A Bivariate Relative Poverty Line for Time and Income Poverty: Detecting Intersectional Differences Using Distributional Copulas

Franziska Dorn* Rosalba Radice† Giampiero Marra‡
Thomas Kneib§

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Abstract

Empirical research on poverty today often goes beyond a focus on income to consider other dimensions of well-being. However, relatively few multidimensional poverty measures explicitly consider time, despite its particular relevance to women's double burden of paid and unpaid work. We construct a bivariate relative poverty line between income and leisure, based on their joint distribution in the population. Because the strength of the dependence between income and leisure influences the vulnerability to poverty, we incorporate distributional regression into copula models. Utilizing the 2018 Mexican National Survey of Households, Income and Expenses, we investigate differences in bidimensional poverty with respect to gender and ethnicity. We find that the fraction defined as bidimensional poor is 18 percentage points higher than the poverty rate computed from separate time and income measures. Those below the relative but above the absolute poverty line are primarily non-indigenous women whose poverty is made visible by our approach.

Keywords: bivariate relative poverty line, bivariate distributional copula model, income distribution, leisure time distribution, Mexican National Survey of Households, intersectionality

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*University of Goettingen, Center for Statistics, Germany,Email: fdorn@uni-goettingen.de

†Cass Business School City, University of London, UK

‡University College London, Department of Statistical Science, UK

§University of Goettingen, Center for Statistics, Germany

1 Introduction

Income alone cannot adequately define poverty. Available time for leisure is also an important determinant of living standards. While a growing literature defines poverty in multidimensional terms, it rarely includes leisure, despite its particular relevance to women's double burden of paid and unpaid work. Further, multidimensional poverty indices usually summarize poverty dimensions into one measure to calculate a univariate poverty threshold. Such indices obscure the interconnected nature of leisure and income. The strength of this dependence can shed light on differences in vulnerability to poverty at the intersection of gender and ethnicity.

This paper constructs a bivariate relative poverty line for income and leisure based on their distribution in the population. We share the motivation of previous approaches that incorporate measures of time-use into gender-sensitive poverty assessment (Vickery, 1977; Bardasi and Wodon, 2010; Zacharias et al., 2012; Merz and Rathjen, 2014). We define the bivariate relative poverty line as a specific quantile of the joint leisure and income distribution of the population. This approach avoids the need to reduce bidimensional poverty measures to scalar poverty indices and allows for different units of measurement as well as nonlinear substitutability.

To capture the conditional dependence between income and time poverty, we develop an applied distributional copula model. Copulas provide a convenient mathematical tool for modeling the joint distribution of leisure and income. Distributional aspects can unveil persistent poverty caused by a higher strength of the dependence at lower levels of income and leisure. We expect differences in this dependence between income and leisure by gender and ethnicity.

We illustrate our model using data from the 2018 Mexican Survey of Households, Incomes and Expenses (ENIGH), which provides a rich household dataset including information on household income, consumption by gender, and individual leisure time (INEGI, 2020). The analysis focuses on couples or single adult households with or without children, to better proxy income sharing, which we base on the consumption share of male and female household members. While previous research acknowledges the importance of temporal constraints on women in particular (Rodin et al., 2012; Lyon et al., 2017), the only multidimensional poverty index estimated for Mexico does not include any measures of time allocation (Ortega Diaz, 2014). Indigenous people are also particularly likely to suffer from time constraints, given their economic vulnerability (González de Alba, 2010; Canedo, 2018, 2019). We expect vulnerability to time and income poverty to be most severe for indigenous women.

Estimation of the bivariate relative poverty line yields insights beyond those provided by standard approaches. Overall, the percentage of those below the bivariate relative poverty line is 18 percentage points higher than indicated by the separate absolute leisure and income poverty thresholds. While indigenous women are absolutely poor in standard poverty assessments, many non-indigenous women fall above the absolute poverty line but below the relative poverty line, a pattern not apparent in standard poverty assessment. The most important factors increasing the vulnerability of this group are low educational levels and high numbers of children.

Section 2 outlines the current literature on time and income poverty to motivate the analysis of the distributional dependence between income and leisure time. Section 3 defines the bivariate relative poverty line and introduces distributional copula models. Section 4 outlines the rich data set for Mexico used to apply our method. The results in Section 5 provide evidence of differences by gender and ethnicity. Section 6 concludes.

2 Literature Review

Time is widely considered a relevant resource for well-being (Narayan et al., 2000; WB, 2011; Ferrant et al., 2014; UN Women, 2015). Like income, time availability determines opportunities for achievements and well-being in life (Burchardt, 2008). Due to the constraints of paid and unpaid work, people cannot always choose the leisure time they prefer (Bittman and Folbre, 2004). Especially in poor households, the need for market income requires household members to work long hours. Women perform a disproportionate share of unpaid work, which reduces the time they can devote to paid work (Connelly and Kongar, 2017). Deprivation of time for leisure is an important dimension of poverty.

Both utilitarian and capability approaches acknowledge leisure time as a component of well-being, but seldom incorporate it into definitions of poverty (important exceptions are discussed below). Utility-maximizing choices based on subjective perceptions do not provide any rationale for a specific threshold. By contrast the capability approach postulates a minimum level of resources and functionings required to live a valuable life (Sen, 1976, 1987). Both income and time are often necessary for the realization of capabilities and functionings (Sen, 1976). This minimum level, however, is difficult to operationalize and seldom includes consideration of leisure time (Ortega Diaz, 2014; Alkire et al., 2015; Santos and Villatoro, 2018).

Several bidimensional poverty approaches show that relationships between income and time allocation differ on the household and individual levels. Vickery (1977) argues that hours devoted to unpaid work increase household consumption and constructs a threshold curve between money and time on the household level. Within the household, however, gender differences are apparent. Responsibilities for housework and family care reduce both the quantity and quality of women's leisure time (Badgett and Folbre, 1999; Antonopoulos et al., 2017). By limiting opportunities for directly remunerative work, these responsibilities also lower women's bargaining power in the household (Antonopoulos and Hirway, 2010; UN Women, 2015; Amarante and Rossel, 2018).

Time and income poverty analyses that take individuals as units of analysis use separate thresholds, scalar indices or bivariate measures to detect gender differences. Bardasi and Wodon (2010) define an individual as time and income poor if the individual works more than the time poverty threshold and lives in an income poor household. The Levy Institute Measure of Time and Income Poverty (LIMTIP) measure defines households as 'hidden' poor if the household members work long hours and would fall below the income poverty line, if they purchased market substitutes for their unpaid work. This household measure is supplemented by individual time-use measures that capture gender differences (Zacharias et al., 2012; Antonopoulos et al., 2017).

Of the existing individual approaches, Merz and Rathjen (2014) are the closest to ours. Their bidimensional poverty line is constructed based on a model of utility maximization and the assumption of constant elasticity of substitution between income and leisure. Thus, they base their approach on self-reported subjective well-being. We, on the other hand, relax the aforementioned assumptions by developing a data-driven approach based on reported leisure time. A specifically set quantile level of the joint distribution between income and leisure – corresponding to a certain percentage of the combined observations of income and leisure – defines the bivariate relative poverty line. To capture the influence of the dependence structure – i.e. the shape of the joint distribution of leisure and income – on the vulnerability to poverty, we use distributional copula models.

Copula regression models are proven tools to account for the dependence structure of poverty dimensions while controlling for covariates (Nelsen, 2006; Duclos et al., 2006; Marra and Radice, 2017; Aaberge et al., 2018; Hohberg et al., 2020; García-Gómez et al., 2021). We incorporate distributional aspects into copula models to disentangle persisting poverty by analyzing the varying strength of the dependence between income and leisure. Specifically, vicious cycles are uncovered, as we expect the dependence to be more pronounced at the tails of the distribution between income and leisure. For example, time constraints hinder people in getting decent jobs. At the same time, low wages lead to higher working hours and more domestic work, as fewer market substitutes can be purchased. The income poor therefore have less leisure time (Ghosh, 2016). We expect these dependencies to be more pronounced among women, due to their double work burden (Psacharopoulos and Tzannatos, 1992; Colinas, 2008; Ferrant et al., 2014).

The Mexican survey of Households, Incomes and Expenses enables us to explore these issues. Mexican poverty is exacerbated by a weak social safety net and conservative gender norms (Segrest et al., 2003; Pedrero Nieto, 2005). Women devote substantial time to family care but are often forced into low-income jobs to contribute to the financial support of the family (Rodin et al., 2012; Lyon et al., 2017). Ethnic differences are significant and indigenous people in rural areas are especially vulnerable to poverty (González de Alba, 2010; Carré et al., 2016; Canedo, 2019). Thus, intersections between gender and ethnicity shape the trade-offs between income and leisure.

This paper adds to the literature on bidimensional poverty in time and income in four aspects. First, we construct a measure for income division in the household, based on the consumption spending by gender. Second, we derive a bivariate relative poverty line based on the underlying data. Third, we take into account the varying strength of dependence between income and leisure time by applying distributional copula models. Fourth, we add to the Mexican poverty assessment by using the ENIGH 2018 to analyze differences based on gender and ethnicity.

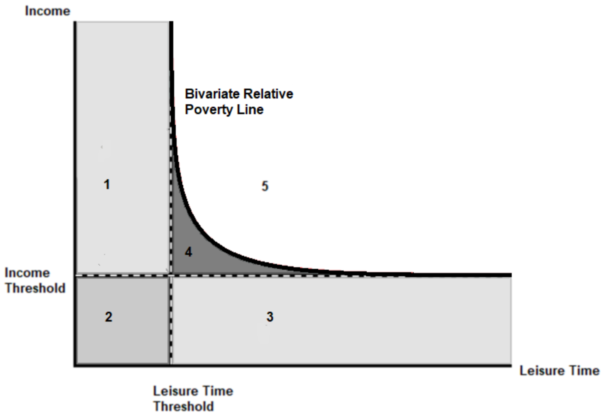
3 Methodology

To identify the poor, we construct a bivariate relative poverty line described in Section 3.1. Bivariate distributional copula models identify the dependence structure and provide estimates of the likelihood of falling below the bivariate relative poverty line (see Section 3.2 and 3.3).

