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# Measuring precarious work of elderly: The construction of an index with 2SLS-MIMIC<sup>1</sup>

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## Abstract

This paper assesses the creation of composite indicators to operationalize the concept of precarious work applied to older workers. The literature on the topic, while focusing strongly on theorizing and conceptualization, has overlooked the measurement of the concept so far. Many studies dealing with precarious work do not interrogate the actual existence of an underlying concept and its composing dimensions. This paper attempts to fill in the gap in the literature by developing an indicator to measure precarious work using the Survey of Health, Ageing and Retirement in Europe (SHARE2). This paper proposes a Multiple Indicator Multiple Cause (MIMIC) model, in which precarious work is modelled as a concept underlying several dimensions assessed in the literature (job stability, income, employability, integration in social security). As basic assumptions of MIMIC are clearly violated in case of a variable being both an indicator and a cause, i.e. in the presence of reverse causality, we utilize a version of Bollen's 2SLS estimator for structural equation models combined with Jöreskog's method of the analysis of covariance structures to derive a new, 2SLS estimator for MIMIC models. Novel methodology allows to derive an indicator for precarious status of older workers which addresses the issue of the definition of precarious work as a multidimensional concept, not modelled adequately so far.

**Keywords:** precarious work, elderly, composite indicator, MIMIC, reverse causality, 2SLS

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**JEL:** C38, C36, C31, J14, J21, D31

## 1. Introduction

This paper's main goal is to create clarity on the conceptual-operational link of precarious work and its measurements, by means of the construction of a complex index that problematizes the issues often ignored by the literature: dimensions and subdimensions, logics of aggregation and necessary and sufficient conditions. The index is built on the basis of data from the Survey of Health, Ageing and Retirement in Europe (SHARE), a large-scale panel study of the EU's ageing population.

Precarious work (or precarious employment) is an ever-present element of the academic and policy debate. A quick search on Google Scholar renders 16800 references dating back to the 1900s and Seymour (2012) mentions it in the context of the Second Industrial Revolution. However, the term gained importance and became a matter of research when contraposed to the standard employment relationship that emerged after the Second World War in much of the industrialized world (Vosko, 2006). The notion has furthermore been the subject of theoretical reflections, statistical studies and political platforms; it has become, for instance, a recurrent item in the trade unions' discourse (International Labour Organization, 2012).

This widespread use has generated a myriad of definitions and operationalizations, partly overlapping, partly contradictory, which result in a murky landscape. Conceptualizations may vary along several dimensions: the process by which they are constructed (inductively from empirical realities or deductively from theoretical/philosophical constructs); the incorporation of objective elements pertaining to the job or the political economy, or subjective elements such as workers' identities; the analytical level at which the concept is situated; the variety of substantive dimensions included in the concept; the ontological nature of the concept (a conceptual lens applicable to all forms of work or a specific category of work) and the instrumental character of the definition (used for political or purely analytical means). The fact that the concept is often used interchangeably with "contingent, atypical and non-standard work" (International Labour Organization, 2012) only adds further to the complexity.

The variety of conceptualizations is consequently reflected in a complex operationalization landscape, characterized by a myriad of indicators and indices. Precarious work may be defined by a single indicator such as contract duration (Eurostat, 2018) or by complex indices involving several measures. Here, there is little variety in the type of sources used (surveys), but a large one in the surveys' purpose, geographical delimitations and the aggregation methods. It should be noted that no large-scale survey to date has attempted to measure precarious work explicitly.

The above landscape displays a strong disconnect between the highly dense conceptual language and the often meagre operationalizations. The construction of indices is often not problematized in several ways: there is little discussion on the distinction between dimensions, subdimensions and indicators of the concept, on the causal relationships between its different components, on the necessity or sufficiency of measurements, and on the methodology of aggregation.

This paper's objective is, in this context, to construct an index that takes into account the aspects mentioned above. It adopts a pragmatic approach by acknowledging that a) the probability of creating a consensus definition given the existing complexity is limited and b) the conceptualization of "precarious work" does not matter much if the operationalization is to be limited by existing data. Therefore, rather than adding yet another definition to the existing

repertory, it builds on the existing review works to focus on the conceptual-operational link and constructs an index of precarious work using novel methodology presented below.

We construct the index following methodology of Multiple Indicators Multiple Causes (MIMIC) which has become standard in economics in the estimation of latent constructs such as shadow economy. While it suffers from problems and critiques, largely oriented towards its causal structure, in recent years it has received novel developments and applications (see e.g. Hassan and Schneider, 2016). Yet, to date the issue of possible reverse causal “arrows”, i.e. reverse causality in those models has remained to our knowledge completely unaddressed (with the only exception of the contribution of Tekwe et al., 2017, who addressed the possibility of measurement error as the cause of endogeneity in MIMIC models). As reverse causality should be a common consideration for such models (for modelling shadow economy, level of GDP can be both its predictor and consequence), in our article we develop a novel 2SLS-MIMIC perspective, building on previous work of key figures in the structural modelling area in statistics, Kenneth Bollen and Karl Jöreskog (as well as econometrician Arthur Goldberger). We develop the estimation approaches from both static as well as dynamic perspectives and apply the new perspective the empirical problem under study, construction of the index of precarious work of the elderly. Namely, as precarious work has severe problems of concise definition due to its multidimensional and latent nature, the approach developed in this article seems the most appropriate, as well as having a large potential for similar endeavors in the present of latent and hard to measure economic, social and health-related concepts.

Instead, a brief description of MIMIC and the new 2SLS estimator could be provided here. Apart from that, the SHARE dataset and some basic sample info should be mentioned here—similar to the previous version that stated that the index is constructed on the basis of several indicators from SHARE Wave #, encompassing # countries and # respondents.

The article is structured in the following way. Section 2 presents initial literature review and overview on the research problem of deriving the index of precarious work of the elderly. Section 3 presents the novel 2SLS-MIMIC estimation approach derivation and its properties. Section 4 presents the derivation of the dynamic estimation approach and a simulation study to study the properties of the new approach. Section 5 presents the application to index of precarious work taking into account its different dimensions. We conclude in Section 6 with discussion of the findings and possibilities of future research.

