover, although some municipal-level covariates are not significant, our results point out the crucial role of local socioeconomic factors in characterizing obesogenic environments in Mexico. We emphasize a U-inverted association between bodyweight and municipal average income indicating that adults living in municipalities with intermediate development levels are more at risk of excess weight. We also show that adult bodyweight is positively associated with municipal deprivation.

Concerning the influence of income inequality, the results reported in Table 2 show a negative effect of municipal-level Gini index on individual BMI (significant at the 1% level). The disaggregation by gender reveals that this effect is driven by a strong negative effect among women (significant at the 1% level). Indeed, a one-point increase in the municipal-level Gini Index leads to a 0.52 kg/m² decrease in women's BMI. The alternative specifications, in which we detect the effect of inequality on BMI clinical categories, are in line with the results on the continuous BMI variable. A one-point increase in the Gini index decreases the probability for women to be overweight and obese by 1.8 and 3.2 percentage points, respectively. In contrast, the results showing the effect of the Gini index on the probability of female underweight are not significant. Likewise, income inequality has no significant effect on male nutritional outcomes. Tables S3.4 and S3.5 in Supplementary Materials respectively present IV binary logit regressions (marginal effects) and IV ordered logit regressions of BMI clinical classification (underweight, normal-weight, overweight and obesity) on income inequality. These results are fully consistent with those reported in Table 2.

5.2. Exploring potential pathways

We explore three potential pathways through which the municipal-level Gini index is likely to have an impact on bodyweight: the social capital, public policy and psychological pathways. These pathways are respectively proxied by fast-food attendance, access to piped water, and bad sleep quality. To control for the endogeneity of the municipal-level Gini index, we implement a 3SLS model with the same instruments for the Gini index as in the previous step. The results are summarized in Table 3 (see Table S3.6 in Supplementary Materials for complete results).

(Insert Table 3)

Concerning the social capital pathway, the results for the whole sample show that the Gini index contributes to decreasing the number of visits to fast-foods but that, in turn, fast-food attendance is positively correlated to BMI, especially for women. For men, the results are non-significant. In other words, in more unequal municipalities, women tend to lower their attendance to fast-food institutions, thus lowering their bodyweight compared to women who live in less unequal areas.

Concerning the public policy pathway, the results show that the Gini index significantly and negatively affects access to piped water by approximately the same magnitude for the whole sample, men and women. This similarity is expected as the relationship between income inequality and access to piped water involves households and not specifically women or men. However, and interestingly, access to piped water has a larger positive effect on women's bodyweight compared to men's bodyweight (0.80 vs. 0.48). These results suggest that inequality has a negative impact on access to water for all households but that this lower access particularly impairs female BMI.

Concerning the psychological pathway, the results show that inequality significantly lowers sleep quality, while sleep quality increases with adult BMI in the whole sample.

Disaggregating the results on the lines of gender reveals specific patterns. Among women, the Gini index significantly increases reporting a bad reported sleep quality and BMI is negatively correlated to a bad quality of sleep. This pathway can explain why inequalities limit weight gain for women. For men, these results are less clear and significant: the Gini index does not affect reported sleep quality but BMI is positively correlated to sleep quality.

Finally, we also tested how each pathway affects the probability of being underweight, overweight and obese (Tables S3.7, S3.8 and S3.9 in Supplementary Materials). The results observed for overweight and obesity are fully in line with those for BMI. Indeed the negative influence of income inequality on the continuous BMI variable through the three pathways primarily reflects dynamics related to belonging to the overweight or obese categories.

Overall, the exploration of potential pathways yields interesting results. For women, the Gini index negatively affects fast-food attendance (social capital pathway), access to piped water (public policy pathway) and sleep quality (psychological pathway) which are all positively correlated to bodyweight. Through its effect on these pathways, income inequality prevents women’s bodyweight from increasing. For men, the results are more ambiguous and do not allow to make clear conclusions.

5.3. Robustness checks

We propose to further explore the impact of inequality on bodyweight through several robustness checks. First, we estimate the effect of income inequality on BMI using alternative inequality measurements from the CONEVAL SAE estimations (Gini index and extreme income poverty rate). We also test the results using alternative inequality indices, namely the three entropy indices GE(0), GE(1) and GE(2), derived from our own SAE estimates. These estimations are respectively reported in Table S3.10 and S3.11 in Supplementary Materials and largely confirm our previous results. A notable exception concerns the CONEVAL Gini index that is never significant (even if the expected negative sign is confirmed). It should be noted that we tested the effect of the CONEVAL Gini index on waist circumference instead of BMI. These estimates (available upon request) exhibit a significant negative effect (at the 10%-level) in the female sample. Second, we also test the robustness of our results by replacing the BMI by waist circumference. The IV multilevel and 3SLS estimations are respectively presented in Tables S3.12 and S3.13 in Supplementary Materials and reveal consistent findings.