3.1 Bivariate Relative Poverty Line

To account for bidimensional poverty in leisure and income, we derive a bivariate relative poverty line using data from Mexico. This relative approach to poverty specifies poverty as a quantile of the population's joint time and income distribution. We specify the bivariate relative poverty line as a specific quantile line of the bivariate cumulative distribution function (CDF) of income and leisure. For the population-based poverty assessment, we utilize the empirical CDF of the observed data, considering all leisure and income combinations. This resembles similar population-based definitions for univariate poverty lines. The bivariate relative poverty line avoids the assignment of a monetary value to leisure time by keeping separate units of measurement instead of composing an index. Our data-based approach

Figure 1: Time and income poverty approaches



allows for nonlinear substitutability among income and leisure time.

Figure 1 illustrates the bivariate relative poverty approach in contrast to the union and intersection approach to time and income poverty. The dotted black lines illustrate the separate absolute thresholds and the black line the bivariate relative poverty line. Area 1 plus area 2 define univariate time poor and area 2 plus area 3 define univariate income poor. These areas combined define the union approach. Area 2 represents joint absolute leisure and income poverty defined as intersection approach (Merz and Rathjen, 2014). Area 4 defines individuals that are simultaneously time and income poor according to our bidimensional approach but neither income nor time poor according to univariate measures. Instead of defining only an area of time but not income poor, the bivariate approach defines a space including all those living at the societal margin of the joint distribution of income and leisure.

Depending on the distribution of income and leisure the line varies in proximity to the origin, but will not be below the set quantile. Thus, in our case the absolute income poverty level for Mexico. This quantile line implicitly accounts for the substitutability between income and leisure observed in the data. Area 5 includes all non-bidimensional poor individuals.

To formalize the basic idea of bivariate relative poverty line illustrated above, let $F_{1,2}(q_1, q_2)$ be the joint CDF of income and leisure (either estimated from a statistical model or via the empirical CDF). The black curve is then defined by fixing a quantile level $\tau \in [0, 1]$ and determining the contour line with $F_{1,2}(q_1, q_2) = \tau$ (Klein and Kneib, 2020). The area below the bivariate relative poverty line of level $\tau \in [0, 1]$ is then given by $\mathcal{Q}_\tau = \{q = (q_1, q_2) \in R^2 : F_{1,2}(q_1, q_2) \leq \tau\}$ and the poverty risk can be quantified as

$$P(Y_i \in \mathcal{Q})$$

where $Y_i = (Y_{i1}, Y_{i2})$, i.e. the poverty risk reflects the probability of falling below the bivariate relative poverty line. This can be assessed both in an ex-post and an ex ante approach, where the latter relates to vulnerability to poverty in the future as well as in a model-based fashion (when the joint CDF of Y_i is derived from a statistical model) or purely data-based by employing the bivariate empirical CDF. We use the population-based bivariate relative poverty line and therefore rely on the empirical CDF of all data in the following. Note that $P(Y_i \in \mathcal{Q})$ is substantially larger than the quantile level τ utilized to construct the poverty line even if Y_i follows exactly the CDF that was used to construct the poverty line. Note also that once conditioning on covariates, the distribution of the bivariate outcome Y_i will deviate from the population-based CDF such that the actual poverty risk varies according to covariates.

Let now $\mathcal{Q}_{1,\tau} = \{q_1 \in R : F_1(q_1) \leq \tau\}$ and $\mathcal{Q}_{2,\tau} = \{q_2 \in R : F_2(q_2) \leq \tau\}$ be the areas below the univariate poverty lines at level τ derived from the marginal CDFs F_1 and F_2. Then conventionally, the poverty risk in a bivariate setting is either defined as

$$P(Y_i \in \mathcal{Q}_{1,\tau} \cap \mathcal{Q}_{2,\tau})$$

(intersection of the two marginal poverty areas) or

$$P(Y_i \in \mathcal{Q}_{1,\tau} \cup \mathcal{Q}_{2,\tau})$$

(unification of the two marginal poverty areas). The latter defines individuals as poor if they are poor in at least one dimension according to the marginal poverty lines whereas the former considers individuals as poor if they fall below the poverty line in both dimensions.

For both conventional definitions, there are individuals considered poor based on our bivariate relative poverty line but not by any of the two conventional approaches when the same level τ is used for the marginal and the bivariate relative poverty line. Bivariate poor are out in the tails of the bivariate distribution of both potential poverty dimensions although they are not necessarily extreme in the sense of the marginal distributions of income or leisure alone. Similarly, we can consider bivariate vulnerability to poverty, i.e. the ex-ante risk of falling below the bivariate relative poverty line in the future. The common ways of reducing the bivariate scenario to two marginals via intersection or unification may then lead to a severe underestimation of future poverty risks.

To compute either of the poverty risks discussed so far, we rely on Monte Carlo integration where we simulate a large number of replicates from the distribution of the bivariate poverty indicator Y_i and then approximate the desired probability by its empirical frequency. While the conventional poverty risk definitions could also be computed from the bivariate CDF, this is difficult for our new approach where the poverty line is a nonlinear, smooth function.

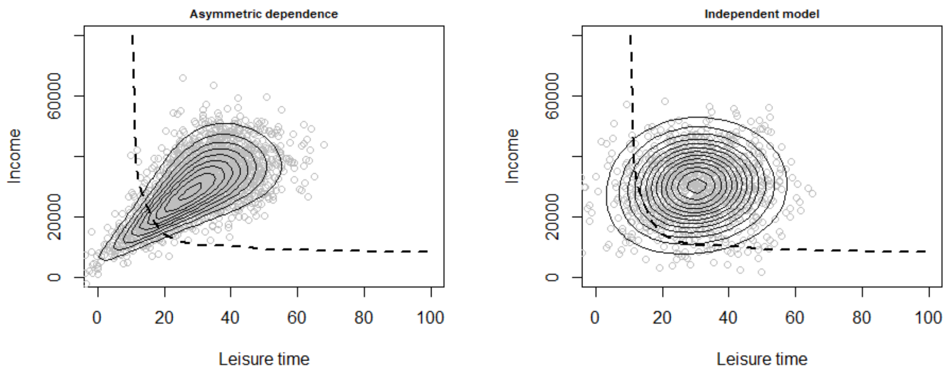
3.2 Bivariate Distributional Copula Regression Models

The advantage of distributional copula regression is twofold: Any aspect of the bivariate distribution is a function of covariates and it allows for different types of dependencies by flexibly specifying the copula. Simple correlation methods do not capture these complexities.

The calculation of joint probabilities based on distributional aspects enables us to evaluate vulnerability to poverty among sub-groups. For example, income and leisure time vary over the range of education, meaning that one additional year of education does not always, ceteris paribus, has the same mean additional impact on leisure time or income. Further, the deviation from the mean can differ over the range of education. In return, these marginal distributions impact the dependence between income and leisure time, which may lead to stronger dependencies at lower levels of income and leisure time (tail dependence). This indicates persistent poverty likely due to vicious cycles. Thus, asymmetric dependencies matter and mean regression methods can lead to wrong interpretations of the statistical significance and the economic relevance of the variables (Kneib, 2013). By incorporating generalized additive models for location, scale and shape into copula models, we can describe asymmetric dependence structures (Marra and Radice, 2017; Stasinopoulos et al., 2017).[1]

Figure 2 illustrates possible dependence structures. The dots picture (stylized) observations of leisure and income combinations. Graphic 1 in Figure 2 visualizes asymmetric dependence structures (tail dependency). In this example, higher dependency occurs in the lower part (tail) of the two variables income and leisure. Graphic 2 in Figure 2 shows the dependence structure for independent poverty dimensions where no simultaneous tendencies of income and leisure can be detected from the contour lines.

Figure 2: Copula Specification



3.3 Model Specification

The bivariate cumulative distribution function models the joint distribution of two variables utilizing copulas as the mathematical tool to separate

[1]The combination of GAMLSS and copulas are implemented in the GJRM package in R (Marra and Radice, 2017).

the marginal distributions from the dependence structure. We first specify the marginal distributions for the dependent variables leisure and income, which comprise the dependent vector (Y_1, Y_2). The copula then binds the two marginal distributions via a cumulative distribution function with uniform margins. We select the copula based on the marginal distributions and defined covariates (Klein et al., 2019).

In a copula specification, the bivariate CDF $F_{1,2}(y_1, y_2) = P(Y_1 \leq y_1, Y_2 \leq y_2)$ is defined as

$$F_{1,2}(y_1, y_2) = C(F_1(y_1), F_2(y_2)) \tag{1}$$

where $C : [0,1]^2 \rightarrow [0,1]$ indicates the copula (i.e. a bivariate CDF with uniform marginals) and $F_j(y_j) = P(Y_j \leq y_j)$, $j = 1, 2$ are the marginal CDFs of the two response elements Y_1 and Y_2. The copula $C(\cdot, \cdot)$ in (1) is uniquely determined, if Y_1 and Y_2 are continuous (Klein et al., 2019). Marra and Radice (2017) enumerate several marginal distributions for continuous variables. For our application in Section 4.3, we only consider copulas with one dependence parameter, which allow for positive and negative dependence simultaneously, such as AMH, FGM, Frank, Gaussian and Plackett.