## **2. Literature review – Conceptualization and operationalization of precarious work**

### **2.1. Conceptualization of precarious work**

As is the case with most social science concepts whose use has become widespread in everyday parlance, the conceptualization of precarious work is fraught with several contradictions, gaps and dilemmas, starting with its history. Most of the articles dealing with precarious work refer to a number of seminal authors (Standing, Vosko, Rodgers & Rodgers, Kalleberg) as the originators of the term. Some authors (Barbier, 2011; Waite, 2009) have placed the first usage of “precarious work” with Bourdieu. Yet, Seymour (2012) traces the use of the term back to the late 19<sup>th</sup> century. For a short history of precarious work refer to the work of Vosko (2006, pp. 6-11). For a more elaborate etymological and conceptual history of the term and a study of its varied meanings across policy contexts see Barbier (2011).

The trade union movement has adopted the struggle against precarious work as a clear line of

action (ITUC, 2011). Other policy actors such as the European Commission have paid attention to the issue (ICF, 2018), and Eurostat reports periodically on the number of workers subject to precarious work (Eurostat, 2018). Recently, the term has adopted a new dimension and received renewed academic interest in the face of the upcoming “gig economy” (Webster, 2016).

Precarious work has, in other words, come to make part of the daily policy and media discourse. In this discourse, as well at the academic level, it often overlaps with terms such as “non-standard employment”, “casual employment” or “atypical employment”, which often point at every employment relationship deviating from the classic open-ended, fulltime contractual arrangement that became the norm in the Western world after World War II. With this dialectic relationship (i.e. the opposition between the “normal” and the “precarious” working relationship) as a cornerstone, several definitions of precarious work have been proposed, both from an academic and a more pragmatic-policy oriented perspective.

The proposed definitions often serve explicit policy purposes or the authors’ idiosyncrasies and, as such, lack a common denominator. Even though Olsthoorn (Olsthoorn, 2014) sees the notion of insecurity as the basis on which the precarious work academic literature is built, the concrete way in which the insecurity notion is developed further displays a large variation.

At the policy level, it is more difficult to find a common denominator across definitions because the definition is often used to serve political agendas. Rather, definitions seem to be the largest common denominator of the organizations’ constituents’ priorities. For instance, a document summarizing the conclusions of a symposium on precarious work at the ILO’s workers’ bureau (2012) does not offer a concrete definition, but rather attempts to describe precarious work along 2,5 pages. The following paragraph offers a summary (2012, p. 27):

“In the most general sense, precarious work is a means for employers to shift risks and responsibilities on to workers. It is work performed in the formal and informal economy and is characterized by variable levels and degrees of objective (legal status) and subjective (feeling) characteristics of uncertainty and insecurity. Although a precarious job can have many faces, it is usually defined by uncertainty as to the duration of employment, multiple possible employers or a disguised or ambiguous employment relationship, a lack of access to social protection and benefits usually associated with employment, low pay, and substantial legal and practical obstacles to joining a trade union and bargaining collectively”.

Likewise, a study commissioned by the European Parliament (Broughton et al., 2016) does not offer an explicit conceptual definition of precarious work, but employment from along two analytical axes: employment relations and risk of individual precariousness. Several forms of employment (e.g. standard employment, part-time work, temporary work) are then assessed in function of several indicators for the risk of individual precariousness. This may be seen as a ‘maximum common denominator’ encompassing a large number of dimensions.

The above considerations make the variety of definitions clear, along several dimensions. First, the origins of definitions differs strongly; some of them have roots in empirical analysis; Vosko (2006) and Cranford et al. (2003) derive their definitions from a characterization of the Canadian labour market, and Bourdieu (in Waite, 2009) coined the term “precarité” from his observations of native as opposed to French workers in Algeria (“travailleurs intermittentes”). As opposed to this, some other definitions (Kalleberg, 2009; Vives et al., 2010) are rather deductive and theoretical.

Second, most of the authors choose to define precarious work along objective lines, i.e. with precarity being a feature of the work itself, whereas Standing (2014) and Kalleberg (2009) choose to include the subjective experience of the workers (i.e. “point of view of the worker”, lack of an “occupational identity” and “occupational narrative”, which points at their subjective experience of the employment relationship).

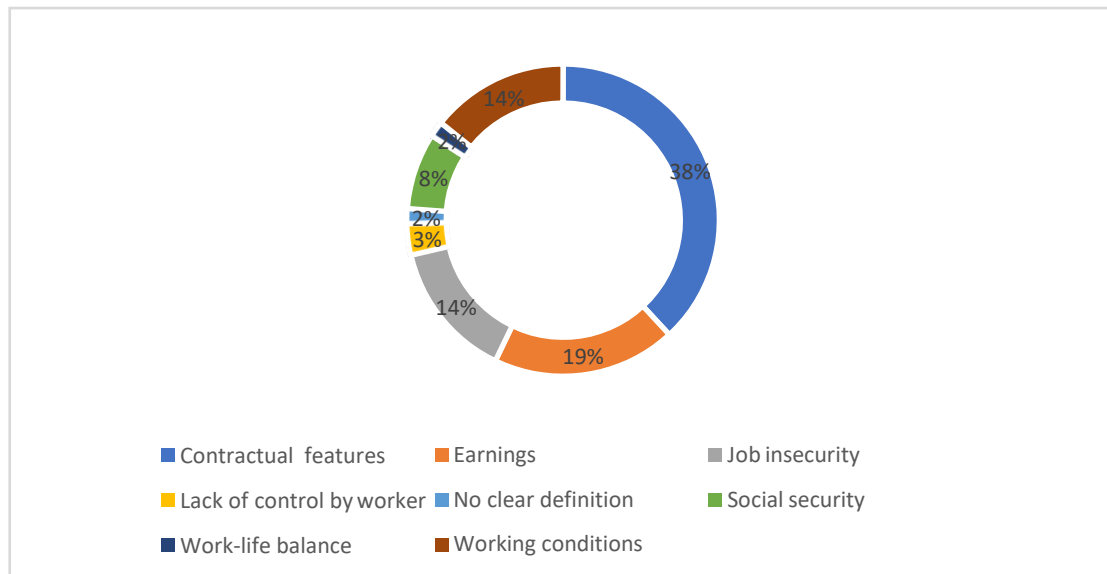
Third, precarious work seems to be situated at a variety of levels: the micro-level (i.e. the worker) can be found in Standing (2014), the meso level of the firm or job can be inferred from ILO (2012) and most of the academic definitions, and some authors (e.g. Cranford et al., 2003) point at regulatory or institutional arrangements, which can be placed at the macro- level. Vosko (2006) states explicitly that the concept encompasses the micro-, meso- and macro-policy levels.

