Revealing the role of factors shaping Americans' objective well-being: A systems science approach with network analysis

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Total number of words (entire manuscript including title page): 10660

Abstract: 113

Number of figures: 5

Number of tables: 2

Abstract

Despite the introduction of multiple factors, multidimensional approaches cannot represent the complexity of the objective determinants of well-being (ODW). This paper proposes an alternative OWD model that adds a systemic approach, by using Bayesian networks algorithms to discover a directed two level network of variables nested in subnetworks of determinants. The network was inferred by using subsamples of the 2013 version of the American Community Survey. Network analysis methods applied to the model provided new insights concerning single ODW relevance and the roles that are useful to focus selective welfare interventions; they also offered a big picture that is fundamental to reason about the unpremeditated universal character of the selective US welfare policies.

JEL classification: I31, C39

Keywords: Well-being; Objective determinants of well-being; Bayesian networks; Network analysis; Complex systems

1. Introduction

In the conceptual levels proposed by Kahneman et al. (National Research Council, 2001), objective determinants of well-being (ODW) are defined to represent the tangible conditions of people's lives that are concerned with the factors of individuals' material access to social assets such as education, health, employment, income and housing, all of which jointly contribute to the social perception and subjective experience of well-being (Huppert & Cooper, 2014; Stoll, 2014). Governments and other social actors must understand well-being in order to develop direct and indirect welfare interventions aimed at increasing the social assets available to the population (Huppert & Cooper, 2014). Thus, a nuanced understanding of the joint ODW is an element that is essential to develop effective welfare interventions.

Representing the ODW joint set complexity is a challenging task that must consider numerous factors and dependences, but the associated difficulties deter the straightforward understanding of people`s needs, with detrimental consequences on decisions about what determinants must be first or strongly intervened to improve welfare efficiency. Awareness of this has prompted a trend toward more comprehensive well-being representations known as multidimensional approaches, which are able to assess the simultaneous contribution of a larger number of factors. Yet, well-being`s multidimensional models remain unsatisfactory as they are limited by the assumptions of classic modeling methods.

The aim of this study was to identify the role and relevance of diverse determinant factors that simultaneously comprise the complex construct of objective well-being by using methods able to overcome some limitations of the linear combination-based techniques that are usually applied for multidimensional models. For this, we proposed a systems science data-driven modeling process involving the use of artificial intelligence methods to infer significant non-linear interdependences among all the variables representing a set of ODW. The model was built using data from the American Community Survey for the year 2013 (ACS-2013) (U.S. Census Bureau, 2015), as is a main and recognized information source used to support federal and state welfare policies and program funding decisions in the US (U.S. Census Bureau, 2009). The interdependences inferred among ODW variables were represented by a network model. The model was further analyzed by network science methods to provide a quantitative basis for each ODW relevance and role. The knowledge gained by the model analysis provides evidence for more efficiently focused interventions and offers some clues with which to scrutinize the US selective welfare model.

The paper is organized as follows. In section 2 we provide background for the complexity of ODW by browsing the vast amount of factors found as relevant by previous research and presenting the progressive ways to measure and model well-being by recognizing the modeling progresses and limitations that justify an alternative approach (2.1.). In section 3, we describe the process and the methods we propose for modeling and analysis, as well as the model itself. In section 4, we show the model analysis results, and in section 5, we discuss the policy implications of our results.

2. The ODW Landscape

Several studies have reported multiple findings about diverse ODW, usually supporting the relationships with subjective well-being outcomes. In the following paragraphs, we illustrate the complexity of well-being by considering some of the multiple objective factors that determine it, including different variable operationalizations and some unexpected, counterintuitive or non-proportional findings that arise when more than one factor is considered.

The material economic living conditions are measured by individuals' or household absolute earnings and the relative income -represented by housing quality, affordability of holiday activities and indicators such as end of month`s balance and the manageability of debt and taxation-. These are positively associated determinants that have received great deal of attention in the literature as well as in tracking general welfare policies (Berloffa & Modena, 2012; Dolan, Peasgood, & White, 2008; Kennelly, 2014; Luhmann, Schimmack, & Eid, 2011; Rojas, 2008; Stoll, 2014; Vylkova, 2015).

Research findings consider employment status as a determinant that is positively related to well-being if the job is perceived as being secure, being high quality, offering a variety of experiences or tasks, and fostering workplace trust and affective commitment (Harriss-white, 2010; Hecht & Allen, 2005; Meyer & Maltin, 2010; Salvatori, 2010). However, according to unexpected findings of higher unemployment rates associated with higher levels of reported well-being, subjective well-being can be paradoxically affected by the population`s perception of unemployment. The authors attribute these findings to individuals' standards downward adjustment (Eggers, Gaddy, & Graham, 2006). Complementing the scenario, hours worked exhibit a nonlinear U-shaped relationship with well-being, but, as expected, longer commutes negatively affect it (Huppert & Cooper, 2014).

According to researchers, there is an inverted U-shaped relation for the education determinant, with the greatest well-being seen in the medium educated group. This seems to be mediated by exogenous factors such as health, income and social mobility (Huppert & Cooper, 2014). Education endogenous factors of teaching quality and social support are positively related to the well-being among individuals enrolled in an educational institution (Saab & Klinger, 2010; Sweeting & Hunt, 2014).

Since additional concerns of social and psychological factors have been gradually included besides the focus on the biological issues of illness and disease, health is recognized as a broad determinant closely related to well-being and quality of life (Placa & Knight, 2013). Along this line, several studies have reported that subjective and objective health problems, disability and mental ill-health are negatively related to low levels of well-being, as expected (Binder & Coad, 2013; Denny et al., 2014; Steptoe, Deaton, & Stone, 2015; Sun, Ji, & Kim, 2014; Wang, Jia, Zhu, & Chen, 2015). However, this negative association is weaker when individuals adapt to chronic disease circumstances (van Mierlo, van Heugten, Post, de Kort, & Visser-Meily, 2015) and due to the moderating effects of other determinants including income, social support and job satisfaction (Emerson et al., 2014) (Arber, Fenn, & Meadows, 2014; Dür et al., 2014; Humboldt, Leal, & Pimenta, 2015; Sacco, Park, Suresh, & Bliss, 2014). Besides, some authors argue that the positively expected relation between well-being and healthy behaviors, such as physical activity, sufficient sleep, and diet, is nuanced by contradictory findings (Goetzke, Nitzko, & Spiller, 2014; Ruiz, 2015).

Studies show that environment determines well-being. This includes a vast range of factors concerning dwelling, such as geographical location, seasonal changes, air pollution, landslide and flooding hazards, wealth derived from the exploitation of natural resources, proximal neighborhoods safety and security, and standard public services availability (Engelbrecht, 2009; Pierewan & Tampubolon, 2014). As expected, lower well-being is reportedly caused by air pollution, noise problems, and diverse stressors such as high crime rates in the neighborhood (Campo et al., 2015; Huppert & Cooper, 2014; Lorenc et al., 2012).

Social membership which is represented by variables of familial support (Brown, Manning, & Stykes, 2015; Forgeard, Jayawickreme, Kern, & Seligman, 2011), social trust, feelings of non-discrimination, access to a fair legal system, social connections and active participation in community and religious activities, has positive relations with well-being (Huppert & Cooper, 2014; Nataliya, 2015).