Copula regression links the parameters of both the marginals and the copula to regression predictors. In the bivariate case, $\boldsymbol{\theta} = (\boldsymbol{\theta}_1', \boldsymbol{\theta}_2', \boldsymbol{\theta}_c')'$ is the J-dimensional vector of the parameters defining the marginal distribution for Y_1 and Y_2 ($\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$, respectively) and the copula ($\boldsymbol{\theta}_c$). These parameters are dependent on covariates $\boldsymbol{z}$ thus $\theta_{ij} = \theta_j(\boldsymbol{z}_i)$, $j = 1, \ldots, J$ for observations $i = 1, \ldots, n$. In our case we consider different types of response distributions for continuous, non-negative responses including $normal$, $log-normal$, $dagum$, $singh-maddala$, $gumbel$, $reverse\ gumbel$ and $gamma$. We use a semiparametric specification for our predictors to obtain more flexibility. The additive linear predictor η_i is a function of an intercept and a covariate vector represented as

$$\eta_i^{\theta_j} = \beta_0 + \boldsymbol{z}_i'\boldsymbol{\beta}^{\theta_j} + \sum_{k=1}^{K} f_k^{\theta_j}(x_{ik}), \quad i = 1, \ldots, n, \, j = 1, \ldots, J, \tag{2}$$

and a strictly monotonically increasing function h_j links the predictor to the distributional parameter θ_j by

$$\theta_j(\boldsymbol{z}_i) = h_j(\eta_i^{\theta_j}), \quad i = 1, \ldots, n, \, j = 1, \ldots, J. \tag{3}$$

The predictor comprises an overall intercept $\beta_0 \in \mathbb{R}$, linear effects $\boldsymbol{z}_i'\boldsymbol{\beta}^{\theta_j}$ based on covariates $\boldsymbol{z}_i$ and regression coefficients $\boldsymbol{\beta}^{\theta_j}$ with K nonlinear effects $f_k^{\theta_j}(z_{ik})$ of continuous covariates z_{ik}, $k = 1, \ldots, K$. We employ penalized splines to model non-linear effects (Eilers and Marx, 1996). Penalized splines achieve a data-driven amount of nonlinearity in the effect estimates. The parameter estimation relies on a very generic penalized maximum likelihood-based framework; the numerical implementation of GJRM is based on a trust region algorithm with integrated automatic multiple smoothing parameter selection (Marra and Radice, 2017).

We apply the bivariate distributional copula model to the 2018 Mexican National Survey of Households on Income and Expenditures outlined in the following section.

4 Data

For our analysis, we use the 2018 Mexican National Survey of Households on Income and Expenditures (Encuesta Nacional de Ingresos y Gastos, ENIGH). This cross-sectional data set contains information on household income and expenses, time-use, occupational and sociodemographic characteristics of household members and information on the infrastructure of the dwelling and the equipment in the household. With information on each household member, the data set contains 398,247 observations. It is representative on the rural/urban level (INEGI, 2020).

Income pooling and sharing between more than two adults in a household is variable and difficult to proxy. We therefore restrict our analysis to households consisting of couples or single adults with or without children (to overcome any ambiguity about income sharing that may arise in households with additional adults).This sample includes 69,079 complete cases.[2]

[2]Complete cases contain information for all variables of interest. Reducing the data set

4.1 Income

Conventional poverty assessment approaches monetary well-being in two ways: either based on income or consumption.[3] However, Mexico only estimates an income poverty line. We follow Mexico's poverty assessment by using income measures (WB, 2020). The average Mexican income poverty level for 2018 is 1,501 Mexican Pesos, based on the estimated cost of a food basket, necessary to secure an above-poverty standard of living. It is estimated on a monthly basis and adjusted by the National Index of Consumer Prices (CONEVAL, 2020).

The ENIGH reports current income on an individual and a household level. Income is the sum of wages, private, institutional and governmental transfers, capital rent and other income. The household income measure sums up the income of all household members into a quarterly value (INEGI, 2020). As the ENIGH calculates quarterly averages, the income measure is less prone to monthly variation and thus a sufficiently stable welfare measure for Mexico. For our analysis, we use the monthly average, be dividing the quarterly value.

The ENIGH also includes information on individual and household expenditures. This measure refers to regular direct expenses that households spend on goods and services for their own consumption. It sums up spending on food, clothing and footwear, housing, cleaning, health, transportation, education and recreation, personal care and expenses for transfers. Expenditures can be divided into general household goods and personal goods. The data set indicates whether spending on personal goods was intended for females or males (child or adult) household members (INEGI, 2020). Again, we divide the quarterly value into a monthly average.

to complete cases relies on the implicit assumption that missing data have been introduced completely at random.

[3] In more industrialized countries, with a low share of self-employment, income is a reliable measure, as it barely varies over a year. In this case, collecting income data is more cost effective. In developing and transition countries, with a high share of self-employed people and large agricultural sector, income is likely to vary considerably more since seasonal differences matter. Consumption is less prone to short-term fluctuation, as savings or dissavings can even out income variation and is considered the better measure of welfare in these settings (Deaton and Zaidi, 2002).

To compare the income of households, we use equivalence scales. Due to economies of scale, households with four family members do not necessarily need the double amount of income or expenditures of families of two members (Folbre et al., 2017). We apply the square root equivalence scale to account for the cost of living of households of different composition (taking the square root of household members as the scaling parameter) (OECD, 2020).

Family household-members often pool a significant portion of their income, which makes them an essential entity of distribution and production. Therefore, household family income better indicates material living standards than individual earnings (Folbre et al., 2017). For an individual-based analysis, we divide family income among family members. Due to a lack of information on income pooling and sharing, this analysis compares three ways to divide the income between household members. First, we take a conservative approach and follow Merz and Rathjen (2014) by dividing the income equally among adult household members. Second, we take the ratio of the average share of female and male wages — based on all couple households in our sample — as a proxy for intra-household income division. Third, we use household specific expenditure shares for male and female household members as an approximation for intra-household income sharing. Even though we cannot distinguish whether the expenditure is made for children or adults, it gives an approximation of income sharing based on gender in the household.

Table 1 reports average incomes by gender and ethnicity according to different forms of income pooling. The row average household share assigned to women reports the share of the income assigned to women. The columns equal, inc. share and exp. share show averages for equal income sharing, income sharing according to the average income share of men and women in Mexico and income by household specific expenditure share for men and women, respectively. The average share of income generated by women in relation to men specifies the income share. In contrast the expenditure share is calculated individually for each household. Table 1 reports the average of the household shares. The difference in income between men and women for equal income sharing occurs due to single adult households.

Summary statistics in Table 1 reveal differences in average income by gender and ethnicity.[4] Women have less income on average than men and indigenous people have less income than non-indigenous people. Non-indigenous women are richer than indigenous men, while non-indigenous men are the richest and indigenous women the poorest. This holds for all three different ways of income division.

The expenditure share provides the most plausible approximation for intra-household income division, as it uses household specific information on expenditures by gender. We argue that relative consumption expenditures are a reasonable indicator of relative income shares. The average share for women based on the expenditure measure (0.39) is slightly higher than the share for women based on the share of average incomes in Mexico between men and women (0.36) but below the equal share (0.5) of household income division. Household income division based on equal shares thus serves as upper bound and household income division based on the average share of income of men and women in Mexico serves as lower bound of the distribution of pooled household income division between men and women.

Table 1: Monthly Income

	Equal share	Inc. share	Exp. share
Average household share assigned to women	0.5	0.36	0.39
Ind. Women	2396	1923	2271
	(3212)	(2867)	(3201)
Non-Ind. Women	5220	4221	4869
	(7337)	(6470)	(6921)
Ind. Men	2449	2938	2633
	(3813)	(4184)	(3940)
Non-Ind Men	5417	6482	5904
	(8483)	(9461)	(9217)

Standard deviations are in parentheses.

[4]We use individual sampling weights for descriptive statistics and regression analyses.

4.2 Leisure Time

The ENIGH reports a comprised set of time-use activities. The data is collected in form of an activity list, more reliable diary-based data is unfortunately not available. Other than income, leisure is an individual measure. The short activity list includes the following question, which we use as a measure for leisure: *How much time did you spend on activities you enjoy last week?*[5] This measure is reported in hours and minutes spent on personal activities during the previous week (INEGI, 2020).

As Table 2 indicates, women have less leisure time than men, and the gender gap is biggest between indigenous women and non-indigenous men. Table 2 reports summary statistics for leisure, time spend on paid and unpaid work (including commuting) – market work, community work, care for other people, repair work, housework, collection of wood and water – based on the underlying data set ENIGH.[6] Non-indigenous women have the least amount of leisure while men have the most.

Table 2: Time-use in minutes per week

	Leisure	Work commute	Work
Ind. Women	1006	3351	3365
	(902)	(1649)	(1631)
Non-Ind. Women	1093	3345	3372
	(899)	(1713)	(1727)
Ind. Men	1095	3256	3334
	(924)	(1496)	(1538)
Non-Ind. Men	1147	3332	3340
	(966)	(1492)	(1527)

Standard deviations are in parentheses.

[5] Durante la semana pasada cuánto tiempo le quedó para realizar actividades que a usted le gustan? (INEGI, 2020).

[6] The values conform to the more detailed 2014 time-use survey of Mexico (ENUT), which also shows that women have less leisure time. Values are displayed in Table A1.