Fourth, the ontological nature of the concept differs strongly along authors. Some (Broughton et al., 2016; Campbell & Burgess, 2018; Julià et al., 2017; Kalleberg, 2009) see precarious work not as a substantive category (defined by dimensions such as the nature of contracts or the level of pay, but rather as a “lens” or perspective to look at every form of employment, with some of those forms being closer to precariousness along a continuum. Others (Cranford et al., 2003; ESOP in Srakar & Prevolnik Rupel, 2017; Vives et al., 2010; Vosko, 2006) see it as a list of substantive dimensions, with Vosko (2006) and Cranford et al. (2003) the clearest exponent.

Fifth, there is a clear fault line running along the academic-policy distinction. Policy definitions clearly serve a political agenda. This normative element (i.e. the dialectic relationship between workers and employers) behind the concept may be distilled from the quote of ILO above. Conversely, the academic literature seeks conceptual and philosophical clarity as opposed to direct engagement. It should be noted, however, that a certain normative dimension is inherent to the concept. Vosko (2006, p. 13) argues, for instance, that political understandings of precarious work “are (...) inadequate in explaining the dynamics, level or form of precarious employment (...)”, although she concedes that the term “precarious” in itself implies engagement on the part of social scientists studying the phenomenon.

Sixth, there is a wide array of substantive elements of the “precarious work” concept. Aside from the seminal works discussed above, there is often little overlap among the works cited by authors who attempt to define or review the concept. Due to this apparent lack of conceptual boundaries, defining a scope for the literature on precarious work proves to be a rather cumbersome process. Some (Olsthoorn, 2014) may choose to focus on articles dealing with precarious work or job insecurity explicitly, whereas others (Srakar & Prevolnik Rupel, 2017) cover works dealing with the different forms of non-standard relationships of precarious work such as part-time work, pay gaps or low income. Campbell & Burgess (2018) and Burgess & Campbell (1998) choose rather a territorial focus, citing Australian works on a variety of topics (job quality, income, part-time work, et cetera). Figure 1 below shows the variety of dimensions present across a selection of 37 articles (list available with the authors).

**Figure 1:** Dimensions of precarious work (N=37)



Source: Own elaboration.

The variety of substantive dimensions, together with the rest of the characteristics mentioned above, is summarized below.

**Table 1:** Conceptual variety of precarious work

<i>Dimension</i>	<i>Category</i>	<i>Examples</i>
Construction	Inductive Deductive	Bourdieu, Cranford et al. 2003, Kalleberg 2008, Olsthoorn 2014, Rodgers 1989, Standing 2014, Vives et al. 2010, Vosko 2006
Perspective	Objective Subjective	Campbell & Burgess 2018, Vosko 2006 Standing 2014
Substantive components	<i>See figure 1</i>	
Level of analysis	Micro Meso Macro	Standing 2014, Vosko 2006 ILO 2012, Vosko 2006 Cranford et al. 2003, Vosko 2006
Ontological nature	Perspective Substantive category	Campbell & Burgess 2018, European Parliament 2016, Kalleberg 2008, Julià et al. 2017 Cranford et al. 2003, ESOPE in Srakar & Prevolnik Rupel 2017, Vives et al. 2010, Vosko 2006
Purpose	Political Academic	ILO 2012 Kalleberg 2008, Olsthoorn 2014, Rodgers 1989, Standing 2014, Vives et al. 2010, Vosko 2006

Source: Own elaboration.

## 2.2. Operationalization of precarious work

Most of the studies measuring precarious work may be characterized by a common feature: they are constrained by existing data instead of relying on explicit operationalizations of the concept. The studies can be roughly grouped into three categories: those operationalizing precarious work in terms of single indicators, those using multiple indicators without summarizing or aggregating them, and those using composite indicators (i.e. indices). The



remainder of this section focuses on the third group (indices) and discusses the first two groups only briefly, given the fact that these have already been the subject of extensive analysis (see Olsthoorn, 2014; Srakar & Prevolnik Rupel, 2017) and because they overlap partially with the dimensions mentioned in Figure 1 above.

One of the most common operationalizations on the basis of a single indicator is temporary employment. Eurostat (2018), for instance, regards precarious work as the percentage of workers whose contract has a maximum duration of three months. This is also used by Comi & Grasseni (2012). Other measurements include part-time work (Allaart & Bellmann, 2007; Fagan, Smith, Anxo, Letablier, & Perraudin, 2007; Bardasi & Gornick, 2008; Booth & van Ours, 2013), self-employment and individuals working for pay but neither employed nor self-employed (Srakar & Prevolnik Rupel, 2017). Barbier (2011) calls temporary employment, self-employment and part-time employment “three classic indicators” of the mainstream approach towards precarious work.

The second group of studies gives overviews of several indicators from different sources, among which the ones mentioned above. Matteazzi et al (2013) look at part-time work and wages; McKay et al. (2011) explores part-time, fixed-term, temporary agency, subcontracted, posted, seasonal, migrant, seasonal migrant and undeclared work, as well as bogus self employment. Fagan et al. (2016) looks at the following indicators to describe precarious work: in-work poverty and low pay, social security, labour rights, stress and health, career development and training, and low level of collective rights.

The third group consists, as stated above, of studies that attempt to operationalize precarious work more or less as a single concept by means of a series of indicators; in some of these works, several items are added in order to create a single measure or index.

The studies discussed above offer a more nuanced view of precarious work than those from the first two groups. They display several common characteristics. First, most of them (with the exception of Greenhalgh & Rosenblatt, 1984, which merely outlines a methodology) draw from survey data, which implies that a subjective element is ever-present in the measurement of precarious work (this is most clear in Vives et al., 2010, which involves an ordinal scale). Second, most of them include some measurement of wage or, more generally, income. Olsthoorn (2014) includes wage, supplementary means and unemployment benefits; Tangian (2007) focuses more narrowly on earnings from work (though he uses several proxies); Vives (2010) includes a more general indicator on possible economic deprivation. Third, the aggregation techniques are split into additive, with (weighted) averages being used, or multiplicative (Greenhalgh & Rosenblatt, 1984; Olsthoorn, 2014), in which different dimensions are multiplied. This reflects conceptual choices regarding the necessity of conditions.

