Understanding the multidimensional structure of poverty in Argentine households

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Abstract

A question of great interest for the design of multidimensional poverty measures is whether they should include a monetary poverty indicator. One of the most common arguments for keeping income poverty separate from non-monetary poverty is that they reflect different dimensions of the phenomenon. This paper explores the multidimensional structure of poverty in Argentina and investigate whether monetary poverty should be considered as another indicator of multidimensional poverty using generalized structural equation modeling (GSEM) methods. Using categorical data from the Encuesta Permanente de Hogares (EPH), a generalized confirmatory factor analysis model (GCFA) and a GSEM with a second-order factor are analyzed. The GCFA model postulates the traditional assumption that monetary poverty is just another dimension of poverty, while the GSEM supports the hypothesis that monetary poverty is a cause of non-monetary poverty. The results show that the data fit well in both cases, but that it is more plausible to consider that the non-monetary factors are indicators of a higher order dimension and that this non-monetary poverty, as a whole, is explained by monetary poverty. Finally, the implications of these results for the design of multidimensional poverty indicators in Argentina are discussed.

Keywords: multidimensional poverty, monetary poverty, generalized structural equation modeling, Argentina

JEL Classification: C38, I32

Statements and Declarations

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1. Introduction

The multidimensional approach, a phenomenon increasingly promoted and accepted by researchers, governments and society, considers poverty as a complex phenomenon related to multiple deprivations present in dimensions where the monetary element could be just one of these deprivations (Salecker, Ahmadov & Karimli, 2020). This line of sight is opposed to the unidimensional feature of poverty, which traditionally considers low monetary income as the only conceivable source of deprivation. One of the challenges in assuming a multidimensional position emerges when we ask ourselves which dimensions must be thought over, and this argument is closely related to the specific definition of poverty (Kim, 2016).

According to Walker (2015), people are usually aware of poverty at once when they come across it, but many times they face difficulties in asserting exactly what it implies. Although general agreement has been reached when considering poverty as a multidimensional phenomenon, there is little unanimity as to which poverty dimensions should be included (Ntsalaze & Ikhide, 2018; Kim, 2016) and how they interrelate with each other (Chan y Wong, 2020).

In this sense, a question of great interest for the design of multidimensional poverty measures is whether they should include a monetary poverty indicator. One of the most common arguments for keeping income or consumption poverty separate from non-monetary poverty is that they reflect different dimensions of the phenomenon (Santos et al., 2015). The standard method of current income captures cyclical fluctuations in welfare related to the labour market. Instead, non-monetary measures of multidimensional poverty capture the deprivations reflected in less volatile and more structural indicators such as precarious housing and unfavourable socio-environmental conditions. Some empirical studies show that monetary measures of poverty are imperfect predictors of non-monetary measures (Bader et al., 2016; Bourguignon et al., 2010; Roelen, 2017; 2018; Roelen et al., 2009; 2012; Ruggeri et al., 2003; Wang et al., 2016). An analysis of the mismatch between income poverty and the multidimensional poverty index carried out in Chile showed that, although 20.4% of the population was multidimensionality poor and 14.4% was income poor, only 5.5% it was poor on both measures (Ministry of Social Development, 2015). These mismatches may be because these measures might be capturing different phenomena or differences in how each indicator is captured and calculated. These findings justify the development of new research to understand the causes of these mismatches and their policy implications (UNDP, 2019).

The most widespread method to solve the dimension selection problem is to embrace a normative approach, such as the Alkire-Foster axiomatic counting methodology (Alkire & Foster, 2011). Methods such as this one assign the dimension definitions and their indicators to subjective decisions based on socio-political agreements and data availability. Their advantages are that they can seize deprivation joint distribution, identify the poor and provide a rate to summarize multidimensional poverty measurement in a single indicator (Alkire, Foster, Seth, Santos, Roche & Ballon, 2015).

The use of statistical techniques is a further way to work out the issue associated with dimension identification. Those who stand up for the usage of these methods are very interested in exploring the complex nature and structure of poverty starting from the data themselves. Alkire et al. (2015) divide them into two large groups: one related to descriptive techniques and the other based on latent variable modelling. The first group comprises cluster analysis (CA), principal component analysis (PCA) and multiple correspondence analysis (MCA). These methods are quite involved in the problem of dimension reduction. The second group covers factor analysis (FA), latent class analysis (LCA) and structural equation models (SEM). According to Walker (2015), this second group can be subdivided into two other groups. On the one hand, methods such as FA and LCA are intended to identify poverty dimensions, and on the other hand, SEM is mainly used for contrasting theories about the relationships between dimensions. In SEM, the poverty dimensions and the path relationship among them are specified beforehand by applying the proper theoretical basis or the previous exploratory analysis, and the actual presence is then contrasted against reality according to that captured by the available data.