Individuals' characteristics such as gender, age, race and ethnicity appear to play a role in determining well-being. In the case of gender, results show that women tend to have higher levels of life satisfaction despite higher incidence of illness, anxiety and depression. Age, explained by successfully fulfilling the changing priorities through the course of life, the findings show that the highest level of well-being is reached in young adulthood and early old age (Dolan et al., 2008; Huppert & Cooper, 2014), (Lin, Hwang, & Deng, 2015). In the case of race and ethnicity, Dolan et al (2008) found that Hispanics and individuals of European descent (i.e., White) experience greater well-being than African Americans.

Migration is driven by the objective to improve one`s life. Nevertheless, the literature suggests that movement into higher income cultures often results in well-being decreases due to an insufficient income increase relative to higher cost of living in the destination locations, and due to the fall in the relative social position (Stillman, Gibson, & Bank, 2015). In communities that accept migrants, the natives' well-being improves with the migrants' intermediate social assimilation. However, natives' well-being improvements are low when migrants are not assimilated or the assimilation process has been completed (Akay, Constant, & Giulietti, 2014).

The emergent determinant of technology access bears substantially on well-being improvement, as the Internet facilitates mechanisms to stay connected with friends and family, to find new social contacts, to link to entertainment, to find satisfying jobs, and to obtain otherwise hard to reach goods. However, the sheer volume of information available can hinder Internet utilization, thus increasing technology access disparities (Ahmet & Uysal, 2015; Ahn & Shin, 2013; Contarello & Sarrica, 2007; Felton, 2014; Graham & Nikolova, 2013).

The majority of these summarized findings arise from focused research on single determinants chosen according to the researchers' interests and thematic specialization. However, the relative importance of determinants cannot be addressed in an isolated way.

2.1. Measurement and modeling well-being progression

Beyond the academic field, indicators and indexes of well-being and its determinants are regularly monitored to inform national and supranational human development policies (Clark & McGillivray, 2007). The Gross Domestic Product (GDP) is one of these commonly used indicators. However, a country`s sole reliance on GDP generates concerns because the indicator unsuccessfully seizes important nuances of national development and well-being strengths (Dowrick, 2004). This has motivated international institutions -such as the OECD, UN, European Commission and World Bank, the European Parliament, and Eurostat, led by renowned economists as Stiglitz, Sen and Fitoussi-, to undertake the development of national progress and well-being comprehensive measures. These initiatives are comprised of objective and subjective concepts of capabilities, quality of life, living standards, social welfare, needs fulfillment, life satisfaction, and happiness to better capture the numerous dimensions of peoples' lives (Agee & Crocker, 2013; Bleys & Whitby, 2015; Clark & McGillivray, 2007; Gasper, 2004; Klasen, 2004; Stoll, Michaelson, & Seaford, 2012).

Consequently, the need to model multiple aspects of well-being favors multidimensional approaches over single indicator reductions (Clark & McGillivray, 2007). Multidimensional approaches are present on the Millennium Development Goals (MDG) set of indicators, and on indexes such as the Human

Development Index (HDI), the Human Well-being Index (HWBI), the General Index of Development (GID), the Socioeconomic Development Index (SID), and the Index of Economic Well-being, among various others (Fulford et al., 2015; Harkness, 2006; McGillivray & Noorbakhsh, 2004).

In usual multidimensional approaches, diverse objective and subjective well-being determinants are jointly included in linear combination-based models, which agree with the statement of 'separable dimensions' represented by the factors independence assumption. This assumption holds true for the linear relationships between the response (dependent) and each predictor (independent) variable and for the predictor variables additive effect (McGillivray & Noorbakhsh, 2004). Consequently, assumption violation is a concern about multidimensional models because this can lead to misleading results. Additional concerns arise from weak theoretical foundations, a biased selection of factors, leaving out essential dimensions, an inadequate representation of factors by variables, and the effects of correlations between factor variables, among others (Bleys & Whitby, 2015; McGillivray & Noorbakhsh, 2004; Otoiu, Titan, & Dumitrescu, 2014).

Despite the potential concerns, multidimensional models are highly valued because they provide coefficients that approximate the "crucial question" of each factor's relevance (Aristei & Perugini, 2010). Recent studies within the multidimensional approach add to the findings and help to overcome some of the described theoretical and methodological concerns. For example, Lin et al. (2015) examined well-being changes over a person`s life span using a semiparametric varying-coefficient partially linear ordered probit model of age, including its interactions with income, race, family and employment. Their conclusions supported age as an indirect moderating factor and employment and race as relevant well-being determinants. Campo et al. (2015) developed a multilevel model of the associations between neighborhood variables and health outcomes, including a systematic approach to age and gender interactions. The findings supported age and gender as modifiers of the neighborhood effects on well-being. Casas & Gonzalez (2008) highlighted the complexity of psychological well-being in terms of non-linearity. They proposed a non-linear regression model that included interaction and quadratic terms. Despite the fact that non-linear variable transformation does not necessarily imply model non-linearity, and that non-linearity is just one of many complex features, they reported associations of material values, gender and social support with well-being. Kant et al. (2014) applied path analysis to model well-being in two Canadian First Nations communities, where they identified the most important factors as being social, cultural and land use.

3. Methodology

3.1. Data preprocessing, variable selection and transformation

This study dataset was a randomly selected probabilistic subsample of 31,331 registries from the 2013 version of the American Community Survey (ACS-2013), which is one of the Census Bureau regular major surveys. It is developed in the US every year to inform the decision making about federal and state investments (U.S. Census Bureau, 2009, 2015). The ACS-2013 source was the Integrated Public Use Microdata Series project (IPUMS-USA) developed by the Minnesota Population Center of the University of Minnesota (Minnesota Population Center, 2015). This provides a de-identified and harmonized version of the entire dataset – which originally comprised a probabilistic sample of 3,132,795 individuals (1,359,520 households) – with 240 variables in ratio, ordinal and nominal levels of measurement. IPUMS-USA asserts the statistical representativeness for the country and for individual states for the entire dataset and for each of one hundred predefined random subsamples, which were utilized in this study.

As determinants or factors correspond to wide-ranging concepts, (e.g., economy, health, and education) that can be measured by single or several variables, we represented them using the key topics explored in the survey and defined by IPUMS-USA to group the variables. The groups of household level variables explored were originally labeled ‘geographic information’, ‘group quarters information’, ‘economic characteristics’, ‘dwelling, appliances, mechanical and other house equipment’, and ‘household composition and type’. The groups of variables for the person observation unit were ‘familiar relationships’, ‘demographics’, ‘race’, ‘ethnicity and nativity’, ‘health insurance’, ‘education’, ‘work’, ‘income’, ‘occupational standing’, ‘migration’, ‘disability’, ‘veteran status’ and ‘place of work and commuting’.