For our analysis, we include and combine different dimensions of precarious work in one composite indicator. As precarious work is unmeasured, i.e. latent in our analysis, we use frequently used models in latent variable modelling deriving from structural equation tradition, Multiple Indicators Multiple Causes (MIMIC)<sup>3</sup>. We construct a novel estimator taking into account possibilities of variables being causes and indicators (i.e. reverse causality) based on instrumental variable strategies from econometrics and statistics.

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<sup>3</sup> The models have been pointed to as an important path for future research in a recent Econometric Society presidential address by Orazio Attanasio (Attanasio, 2020).

### 3. Data and Methods

#### 3.1. 2SLS-MIMIC

Multiple Indicators Multiple Causes (MIMIC) models are type of structural equation models, a theory-based approach to confirm the influence of a set of exogenous causal variables on the latent variable, and also the effect of the latent variable on observed indicator variables (see e.g. Zellner, 1970; Goldberger, 1972; Jöreskog and Goldberger, 1975; Weck, 1983; Frey and Weck, 1983; Frey and Weck-Hannemann, 1984; Aigner et al., 1988; for some more recent applications see e.g. Lester, 2008; Proitsi et al., 2009; Rose and Spiegel, 2010). MIMIC models are commonly used in economics for modelling the underground economy (for discussion on this topic see e.g. Thomas, 1992; Schneider, 1994; 1997; 2003; 2005; Lippert and Walker, 1997; Johnson et al., 1998a, 1998b; Tanzi, 1999; Giles, 1999; Mummert and Schneider, 2001; Giles and Tedds, 2002; Giles et al., 2002; Dell'Anno and Schneider, 2003; Buehn and Schneider, 2008; Barbosa et al., 2013; Nchor and Adamec, 2015; Breusch, 2016).

In a common MIMIC model, multiple indicators reflect the underlying latent variables/factors, and the multiple causes (observed predictors) affect latent variables/factors. Basic assumptions of MIMIC are clearly violated in case of a variable being both an indicator and a cause, i.e. in the presence of reverse causality. Furthermore, the model is then unidentified. To resolve the situation, which can arise frequently (for example, in modelling shadow economy, GDP can be both a predictor and consequence), we utilize a version of Bollen's (1996) 2SLS estimator for structural equation models combined with Jöreskog (1970)'s method of the analysis of covariance structures to derive a new, 2SLS estimator for MIMIC models. As MIMIC estimation lacks closed form solutions for parameters we study and use Madansky-Hägglund-Jöreskog and Bollen's IV and 2SLS approaches to estimate the covariance matrices of latent variables. Second, we use this estimated covariance matrix of the latent variables and apply Jöreskog's (1970) maximum likelihood procedure to estimate coefficient estimates for the latent variable model. Our 2SLS empirical estimation is based on static MIMIC specification but we point also to dynamic/error-correction (Buehn and Schneider, 2008) MIMIC specification and 2SLS solution for it. We derive basic asymptotic theory for static 2SLS-MIMIC, present a simulation study and apply findings to the empirical case of estimating precarious status of older workers using dataset of Survey of Health, Ageing and Retirement in Europe.

The formal mathematical representation of the MIMIC model reads as follows (see e.g. Hodge and Traiman, 1968; Jöreskog and Goldberger, 1975):

$$y^* = \alpha'x + \epsilon \quad (1)$$

$$y = \beta y^* + u \quad (2)$$

where  $y = (y_1, y_2, \dots, y_p)'$  are indicators of the latent variable  $y^*$  and  $x = (x_1, x_2, \dots, x_q)'$  are causes of  $y^*$ .

The model is based on the following assumptions (see e.g. Jöreskog and Goldberger, 1975; Trebicka, 2014):

$$E(\epsilon u') = 0', E(\epsilon^2) = \sigma^2, E(uu') = \Theta^2 \quad (3)$$

Applications of MIMIC models, typically, also make distributional assumptions, for example

that the joint distribution of the variables is Gaussian, the relation is linear, and each measured variable and each latent common cause has specific sources of variance that are independent of the sources of variance specific to other variables (Trebicka, 2014).

Clearly, if  $x$  and  $y$  are in endogeneous relationship, for example if both have an influence to each other (so-called reverse causality) assumptions in (3) are violated. In this case it is also impossible to identify the relationships in (1) and (2).

Deriving from (1) and (2), the reduced form model and formula for variance-covariance matrix is described in (Jöreskog and Goldberger, 1975):

$$y = \beta(\alpha'x + \epsilon) + u = \Pi'x + v \quad (4)$$

$$\Pi = \alpha\beta' \quad (5)$$

$$v = \beta\epsilon + u \quad (6)$$

$$\Omega = E(vv') = E[(\beta\epsilon + u)(\beta\epsilon + u)'] = \sigma^2\beta\beta' + \Theta^2 \quad (7)$$

The formulas for the MIMIC parameters ( $\alpha$ ,  $\beta$ ,  $\Theta$ ) cannot be expressed in closed form (Jöreskog and Goldberger, 1975). Implicit forms can be derived following Jöreskog and Goldberger (1975) as:

$$\hat{\alpha} = \left(\frac{1}{\hat{\kappa}^2}\right) P\hat{\Omega}^{-1}\hat{\beta} = \left(\frac{1}{\hat{\pi}^2}\right) \hat{P}\hat{\Theta}^{-2}\hat{\beta} \quad (8)$$

$$\left[S + \left(\frac{1}{\hat{\kappa}^2}\right) Q\right] \hat{\Omega}^{-1}\hat{\beta} = (1 + \hat{\rho}^2)\hat{\beta} \quad (9)$$

$$\pi^2 = \beta'\Theta^{-2}\beta, \kappa^2 = \beta'\Omega^{-1}\beta = \frac{\pi^2}{(1+\pi^2)} \quad (10)$$

$$P = (X'P_XX)^{-1}X'P_XY, Q = Y'XP \quad (11)$$

$$S = (Y - XP_XP)'(Y - XP_XP) = Y'(I - XP_X(X'P_XX)^{-1}P_XX')Y \quad (12)$$

$$P_X = X(X'X)^{-1}X' \quad (13)$$

To derive the properties of a new estimator able to correct for the violation of the assumptions in (3) due to endogeneity in the model, we use Jöreskog's (1970) method of the analysis of covariance structures and proposal from Jöreskog and Goldberger (1975) to transform the MIMIC model into Jöreskog (1970) covariance structure modelling framework.