Obviously, the normative approach is not the most appropriate to analyse whether poverty based on income and non-monetary poverty are indicators of the same construct or reflect different dimensions of the phenomenon, as it assumes that dimensions are predetermined. Statistical methods seem more suitable (Nájera Catalán & Gordon, 2020).

In the case of Argentina, there is still no regular and systematic official measurement of multidimensional poverty due to the lack of consensus on its composition and limitations in the available data sources. Therefore, the question of whether monetary poverty should be part of a multidimensional poverty index is still unresolved and is a very relevant issue. However, the analysis of multidimensional poverty in this country has been focused mainly on the development of composite indicators where poverty is a linear combination of independent factors built by applying PCA, more appropriate for continuous indicators. Thus, the possibility of a reflective measurement model is ignored, which contemplates the dimensions of poverty as latent variables, not directly observable, and the indicators as particular manifestations of these different facets of the phenomenon, possibly correlated with each other. It also omits that the available indicators are mainly binary variables. Works carried out by Conconi and Ham (2007), Conconi (2011), Carranza Mena, Pagani and Sánchez Fernández (2011) and Gasparini, Sosa Escudero, Marchionni and Olivieri (2013) give examples of descriptive techniques application, basically PCA, for the identification of dimensions. On the other hand, the works of Fagnola and Moneta Pizarro (2021) and Moneta Pizarro and Satorres Bechara (2021) are examples of applications with FA.

There are no records in Argentina of the application of more appropriate techniques to explore the relationships between the dimensions of poverty, such as SEM, and even less of methods that take into account the binary nature of the available data, for example, the generalized structural equations models (GSEM). The research background in Argentina represents significant advances in terms of the analysis of multidimensional poverty, but does not establish hypotheses that allow us to investigate the relationships between its dimensions. These antecedents are mostly studies based on Sen's capabilities approach (1984, 1985, 19982, 2000), but they only contribute a supporting conceptual framework for the understood multidimensionality hypothesis. This means that this framework is not used to assume theoretical models that make sense of causal relationships and serve to confirm multidimensional structure.

This paper demonstrates how SEM can be implemented to explore the multidimensional structure of poverty in Argentina and investigate whether monetary poverty should be considered as another indicator of multidimensional poverty. However, given the categorical nature of the available data, the generalized version of these models, GSEM, is used. Specifically, a generalized confirmatory factor analysis (GCFA) model is compared with a full GSEM that includes a second-order factor. The first model proposes to relate each factor with a dimension of poverty without a causal structure that links them. The second model includes structural relationships and proposes two alternative hypotheses at the same time. On the one hand, it assumes the unidimensionality of the non-monetary dimension of poverty, where the non-monetary factors are first-order measures of a single higher-order dimension; on the other hand, it is proposed that non-monetary poverty, represented by the higher order construct, is a consequence of the monetary dimension of poverty. Considering Walker (2015) as regards this concept, he asserts that poverty is not only the lack of monetary resources necessary to meet specific needs but also refers to the multiple consequences of this scarcity, such as deficiency in education, healthcare, housing and employment (poverty nonmonetary factors), suffered by poor people all at the same time. It also follows Chan and Wong (2020), who applied SEM to Hong Kong data and found that monetary income has a significant impact on the nonmonetary dimensions of poverty.

2. Literature Review

At the international level, there are some precedents in the application of SEM to the analysis of multidimensional poverty that focus more on the development of causal models and less on obtaining synthetic indices. Some examples are Di Tommaso (2007) with data from India, Ballon and Krishnakumar (2008) with an application to child poverty in Bolivia, Wagle (2009) for Nepal and the United States, Kim (2016) using data from the United Kingdom, Ballon (2018) for female empowerment in Cambodia, Chan and Wong (2020) with data from Hong Kong, Zhang and Huai (2023) in a paper applied to poverty among farmers in China, and Clausen et al. (2024) to explore the association between multidimensional poverty and depression using data from Peru. However, the models proposed in this background involve the use of dimensions and variables that seem to be exclusively adjusted to the context of those countries or to the availability of data specific to each case.