4.3 Empirical Model Specification

Our empirical strategy is conducted in two parts: First, we define the marginal distributions of the continuous outcome variables income and leisure time. Second, based on these marginal distributions we determine the copula specification. The same set of covariates specifies the marginal distributions and the copula. The model includes the following variables: Age (*age*) is flexibly modeled using three basis functions to account for potentially non-linear effects (Fahrmeir et al., 2013). Based on the Mincer wage equation (Lemieux, 2006), we include an ordinal variable for education, a dummy variable for urban citizens, for having a partner, as well as for being indigenous to control for potential differences between the corresponding groups (González de Alba, 2010). We add the ordinal variable for children under fourteen ($child14$) as we expect people with younger children to work more and earn less, as they are more restricted in time (Maani and Cruickshank, 2009; Rodin et al., 2012; Ponthieux and Meurs, 2015). To account for gender differences and independent observations, we separate the regression for male and females. This leads to the (gender-specific) regression specification:

$$\begin{aligned}\eta_g^{\theta_j} = \beta_{0g}^{\theta_j} + s(age)_g^{\theta_j} + \beta_{2g}^{\theta_j} educ + \beta_{3g}^{\theta_j} urban + \\ \beta_{4g}^{\theta_j} ethni + \beta_{5g}^{\theta_j} child14 + \beta_{6g}^{\theta_j} partner.\end{aligned} \tag{4}$$

For the female as well as male sample we find that the income variable follows a Dagum distribution (see Table A3) while leisure time can be modelled with a Singh Madala distribution (see Table A4). The analysis of model residuals, displayed in Figure A7 for women and Figure A8 for men, support these model specifications. Both distributions are part of the Burr system of distributions which requires to model three parameters (see Kleiber and Kotz (2003)). These two distributions form the response vector for the bivariate distributional copula model.

Using the marginal distributions from the GAMLSS framework and the set of variables specified in Equation 4 leads to a Gaussian copula for model on women and the Farlie-Gumbel-Morgenstern copula for the model on men. We base the selection on the copula specification on the lowest AIC level displayed in Table A5.

It follows, that the bivariate distribution depends on seven parameters $\theta_j, j = 1, \dots, 7$ (three for each marginal and one dependence parameter). Each parameter $\theta_j = h_j(\eta_j)$ is related to one predictor η_j with separate specifications for men and women $g = 1, 2$, i.e.

$$\begin{pmatrix} Time \\ Income \end{pmatrix} \sim D(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7) \tag{5}$$

Before giving the results for Equation 4, we show the results for the poverty line.

5 Results

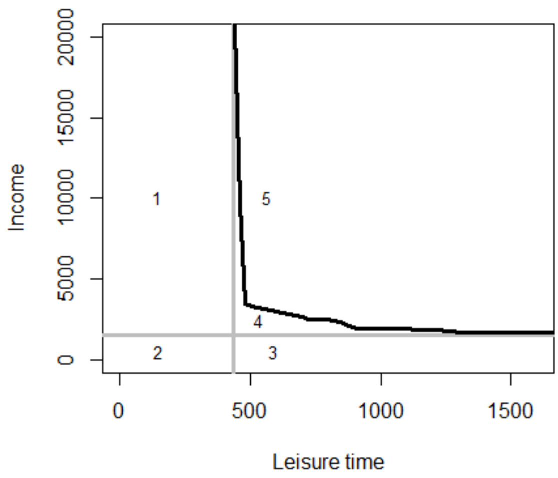
This section outlines the results for the poverty line, variation in the relationship between income and leisure time and vulnerability to poverty.

5.1 Bivariate Relative Poverty Line

The poverty line is set to a quantile level of the joint distribution between income and leisure time. As there is no commonly used leisure time threshold, the quantile for the leisure poverty threshold is aligned with the Mexican income poverty threshold. The Mexican income poverty level, based on a food basket, is on average 1,501 Mexican Pesos in 2018 (CONEVAL (2020)). The poverty threshold is equivalent to the 15% quantile of the income distribution of the population. We set the quantile level of the bivariate relative poverty line to 15%, to ensure the inclusion of the absolute income poor.

Figure 3 shows the estimated poverty line based on the data. The black line represents the bidimensional relative poverty line. The grey lines represent the single absolute poverty thresholds at 1,505 Pesos (estimated observed value for the 15 % quantile). The equivalent 15% quantile for leisure is 420 minutes. The black line exhibits a non-smooth shape, because we use a data driven approach and certain values are not observed. The time variable is reported in minutes, but we suspect that it is unlikely to report more precise

Figure 3: Relative versus absolute poverty line



Income is reported in Mexican Pesos and leisure time in minutes per week.

values than 15 minute units. Further, a vast number (approximately 8000 observations) of individuals report 420 minutes of leisure time per week.[7]

Table 3 displays the shares of individuals below the different poverty lines. The first column shows the share of the total population. The following columns show the share of sub-groups – indigenous women, non-indigenous women, indigenous men, non-indigenous men – in relation to their group. Areas in the table refer to Figure 3. Area 1 refers to absolute leisure time poverty, area 3 to absolute income poverty, area 2 to absolute leisure time and income poverty, area 4 to below the relative but above absolute poverty threshold, area 1 & 2 & 3 represents the union approach, area 1 & 2 & 3 & 4 combines all individuals in relative poverty and area 5 are all non-poor individuals. Numbers display the percentage share in the according areas by group.

As Table 3 indicates, more Mexicans experience relative than absolute bidimensional poverty. The percentage of Mexicans experiencing relative poverty about 18 percentage points higher than those experiencing absolute

[7]This equals an hour a day and might reflect bunching around a plausible guess-estimate.

Table 3: Poverty levels

Poverty approach (Area)	Total Population	Women Non-ind.	Women Ind.	Men Non-Ind.	Men Ind.
Leisure (1 & 2)	14.79	14.21	14.98	15.49	14.39
Income (3 & 2)	15.27	14.89	52.30	9.86	44.71
Intersectional (2)	2.20	2.05	7.95	1.48	6.60
Below relative & Above absolute (4)	17.86	19.94	16.99	15.60	16.28
Union (1 & 2 & 3)	27.86	27.05	59.34	23.87	52.50
Relative bidimensional (1 & 2 & 3 & 4)	45.72	46.99	76.33	39.47	68.78
Non-poor (5)	54.28	53.01	23.67	60.53	31.22

Total shares in percentages by group.

poverty.[8] The difference between absolute and relative bidimensional poverty becomes clear, considering area 4 (being in bidimensional relative poverty but not in absolute poverty) and area 2 (joint absolute leisure and income poverty). Only 2.2 percent of the total population are absolute time and income poor (intersection approach), but 18 percent of the total population experience relative poverty above absolute poverty. These individuals are at the margins of the bidimensional poverty distribution but invisible in binary absolute poverty assessment. The picture is more diverse considering subgroups of indigenous and non-indigenous men and women.

While indigenous women are more likely to live in absolute poverty, non-indigenous women are especially likely to live in relative poverty above absolute poverty. More indigenous people fall below the joint absolute poverty thresholds. The highest share exhibit indigenous women followed by indigenous men, with a difference of around 1 percentage point. The share of non-indigenous people within the intersection of absolute leisure and income poverty is much lower (2 percent of non-indigenous women and 1.5 percent of non-indigenous men). The difference to their indigenous counterparts is 5

[8] A high amount of observations lay at the poverty threshold of 420 minutes (around 8000 observations).

percentage points for men and 6 percentage points for women. The picture is different below the relative poverty line but above the absolute poverty lines. The highest share is among non-indigenous women, while non-indigenous men exhibit the lowest share. The difference between non-indigenous women and non-indigenous or indigenous men is around 4 percentage points and 3 percentage points higher compared to indigenous women.

The strength of dependence between income and leisure impacts the likelihood of falling below the bivariate relative poverty line. Different characteristics have a varying impact on the strength of dependence. Results in Section 5.2 analyse these effects on the strength of dependence. We therefore investigate specific cases at the intersection of gender, ethnicity and other characteristics in Section 5.3.

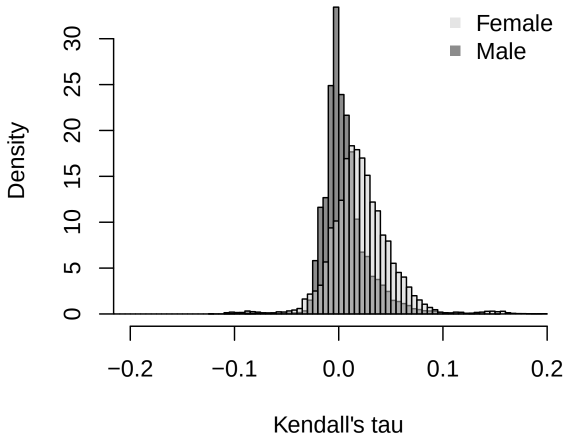
5.2 Strength of Dependence between Income and Leisure

To analyze the interdependence between income and time poverty, we are specifically interested in the impact of the covariates on the dependence parameter, the copula parameter θ_7 from Equation 4. Positive and negative impacts of the covariates need to be put in relation to the initial predictor. It follows, that the sign of the impact can either strengthen or weaken the relationship. To identify the change in the dependence, we use Kendall's τ for the specific cases.

To obtain comparable quantifications of the dependence between income and leisure, we rely on Kendall's τ – it takes values between -1 and 1 – as a dependence measure which takes into account the copula structure. The population version measures the concordance and discordance for two independent and identically distributed random vectors (Nelsen, 2006).

The results for Kendall's τ show a difference in the strength and the distribution of the relationship between income and leisure for men and women. Figure 4 displays the range of the Kendall's τ for female (light grey) and male (dark grey) sample and their overlapping area (grey). The center of the female sample locates right of the male sample which centers, with a high

Figure 4: Kendall's τ men and women: histogram



density, around zero. The density of the female sample spreads wider.[9]

To interpret the size of the effects of the covariates on the dependence structure we estimate average marginal effects (as specified in Williams (2012)) in Table 4. We adopt the significance levels from the copula parameter coefficients displayed in Table A12 for women and Table A18 for men.[10] [11]

Between men and women not only the statistical significance of the coefficients but also the magnitude of the effects on the strength of the dependence differs.[12] While nearly all variables in the male sample are not associated with the dependence between income and leisure, most variables in the female sample have a significant relation with the dependence structure. Specifically, the higher the educational level the higher the positive association with the dependence structure. In addition, having one or two

[9]The summary statistics in Table A2 support this notion.

[10]We report the full regression results for all parameters in Table A6-A11 for women and Table A13-A18 for men.