Jöreskog (1970) develops a general covariance structure model for a multivariate normal vector  $z$  as:

$$E(z'z) = \Sigma = B(\Lambda\Phi\Lambda' + \Psi^2)B' + \Theta^2 \quad (14)$$

$$E(z) = AEP \quad (15)$$

where  $A$  is an  $N \times g$  matrix of rank  $g$  and  $P$  is a  $h \times p$  matrix of rank  $h$ , both being fixed matrices with  $g \leq N$  and  $h \leq p$ ;  $E$ ,  $B$ ,  $\Lambda$ , the symmetric matrix  $\Phi$ , and the diagonal matrices  $\Psi$  and  $\Theta$  are parameter matrices.

Based on the model in (14) and (15), Jöreskog derives the log-likelihood function as:

$$\log L = -\frac{1}{2}pN \log(2\pi) - \frac{1}{2}N \log|\Sigma| - \frac{1}{2} \sum_{a=1}^N \sum_{i=1}^p \sum_{j=1}^p (x_{ai} - \mu_{ai}) \sigma^{ij} (x_{aj} - \mu_{aj}) \quad (16)$$

where  $\mu_{ai}$  and  $\sigma^{ij}$  are elements of  $E(X) = AEP$  and  $\Sigma^{-1}$ , respectively.

Writing

$$T = \frac{1}{N}(X - AEP)'(X - AEP) \quad (17)$$

we can readily see that maximizing  $\log L$  is equivalent to minimizing

$$F = \log|\Sigma| + tr(T\Sigma^{-1}) \quad (18)$$

For MIMIC model, taking  $z = (x', y')$  we have in the random case

$$\Sigma = \begin{pmatrix} \Phi & \Phi\alpha\beta' \\ \beta\alpha'\Phi & (1 + \rho^2)\beta\beta' + \Theta^2 \end{pmatrix} \quad (19)$$

This covariance structure may be specified in terms of Jöreskog's model by setting

$$\begin{aligned} B &= \begin{pmatrix} I_{k \times k} & 0_{k \times 1} \\ 0_{m \times k} & \beta_{m \times 1} \end{pmatrix}, \Lambda = \begin{pmatrix} I_{k \times k} \\ \alpha'_{1 \times k} \end{pmatrix}, \\ \Psi &= \begin{pmatrix} 0_{k \times k} & 0_{k \times 1} \\ 0_{1 \times k} & I_{1 \times 1} \end{pmatrix}, \Theta = \begin{pmatrix} 0_{k \times k} & 0_{k \times m} \\ 0_{m \times k} & \Theta_{m \times m} \end{pmatrix} \end{aligned} \quad (20)$$

and taking  $\Phi$  free (Jöreskog and Goldberger, 1975).

As our parameters and estimator cannot be expressed in closed form, we adopt a strategy from Jöreskog and Sorbom (1993), who use 2SLS estimator for equations from the latent variable model using two part strategy: first, using Bollen's 2SLS estimators for the factor loadings of the measurement model along with formulas from Hägglund (1982) to estimate the covariance matrices of latent variables. Second, we use this estimated covariance matrix of the latent variables and apply Jöreskog's (1970) maximum likelihood procedure to estimate coefficient estimates for the latent variable model. Our analysis was firstly presented in Srakar, Vecco and Verbič (present version 2020) and applied in Vecco and Srakar (2018).

In his seminal article, Bollen (1996) constructs a new 2SLS estimator for structural equation models, based on limited information maximum likelihood, as follows. His initial latent variable model reads as:

$$\eta = \alpha + B\eta + \Gamma\xi + \zeta \quad (21)$$

where  $\eta$  is an  $m \times 1$  vector of latent endogenous random variables,  $B$  is a  $m \times m$  matrix of coefficients that give the impact of the  $\eta$ 's on each other,  $\xi$  is an  $n \times 1$  vector of latent exogenous variables,  $\Gamma$  is the  $m \times n$  coefficient matrix giving  $\xi$ 's impact on  $\eta$ ,  $\alpha$  is an  $m \times 1$  vector of intercept terms, and  $\zeta$  is an  $m \times 1$  vector of random disturbances with the  $\mathbb{E}(\zeta) = 0$  and  $Cov(\xi, \zeta') = 0$ .

Writing  $y_1 = \eta + \varepsilon_1$  and  $x_1 = \xi + \delta_1$  above equation transforms into:

$$y_1 = \alpha + By_1 + \Gamma x_1 + u \quad (22)$$

where  $u = \varepsilon_1 - B\varepsilon_1 - \Gamma\delta_1 + \zeta$ .

Bollen considers a single equation from  $y_1$  as:

$$y_i = \alpha_i + B_i y_1 + \Gamma_i x_1 + u_i \quad (23)$$

where  $y_i$  is the  $i$ -th  $y$  from  $y_1$ ,  $\alpha_i$  is the corresponding intercept,  $B_i$  is the  $i$ -th row from  $B y_1$ ,  $\Gamma_i$  is the  $i$ -th row from  $\Gamma$ , and  $u_i$  is the  $i$ -th element from  $u$ .

Defining  $A_i$  to be a column vector that contains  $\alpha_i$  and all the nonzero elements of  $B_i$  and  $\Gamma_i$  strung together in a column. Let  $N$  equal the number of cases and  $Z_i$  be an  $N$  row matrix that contains 1's in the first column and the  $N$  rows of elements from  $y_1$  and  $x_1$  that have nonzero coefficients associated with them in the remaining columns. The  $N \times 1$  vector  $y_i$  contains the  $N$  values of  $y_i$  in the sample and  $u_i$  is an  $N \times 1$  vector of the values of  $u_i$ . The we can rewrite above as:

$$y_i = Z_i A_i + u_i \quad (24)$$

As ordinary least squares is inappropriate for this estimation, we can use two-stage least squares (2SLS) estimator as an alternative and consistent estimator of  $A_i$ .