Despite the great global acceptance that progress in multidimensional poverty studies has had (Alkire & Santos, 2010, 2013) and the growth of poverty in Argentina, research works in this area are very few at the national level in this country (Arévalo & Paz, 2015). Among the main argentine bibliographic antecedents, outstanding works are those by Conconi and Ham (2007), Conconi (2011), Santos, Villatoro, Mancero and Gerstenfeld (2015), Arévalo and Paz (2015), Salvia, Bonfiglio and Vera (2017), Durán and Condorí (2017), Ignacio-González and Santos (2020), Fares, Favata and Martínez (2021), Macció and Mitchell (2023), Sione (2024), and Poggiese and Ibañez Martín (2024). These studies share the particularity that they are mainly centred in the construction and use of synthetic indicators such as those corresponding to Bourguignon and Chakravarty (2003) and Alkire and Foster (2011).

Some relevant works applying statistical techniques are of great interest for this research. Exemplary antecedents belong to Conconi and Ham (2007), Conconi (2011), Carrazán Mena et al. (2011) and Gasparini et al. (2013). However, in these cases, factor identification is performed through PCA, and therefore, there is neither progress for the structural model contrast nor attention to the lack of continuity and normality of the variables used as poverty indicators.

Recently, some works were included in the literature about argentine multidimensional poverty where robust FA methods are applied with tetrachoric and polychoric correlation matrices for dimension validity. In this way, problems related to the indicator normality absence are overcome. Works by Fagnola and Moneta Pizarro (2021), Moneta Pizarro and Satorres Bechara (2021) and Gutiérrez Montecino and Moneta Pizarro (2021) refined the indicators of multidimensional poverty obtained from the Encuesta Permanente de Hogares (EPH) through strong techniques of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The model originally proposed by Fagnola and Moneta Pizarro (2021) has 15 indicators distributed among 5 factors (exclusion, sanitation, health, infrastructure and economic capacity) and takes into account only one EPH wave (third quarter 2017). After considering EFA and CFA tools, 13 indicators remained and were grouped into 4 factors. The work of Moneta Pizarro and Satorres Bechara (2021) is an extension of the previous work to longitudinal data of representative periods related to the different phases of the argentine economic cycle, allowing the contrast of the longitudinal invariance of the factor structure. These authors enlarged the proposal to 18 indicators in 5 factors, but after consistency analyses, construct validity and longitudinal invariance, there remained 10 selected indicators in 3 factors (housing, environment and income). Lastly, Gutiérrez Montecino and Moneta Pizarro (2021) also contrast multiregional invariance, and a measuring model with 7 indicators and 3 factors remains validated. These papers represent significant advances in the identification with robust methods of the factor structure of multidimensional poverty in Argentina, but they do not analyse possible relationships between the latent constructs.

At both international and national level, there is no evidence of applications of GSEM, the most advanced version of SEM, in the available literature on multidimensional poverty. GSEM is a novel alternative that is considered more appropriate for dealing with complex data structures (Skrondal & Rabe-Hesketh, 2004).

3. Data

The elements used are microdata at the household level from the cross-section corresponding to the 2022 first quarter of the EPH from the National Institute of Statistics and Census (INDEC, for its acronym in Spanish). It is a sample of 16898 observations corresponding to households in 32 urban agglomerates in all regions of the country. Using this kind of data represents some disadvantages: they correspond to urban conglomerate samples with more than one hundred thousand inhabitants, and the questionnaire applied was not specifically designed to demonstrate multidimensional poverty characteristics. Survey conclusions are then limited by these restrictions. Another problem is that prospect variables to set up poverty indicators are mostly of dichotomous type (for example, whether the household head is employed or unemployed, whether the family has medical coverage, or if the housing has running water, among others). Therefore, this reveals limitations for the multivariate analysis and particularly for SEM application, working with preferably normal continuous variables and distributions. Nevertheless, this drawback is overcome by using GSEM, a more advanced and appropriate strategy of statistical modelling for these kinds of data.

With respect to the variables, the measurement model validated by Gutiérrez Montecino and Moneta Pizarro (2021) is used as the starting point, considering that it has 7 indicators grouped into 3 factors. The first factor is related to the conditions of the housing infrastructure, and the indicators are:

- Roof: It takes the value 1 if the roof is of low quality (plastic, cardboard, cane, planks or sheets without

ceiling or inner lining) and 0 otherwise.
- Bathroom: it takes the value 1 if it does not have a bathroom with drainage inside the housing and 0 otherwise.