Data preprocessing followed the guidelines for multivariate modeling presented by Tabachnick & Fidel (2013) and the non-redundant variables were selected using the “Clarity test” proposed by Kjaerulff & Madsen (2008). Accordingly, the redundant variables were identified by quantitative and qualitative criteria. The quantitative criteria was assessed through collinearity and concurvity to look for extreme values of the bivariate Pearson, Spearman, Phi and Contingency coefficients, as well as Tolerance, and Variance Inflation Factors (VIF) coefficients, which were applied according to the variable scale of measurement (Sheskin, 2004). For the Pearson, Tolerance and VIF coefficients, we utilized cutoff values available in the literature (Dormann et al., 2013). In cases of cutoff values were not available, the extreme coefficients were identified by z-score transformation values beyond two standard deviations and percentile values above or below two times the interquartile range. Qualitative criteria for variable check-up followed the variable list provided by IPUMS-USA to exclude duplicated or equivalently defined variables, and those created by the other variables’ linear combination. As a result, the dataset was reduced to a final version of 153 variables (which we subsequently refer to as the ‘original’ dataset).

As the majority (75%) of variables were categorical, the remaining continuous variables were transformed to categorical, i.e. discretized or binned (Nagarajan, Scutari, & Lèbre, 2013), to uniformly apply the modeling methods. The age variable was discretized according to the sets of intervals defined by the United Nations Department of International Economic and Social Affairs (1982). Variables with no available reference intervals were discretized by case class discovery using unsupervised clustering methods, which corresponds to an automated unbiased procedure to balance binning accuracy and information loss. The algorithms utilized, based on Likelihood and Euclidean distances under BIC and AIC penalties, were available in the SPSS 22.0 Two Step cluster procedure (IBM Corp., 2013, 2015). For variables with meaningful zero values, we assigned a specific category. In the case of variables with several categories, such as those describing geographic areas, the original categories were binned into broader classes. The survey’s original filter category, included in many variables to represent the ‘not applicable (NA)' answer, was preserved. The original 153 selected variables were transformed to binary. As a result, we obtained a second alternative dataset containing 653 binary variables, of which 11% represented NA values (which we subsequently refer to as the 'binary' dataset).

3.2. Model development methodology

Inferencing network structures from data is a common procedure in Systems Science research (Kolaczyk, 2010). For example, it is utilized in Systems Biology to reconstruct and integrate genomic, proteomic and metabolic pathways (Barabasi, Gubahce, & Loscalzo, 2011; Lopez-Kleine & Leal, 2014) and in Neuroinformatics to understand the brain`s anatomical tracts and functional networks (Friston, 2011). Consequently, in the Artificial intelligence (AI) field, several available methods have been defined and implemented by computational algorithms, to simultaneously explore numerous variables in large datasets. One of these AI approaches is Bayesian networks (BN), first proposed by Judea Pearl in the 1980s and further developed by diverse fields investigators (Sambo, Ferrazzi, & Bellazzi, 2014). The general form of the BN model is given by the chain rule expression:

$$P(X_v) = \prod_{v \in V} P(X_v / X_{pa(v)}) \tag{1}$$

where $P(X_v)$ is the joint probability distribution over the set of X_v variables, $P(X_v / X_{pa(v)})$ is the conditional probability distribution of X_v given $X_{pa(v)}$, which is the parent variable for each X_v variable (Kjærulff & Madsen, 2008). The chain rule in (1) factorizes the pairwise dependence upon conditional independence relationships (i.e., relationships existing between two variables given a third one), and extends to more complex structures like Markov blankets neighborhoods (See Pearl (2009), Kjærulff & Madsen (2008), Nagarajan, Scutari, & Lèbre (2013) and Neapolitan (2000) for a detailed presentation).

The full structure factorized by the chain rule is represented by a directed acyclic graph (DAG) defined as $G = (V, E)$, where V denotes the set of nodes (vertices) on behalf of the X_v variables, and E (edges) denotes the set of directed links symbolized by arrows which encode the conditional probability distribution between variables. In this way, the chain rule and the DAG formally incorporate probability and graph theory as the basis for several BN computational algorithms (Nagarajan et al., 2013). To assign the links, specific structure learning algorithms look for the relevant (significant) statistical dependence between the variable nodes conditionally controlled by all the other variables at once. The link direction obeys heuristics or optimization methods (detailed descriptions in Kjærulff & Madsen (2008) and Nagarajan et al (2013)).

Diverse uses of BN suit different but related goals. One of these goals is to model complex systems from expert knowledge or data. A second goal is probabilistic reasoning, which consists of predicting the values of target variables (nodes) after inducing changes on values in other network variables. A third goal is to classify new observations using supervised or unsupervised techniques (Bielza & Larrañaga, 2014). This study corresponds with the first goal. Hence, to infer the ODW network model, we applied the 'Greedy Tick Tinning' BN algorithm for structure learning that is available in GeNIe software (version 2.0 build 2.0.5590.0) (DSL, 2015) to both the 'original' and 'binary' datasets (described in 3.1), obtaining two types of networks with equivalent notations.

To select the most accurate model of the two types of obtained networks (original and binary), we followed model validation and test procedures. We used the Swap Validation procedure described by the MAQC Consortium (2010) to match the model estimations with other likewise randomly selected subsample such as the validation dataset (31,490 cases), and to compute the internal, external, and swap model accuracies. The accuracy results for the 'original' model were: internal 61.31%, external 61.23% and models swap 61.16%. The accuracy results for the 'binary' model were: internal 82.52%, external 81.03% and model swap 81.11%. Performance tests were developed for both models using a third independent, randomly selected subsample (627,951 cases, 20% of the full dataset). The model performance accuracy of the 'original' model was 61.23%, and of the 'binary' model was 82.43%.

According to validation and performance test results, the 'binary' model was selected to follow the subsequent process. Thus, as described by Batagelj et al. (Batagelj, Doreian, Ferligoj, & Kejzar, 2014), the 'binary' model was shrunk from 653 nodes to 19 nodes representing the ODW. This 'shrunken' network corresponds to subnetworks enclosing the ACS-2013 topic specific variables (described in 3.1) and the links among them. Therefore, network shrinkage did not reduce the model complexity because the full binary model lay beneath, but network shrinkage provided focus on the determinants analysis. The 'binary' and 'shrunken' network visualizations are shown in Figure 1 (The node colors are equivalent between both networks to assist determinants visualization. The nodes are arranged by Fruchterman Reingold algorithm available in Pajek software (Batagelj & Mrvar, 2014)).