The 2SLS estimator require instrumental variables for  $Z_i$ . They must be: a) correlated with  $Z_i$ , b) uncorrelated with  $u_i$ , and c) sufficient in number so that there at least as many IV's as the number of explanatory variables on the right-hand side of the equation. Generally, in Bollen's 2SLS estimation, the pool of potential IVs comes from those  $y$ 's and  $x$ 's not included in  $Z_i$  (excluding, of course,  $y_i$ ). The exceptions are any variables in  $Z_i$  that are uncorrelated with  $u_i$ , since such variables can serve as IVs. Exogenous (predetermined)  $x$ 's would be an example of IVs that might appear on the right-hand side above.

Assume we collect all eligible IVs for  $Z_i$  and a column of 1's in an  $N$  row matrix  $V_i$ . Then the first stage of 2SLS is to regress  $Z_i$  on  $V_i$  where below provides the coefficient estimator:

$$(V_i' V_i)^{-1} V_i' Z_i \quad (25)$$

Form  $\hat{Z}_i$  as:

$$\hat{Z}_i = V_i (V_i' V_i)^{-1} V_i' Z_i \quad (26)$$

The second stage is the OLS regression of  $y_i$  on  $\hat{Z}_i$  so that

$$\hat{A} = (\hat{Z}_i' \hat{Z}_i)^{-1} \hat{Z}_i' y_i \quad (27)$$

It can be easily shown (Bollen, 1996) that the estimator is consistent and asymptotically normal, as holds for the usual 2SLS estimators from econometrics.

Following Buehn and Schneider (2008), we can write the variance-covariance matrix of the 2SLS-MIMIC as:

$$\Sigma^* = \begin{pmatrix} \Phi^* & \Phi^* \alpha^* \beta' \\ \beta \alpha^{*'} \Phi^* & (1 + \rho^{*2}) \beta \beta' + \theta^2 \end{pmatrix} \quad (28)$$

$$\Phi^* = X' P_X X \quad (29)$$

$$\rho^* = \alpha^{*'} X' P_X X \alpha^* \quad (30)$$

$$\hat{\alpha}^* = \left( \frac{1}{\hat{R}^2} \right) (X' P_X X)^{-1} X' P_X Y \hat{\Omega}^{-1} \hat{\beta} \quad (31)$$

$$P_X = X(X'X)^{-1}X' \quad (32)$$

This covariance structure may be specified in terms of Jöreskog's model by setting

$$\Psi = \begin{pmatrix} 0_{k \times k} & 0_{k \times 1} \\ 0_{1 \times k} & I_{1 \times 1} \end{pmatrix}, \Theta = \begin{pmatrix} 0_{k \times k} & 0_{k \times m} \\ 0_{m \times k} & \Theta_{m \times m} \end{pmatrix} \quad (33)$$

and taking  $\Phi^*$  free.

The final parameter estimation is performed following Jöreskog and Goldberger (1975)'s suggestion of using maximum likelihood estimation, firstly transforming the above problem into Jöreskog (1970)'s covariance structure modelling framework.

The performance of the new estimator can be based on previous findings. Let  $F$  denote a maximum likelihood objective function,  $\eta$  the estimated moment structure and  $\vartheta$  vector of parameters. We can then write the Hessian matrices as:

$$H_{\eta\vartheta} = \left. \frac{\partial^2 F(u, \eta(\vartheta))}{\partial u \partial \vartheta'} \right|_{u=\eta_0, \vartheta=\vartheta_0} \quad (34)$$

$$H_{\vartheta\vartheta} = \left. \frac{\partial^2 F(u, \eta(\vartheta))}{\partial \vartheta \partial \vartheta'} \right|_{\vartheta=\vartheta_0} \quad (35)$$

Under regularity assumptions it may be shown (Dijkstra, 1983; Shapiro, 1983) that the limiting distribution of  $N^{1/2}(\hat{\vartheta} - \vartheta_0)$  as  $N \rightarrow \infty$  is multivariate normal with a null mean and a covariance matrix

$$\Pi = H_{\vartheta\vartheta}^{-1} H_{\eta\vartheta}' \Gamma_0 H_{\eta\vartheta} H_{\vartheta\vartheta}^{-1} \quad (36)$$

where

$$\Gamma_0 = \begin{bmatrix} \Sigma_0 & \Gamma_{0\vartheta\omega} \\ \Gamma_{0\omega\vartheta} & \Gamma_{0\omega\omega} \end{bmatrix} \quad (37)$$

with

$$\Gamma_{0\vartheta\omega} = \mathbb{E}[(y - \mu_0) \text{vecs}\{(y - \mu_0)(y - \mu_0)'\}] \quad (38)$$

with typical element

$$[\Gamma_{0\vartheta\omega}]_{i,jk} = \mathbb{E}(y_i - \mu_{0i})(y_j - \mu_{0j})(y_k - \mu_{0k}) \quad (39)$$

and

$$\Gamma_{0_{\omega\omega}} = \mathbb{E}[\text{vecs}\{(y - \mu_0)(y - \mu_0)'\}\text{vecs}\{(y - \mu_0)(y - \mu_0)'\}] - \sigma_0\sigma_0' \quad (40)$$

with typical element

$$[\Gamma_{0_{\omega\omega}}]_{ij,kl} = \mathbb{E}(y_i - \mu_{0i})(y_j - \mu_{0j})(y_k - \mu_{0k})(y_l - \mu_{0l}) - \sigma_{0ij}\sigma_{0kl} \quad (41)$$

so that  $\Gamma_0$  depends on second, third and fourth order central moments of the distribution of  $y$ .

As the data entering 2SLS-MIMIC estimation are independent and identically distributed, we can simply apply reasoning of Lee and Shi (1998) and argue that the derived estimator is consistent, asymptotically normal and efficient. This shows the consistency of our procedure and main properties of the derived estimation process which guarantee the desired behavior of the estimates.

### 3.2. 2SLS-EMIMIC and simulation study

In MIMIC models, it is also possible to consider a dynamic situation. Often, MIMIC models are applied to time series data to derive, for example, estimates of the size and development of the shadow economy over time. As most macroeconomic variables do not satisfy the underlying assumption of stationarity, the problem of spurious regressions may arise. Researchers usually overcome this problem by transforming the time series into stationary ones, employing a difference operator. Alternatively, one could estimate an error correction model (ECM) if the variables were cointegrated and a stationary long run relationship existed between them.