[11]Figure A9 for women and Figure A10 for men display the estimated smooth effects of age on the copula parameter. The estimated centered spline shows a varying effect for different ages on the dependence, indicating a non-linear effect on the dependence which is statistically significant.

[12]We discuss all effects conditional on ceteris paribus interpretation.

Table 4: Marginal Average Effects on Kendall's τ

	Women K's τ	Men K's τ
Preschool	0.079	0.020
Primary	0.109***	0.048
Secondary	0.139***	0.075
High-school	0.169***	0.098
Normal	0.199	0.119
Technical/commercial	0.228***	0.137
Bachelor	0.257***	0.152
Master	0.285***	0.164
PhD	0.313 *	0.174
Indigenous	0.030**	0.029**
Urban	-0.019**	-0.005
Child 1	0.024**	-0.012
Child 2	0.034***	-0.016
Child 3	0.019	-0.021
Child 4	0.014	-0.001
Child 5	-0.049	-0.104*
Partner	0.002	-0.010
Age	0.001***	0.002***

Standard errors in parentheses.
***p < 1%, **p< 5%, *p<10%

children as a women is positively associated with the dependence structure and exhibits an economically relevant magnitude – 0.024 units for one and 0.034 units for two children. In comparison having children, other than having 5 or more, is not associated with the dependence between income and leisure for men. Only the age effect is higher for men than for women, by double the amount of units.

Other characteristics are similarly associated with the dependence between income and time in the female and male sample. Having a partner has neither a statistical nor economic relevance on the strength of the dependence in both samples. Being indigenous is statistical significant in both samples with a similar magnitude of 0.030 and 0.029 units for women and men, respectively.

The dependence structure of the two poverty dimensions varies over the dimensions of the influencing factors. Due to distributional aspects, covariates have a varying economic relevance. Section 5.3 displays the probabilities of being below the separate or joint thresholds or the bivariate relative poverty line for different covariate combinations for indigenous and non-indigenous women and men. Contour plots illustrate the dependence structure.

5.3 Vulnerability to Poverty

The case studies for men and women show differences in the vulnerability to absolute and relative poverty. Table 5 and 6 illustrate specific copula prediction for indigenous and non-indigenous women and men, respectively, with the respective choices for education – primary, secondary, bachelor and master – and number of children under 14. We exclusively consider 30 year old urban citizens with a partner. The columns show the correlation parameter Kendall's τ and the probability of falling below the different specifications of the poverty line: the absolute leisure poverty, the absolute income poverty, absolute bidimensional poverty (intersection approach), above absolute but below bivariate relative poverty line and below bivariate relative poverty line.

For women the strength of the dependence between income and leisure varies strongly with educational level and number of children. We find a recognizable difference in Kendall's τ indicating the relevance of having a master's degree. The difference in the dependence varies significantly by 0.12 units in Kendall's τ, independent of the number of children. The difference is much lower between primary, secondary and bachelor degree, at around 0.01 units in Kendall's τ. Two children compared to no children is associated with a stronger relationship between income and leisure. Non-indigenous women with primary, secondary or bachelor degree with children exhibit a positive relationship, while the relationship is negative with no children.

The likelihood of falling below the absolute bidimensional poverty threshold is higher for indigenous women than for non-indigenous women, while the reverse holds for relative poverty above absolute poverty. This varies significantly with the educational level, which indicates that the distribution of the relationship matters. Low educated non-indigenous mothers are more vulnerable for relative poverty and low educated indigenous mothers are more

Table 5: Probabilities being below the poverty line: women

Education	Kendall's τ	Absolute Income Poverty	Absolute Leisure Poverty	Absolute Bid. Poverty	Below relative & Above absolute Poverty	Relative Bid. Poverty
			Non-indigenous women with no children			
Primary	-0.014	15.8	18.4	2.8	14.54	45.26
Secondary	-0.023	9.3	17.9	1.5	11.9	36.9
Bachelor	-0.017	2	19.4	0.4	3.84	24.9
Master	0.114	0.5	23.9	0.2	2.14	25.76
			Non-indigenous women with two children			
Primary	0.021	31.1	24	7.8	22.9	70.16
Secondary	0.011	19.7	23.5	4.8	22.62	60.06
Bachelor	0.018	3.6	27.4	1.1	9.28	38.5
Master	0.148	0.7	32.7	0.4	3.14	36.26
			Indigenous women with no children			
Primary	0.017	37.8	21	8.2	17.58	68.22
Secondary	0.007	26.4	20.4	5.5	17.46	58.4
Bachelor	0.014	7.1	23	1.7	9.48	36.52
Master	0.144	2.1	27.5	1	4.32	32.56
			Indigenous women with two children			
Primary	0.051	61.2	29.2	18.9	15.32	87.24
Secondary	0.041	47.1	28.8	14.4	19.08	80.86
Bachelor	0.048	12.3	34	4.8	14.4	55.12
Master	0.177	3.3	39	2.1	6.78	46.8

Probabilities are in percentages.

vulnerable for absolute poverty. Non-indigenous women with two children and a primary or secondary educational degree exhibit the highest probability of falling below the relative but above the absolute poverty line. Further, the difference in falling below the relative poverty threshold but above the absolute threshold is bigger for non-indigenous women than for indigenous women. While for indigenous women with secondary education and two children the gap is around 5 percentage points, the difference is around 18 percentage points for non-indigenous women with secondary education and two children.

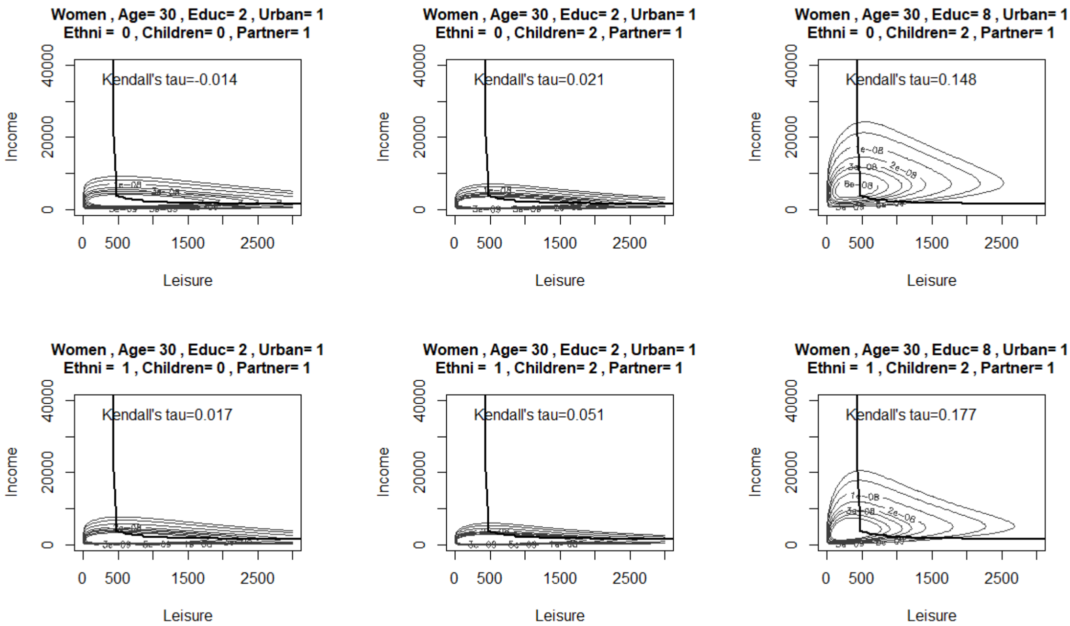
Table 6: Probabilities being below the poverty line: men

Education	Kendall's τ	Absolute Income Poverty	Absolute Leisure Poverty	Absolute Bid. Poverty	Below relative & Above absolute Poverty	Relative Bid. Poverty
		Non-indigenous men with no children				
Primary	-0.001	11.2	17.7	2	11.94	38.22
Secondary	0.015	5.7	18.7	1.1	9.9	32.3
Bachelor	0.015	1.9	20.8	0.4	3.66	25.44
Master	0.002	0.3	23.5	0.1	2.32	25.5
		Non-indigenous men with two children				
Primary	-0.017	19.6	23.8	4.5	20.34	58.98
Secondary	-0.001	10.7	25	2.7	17.66	49.66
Bachelor	-0.001	2.4	27.5	0.7	6.48	35.1
Master	-0.014	0.3	30.5	0.1	2.52	33.14
		Indigenous men with no children				
Primary	0.029	27.4	19	5.6	16.16	55.66
Secondary	0.044	17.8	20	4	15.14	46.86
Bachelor	0.044	7.6	22.2	1.9	8.06	33.92
Master	0.032	2	25	0.6	4	29.7
		Indigenous men with two children				
Primary	0.013	43.7	25.4	11.4	19.22	76.9
Secondary	0.028	30.4	26.6	8.6	20.78	67.96
Bachelor	0.028	10.1	29.2	3.2	12.16	46.86
Master	0.016	2.3	32.3	0.8	5.6	39.02

Probabilities are in percentages.