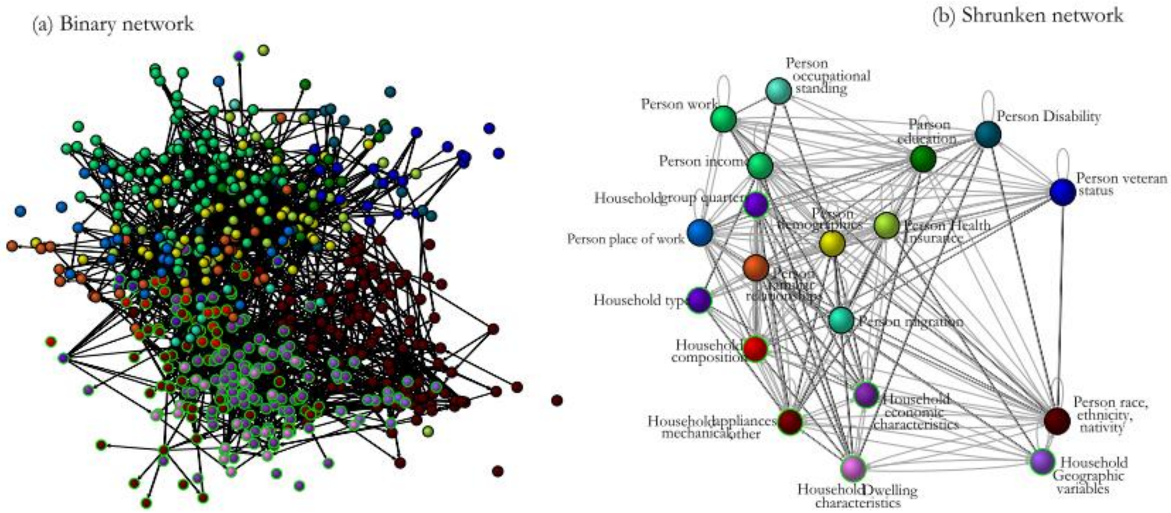

Figure 1. ODW Network models.

3.3. Network analysis methods and model descriptive general features

Data-driven networks inferred with AI techniques can embrace at once several variables and multiple relations among them to provide comprehensive models of complex phenomena. However, even with high quality visualization, a complex network can be difficult to understand. In addition to network visualization, summary statistics of global and local network properties and subnetwork identification methods are common techniques in network science to identify and measure the network features and patterns (Batagelj et al., 2014). Therefore, network properties derived from the nodes' connectivity are expressed in statistical terms, assuming a network is a distribution of node and link value estimations of characteristic parameters.

The ODW nodes relevance and role were identified by network centrality index estimations and hierarchical clustering procedures based on node connectivity dissimilarity. Next, we briefly introduce the centrality indexes used in this study and illustrate their application to compare the 'binary' and 'shrunken' networks, as a part of the modeling process. Formal and deeper descriptions can be found in Kolaczyk (2010) and other texts. The 'density' index is a global measure for the network's total number of links relative to the maximum possible number derived by the binomial coefficient $\binom{N}{2}$. Because density depends on the network size, it can be important to complement density with indices like 'diameter', 'distance' and 'average distance among reachable pairs', which capture other network facets. The 'closeness centrality' index derives from 'distance' index and describes the amount of steps on a path from a node to all other terminal nodes. The index that summarizes 'closeness centrality' for the whole network is 'Closeness centralization'; it accounts for the vertices' (nodes) closeness centrality variation relative to the maximum possible variation of the same index in a network of the same size (De Nooy, Mrvar, & Batagelj, 2005). The 'betweenness centrality' index refers to centrality in terms of mediation, i.e., the node position within a path. 'Betweenness centralization' is a view of the whole network, and is the variation of 'betweenness centrality' to the maximum variation possible for the same index in a network of the same size. The tendency to form groups is measured by the 'clustering coefficient'; it counts the number of the network`s triangles or quadrangles, which are the basic structures of neighborhood groupings (Batagelj et al., 2014; Mrvar & Batagelj, 2015). The 'Watts and Strogatz' and 'transitivity' indexes summarize the network tendency to cluster under different but near formulations (Batagelj et al., 2014; Kolaczyk, 2010).

Node 'degree' along with its variations 'indegree' for the subset of incoming links and 'outdegree' for the outgoing links, are important indexes in network analysis; they count each node`s number of links to describe its centrality and connectivity. Consequently, 'average degree' accounts for the typical node connectivity and 'degree centralization' for the variation of node degrees divided by the maximum possible degree variation in a network of the same size (De Nooy et al., 2005). These point estimations are complemented by examining the degree distribution function fitting.

Node relevance can also be defined in terms of its connection quality when direction is available: 'Hubs' are the nodes pointing to many 'Authority' nodes, and 'Authorities' are nodes pointed by many 'hubs' (Batagelj et al., 2014).

Network analysis using the indexes described was performed with Pajek64 software (4.04 version) (Batagelj & Mrvar, 2014). **Table 1** presents some of the descriptive summary indexes to compare the binary and shrunken networks. Both networks are equivalent, even though the visible nodes and links are fewer in the shrunken model. The ODW shrunken model allows for a representation where each link between determinants is formed by all the links between a different group`s binary variables; each link received a weight according to this number of links. Index results with lower distance and higher density values show the shrunken network is a less sparse model.

Table 1.

General indexes of network models

Network	Binary variables network	ODW determinants shrunken network
Number of nodes/links	653/1951	19/185
Density	0.57%	51.24%
Diameter	15	3
Distance between most distant vertices	8	3
Average distance among reachable pairs	3.69	1.36
Watts-Strogatz Clustering Coefficient	0.05	0.63
Transitivity	0.04	0.58
Betweenness Centralization	0.06	0.05
Average degree	6.69 (in 3.35, out 3.35)	17.79 (in and out 8.89)
Degree centralization	15.20 (in 0.008, out 0.05)	5.70** (in0.30 , out 0.47)

** without loops

However, this compact network still had general properties equivalent to those of the binary network, as the degree distribution functional form was a power law $P(k) = ck^{-\lambda}$ in both cases with slightly different λ parameter estimations and determination coefficient R^2 fitting values (binary model λ =-1.749 R^2 =0.944; shrunken model λ =-1.942, R^2 =0.837). Hence, the shrunken model corresponds to an equivalent change in the observation scale.

Other models were tested to fit the degree distribution (growth, exponential, logistic, cubic and quadratic) with fitting values that were close but lower than the power law function. Both networks' degrees of connectivity patterns fitting power law distributions provide evidence of the networks' asymmetry and differential organization.

Although the previously described indexes can offer node ordering by relevance, the whole network connectivity array was explored to find meaningful role-based groups of nodes (variables). For this, among different available methods, we chose hierarchical clustering because it simultaneously classifies similar nodes on branches and offers a permutation scheme according to the Euclidean distance calculated from the network adjacency matrix.

Despite the fact that the model obtained was a directed network, we omitted link directions for the majority of analyses, as link direction just relies on the algorithm heuristics and has not been curated. Link direction was considered in limited and specific analyses to explain the outgoing links as influence relationships, and the incoming links as supportive dependences (Batagelj et al., 2014), without any causal interpretation.

4. Results

The results are organized as follows: Subsection 4.1 presents the ODW relevance analysis, followed by role analysis in 4.2, and concluding with a focused emphasis on the most relevant determinants in 4.3.

4.1. ODW relevance analysis

The general relevance of each ODW hailed from the centrality indexes computed from their external links, i.e., the connections summarizing the links between the binary variables that belonged to different thematic groups. The values of link weights produced by the shrinkage process and the number of nodes enclosed by each determinant were utilized to adjust the calculation of indexes. According to the indexes, ODW nodes were ranked and examined with the Wilcoxon rank sign test to identify the significant differences between each node index and the median value. Table 2 summarizes the five highest ranked ODW for each index along with their p-values.

Table 2.