Buehn and Schneider reexpress the MIMIC model as follows:

Structural part:

$$\eta_t = \gamma'x_t + \zeta_t \quad (42)$$

where  $x_t' = (x_{1t}, x_{2t}, \dots, x_{qt})$  is a  $(1 \times q)$  vector of time series variable as indicated by the subscript  $t$ . Each time series  $x_{it}, i = 1, \dots, q$  is a potential cause of the latent variable  $\eta_t$ .  $\gamma' = (\gamma_1, \gamma_2, \dots, \gamma_q)$ , a  $(1 \times q)$  vector of coefficients in the structural model describing the »causal« relationships between the latent variable and its causes.

Measurement part:

$$y_t = \lambda\eta_t + \varepsilon_t \quad (43)$$

where  $y_t' = (y_{1t}, y_{2t}, \dots, y_{pt})$  is a  $(1 \times p)$  vector of individual time series variables  $y_{jt}, j = 1, \dots, p$ .  $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{pt})$  is a  $(p \times 1)$  vector of disturbances where every  $\varepsilon_{jt}, j = 1, \dots, p$  is a white noise term. Their  $(p \times p)$  covariance matrix is given by  $\Theta_\varepsilon$ . The single  $\lambda_j, j = 1, \dots, p$  in the  $(p \times 1)$  vector of regression coefficients  $\lambda$ , represents the magnitude of the expected change of the respective indicator for a unit change in the latent variable.

As before, reduced form equation is:

$$y_t = \Pi x_t + z_t \quad (44)$$

where  $\Pi = \lambda\gamma'$  and  $z_t = \lambda\zeta_t + \varepsilon_t$ . The error term  $z_t$  in equation above is a  $(p \times 1)$  vector of linear combinations of the white noise error terms  $\zeta_t$  and  $\varepsilon_t$  from the structural and measurement model, i.e.  $z_t \sim (0, \Omega)$ . The covariance matrix  $\Omega$  is given as  $Cov(z_t) = \lambda\lambda'\psi + \Theta_\varepsilon$ .

We will denote the variables in the above model which are I(1) as  $x_t$  and those that are I(0) as  $v_t$ . Above equation then becomes:

$$y_t = \Pi x_t + T v_t + z_t \quad (45)$$

where  $T = \lambda\beta'$  and  $\tau' = (\tau_1, \tau_2, \dots, \tau_r)$  is the  $(1 \times r)$  vector of coefficients of the I(0) variables in the structural relationship.

Every cointegration relationship has an error correction mechanism where the long run relationship leads to equilibrium and the short run relationship contains a dynamic mechanism (Engle and Granger, 1987). Thus, above equation can be written as:

$$\Delta y_t = A \Delta x_t + T v_t + K z_{t-1} + w_t \quad (46)$$

where  $\Delta y_t = y_t - y_{t-1}$ ,  $\Delta x_t = x_t - x_{t-1}$ ,  $z_{t-1} = y_{t-1} - \Pi x_{t-1}$  and  $A$ ,  $B$  and  $K$  are coefficient matrices in this dynamic, short run model specification. Furthermore, in this specification  $A = \lambda\alpha'$  is the  $[p \times (q-r)]$  coefficient matrix of the first differences of the I(1) causes, and  $B = \lambda\beta'$  is the  $(p \times r)$  coefficient matrix of the I(0) causes. The matrix  $K = \lambda\kappa'$  is the  $(p \times p)$  coefficient matrix for the long run disequilibrium's error correction term and  $w_t \sim (0, \Omega)$  is a white noise disturbance. Together, Together, equations above define the EMIMIC model.

We now translate the model into our 2SLS framework and Jöreskog's analysis.

The variance-covariance matrix for the model in (45) can be written as below:

$$\Sigma = \begin{pmatrix} Var(x_t) & & \\ Cov(x_t, v_t) & Var(v_t) & \\ Cov(x_t, y_t) & Cov(v_t, y_t) & Var(y_t) \end{pmatrix} \quad (47)$$

and in the notation above as:

$$\Sigma = \begin{pmatrix} \Phi_1^* & N & (\Phi_1^* \gamma^* + N\tau)\lambda' \\ N' & \Phi_2 & (N' \gamma^* + \Phi_2 \tau)\lambda' \\ \lambda(\gamma^{*'} \Phi_1^* + \tau' N') & \lambda(\gamma^{*'} N + \tau' \Phi_2) & \lambda(\gamma^{*'} \Phi_1^* \gamma^* + 2\gamma^{*'} N\tau + \tau' \Phi_2 \tau)\lambda' + \theta^2 \end{pmatrix} \quad (48)$$

This can be translated into Jöreskog's analysis and formula (14) as:

$$\Phi = \begin{pmatrix} \Phi_1^*_{(q-r) \times (q-r)} & N_{(q-r) \times r} \\ N'_{r \times (q-r)} & \Phi_2_{r \times r} \end{pmatrix}, \quad B = \begin{pmatrix} I_{q \times (q-r)} & 0_{q \times 1} \\ 0_{p \times (q-r)} & \lambda_{p \times 1} \end{pmatrix}, \quad \Lambda = \begin{pmatrix} I_{(q-r) \times (q-r)} & I_{r \times r} \\ \gamma^{*'}_{1 \times (q-r)} & \tau'_{1 \times r} \end{pmatrix}, \\ \Psi = \begin{pmatrix} 0_{(q-r) \times (q-r)} & 0_{(q-r) \times 1} \\ 0_{1 \times (q-r)} & I_{1 \times 1} \end{pmatrix}, \quad \Theta = \begin{pmatrix} 0_{q \times q} & 0_{q \times p} \\ 0_{p \times q} & \Theta_{p \times p} \end{pmatrix} \quad (49)$$