The second factor is related to the environment or surroundings of the housing and the indicators are as follows:

- Dumpsite: it takes the value 1 if the housing is less than 3 blocks from a dumpsite and 0 otherwise.
- Floodable area: it takes the value 1 if the housing is in a floodable area (in the last 12 months) and 0 otherwise.

Finally, the third factor includes indicators related to economic home resources:

- External support takes the value 1 if the home receives external monetary or material support in the form of subsidies, assistance programs, charity and others and 0 otherwise.
- Medical coverage: It takes the value 1 if any of the members of the housing unit does not pay or is deducted payment for medical coverage services and 0 otherwise.
- TFI<TBB: it takes the value 1 in the case that the total family income is less than the total specific basic basket of that home and 0 otherwise.[1]

The first two factors are related to nonmonetary dimensions of poverty, while the third factor is strictly associated with a monetary dimension. Descriptive statistics for all these variables are presented in the following table, where the means, since all variables are binary, represent the proportion of observations with values equal to 1.

Table 1. Descriptive statistics

Variable	Obs.	Mean	Std. dev.
Roof	16898	0.0728	0.2598
Bathroom	16898	0.0867	0.2814
Dumpsite	16898	0.0518	0.2216
Floodable	16898	0.0541	0.2262
External support (Ext_supp)	16898	0.2310	0.4215
Medical coverage (Med_cov)	16898	0.3628	0.4808
TFI<TBB	14854	0.3161	0.4650

4. Methodology

As stated above, GSEM techniques are applied in this work. This modelling combines SEM capacities with generalized linear model (GLM) capacities. Similar to the econometric methods of simultaneous equations, SEM allows the simultaneous examination of a group of dependency relationships where some variables act as predictor and dependent variables at the same time but with the capacity to estimate and evaluate the relationship among latent (unobservable) variables. These variables are constructs assumed from the theory that they can be measured through observable variables (Cupani, 2012). Compared with other analysis techniques where the constructs are represented by a single measurement and the measurement error is not modelled, multiple measures are used in SEM to represent each construct and control the specific measurement error of each variable, thus allowing the assessment of the validity of each construct (Ruiz, Pardo & San Martín, 2010).

[1] This is the classic indicator of monetary poverty (unidimensional) in Argentina. The total basic basket (TBB) is the value of a set of goods and services for basic consumption. Households whose total family income (TFI) is not enough to cover the TBB are considered poor.

As Kline (2015) shows, every SEM has two elements: (a) a measurement model representing the relationships between the latent variables and their manifest indicators and (b) a structural model describing the interrelationship among the latent constructs. By using the measurement model, the aim is to verify the adequacy of the indicators selected in the measurement of relevant constructs. The structural relationship model is the one truly desired to be estimated. It includes the effects and relationships among the constructs, which are normally latent variables. It is similar to a regression model, but it may have concatenated effects and loops among variables.

Another particular characteristic of SEM is that it has several statistical tests and a group of goodness of fit indicators, but the adjustment is verified when the values of the estimated parameters reproduce the observed covariance matrix as strictly as possible (Kahn, 2006). For this purpose, in SEM, the model estimation is based on the existing correlations among measured variables in a cross-sectional sample. Instead of reducing the difference between the predicted values and the ones observed at the individual level (least squares method), the difference between the covariances observed in the sample and the covariances predicted by the structure model is reduced. According to Long (1983), this is the reason why these models are also called covariance structure models. Therefore, the model residuals are the differences between the covariances observed and the covariances predicted by the theoretical structure model (Ruiz et al., 2010).

By combining SEM with GLM, in GSEM, it is possible to work with response variables that may be continuous, binary, ordinal, count or multinomial variables. In addition, both normal linear regressions and the large spectrum of regressions of the exponential family (Gamma, Logit, Probit, Poisson, Negative Binomial and their variants) can be modelled (Skrondal & Rabe-Hesketh, 2004). In this research, the presence of binary variables makes it necessary to apply GSEM instead of SEM.