First five ranked ODW for the different network analysis indexes

Index	Rank	ODW	Sig.	Index	Rank	OWD	Sig.
Degree (all) centrality	1st	P. race, ethnicity, nativity	0.000	Weighted degree (all)	1st	HH. economic characteristics	0.000
	2nd	HH. economic characteristics	0.000		2nd	P. race, ethnicity, nativity	0.000
	3rd	P. income	0.003		3rd	P. demographics	0.001
	4th	P. demographics	0.006		4th	P. income	0.001
	5th	HH. appliances	0.049		5th	HH. appliances	0.314
Indegree centrality	1st	P. race, ethnicity, nativity	0.000	Weighted indegree	1st	HH. economic characteristics	0.000
	2nd	HH. economic characteristics	0.000		2nd	P. race, ethnicity, nativity	0.000
	3rd	P. income	0.005		3rd	P. demographics	0.000
	4th	HH. appliances	0.030		4th	P. income	0.001
	5th	P. demographics	0.044		5th	HH. appliances	0.334
Outdegree centrality	1st	P. race, ethnicity, nativity	0.000	Weighted outdegree	1st	P. race, ethnicity, nativity	0.000
	2nd	P. demographics	0.001		2nd	HH. economic characteristics	0.000
	3rd	P. income	0.001		3rd	HH. appliances	0.005
	4th	HH. economic characteristics	0.003		4th	P. work	0.014
	5th	HH. appliances	0.117		5th	HH. Dwelling characteristics	0.033
Laplacian centrality	1st	P. race, ethnicity, nativity	0.000	Closeness (all, in and out)	1st	P. race, ethnicity, nativity	0.000
	2nd	HH. economic characteristics	0.000		2nd	HH. economic characteristics	0.000
	3rd	P. income	0.000		3rd	P. income	0.005
	4th	P. demographics	0.000		4th	P. demographics	0.016
	5th	HH. appliances	0.000		5th	HH. appliances	0.033
Betweenness centrality	1st	P. race, ethnicity, nativity	0.000	Prestige centrality	1st	P. race, ethnicity, nativity	0.000
	2nd	P. demographics	0.000		2nd	HH. economic characteristics	0.000
	3rd	P. income	0.000		3rd	P. income	0.005
	4th	HH. economic characteristics	0.002		4th	P. demographics	0.016
	5th	HH. appliances	0.136		5th	HH. appliances	0.033
Hub weights	1st	HH. appliances	0.000	Authority weights	1st	P. race, ethnicity, nativity	0.000
	2nd	P. race, ethnicity, nativity	0.000		2nd	HH. economic characteristics	0.000
	3rd	HH. Dwelling characteristics	0.001		3rd	P. demographics	0.020
	4th	P. work	0.001		4th	P. income	0.024
	5th	HH. economic characteristics	0.009		5th	HH. appliances	0.334

HH. for Households, P for persons. p-values from Wilcoxon rank sign test for one sample index values of the ODW are highly significant if are <0.01. Non-significant values are gray shaded.

The full set of indexes contributed to define the relevance pattern. The results highlighted the determinants of culture, demographics, income, and work as the most important at the person level; at the household level, the most important determinants were the economic characteristics, and less importantly the appliances and dwelling. Unambiguously, the 'Person race, ethnicity and nativity' ODW had the uppermost statistically significant values in 9 of 12 indices, while the 'Household economic characteristics' ranking was first in 2 of 12 indices and second in 7 of 12 indexes. Making a concession for links direction, the 'person race, ethnicity and nativity' node influenced and provided support for other determinants in the network, having the highest ranked indegree and outdegree indexes, respectively. According to the highest weighted indegree index, the 'Household economic characteristics' determinant was the most important 'supporter'. Additionally, the quality of the connections associated with these two nodes bore on their high hub and authority weights. However, household 'appliances' and 'dwelling' occupied the first and third place as hubs, respectively, while 'Person work' was the fourth ahead of 'Household economic characteristics'. The person's 'income' and 'demographic characteristics' determinants achieved the third and fourth places as authority nodes. This last ODW included diverse demographic variables such as 'age' and 'sex', which are usually fixed and determined by biological circumstances, but also included other less stable such as 'marital status' and 'person role in the household', which led to considerations on how 'demographic characteristics' changes can be influenced by other factors.

4.2. ODW role analysis

The manner in which the ODW are arranged in network to occupy diverse positions is relative to the locations of other nodes. For this reason, we applied a hierarchical clustering method, which evaluated the whole network array encoded in the adjacency matrix (adjusted and weighted, as described in subsection 4.1), to compute a dissimilarity matrix. The dissimilarity matrix is the basis to define the branch hierarchy and the related order permutation.

As shown in Figure 2, the permutation obtained by this procedure was applied to reorder the adjacency matrix, to preliminarily reveal some denser parts of the network, in support of the differential roles of the ODW in the system (The gray scale in the figure legend was assigned automatically by percentiles. Each cell contains the adjusted and weighted link values).

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
P. Race, ethnicity, nativity	1	26.5	1.15	1.18	0.03	0.28	0.27	0.37	0.06	0.09	0.11	0.09	0.28	0	0	0	0	0	0	0.06
HH. Economic characteristics	2	6.55	28.4	0.33	0	4.08	2.14	0	0	1.07	0	0.13	0.23	0	0	0	0	0	0	0.17
HH. Geographic variables	3	12.5	1.87	0.25	0	0.42	0	0	0	0.05	0	0.09	0.05	0	0	0	0	0	0	0
HH. Composition variables	4	1.64	5.19	0	0.77	1.55	0.62	0.44	0	0.31	0	0.09	0.14	0.47	0.08	0	0	0.01	0	0.04
HH. Appliances, mechanical	5	3.27	3.6	0.22	0.03	2.88	0.09	0	0	0	0.11	0.04	0.05	0	0	0	0.03	0	0	0.02
P. Income	6	0.73	1.44	0	0.06	0.07	6.33	0.66	2.29	0.05	0.38	0.73	0.65	0.09	0	0.07	0.29	0	0.01	0
P. Demographics	7	2.18	1.44	0	0.62	0.14	1.52	3.91	1.05	0.05	0.57	0.04	1.07	1.03	0.12	0.58	0.23	0.01	0	0.17
P. Work	8	0	0	0	0	0	1.52	0.15	3.4	0	0.11	0.34	0.28	0	0	0.03	0.07	0	0	0.02
HH. Dwelling characteristics	9	0.55	2.16	0.03	0	0.7	0	0	0	1.38	0	0	0	0	0	0	0.03	0	0	0
P. Education	10	1.09	0.14	0	0	0	0.18	0.89	0.49	0	0.91	0.09	0.23	0.09	0	0	0	0	0	0.02
P. Place of work	11	1.46	0.29	0	0	0.21	0.45	0.15	0.25	0	0.04	0.9	0.05	0.04	0	0	0.03	0	0	0
P. Health Insurance	12	1.27	0.29	0	0.25	0.49	0.89	1.62	0.31	0	0.19	0.04	0.93	0.39	0.05	0.1	0.16	0	0	0.08
P. Familiar relationships	13	0.73	0.14	0.03	0.22	0.35	0.27	1.48	0	0.27	0	0.13	0.23	0.73	0.05	0.03	0	0	0	0.04
HH. Type	14	0	1.3	0	0.37	0.21	0.45	0.59	0	0	0	0	0.14	0.09	0	0	0	0	0	0
P. Veteran status	15	0.55	0	0	0.03	0	0.18	0.15	0.06	0	0	0	0.19	0	0	0.82	0.16	0	0	0.02
P. Disability	16	0.18	0	0	0	0	0.27	0	0.06	0	0	0	0.09	0	0	0.03	0.46	0	0	0
HH. Group quarters	17	0.18	0.14	0	0	0.14	0	0.07	0	0.09	0	0.09	0	0	0	0.03	0.03	0	0	0
P. Occupational standing	18	0	0	0	0	0	0	0	0	0	0.08	0	0	0	0	0	0	0	0	0
P. Migration	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02

Legend
0
up to Pc 50
Up to Pc 75
Up to Pc 85
Up to Pc 99
Up to Pc 99.5
Up to max

Figure 2 ODW reordered network adjacency matrix according to the permutation produced by hierarchical clustering.