6. Discussion and conclusion

Using an original database combining different sources of information and an IV multilevel strategy, this article aimed to detect the effect of municipal income inequality on excess weight. Our results highlight a negative impact of municipal income inequality on individual BMI, waist circumference, overweight and obesity in Mexico, especially for women. This gendered result is consistent with previous empirical studies focusing on the US (Bjornstrom, 2011; Fan et al., 2016) and is robust to alternative inequality measures. Another contribution of this article relies on the identification of explanatory mechanisms behind our main findings. 3SLS estimations identify three potential pathways to explain why municipal income inequality leads to weight loss among Mexican women.

We find that income inequality contributes to reducing individual bodyweight by decreasing individual fast-food attendance (considered as a proxy of social capital). This result is consistent with the literature arguing that income inequality has destructive effects on social cohesion and related activities such as outings with friends (Leyden, 2003). These social activities are associated with risky feeding behaviors such as fast-food, restaurant and bar attendance. Furthermore, women’s sensitivity to the lack of social capital is not surprising considering that they are more dependent on mutual aid (a means of insurance against risks and shocks in developing countries) than men. In the absence of such informal mechanisms, women are more vulnerable to family and income shocks (Perezneito and Campos, 2010), hence more vulnerable to transitory food deprivations, infectious diseases and weight loss (Hadley et al., 2007). In a short digression, it is interesting to put our results into perspective with the worldwide lockdown that occurred in 2020 during the COVID-19 pandemic. This episode represents an unprecedented opportunity to study the nutritional impacts induced by a decrease of social capital and outside activities (initially related to weight-gain). Even if it is still too early to appreciate effects on overweight and obesity trends, several authors conclude on an improvement of diet quality, namely due to a reduction of outside food consumption. For instance, Bracale and Vaccaro (2020) find that households use homemade food as substitute for potentially more caloric snacks bought outside, at the beginning of the Italian lockdown. Likewise, comparing pre-COVID-19 intakes and lockdown-based intakes among adolescents in Italy, Spain, Chile, Colombia and Brazil, Ruiz-Roso et al. (2020) observe a significant increase in vegetable and fruit intakes against a significant fall in fast-food intakes.

Our estimates show that the lack of basic public services in municipalities such as daily water accessibility is a significant driver of the association between local income inequality and weight loss, at least for women. This result is consistent with the assumption that human capital-oriented investments are low in unequal municipalities because of poor taxation and redistributive policy (Coburn, 2000). Two explanations may justify why the lack of public investments in water sanitation (and potentially health services) decreases female bodyweight: (i) it increases the prevalence of infectious diseases associated with weight loss such as diarrhea, cholera and tropical fevers (Gundry et al., 2004); (ii) it increases the physical effort associated to fetching and transporting water daily (i.e. higher energy expenditures). This gender-specific result might be explained by different roles held by men and women regarding water-related tasks such as fetching water when water taps or wells are far from home (deWilde et al., 2008), in addition to a higher vulnerability of women against infectious diseases related to poor sanitation systems (Corburn and Hildebrand, 2015; Perezneito and Campos, 2010). Indeed, women are potentially more dependent on sanitation and health services than men (e.g. pregnancy and delivery), and thus are more likely to get infectious diseases.

We also note some evidence of psychological disorders associated with income inequality. Specifically, we find that women living in unequal municipalities report a lower quality of sleep compared to women from more equal municipalities, contributing to a significant weight loss. This result is consistent with the epidemiological literature that finds stronger damaging effects of income inequality on mental well-being among women (Ribeiro et al., 2017) and more specifically a significant association between psychosocial stress and impaired sleep (Âkerstedt, 2006). The higher psychosocial sensitivity of women regarding income inequality has two main explanations. Not only do women view wellbeing in a more relative than an absolute way (Corazzini et al., 2012), but they are also more often affected by stress, depression and eating disorders than men (Chen and Qian, 2012). In contrast, Udo et al. (2014) conclude on a positive link between stressful life events and female BMI. However, there is no consensus in the literature about the nutritional consequences of stress. Hence, more research should be conducted to understand why income inequality potentially creates a specific stressful atmosphere, which is associated with female sleep disorders and weight loss. In addition, the psychological pathway may also involve social comparisons and imitation behaviors in reaction to a high perceived level of inequality. In relatively unequal societies, there is an imitation of lifestyles from dominant social groups by the poorest, the latter considering the former as a model to follow (Bjornstrom, 2011; Fan et al., 2016). In other words, people from underprivileged classes would aspire to resemble, in terms of physical appearance and taste, the dominant class (e.g. adopting thinness as a beauty standard). However, some evidence emphasizes that richer individuals are not so thin in Mexico, since their job-oriented and stressful lifestyles are associated with weight gain (Levasseur, 2015). Hence, this mechanism is not likely to occur in Mexico. Nonetheless, as we only explored a limited number of pathways, more research would be needed to identify additional drivers.