In turn, educational level and number of children barely influence the relationship between income and leisure time for men. These findings support the results from Table 4, implying that we can neither identify a statistical nor an economic relevance for the reported variables. However, educational level and number of children increase the likelihood of falling below the absolute as well as the relative poverty threshold. Like for women, the likelihood of falling below the relative poverty line but above the absolute poverty line is much higher, with a greater difference among non-indigenous men. Only non-indigenous men with primary school degree and two children have a

Figure 5: Contour plots women



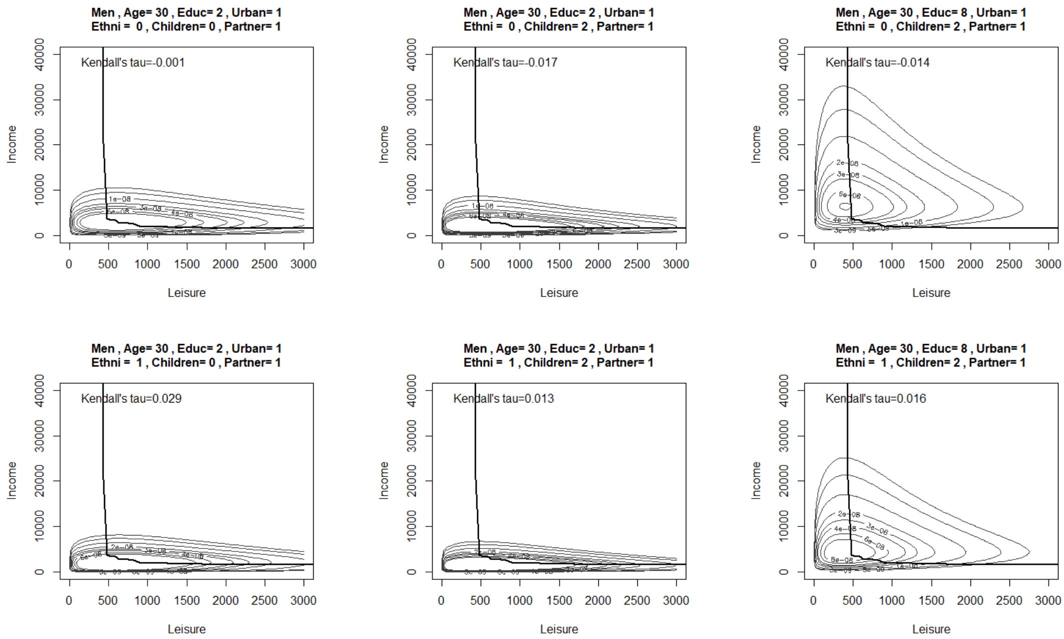
Leisure in minutes per week and income in Mexican Pesos

higher probability of falling below the relative poverty line but being above the absolute poverty line compared to their indigenous counterparts.

The intersection of gender and ethnicity matters to falling into relative poverty, being most severe for low educated non-indigenous women with children compared to all other indigenous and non-indigenous men and women. Low educated non-indigenous people with children have the highest vulnerability of falling into relative poverty but above absolute poverty. Men are less likely of falling into relative poverty than their female counterparts. For example low educated indigenous men with children are more likely to fall into absolute poverty than their female non-indigenous counterparts. However, in turn low educated non-indigenous women are more likely to fall into relative poverty, above absolute poverty, compared to their male indigenous counterparts. Thus, those vulnerable to relative bidimensional poverty become visible with our approach.

The intersection of gender and ethnicity also matters for the strength of

Figure 6: Contour plots men



Leisure in minutes per week and income in Mexican Pesos

dependence. Highly educated indigenous women with children exhibit the highest dependence, while highly educated men with children exhibit the lowest dependence. Overall the dependence is the highest among highly educated women. Women with children exhibit a higher dependence than their male counterparts, while the reverse holds for individuals without children.

In all investigated cases indigenous people are more likely to fall below the bivariate relative poverty line than non-indigenous people and women more than men. The probability varies between 10 and 20 percentage points at the intersection of gender and ethnicity, with all other characteristics being equal.

Figure 5 and Figure 6 give examples of contour lines for specific samples of women and men, respectively. The first column represents contour plots for non-indigenous women/ men (ethni=0) and the second column shows indigenous women/ men (ethni=1) all other variables are the same for the cases by row. The educational level (*educ*) is either a masters (8) or primary school (2) degree. The sample version of Kendall's τ shows the strength of dependence for the defined covariate combinations.

The shape of the contour lines indicates a relevance of the distributional aspects, as the variation in income is higher for low levels of leisure. The center of the contour lines indicates the highest density of the correlation. The location differs according to the variable combinations, being below and above the bivariate relative poverty line.

6 Conclusion

Developing a relative poverty line, based on the joint distribution of leisure and income, illuminates persisting poverty and vulnerability to poverty at the intersection of gender and ethnicity. As these two poverty dimensions are interlinked, the strength of their dependence influences the level of poverty. As a consequence, the relative poverty threshold includes 18 percentage points more people than a joint absolute leisure and income poverty approach. While indigenous women are more likely of falling into absolute time and income poverty, non-indigenous women are most likely to fall into relative poverty above absolute poverty. These patterns are not revealed by more conventional definitions and measurements of poverty.

Poverty among women is characterized by much stronger dependence between leisure and income than poverty among men, and could help explain women's greater vulnerability. The strength of the dependence between leisure and income varies with educational level and number of children. These variables thus intensify the vulnerability to bidimensional poverty for women but not for men. While indigenous mothers are more vulnerable to absolute poverty, low educated non-indigenous mothers are more vulnerable to relative poverty above absolute thresholds.

In sum, integrating income and leisure as poverty measures into a bivariate relative poverty line unveils differences based on gender and ethnicity in the lower levels of the leisure time and income distributions. The picture that emerges is more complex and diversified than offered by standard approaches, highlighting the impact of the double work burden at the intersection of gender and ethnicity.

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A Appendix

A.1 Summary statistics

Table A1: Time-use in minutes per week

	ENIGH			ENUT
	Leisure	Work	Work commute	Leisure
Ind. Women	1006	3351	3365	1009
	(902)	(1649)	(1631)	(741)
Non-Ind. Women	1093	3345	3372	1236
	(899)	(1713)	(1727)	(909)
Ind. Men	1095	3256	3334	1145
	(924)	(1496)	(1538)	(840)
Non-Ind. Men	1147	3332	3340	1287
	(966)	(1492)	(1527)	(888)

Standard deviations are in parentheses.

Table A2: Kendall's τ men and women: summary statistics

Kendall's τ	Mean	sd	Min.	1st Quant.	Median	3rd Quant.	Max.
Women	0.022	0.028	-0.123	0.005	0.019	0.0.036	0.197
Men	0.006	0.026	-0.523	-0.008	0.003	0.016	0.203

A.2 Model Specification

This section displays the AIC and BIC levels for different choices of the marginals for income in Table A3, for leisure in Table A4 and the copula specification in Table A5. This section further shows the qq-plot of the model residuals for women in Figure A7 and men in Figure A8.

Table A3: Distributional specifications: income

	Women		Men	
Marginal Distribution	AIC	BIC	AIC	BIC
Normal	745671	746014	726609	726950
Log-normal	718720	719063	692459	692792
Dagum	713000	713515	691533	692043
Singh-Maddala	713066	713571	691562	692065
Gumbel	783672	784009	764211	764552
Reverse Gumbel	720177	720521	699663	700005
Gamma	718076	718417	697320	697653

Table A4: Distributional specifications: leisure

	Women		Men	
Marginal Distribution	AIC	BIC	AIC	BIC
Normal	596273	596614	514256	514591
Log-normal	579365	579704	498626	498960
Dagum	577405	577916	497419	497921
Singh-Maddala	576943	577454	497051	497553
Gumbel	621874	622214	535564	535899
Reverse Gumbel	580860	581201	500847	501182
Gamma	577373	577705	497352	497684

Figure A7: Histogram and Q-Q Plot for model residuals for women

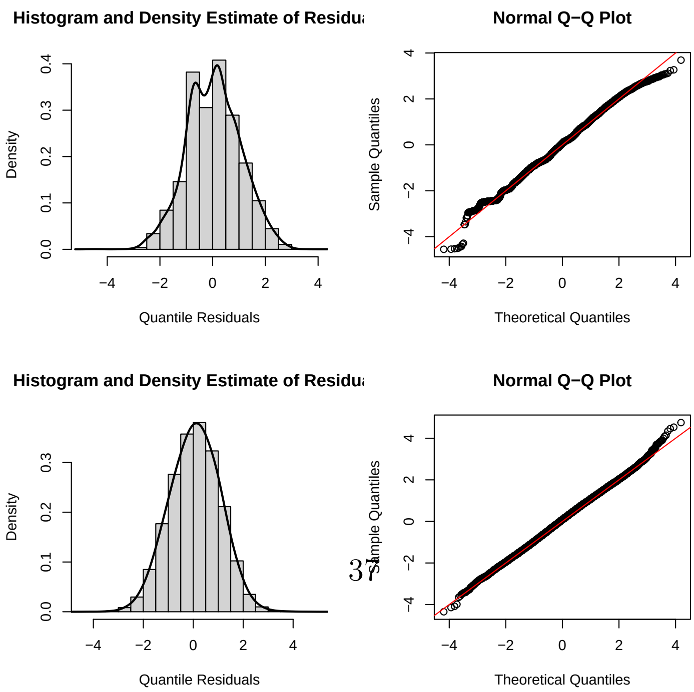
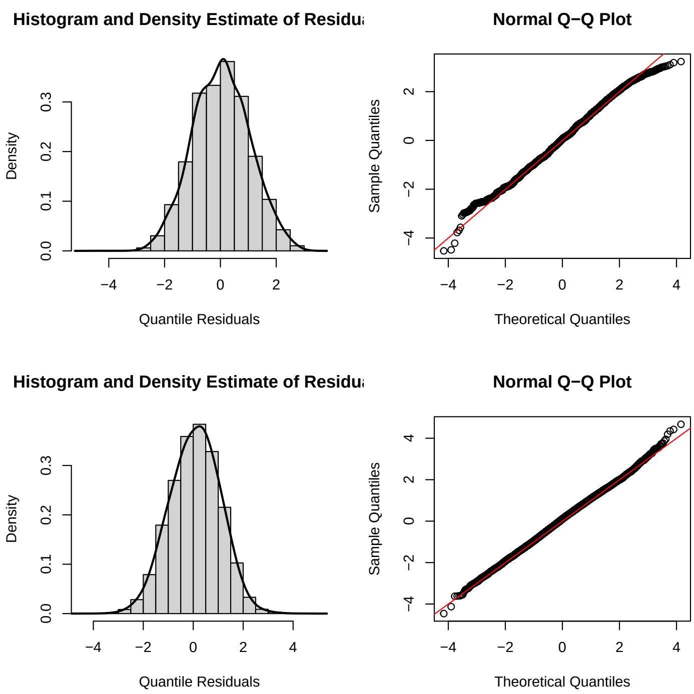


Table A5: AIC and BIC Copula Specification

	Women		Men	
Copula	AIC	BIC	AIC	BIC
Gaussian	1207763	1208943	1049535	1050700
Ali-Mikhail-Haq	1207782	1208963	1049544	1050688
Frank	1207780	1208960	1049538	1050691
Farlie-Gumbel-Morgenstern	1207780	1208960	1049543	1050687
Plackett	1207780	1208960	1049539	1050692

Figure A8: Histogram and Q-Q Plot for model residuals for men



A.3 Results women

This section shows the respective parameter estimates in Table A6-A12 and splines in Figure A9 for the distribution parameter of the marginals $\theta_1 - \theta_7$ for the sample of women.