In this work, first, a measurement model (without a structural part) with a logit link is specified, that is, a CFA model adapted for variables of dichotomous or binary response (GCFA). In this model, as indicated in Figure 1 below, it is assumed that each latent factor is one poverty dimension that can be measured through observable indicators and that the factors may be correlated. This first model is therefore made up of three measurement sub-models, one for each factor. Two observed indicators, roof and bathroom, help us to approach the housing conditions; two other observed indicators, dumpsite and floodable area, are assumed manifestations of the environment conditions; and three indicators observed measure the economic home resources. The three measurement models are jointly estimated, and this permits correlations among factors. As McGartland Rubio et al. (2001) indicate, the verification of these correlations is usually understood as the result of the existence of a higher-order factor. Nevertheless, this may not necessarily be the reason, since the correlation can be because the factors measure different dimensions of one construct, poverty in this case.

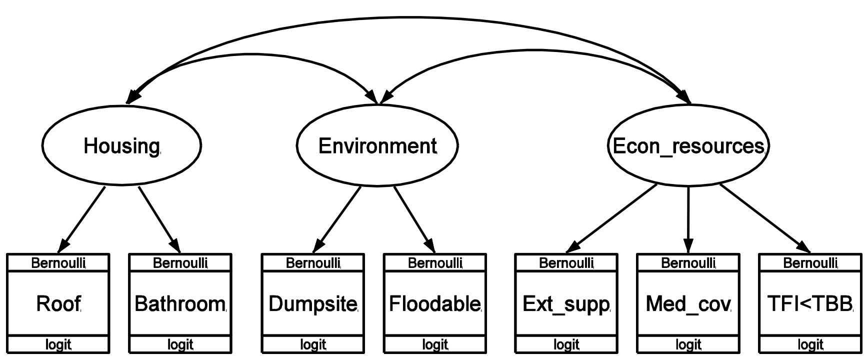

Fig. 1 GCFA model

Using matrix notation, this first model can be represented through the measurement equation (1):

$$\text{logit}[\Pr(w = 1|\xi)] = \Lambda_w \xi \qquad (1)$$

where w is the vector of observed indicators, 1 is a vector of ones, ξ is the vector of latent factors (poverty dimensions) with covariance matrix Φ and Λ_w is the matrix of model coefficients (factor loadings).

Second, a full GSEM is specified where two factors, housing and environment, are demonstrations of nonmonetary poverty, that is, a second-order construct, and the factor related to economic resources or monetary poverty is an exogenous latent variable explaining nonmonetary poverty. This model is represented in Figure 2. It should be noted that the measurement indicators for each factor are the same as those in the first model.

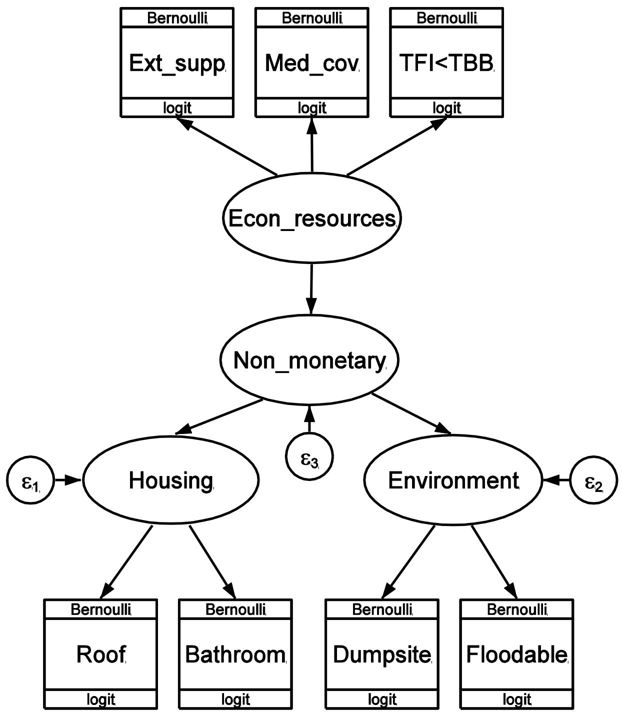

Fig. 2 Full GSEM path diagram

The full GSEM can be expressed in matrix form using equations (2), (3) and (4).

$$\eta = \mathrm{B}\,\eta + \Gamma\,\tau + \varepsilon \qquad (2)$$
$$\mathrm{logit}[\Pr(y = 1|\eta)] = \Lambda_y \eta \qquad (3)$$
$$\mathrm{logit}[\Pr(x = 1|\tau)] = \Lambda_x \tau \qquad (4)$$