To conclude, our results have important implications for public policy and nutrition in a country where obesity is a major public health concern. However, they should not in any case be considered as making a case for inequality. Although income inequality has a negative effect on female overweight and obesity, our pathway analysis shows that municipal inequality may have several damaging externalities on psychological health and social cohesion, and may decrease accessibility to basic public services such as health and water sanitation. Therefore, we encourage public policy to tackle inequalities by accompanying redistributive mechanisms with adequate nutrition-related components. For instance, the implementation of conditional cash transfers has already shown its beneficial impacts to fight simultaneously poverty and obesity, especially in Mexico (Levasseur, 2019). Once again, targeting women as first beneficiary seems relevant to reduce the prevalence of obesity, since they are particularly vulnerable to local income inequality. Finally, our results call for an increased decentralization of policies fighting obesity. We suggest that the implementation of anti-obesity urbanization policies at the local level may help to reduce the spread of obesogenic built environments in Mexico.

Despite the new insights provided by this study, we argue that further research on the topic is required, especially to overcome some potential limitations. Future research applied to Mexico or other contexts should be based on larger samples of municipalities to improve the representativeness of the results. Likewise, despite constraints on data availability (especially in the context of developing countries), future research should also improve the specification of econometric models by not only controlling for omitted environmental determinants of obesity (e.g. occupational characteristics, time allocation), but also for genetic determinants. Indeed, it is now widely acknowledged that BMI and obesity have a strong genetic basis (Albuquerque et al., 2017). For this reason, the use of individual genetic information based on the collection and analysis of genetic samples is becoming more common in the social science literature addressing the determinants of obesity, at least in rich countries (Willage, 2018). Finally, relying on longitudinal datasets may also facilitate the identification of a causal relationship between inequality and bodyweight.

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Table 1: BMI-based categories by gender

BMI categories (%)	Men	Women	Whole sample
Underweight	1.14	0.94	1.00
Normal weight	28.93	21.24	23.88
Overweight	41.26	36.89	38.39
Obesity	28.67	40.93	36.73
Total	100	100	100

Source: Authors' calculations.

Table 2: IV multilevel estimations of the impact of inequalities on BMI-based indicators

Dep. var.:	Body mass index (kg/m²)			Underweight (<18.5kg/m²)		Overweight (>25kg/m²)		Obesity (>30kg/m²)	
	Whole Sample	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Gini Index	-0.4332***	-0.5168***	-0.2678	-0.0007	-0.0017	-0.0177*	-0.0082	-0.0317**	-0.0178
	(0.1315)	(0.1682)	(0.2558)	(0.0017)	(0.0025)	(0.0094)	(0.0142)	(0.0126)	(0.0193)
Fitted residuals from stage 1	0.4100***	0.4895***	0.2573	0.0018	0.0007	0.0131	0.0086	0.0268*	0.0136
	(0.1372)	(0.1727)	(0.2752)	(0.0021)	(0.0025)	(0.0103)	(0.0152)	(0.0137)	(0.0212)
Observations	6,106	3,983	2,123	3,983	2,123	3,983	2,123	3,983	2,123
Number of municipalities	214	214	214	214	214	214	214	214	214
Overidentification test (J stat)	1.766	0.755	3.305	1.531	0.867	0.010	2.333	1.983	4.896
P-value	0.414	0.686	0.192	0.465	0.648	0.995	0.311	0.371	0.087