The grouping pattern that seemed to emerge in the permuted adjacency matrix was confirmed by the dendrogram findings. Figure 3 shows a dendrogram-modified version with optimal separated branches.

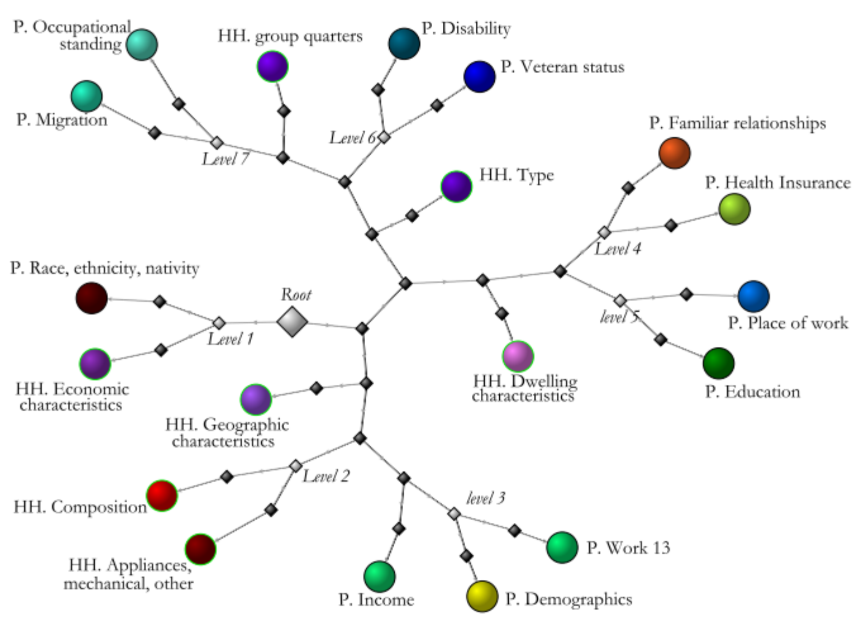

Figure 3. Summary dendrogram of ODW connectivity patterns similarity. Visualization by 2D plane separation. The black diamonds are intermediate referents signaling the branches according to distance values). The white small diamonds signal the seven sub-branch levels.

Based on quantitative distances, the dendrogram branches defined sets of similar ODW by levels and particular isolated nodes located on single sticks. Adjoining to the dendrogram root that is represented by a big white diamond in Figure 3, the first branch and first level are defined by the highest dissimilarity values where the two main determinants of 'Person race, ethnicity and nativity' and 'Household economic characteristics' are located: these were previously identified as the most relevant determinants in the network. These two main nodes respectively match the individuals' cultural identity which is worthwhile to a person`s introduction to society, and the economic role and status endorsed by the fundamental social structure of the household.

At the bottom of Figure 3, the second branch had two sub-branches representing two levels: The second level bonded 'household composition' and access to 'appliances and other mechanical devices' (in this group ACS-2013 included variables for communication and internet devices), preceded by a stick for 'household geographic characteristics'. The third level linked 'person work' and 'demographic characteristics', led by a stick for 'person income'. In this way, the second and third sub-branches and their related sticks corresponded to the physical and emotional immediate supporting contexts that operate on a daily basis for households and persons, respectively.

The third branch at the right of Figure 3, was introduced by the isolated stick of 'dwelling characteristics' which corresponds to the physical base supporting households. This branch included the person's intermediary assets of 'familiar relationships', access to 'health insurance' (fourth level), and 'place of work' and 'education' (fifth level) determinants. Determinants located at this branch commonly had an intermediation role because they are means to access other social system assets or services transiently or through finite time lapses.

The fourth branch had two sub-branches, each preceded by isolated sticks. The first sub-branch (sixth level) included 'person disability' and 'veteran status' determinants, preceded by a stick for 'household type', which discriminates family or non-family households, therefore pointing to groups of individuals relegated from the family structure. The second sub-branch (seventh level) included 'migration', which described people`s internal and external moves, and an 'occupational standing index', as the nodes sharing the less connected pattern. The preceding node in a stick was 'Group quarters', which signaled those non-household groups of individuals sharing collective living spaces. So, determinants in this fourth branch seemed to be capable of characterizing disadvantaged subpopulations. But a more in-depth analysis is required to draw more conclusive results.

Figure 4 presents the ODW network reorganized by permutation and dendrogram levels. This network allows for a better ODW role representation, incorporating the branches and levels described before, which support their differential positions.

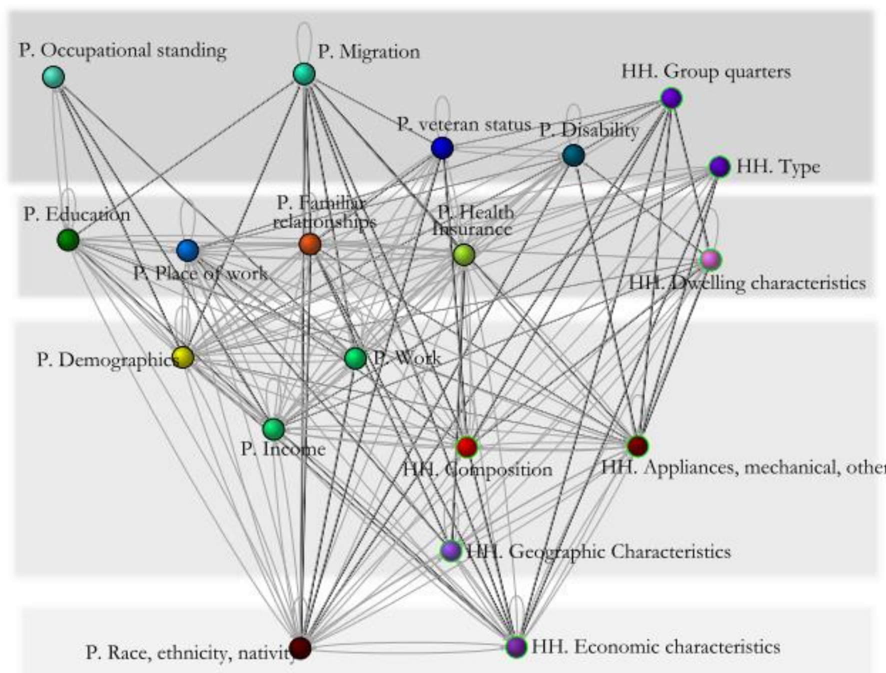

Figure 4. ODW network rearranged by levels, according to hierarchical clustering permutation and dendrogram.