Equation (2) represents the structural part of the model, while equations (3) and (4) are the measurement model for latent factors. In the structural part, η is the vector of endogenous latent variables (η_1, η_2, η_3), with η_1 and η_2 being the first-order factors (housing and environment) and η_3 being the second-order factor (nonmonetary poverty), τ is the only exogenous latent variable (economic resources), B is the 3×3 coefficient matrix of the endogenous latent variables, Γ is a coefficient vector of order 3 whose elements are all equal to zero except the third one that represents the effect of τ on η_3 and ε is the vector of disturbances $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ associated with the endogenous latent variables included in η with a diagonal matrix of covariances Ψ. In the measurement model, y is the vector of indicators used to measure η_1 and η_2, x is the vector of indicators for the measurement of τ, Λ_y and Λ_x are factor loading matrices and 1 is a vector of ones.

With the help of Stata 17, both models are estimated with maximum likelihood (ML), which is the only available method for GSEM. In the case of the second model, its high complexity hindered difficulties in achieving convergence in the estimation process. This problem was temporally solved by modifying the numerical integration model and reducing the number of integration points.

The results were satisfactory by using the model of the non-adaptive Gauss-Hermite quadrature and by reducing the points of numerical integration to 3. Afterwards, these estimations were used as improved initial values to re-estimate the model with the default options, which allowed arriving at a solution with greater accuracy. This was achieved with the adaptive Gauss-Hermite quadrature algorithm based on the mean and the variance and 7 points of numerical integration.

5. Results

Table 2 indicates the estimation results of the pure measurement model, that is, the GCFA model, which permits us to contrast the convergent and discriminant validity of the three factors proposed for multidimensional poverty. By observing such results, all the indicators are significantly related to their corresponding latent constructs. This supports the convergent validity of the model, that is, that the indicator variables of each factor are strongly correlated with each other, sharing a high proportion of the variance (Aldás & Uriel, 2017). The covariances among the latent factors are also significantly different from zero. Departing from the estimated variances and covariances, the correlations obtained are equal to 0.51 between housing and environment, 0.60 between housing and income and 0.32 between environment and income. These moderate correlation values indicate discriminant validity.

Table 2. Results of the GCFA model

Variables		Coefficient	Std. Err.	z	P>|z|	[95 % Conf. Int.]	
Roof							
	Housing	1	(restricted)				
	constant	-4.232543	0.1449429	-29.2	0.000000	-4.516626	-3.94846
Bathroom							
	Housing	0.9593894	0.0813283	11.8	0.000000	0.7999889	1.11879
	constant	-3.85143	0.1272349	-30.27	0.000000	-4.100806	-3.602054
Dumpsite							
	Environment	1	(restricted)				
	constant	-4.199538	0.167694	-25.04	0.000000	-4.528213	-3.870864
Floodable area							
	Environment	1.288781	0.1995092	6.46	0.000000	0.8977506	1.679812
	constant	-4.802548	0.3051847	-15.74	0.000000	-5.400699	-4.204397
External support							
	Economic resources	1	(restricted)				
	constant	-1.809089	0.0375684	-48.15	0.000000	-1.882722	-1.735457
Medical coverage							
	Economic resources	1.474708	0.0745719	19.78	0.000000	1.32855	1.620866
	constant	-1.093027	0.0417698	-26.17	0.000000	-1.174894	-1.011159
TFI<TBB							
	Economic resources	1.263382	0.0554054	22.8	0.000000	1.15479	1.371975
	constant	-1.422182	0.0424695	-33.49	0.000000	-1.505421	-1.338944
var(Housing)		5.305203	0.5600140			4.313697	6.524607
var(Environment)		3.453833	0.5148337			2.578813	4.625756
var(Economic resources)		3.105572	0.1776731			2.776153	3.474079
cov(Housing/Environment)		2.188527	0.2328391	9.4	0.000000	1.73217	2.644883

cov(Housing, Econ. res.)	2.471096	0.1573252	15.71	0.000000	2.162744	2.779448
cov(Environment, Econ. res.)	1.075617	0.1115909	9.64	0.000000	0.8569024	1.294331

The fact that the covariances among factors are significant demonstrates that the presence of a second-order factor and structural relationships among the latent variables are reasonable. In this way, the specification corresponding to the full GSEM is plausible. Table 3 exhibits the results from this estimation. According to the measurement modelling, all the indicators of this second model are also significantly related to their corresponding latent factors, and as expected, the estimated coefficients assume very similar values to those of the pure measurement model. By analysing Table 3, estimated covariances among constructs are not included since they have been replaced by structural relationships. All these structural coefficients were also significant. Therefore, the empirical evidence supports the hypotheses presented for this second model.