Table A6: Estimates for copula parameter θ_1 for women

	Estimate	Std. Error	z value	Pr(>|z|)
None	8.050	0.142	56.565	0.000
Preschool	1.855	1.703	1.089	0.276
Primary	-0.049	0.124	-0.391	0.696
secondary	-0.080	0.131	-0.615	0.539
High-school	-0.271	0.136	-1.997	0.046
Normal	-0.488	0.296	-1.648	0.099
Technical/commercial	-0.411	0.152	-2.696	0.007
Professional	-0.403	0.139	-2.897	0.004
Master	-0.529	0.244	-2.173	0.030
PhD	-0.660	0.393	-1.678	0.093
Indigenous	-0.392	0.084	-4.667	0.000
Urban	-0.071	0.058	-1.240	0.215
Child 1	-0.427	0.079	-5.388	0.000
Child 2	-0.570	0.083	-6.877	0.000
Child 3	-0.406	0.112	-3.623	0.000
Child 4	-0.520	0.188	-2.774	0.006
Child 5	0.000	0.604	0.000	1.000
Partner	0.027	0.065	0.419	0.676
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	179	0.000

Table A7: Estimates for copula parameter θ_2 for women

	Estimate	Std. Error	z value	Pr(>|z|)
None	8.192	0.048	169.331	0.000
Preschool	0.230	0.174	1.325	0.185
Primary	0.131	0.042	3.131	0.002
secondary	0.244	0.044	5.493	0.000
High-school	0.282	0.050	5.609	0.000
Normal	1.104	0.133	8.301	0.000
Technical/commercial	0.469	0.066	7.063	0.000
Professional	0.800	0.055	14.453	0.000
Master	1.369	0.099	13.804	0.000
PhD	1.368	0.271	5.041	0.000
Indigenous	-0.364	0.044	-8.356	0.000
Urban	0.272	0.023	11.635	0.000
Child 1	-0.190	0.028	-6.723	0.000
Child 2	-0.363	0.031	-11.908	0.000
Child 3	-0.527	0.039	-13.370	0.000
Child 4	-0.668	0.075	-8.921	0.000
Child 5	-0.825	0.122	-6.773	0.000
Partner	-0.638	0.023	-27.959	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	62.91	0.000

Table A8: Estimates for copula parameter θ_3 for women

	Estimate	Std. Error	z value	Pr(>|z|)
None	0.462	0.026	17.451	0.000
Preschool	-0.088	0.100	-0.872	0.383
Primary	0.026	0.021	1.240	0.215
Secondary	0.036	0.025	1.461	0.144
High-school	0.085	0.028	3.040	0.002
Normal	0.073	0.072	1.012	0.311
Technical/commercial	0.090	0.033	2.690	0.007
Professional	0.088	0.029	2.995	0.003
Master	0.047	0.068	0.680	0.497
PhD	0.263	0.150	1.747	0.081
Indigenous	0.041	0.024	1.743	0.081
Urban	0.007	0.014	0.482	0.629
Child 1	0.085	0.021	4.033	0.000
Child 2	0.116	0.023	5.007	0.000
Child 3	0.040	0.029	1.380	0.168
Child 4	0.062	0.053	1.171	0.241
Child 5	0.086	0.102	0.842	0.400
Partner	-0.011	0.016	-0.683	0.495
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	97.6	0.000

Table A9: Estimates for copula parameter θ_4 for women

	Estimate	Std. Error	z value	Pr(>|z|)
None	1.238	0.040	30.681	0.000
Preschool	0.249	0.235	1.059	0.289
Primary	-0.118	0.035	-3.402	0.001
Secondary	-0.175	0.037	-4.669	0.000
High-school	-0.383	0.040	-9.653	0.000
Normal	-0.165	0.097	-1.698	0.089
Technical/commercial	-0.334	0.047	-7.108	0.000
Professional	-0.532	0.041	-13.092	0.000
Master	-0.419	0.070	-5.938	0.000
PhD	-0.378	0.187	-2.016	0.044
Indigenous	-0.128	0.034	-3.763	0.000
Urban	0.089	0.020	4.490	0.000
Child 1	0.099	0.024	4.187	0.000
Child 2	0.063	0.025	2.490	0.013
Child 3	-0.003	0.032	-0.092	0.927
Child 4	-0.019	0.061	-0.306	0.760
Child 5	-0.142	0.093	-1.527	0.127
Partner	0.010	0.019	0.519	0.604
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	139.8	0.000

Table A10: Estimates for copula parameter θ_5 for women

	Estimate	Std. Error	z value	Pr(>|z|)
None	1.502	0.172	8.752	0.000
Preschool	2.940	2.658	1.106	0.269
Primary	-0.018	0.149	-0.118	0.906
Secondary	-0.075	0.158	-0.474	0.635
High-school	-0.255	0.165	-1.544	0.123
Normal	-0.508	0.353	-1.440	0.150
Technical/commercial	-0.401	0.185	-2.169	0.030
Professional	-0.378	0.168	-2.247	0.025
Master	-0.439	0.288	-1.525	0.127
PhD	-0.344	0.573	-0.599	0.549
Indigenous	-0.384	0.102	-3.773	0.000
Urban	-0.111	0.071	-1.556	0.120
Child 1	-0.274	0.097	-2.813	0.005
Child 2	-0.372	0.102	-3.635	0.000
Child 3	-0.139	0.137	-1.013	0.311
Child 4	-0.193	0.231	-0.832	0.405
Child 5	0.489	0.837	0.585	0.559
Partner	0.023	0.079	0.290	0.772
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	88.63	0.000

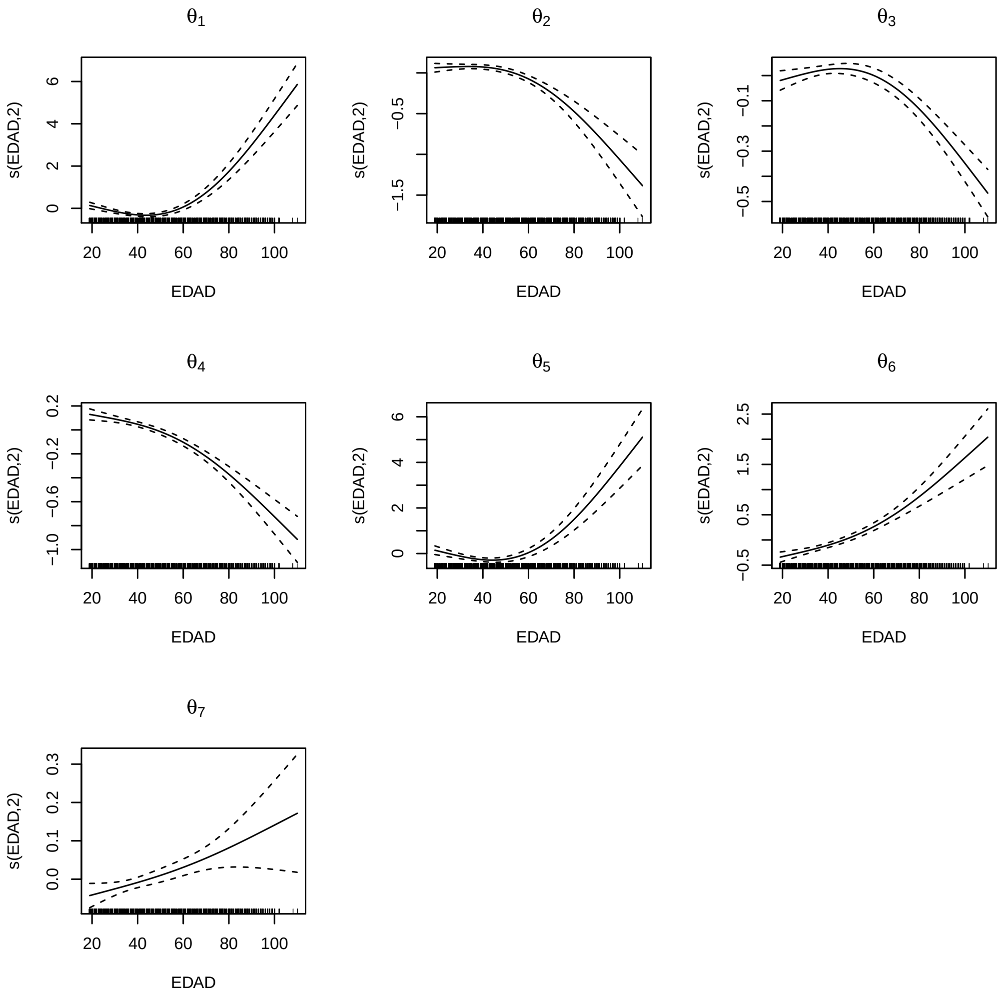
Table A11: Estimates for copula parameter θ_6 for women