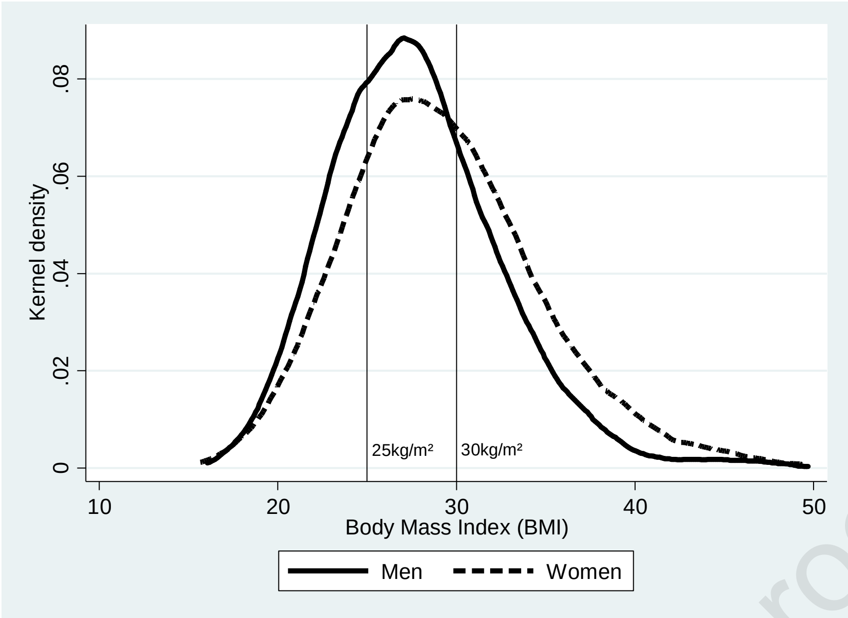
Notes: Bootstrapped standard errors (500 replications) in parentheses. Levels of statistical significance: *** p<0.01, ** p<0.05, * p<0.1. All control variables are included. Sargan-Hansen overidentification tests are performed using two-stage least square (2SLS) estimator.
Source: Authors' calculations.

Table 3: 3SLS estimations of the relationship between income inequality, potential pathways and BMI

	Whole Sample			Women			Men		
(Eq.1) Dep. var.:	**Gini Index**	**Gini Index**	**Gini Index**	**Gini Index**	**Gini Index**	**Gini Index**	**Gini Index**	**Gini Index**	**Gini Index**
Rainfall	0.000257***	0.000292***	0.000366***	0.000286***	0.000290***	0.000398***	0.000239**	0.000294***	0.000315***
	(5.82e-05)	(3.78e-05)	(4.00e-05)	(7.10e-05)	(4.58e-05)	(4.86e-05)	(0.000101)	(6.63e-05)	(6.94e-05)
Temperature	0.114***	0.138***	0.139***	0.0914***	0.115***	0.113***	0.161***	0.178***	0.180***
	(0.0110)	(0.00746)	(0.00783)	(0.0131)	(0.00891)	(0.00945)	(0.0201)	(0.0135)	(0.0139)
Altitude	0.00133***	0.00140***	0.00140***	0.00127***	0.00136***	0.00135***	0.00143***	0.00146***	0.00145***
	(5.28e-05)	(3.74e-05)	(3.77e-05)	(6.30e-05)	(4.46e-05)	(4.52e-05)	(9.54e-05)	(6.73e-05)	(6.74e-05)
(Eq.2) Dep. var.:	**Fast-food attendance**	**Access to piped water**	**Bad quality of sleep**	**Fast-food attendance**	**Access to piped water**	**Bad quality of sleep**	**Fast-food attendance**	**Access to piped water**	**Bad quality of sleep**
Gini Index	-0.128***	-0.632***	0.0405***	-0.144***	-0.654***	0.0429***	-0.0631	-0.597***	0.00576
	(0.0355)	(0.0430)	(0.0106)	(0.0402)	(0.0522)	(0.0115)	(0.0662)	(0.0755)	(0.0164)
(Eq. 3) Dep. var.:	**BMI**	**BMI**	**BMI**	**BMI**	**BMI**	**BMI**	**BMI**	**BMI**	**BMI**
Fast-food attendance	3.283**			3.681***			-1.161		
	(1.326)			(1.324)			(1.295)		
Access to piped water		0.738***			0.804***			0.479**	
		(0.123)			(0.143)			(0.217)	
Bad quality of sleep			-8.067*			-10.82***			-20.70***
			(4.875)			(4.047)			(7.986)
Observations	2,847	6,106	6,106	1,884	3,983	3,983	963	2,123	2,123

Notes: Standard errors in parentheses. Levels of statistical significance: *** p<0.01, ** p<0.05, * p<0.1. All control variables are included.
Source: Authors’ calculations.

Figure 1: BMI distribution (Epanechnikov kernel).



Source: Authors' calculations.

Highlights

We examine the effect of municipal income inequality on adult bodyweight in Mexico.

Municipal income inequality measures are generated through small area estimation.

Income inequality has a negative impact on bodyweight, especially for women.

Social capital, public policy and psychological pathways explain this effect.