Table 3. Results of full GSEM

Variables	Coefficient	Std. Err.	z	P>|z|	[95 % Conf. Int.]	
Measurement model						
Roof						
Housing	1	(restricted)				
constant	-4.246725	0.1571272	-27.03	0.000000	-4.554688	-3.938761
Bathroom						
Housing	0.955539	0.0866052	11.03	0.000000	0.7857958	1.125282
constant	-3.854903	0.1302366	-29.6	0.000000	-4.110162	-3.599644
Dumpsite						
Environment	1	(restricted)				
constant	-4.19829	0.1645436	-25.51	0.000000	-4.52079	-3.875791
Floodable Area						
Environment	1.289765	0.1964518	6.57	0.000000	0.9047261	1.674803
constant	-4.803195	0.3025952	-15.87	0.000000	-5.396271	-4.21012
External support						
Economic resources	1	(restricted)				
Constant	-1.809797	0.0395883	-45.72	0.000000	-1.887389	-1.732206
Medical coverage						
Economic resources	1.474086	0.0779903	18.9	0.000000	1.321228	1.626944
Constant	-1.093534	0.0417848	-26.17	0.000000	-1.17543	-1.011637
TFI<TBB						
Economic resources	1.263164	0.0579683	21.79	0.000000	1.149548	1.376779
constant	-1.422828	0.0424854	-33.49	0.000000	-1.506098	-1.339558
Structural model						
Housing						
Non-monetary poverty	1	(restricted)				
Environment						
Non-monetary poverty	0.4383168	0.0493818	8.88	0.000000	0.3415303	0.5351033
Non-monetary poverty						
Economic resources	0.7941819	0.057259	13.87	0.000000	0.6819563	0.9064074
var(e.Non-monetary poverty)	3.001571	0.4559609			2.228665	4.042523
var(e.Housing)	0.383752	0.3345924			0.0694848	2.119391
var(e.Environment)	2.492091	0.3747607			1.855924	3.346321
var(e.Economic resources)	3.104728	0.1953692			2.744483	3.51226

Comparing the models with the Akaike (AIC) and Schwarz (BIC) information criteria, the full GSEM has lower values in both cases. The GCFA model has an AIC equal to 82658.00 and a BIC equal to 82789.49, while the GSEM model achieves an AIC equal to 82657.17 and a BIC equal to 82788.66. Consequently, GSEM is the relatively best fit to the data.

6. Discussion

The results show that with the EPH data, in spite of their limitations for multidimensional poverty analysis, it is possible to confirm the presence of at least three dimensions of poverty. One of them is associated with the material conditions of the housing, another one is related to the environmental surrounding and the last one corresponds to the monetary income. However, it is more realistic to consider that the nonmonetary factors of poverty, such as housing and environmental conditions, are different indicators of the same dimension of higher order and that this nonmonetary poverty, as a whole, is explained by the monetary dimension. Empirical support is then provided for the identification of two dimensions instead of three. One dimension is associated with the lack of monetary resources, and the other is related to nonmonetary deprivations.

In this way, it cannot be excluded that poverty is multidimensional in Argentina, but a structural relationship is supported among its dimensions. This means, as Walker (2015) points out, that poverty is manifested not only by the presence of inadequate monetary income but also by the multiple consequences of this absence regarding housing and environment, which are part of a nonmonetary dimension of the phenomenon. This conclusion, seeming quite obvious, is opposed to a great part of the literature about multidimensional poverty developed up to present time, which sometimes implicitly and other times explicitly associates the correlation among poverty factors to the presence of different dimensions or attributes of one same construct. Kim (2016), who in his measurement model includes economic resources as one more poverty dimension and is based on Kangas and Ritakallio (1998), Lelli (2001), Whelan (1993a) and Whelan (1993b), affirms that this it is common because these resources can be applied to other functions related to poverty, for example, to healthy food purchases. The criticism that can be made of this type of position is that they do not inquire in depth about these links and the possible presence of structural relationships between the dimensions. The exception to this may be the trap models of poverty. Beneath the theoretical framework of these models, poverty is characterised as a vicious circle due to the presence of self-reinforcing mechanisms that provoke its continuation (Santos, 2014) and therefore postulate in this way the possibility of causal relationships among their dimensions.