In general, determinants located at the same levels have equivalent roles (De Nooy et al., 2005). The individual culture and household economy ODW identified as the most important due to its particularly denser connectivity, were set at the bottom. From there, these nodes were connected to the majority of the other determinants. The determinants with intermediating roles were located at the network`s midpoint, and the marginal determinants with a low connectivity pattern, thus less integrated into the whole network, were placed at the top.

4.3 Focused analysis results on culture and household economy ODW

We now focus on understanding why 'Race, ethnicity and nativity' (i.e., culture) and 'Household economic characteristics' (i.e., household as an economic agent) are the most well-connected determinant nodes in the ODW network.

The visualization in Figure 5a offers a graphical overview of the ODW network removing the links that do not directly connect cultural determinants. This visualization displays this node high connectivity within the model (links to 88.89% of other determinants) as a reason behind its main relevance. It leaves out just two nodes, '*Household type*' and '*Occupational standing*'. Similarly, a black loop around the node represents the determinant´s own weight (26.54) that renders its number of inner links adjusted by the amount of binary nodes.

The culture determinant`s incoming (54%) and outgoing (46%) connections afforded for both supportive and influencing roles in the model; the supportive role prevailed as the ratio between the outgoing and incoming (out/in) links was 0.86. This supportive role had likewise been preeminent in the subset of cyclic relationships established with other nodes by both incoming and outgoing links, which accounted for 76.92% of the culture node's connections, while the out/in link weight ratio remained below the unit for all the cases (0.14 on average).

Culture`s stronger cyclic relationships stood with the nodes of household 'geographic characteristics' and 'economy'. With a statistically significant difference between its weights and the mean, these last nodes sent stronger incoming links for the culture determinant ($p=1.07\times10^{-7}$, $p=3.00\times10^{-4}$, respectively), and also received stronger outgoing links from it ($p=8.17\times10^{-6}$, and $p=1.11\times10^{-5}$, respectively). The solely incoming links to the culture determinant came from the 'familiar relationships', 'person disability', and 'household group quarters' nodes and, in a comparable manner, the solely outgoing links were toward 'migration' and 'work'. Nevertheless, none of these were statistically significant (all p-values>0.05).

Explanations into the last findings were assisted by a preliminary exploration of the culture determinant internal binary variables and their links with other likewise binary variables in different determinants by examining the non-shrunken 'binary' subnetworks. Variables in this subnetwork included multiple detailed birthplaces, race, ethnicity, language, citizenship status and the amount of years one has lived in the US.

The variable (node) representing the 'all lifetime living in the US' category connected almost all birthplaces, as well as the node 'just speaking in English'; However, it also significantly connected the node of 'no English speaking at all'.

In regards to the links received by the culture determinant from the household economy, we found that the cost of living and the opportunities to own land, or to obtain profits derived from land use, such as those derived from productive farm units, have influence connections of 'influence' (i.e., outgoing links) with the nodes of birthplace and race. This is attributed to the fact that household settlement economic contexts determine the subsequent generations' birthplace, or induce the more frequent establishment of selected racial groups. The links from culture to the household economy determinant had a similar content, though they were less numerous.

The detailed connections from culture to household geographic characteristics depended on the links between birthplace and the region of actual household location, as expected. By contrast, racial determination and household geographical location links were almost absent (just one relation of dependence was significant for Chinese people living in the New England region). The solely 'all lifetime' lived in the US' category significantly influenced the household geographical location in the Middle Atlantic region. The detailed connections from 'household geographic characteristics' to culture had similar findings, though we additionally found that the 'naturalized' and 'non-citizen' variable nodes were associated with the 'non-identified metropolitan areas' node, and the 'South Atlantic Division' household geographical location was associated with the Cuban Hispanic and African American populations.

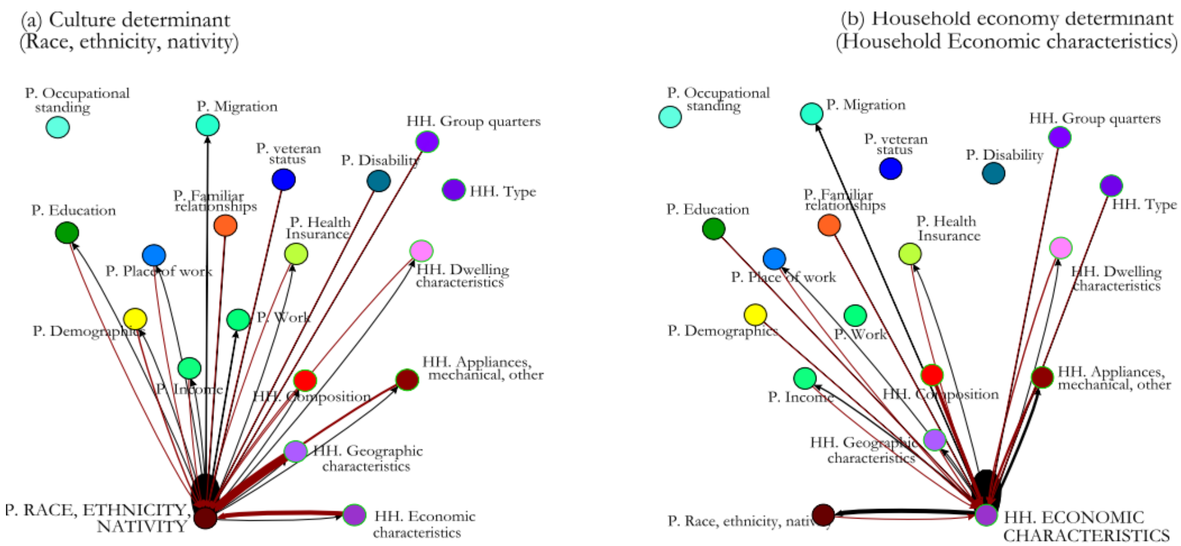

Figure 5. Two main determinants in the ODW network model: Red arrows represent incoming links and black outgoing links. Line width was defined by its weights.

The second relevant determinant of 'Household economic characteristics' (shown in Figure 5b, also located on the first level), had the strongest loop weight (28.38) and connected 77.77% of the nodes in the network. From those 61.90% were incoming links, for a 0.61 out/in ratio, which bore for a predominant supportive role. However, the subset of cyclic relations was established with a 38.89% of the network nodes and comprised 66.67% of its links; it had a 1.46 out/in average link weight ratio, which made this node influential in this kind of relationships.

Culture was the determinant most influenced by household economy, with statistically significant differences between its weights and the mean in the case of outgoing and cyclic links, as well as in the case of the full set of links. Person income ($p=2.29 \times 10^{-6}$) was another determinant importantly influenced by household economy. In terms of cyclic relations with household economy, 'household appliances' also had significant results for both incoming and outgoing links ($p=9.05 \times 10^{-9}$ and $p=3.70 \times 10^{-11}$, respectively). The main nodes influencing household economy were household composition (with a difference to in-links mean weight $p=6.27x10^{-7}$) and dwelling characteristics (with a difference to all links mean weight $p=3.36x10^{-5}$). The non-connected nodes were occupational standing, disability, veteran status and work.