	Estimate	Std. Error	z value	Pr(>|z|)
None	-0.666	0.090	-7.369	0.000
Preschool	-0.156	0.451	-0.345	0.730
Primary	0.174	0.078	2.219	0.026
Secondary	0.344	0.085	4.069	0.000
High-school	0.707	0.093	7.564	0.000
Normal	0.283	0.245	1.158	0.247
Technical/commercial	0.554	0.118	4.697	0.000
Professional	0.695	0.096	7.206	0.000
Master	0.555	0.172	3.237	0.001
PhD	0.485	0.471	1.030	0.303
Indigenous	0.006	0.077	0.082	0.935
Urban	0.069	0.045	1.545	0.122
Child 1	-0.046	0.054	-0.860	0.390
Child 2	0.062	0.058	1.073	0.283
Child 3	0.208	0.076	2.734	0.006
Child 4	0.281	0.148	1.901	0.057
Child 5	0.355	0.219	1.623	0.105
Partner	0.259	0.042	6.183	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	112.3	0.000

Table A12: Estimates for copula parameter θ_7 for women, $n = 36223$

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-0.059	0.028	-2.134	0.033
Preschool	0.027	0.159	0.169	0.866
Primary	0.089	0.025	3.622	0.000
Secondary	0.074	0.026	2.834	0.005
High-school	0.074	0.028	2.613	0.009
Normal	0.068	0.069	0.983	0.326
Technical/commercial	0.144	0.034	4.288	0.000
Bachelor	0.085	0.029	2.954	0.003
Master	0.291	0.049	5.918	0.000
PhD	0.191	0.108	1.766	0.077
Indigenous	0.048	0.022	2.220	0.026
Urban	-0.030	0.013	-2.291	0.022
Child 1	0.037	0.016	2.327	0.020
Child 2	0.054	0.017	3.211	0.001
Child 3	0.030	0.022	1.387	0.165
Child 4	0.022	0.039	0.571	0.568
Child 5	-0.077	0.070	-1.110	0.267
Partner	0.003	0.013	0.221	0.825
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	15.93	0.000

Figure A9: Smooth Spline Women θ_1-θ_7 for age



A.4 Results Men

This section shows the respective parameter estimates in Table A13-A19 and splines in Figure A10 for the distribution parameter of the marginals $\theta_1 - \theta_7$ for the sample of women.

Table A13: Estimates for copula parameter θ_1 for men

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	7.691	0.167	46.148	0.000
Preschool	1.476	2.515	0.587	0.557
Primary	0.282	0.144	1.966	0.049
Secondary	0.083	0.148	0.564	0.573
High-school	-0.044	0.154	-0.285	0.776
Normal	0.840	0.595	1.410	0.158
Technical/commercial	0.050	0.217	0.230	0.818
Bachelor	0.104	0.162	0.640	0.522
Master	-0.190	0.220	-0.864	0.387
PhD	-0.149	0.371	-0.400	0.689
Indigenous	0.014	0.110	0.128	0.898
Urban	-0.111	0.070	-1.597	0.110
Child 1	0.066	0.082	0.800	0.424
Child 2	-0.107	0.081	-1.319	0.187
Child 3	0.359	0.147	2.443	0.015
Child 4	0.193	0.303	0.639	0.523
Child 5	0.072	0.324	0.224	0.823
Partner	-0.284	0.079	-3.597	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	136.2	0.000

Table A14: Estimates for copula parameter θ_2 for men

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	8.161	0.062	131.298	0.000
Preschool	0.390	0.106	3.687	0.000
Primary	0.180	0.054	3.312	0.001
Secondary	0.258	0.057	4.511	0.000
High-school	0.404	0.060	6.732	0.000
Normal	1.178	0.219	5.379	0.000
Technical/commercial	0.709	0.083	8.578	0.000
Bachelor	0.757	0.064	11.804	0.000
Master	1.119	0.141	7.923	0.000
PhD	1.520	0.195	7.809	0.000
Indigenous	-0.223	0.044	-5.087	0.000
Urban	0.315	0.027	11.804	0.000
Child 1	-0.252	0.030	-8.284	0.000
Child 2	-0.452	0.032	-14.258	0.000
Child 3	-0.615	0.043	-14.179	0.000
Child 4	-0.617	0.078	-7.872	0.000
Child 5	-0.801	0.126	-6.367	0.000
Partner	-0.459	0.031	-14.890	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	106.4	0.000

Table A15: Estimates for copula parameter θ_3 for men

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	0.586	0.039	14.849	0.000
Preschool	-0.527	0.169	-3.124	0.002
Primary	-0.054	0.032	-1.685	0.092
Secondary	-0.021	0.035	-0.605	0.545
High-school	0.018	0.038	0.463	0.643
Normal	-0.055	0.089	-0.618	0.537
Technical/commercial	-0.076	0.056	-1.363	0.173
Bachelor	-0.050	0.038	-1.314	0.189
Master	-0.027	0.064	-0.427	0.669
PhD	-0.045	0.121	-0.369	0.712
Indigenous	-0.006	0.026	-0.211	0.833
Urban	0.002	0.017	0.125	0.900
Child 1	-0.048	0.022	-2.153	0.031
Child 2	-0.028	0.024	-1.177	0.239
Child 3	-0.111	0.031	-3.593	0.000
Child 4	-0.191	0.062	-3.105	0.002
Child 5	0.091	0.098	0.927	0.354
Partner	0.023	0.019	1.177	0.239
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	100.7	0.000

Table A16: Estimates for copula parameter θ_4 for men

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	1.067	0.045	23.820	0.000
Preschool	0.945	0.355	2.663	0.008
Primary	-0.053	0.039	-1.357	0.175
Secondary	-0.136	0.042	-3.229	0.001
High-school	-0.260	0.044	-5.934	0.000
Normal	-0.151	0.149	-1.017	0.309
Technical/commercial	-0.113	0.066	-1.715	0.086
Bachelor	-0.476	0.043	-11.003	0.000
Master	-0.565	0.062	-9.088	0.000
PhD	-0.463	0.104	-4.456	0.000
Indigenous	0.027	0.038	0.705	0.481
Urban	0.119	0.020	5.827	0.000
Child 1	-0.031	0.024	-1.322	0.186
Child 2	-0.084	0.024	-3.509	0.000
Child 3	-0.111	0.032	-3.438	0.001
Child 4	-0.052	0.068	-0.764	0.445
Child 5	-0.256	0.098	-2.624	0.009
Partner	0.144	0.021	6.959	0.000
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	182.4	0.000

Table A17: Estimates for copula parameter θ_5 for men

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	1.060	0.200	5.311	0.000
Preschool	1.272	2.266	0.561	0.575
Primary	0.263	0.171	1.539	0.124
Secondary	0.049	0.177	0.279	0.780
High-school	-0.092	0.185	-0.500	0.617
Normal	0.941	0.785	1.198	0.231
Technical/commercial	0.018	0.253	0.073	0.942
Bachelor	0.141	0.193	0.730	0.465
Master	-0.177	0.260	-0.680	0.496
PhD	-0.194	0.430	-0.452	0.652
Indigenous	0.085	0.134	0.637	0.524
Urban	-0.157	0.085	-1.845	0.065
Child 1	0.242	0.099	2.430	0.015
Child 2	0.088	0.098	0.892	0.372
Child 3	0.657	0.179	3.668	0.000
Child 4	0.392	0.330	1.185	0.236
Child 5	0.152	0.451	0.336	0.737
Partner	-0.221	0.094	-2.347	0.019
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	54.8	0.000

Table A18: Estimates for copula parameter θ_6 for men

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-0.349	0.109	-3.207	0.001
Preschool	-0.839	0.480	-1.749	0.080
Primary	-0.011	0.097	-0.118	0.906
Secondary	0.264	0.103	2.561	0.010
High-school	0.388	0.107	3.621	0.000
Normal	0.034	0.371	0.091	0.927
Technical/commercial	0.048	0.155	0.310	0.757
Bachelor	0.553	0.108	5.101	0.000
Master	0.822	0.198	4.151	0.000
PhD	0.582	0.284	2.045	0.041
Indigenous	-0.308	0.081	-3.822	0.000
Urban	0.013	0.048	0.281	0.779
Child 1	0.159	0.055	2.874	0.004
Child 2	0.334	0.057	5.824	0.000
Child 3	0.448	0.080	5.588	0.000
Child 4	0.288	0.157	1.836	0.066
Child 5	0.538	0.220	2.446	0.014
Partner	0.041	0.050	0.826	0.409
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	188.8	0.000

Table A19: Estimates for copula parameter θ_7 for men, $n = 31112$.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	0.058	0.094	0.622	0.534
Preschool	-9.527	1027.869	-0.009	0.993
Primary	-0.074	0.089	-0.827	0.408
Secondary	-0.004	0.093	-0.047	0.963
High-school	-0.008	0.097	-0.085	0.932
Normal	-0.189	0.264	-0.716	0.474
Technical/commercial	-0.067	0.133	-0.501	0.616
Bachelor	-0.004	0.098	-0.036	0.971
Master	-0.061	0.153	-0.398	0.691
PhD	-0.383	0.319	-1.199	0.231
Indigenous	0.134	0.067	1.984	0.047
Urban	-0.024	0.042	-0.579	0.563
Child 1	-0.055	0.051	-1.075	0.282
Child 2	-0.073	0.053	-1.366	0.172
Child 3	-0.094	0.070	-1.344	0.179
Child 4	-0.006	0.128	-0.048	0.961
Child 5	-0.499	0.274	-1.822	0.068
Partner	0.046	0.046	1.006	0.314
Smooth components' approximate significance:				
	edf	Ref.df	Chi.sq	p-value
Age	2	2	9.397	0.009

Figure A10: Smooth spline men θ_1-θ_7 for age