7. Implications

The implication of these conclusions for future research and public policy designs is that, based on the data used for this research and the evidence found, poverty in Argentina should not be measured by using one multidimensional index but by using two. These should be a monetary poverty indicator on the one hand and a nonmonetary poverty indicator on the other. In other words, income poverty should not be mixed with other dimensions of multidimensional poverty since it is very likely the reason for the nonmonetary dimensions.

Thus, and differently from what was proposed by Santos et al. (2015), the recommendation to keep the income poverty and nonmonetary poverty indicators separate is supported. The arguments that are generally put forward to recommend this are very well compiled in the manual of the United Nations Development Programme and the Oxford Poverty and Human Development Initiative of the University of Oxford (UNDP & OPHI, 2019), where it is stated that if the objective to elaborate a multidimensional poverty measure is to complement the current statistics of monetary poverty, then the inclusion of a dimension related to income adds noise. In these cases, it is appropriate to look beyond the manifestations of economic capacity, broadening the understanding of the phenomenon towards nonmonetary dimensions not captured by the traditional measures of monetary poverty. Among other arguments, it also points out the importance of recognizing that monetary and nonmonetary indicators capture poverty differently. Monetary indicators are generally considered indirect measures of poverty because they focus on the scarcity of resources for the acquisition of basic goods and services, while multidimensional indexes developed based on nonmonetary indicators are considered direct measures of lack of well-being because they reflect real deprivations.

However, this study provides another reason for the monetary and nonmonetary poverty measures to be kept separate, and it is the finding of empirical evidence, at least for the case of Argentina, in favor of the fact that monetary poverty is a good predictor of nonmonetary poverty. This result could be associated with a close relationship between the indicators of one type of poverty and the other, suggesting a certain coincidence between both measures and that they could be combined without problems in a single measurement. However, the correlation is not perfect, as the results show for the structural regression of the nonmonetary dimension as a function of the monetary one. The fact that economic resources partially explain nonmonetary poverty does not mean that they are useful for measuring the same concept. In contrast, both the measurement model proposed through the GCFA and the complete GSEM assume that the household economic capacity indicators are manifestations of one construct, while the rest, the nonmonetary ones, are manifestations of others. The empirical evidence found here confirms that these measures should not be combined, but not because they are independent or do not coincide in the estimation of the poor population but because it is more plausible, as stated in the complete GSEM, that one is the cause of the other. These results can be a constructive contribution to the debate on the relationship between monetary and multidimensional poverty measures, which for the Latin American case is very appropriately discussed in Santos et al. (2015).

8. Conclusion

The aim of this paper was to deepen the multidimensional analysis of poverty in Argentina. By exploring the multidimensional nature of poverty, the study aimed to highlight the importance of considering various dimensions of deprivation beyond monetary income. Furthermore, it set out to address the complexities and challenges associated with determining the specific dimensions that should be incorporated into multidimensional poverty measures, thereby contributing to a more comprehensive understanding and improving the effectiveness of poverty alleviation efforts in Argentina.

Key aspects of the methodology employed included the identification and selection of relevant dimensions, the comparison of rival models to analyse the interrelationships between these dimensions, and the use of advanced statistical techniques such as GSEM to assess multidimensional poverty in Argentina. Ideas from previous research on robust measurement methods were incorporated and empirical data from the EPH were used to validate the proposed models.

The results of the study highlighted the effectiveness of the multidimensional approach in capturing the complexities of poverty beyond mere monetary measures. The testing of the models developed provided valuable insights for a more complete understanding and identified the interrelationships between the different facets of the phenomenon in Argentina. The empirical validation of these models corroborated the robustness of the multidimensional approach in capturing the nuances of poverty and guiding interventions for the development of more appropriate indicators. By exploring various dimensions of deprivation, the research provided evidence on the interconnected nature of the different aspects of poverty and underlined the need to separate the monetary dimension from the non-monetary ones. In this way, the study provides a framework for designing appropriate indicators of multidimensional poverty, as well as for the implementation of more effective and targeted comprehensive policies to combat this scourge.

In summary, this research on multidimensional poverty not only contributes significantly to the academic literature, but also has important implications for policy and practice. By delving into the complexities of poverty measurement beyond income and exploring the multidimensional nature of deprivation, the study offers a more comprehensive understanding of poverty. The conclusions highlight the need to adopt a multidimensional approach, complementary to the traditional monetary one, when developing poverty measures and designing programs for its alleviation.

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