Details from the non-shrunken binary network were already described for the relation between household economy and culture. The influence of household economy over the person's income determinant involved the binary nodes of high family incomes related to mid-range mortgage payments, high owner costs and house values, mid individual income related to low rent payments and mortgages including taxes, and investment profits related to owning house mortgage free.

Part of the links received by household economy from household dwelling and appliances were aligned with bigger domiciles resulting in higher expenses. Additionally, links showed that having multigenerational households diminished costs, but were still deficient in avoiding the need for welfare support (i.e., this node had links with the variable describing food stamps). Similarly, multiple couples living in a household seemed to allow higher expenses to be accommodated; they were also linked to a greater ability to establish home businesses. Conversely, single households included relations with nodes on both extremes of no-income earners and people with higher costs of living. No associations were found between internet access and the variables representing wealthier economic household profiles.

5. Discussion and policy contributions

To overcome multidimensional approach limitations related to the use of classical linear combination-based tools, we proposed applying an alternative methodological process to model ODW complexity mapping simultaneously to all the possible nonlinear dependence relations among determinants conditionally controlled by all other determinant information. The ODW model consisted of a two level directed network of detailed variables nested in determinant subnetworks. Model analysis displayed a heterogeneous connectivity pattern that revealed the ODW differential roles. The relevance analysis results indicated that individuals' culture and the economic role of the household were the major determinants. Provided that network incoming and outgoing links have a supportive and influencing role respectively (Batagelj et al., 2014), the former links' predominance signaled culture and household economy as supportive determinants.

Additional analysis using hierarchical clusters and permutations revealed different levels of determinants: (1) A fundamental level of highly connected determinants ruling and giving coherence to the system (occupied by person's culture and households economy); (2) a stabilizing intermediary level of determinants focused on material assets (for the household: geographic location, material composition, appliances, mechanical and other house equipment; for the person: demographic characteristics, income and work); (3) a second intermediary level of determinants supporting and enabling transactions and transient interactions with other social subsystems (for the household: dwelling and for the persons: education, place of work and commuting, health insurance, and familiar relationships); and (4) a final level in the network margin with determinants describing whether the social support of a household is present or not (Household type), which coincidentally signals specific marginalized subpopulations (for the persons: veteran status, disability, and migration and for households: the group quarters).

The described array of determinants seemed comprehensible and intuitive. However, it was not anticipated to find the main role of culture in the first level or house equipment holding a stabilizing intermediate role instead of house dwelling. The house equipment (node labeled as 'appliances, mechanical and other house equipment') location in the model was due to internet access variables newly included in the ACS-2013, which have become highly relevant in current societies where the growing information is shaping people`s daily lives, thus making this variable the provider of a new kind of social inclusion.

Our findings regarding the main relevance of the culture determinant are aligned with previous results, including the study of two Canadian First Nations communities by Kant et al. (2014), and the US General Social Survey-based study by Lin et al. (2015) even though it just focused on the 'race' variable.

Our results add to this line of research. We found culture relevance using a recent dataset representative of the US general population that was developed to inform welfare investments. We also included variables other than race and ethnicity to represent the culture construct including language, birthplace, and time lived in the US. In this way, our findings presented culture as a more general and powerful matter which transcends the singular communities' manifestations. Culture broadly gathers race and ethnic diversity variables and embraces the individuals' socio-genetic roots. It also involves the way individuals and households access income, work, education, information, including the explicit and implicit values that everybody shares confronted with their personal beliefs: culture bonds individuals with the society in which they live. So, culture is a supporting and influencing mediator between individuals and society, thus it can contribute to social cohesion, as well as social fragmentation.

Our findings motivate one to question whether everyday culture's pervasiveness is prone to selective welfare policies or if it can encourage universal ones. According to Alber (2010), even though the US welfare is qualified as 'residual', it would actually be better labeled as different and complex, because it includes multiple mechanisms besides social insurance, although with a notable standing on selective and targeted schemes. In this way, our findings could provide an intermediate answer, that would not disrupt the current US welfare model, is that the culture factor, understood as an elaborated sense of social belonging, could be transversely considered throughout all other still selective policies.

The relevance of household economy ranked second after the culture determinant is consistent with the manner in which economic factors determine well-being. Two components converge in this determinant: household and economy. This convergence points to household as the essential social institution that produces wealth. Inside a household, individuals' earnings can redistributed between the family members to provide each member with an equitable access to social assets. The cyclic relation between household economy and individuals' income supports the bidirectional influence between both determinants: Individuals' earnings influence the household wealth, but in turn wealth also influences the individual earnings. Thus, household economic role is undeniable as a determinant as it allows for more equitable fulfillment of diverse needs.

However, the household role is more than just economic and the household economy implies more than single incomes pooling together and purchasing power being equitably redistributed. Our model recovered the ubiquitous role of household economy because it connected many other determinants in the model without an economic character as culture, education, household type, composition and familiar relationships.

There is no family or household allowance in the US welfare programs (SSA & Altmeyer, 2015). Nevertheless, multiple hidden and divided benefits of welfare contribute to 'income packaging' at the household setting (Garfinkel & Zilanawala, 2015), including cash and in-kind benefits for child care, free public education, food stamps, health care, and such programs as the Temporary Assistance to Needy Families (TANF) and the Supplemental Security Income (SSI), among others. Hence, households are the unintended key welfare recipients. Our findings concerning the household economy's integrative and distributive relevance support it as a potential target for policy embodiment, as household emerged as a fundamental welfare agent. Similar to the culture determinant, both the household and the household economy, can be transversal to selective welfare interventions, as well as drivers for universal models.

However, the two main determinants of culture and household economy were not directly connected to some peripheral nodes. The model intuitively showed that household wealth (or scarcity of wealth) obviously leaves out other types of social cohabitation (group quarters). Household wealth was also unconnected to the veterans and disabled groups. These findings align with the need to better focus interventions to reestablish social equity; however, the question is: how and under what rationale? A first option is to develop customary policies, which are usually informed by sets of disjointed indicators, to intervene by filling selective well-being gaps. A second option derived from understanding the systemic role of these key determinants suggests that welfare policies targeting culture and household economy would spread over almost the entire system. Therefore, this property could bear for strategies to improve a culture related sense of belonging and an economic household-like support to be extended to the marginal populations. This is aligned with the welfare goals of social cohesiveness and the equitable distribution of well-being for everybody. These two options are not mutually exclusive.

To summarize, our model presented an alternative representation of understanding the objective well-being complexity, and added a systemic approach beyond the multidimensional one. In this way, the model was able to provide new insights concerning single objective determinants of well-being in order to better focus selective welfare interventions; also, it was able to offer a big picture, fundamental approach to thinking about the general welfare models.

Further work includes the continued refinement of the model process and extending the research for results generalization (sampling inference); as well, the well-being dynamics can be tracked using ACS datasets for other years. Comparisons with future ACS versions and including information about welfare interventions can contribute to policy follow-up and evaluation.

Acknowledgements to Dr. William J. Martin II, Dean and Professor of the College of Public Health, and Dr. Philip R.O. Payne , Professor and Chair of the Department of Biomedical Informatics, for their commitment with Data Analytics.

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