The variance-covariance matrix for the model in (49) can be written as:

$$\Sigma = \begin{pmatrix} Var(\Delta x_t) & & & & \\ Cov(\Delta x_t, v_t) & Var(v_t) & & & \\ Cov(\Delta x_t, z_{t-1}) & Cov(v_t, z_{t-1}) & Var(z_{t-1}) & & \\ Cov(\Delta x_t, \Delta y_t) & Cov(v_t, \Delta y_t) & Cov(z_{t-1}, \Delta y_t) & Var(\Delta y_t) & \end{pmatrix} \quad (50)$$

and in the notation above as:

$$\Sigma = \begin{pmatrix} \Phi_3^* & M^{*'} & 0 & (\Phi_3^* \alpha_\Delta^* + M^{*'} \beta_\Delta) \lambda' \\ M^* & \Phi_2 & 0 & (M^* \alpha_\Delta^* + \Phi_2 \beta_\Delta) \lambda' \\ 0 & 0 & \Omega^* & \lambda \kappa^{*'} \Omega^* \\ \lambda (\alpha_\Delta^* \Phi_3^* + \beta_\Delta M^*) & \lambda (\alpha_\Delta^* M^{*'} + \beta_\Delta \Phi_2) & \Omega^* \kappa^{*'} \lambda' & \lambda (\alpha_\Delta^* \Phi_3^* \alpha_\Delta^* + 2 \alpha_\Delta^* M^{*'} \beta_\Delta + \beta_\Delta \Phi_2 \beta_\Delta + \kappa^{*'} \Omega^* \kappa^{*'}) \lambda' + \psi \lambda \lambda' + \theta^2 \end{pmatrix} \quad (51)$$

This can be translated into Jöreskog's analysis and formula (14) as:

$$\begin{aligned} \Phi &= \begin{pmatrix} \Phi_3^* & M^{*'} & 0 \\ M^* & \Phi_2 & 0 \\ 0 & 0 & \Omega^* \end{pmatrix} \\ B &= \begin{pmatrix} I & 0 \\ 0 & \lambda \end{pmatrix}, \Lambda = \begin{pmatrix} I & I \\ \gamma^{*'} & \tau' \end{pmatrix}, \\ \Psi &= \begin{pmatrix} 0 & 0 \\ 0 & I \end{pmatrix}, \Theta = \begin{pmatrix} 0 & 0 \\ 0 & \theta \end{pmatrix} \end{aligned} \quad (52)$$

Below we present results of simulation studies of the performance of the above new estimators. Our simulation results are based on 10000 simulated data sets and corresponding 1000 resamples. We present results for three scenarios: 1) with short time series ( $t=20$ ) and with only one I(1) variable; 2) with short time series ( $t=20$ ) and several (three) I(1) variables; 3) with longer time series ( $t=100$ ) and several (three) I(1) variables. We simulate three criteria of the MIMIC models: root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR) and comparative fit index (CFI).

Results of simulation study for scenario 1, presented in Table 1, confirm the consistency of the proposed approaches. As demonstrated the 2SLS-MIMIC procedure leads to consistent and asymptotically normal estimator which is shown in Table 1 for both error criteria – with enlarging the sample size, the error of the estimates outperforms other, noninstrumented estimators by a sizable amount. Also, the fit of the model is significantly improved for both 2SLS-MIMIC as well as 2SLS-EMIMIC procedures.

**Table 2:** Simulation study, scenario 1

	RMSEA	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
	50	0.1318	0.1261	0.1198	0.1102	0.1051
	100	0.1081	0.0883	0.0910	0.0937	0.0799
	200	0.0940	0.0724	0.0637	0.0759	0.0663
	500	0.0733	0.0622	0.0510	0.0660	0.0477
	1000	0.0587	0.0498	0.0418	0.0482	0.0344
	2000	0.0458	0.0398	0.0368	0.0366	0.0275
	5000	0.0389	0.0299	0.0291	0.0278	0.0231
	10000	0.0296	0.0248	0.0224	0.0223	0.0201
	SRMR	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
	50	0.1702	0.1691	0.1678	0.1622	0.1569
	100	0.1413	0.1522	0.1493	0.1330	0.1177

200	0.1257	0.1111	0.1225	0.0931	0.0871
500	0.1044	0.0867	0.0882	0.0661	0.0775
1000	0.0793	0.0624	0.0697	0.0588	0.0581
2000	0.0682	0.0499	0.0522	0.0518	0.0407
5000	0.0566	0.0444	0.0402	0.0456	0.0297
10000	0.0430	0.0386	0.0350	0.0364	0.0226

	CFI	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
50		0.8611	0.8720	0.8801	0.9102	0.9119
100		0.8783	0.8894	0.8889	0.9193	0.9301
200		0.8871	0.8983	0.8978	0.9377	0.9394
500		0.9048	0.9073	0.9157	0.9564	0.9488
1000		0.9229	0.9255	0.9341	0.9660	0.9678
2000		0.9322	0.9440	0.9434	0.9757	0.9775
5000		0.9415	0.9629	0.9528	0.9854	0.9873
10000		0.9509	0.9725	0.9624	0.9953	0.9971

Source: Own calculations.

With more I(1) variables in the dynamic version of the (correct) model (Table 2, i.e. scenario 2), the difference in performance between 2SLS-MIMIC and 2SLS-EMIMIC procedures grows in favor of the latter, which is particularly pronounced in the fit of the model, where both models significantly outperform the noninstrumented ones.

**Table 3:** Simulation study, scenario 2

	RMSEA	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
50		0.1437	0.1223	0.1330	0.1256	0.0914
100		0.1189	0.0812	0.1083	0.0843	0.0863
200		0.1110	0.0622	0.0714	0.0819	0.0696
500		0.0638	0.0566	0.0597	0.0733	0.0387
1000		0.0516	0.0513	0.0376	0.0511	0.0388
2000		0.0366	0.0410	0.0338	0.0311	0.0316
5000		0.0373	0.0344	0.0340	0.0242	0.0263
10000		0.0278	0.0295	0.0219	0.0216	0.0193

	SRMR	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
50		0.1702	0.1725	0.2014	0.1654	0.1757
100		0.1653	0.1750	0.1478	0.1476	0.1377
200		0.1220	0.1222	0.1286	0.0773	0.0836
500		0.1127	0.0832	0.0749	0.0787	0.0853
1000		0.0706	0.0736	0.0676	0.0624	0.0651
2000		0.0778	0.0524	0.0481	0.0518	0.0415
5000		0.0521	0.0413	0.0374	0.0542	0.0267
10000		0.0430	0.0348	0.0304	0.0419	0.0181

	CFI	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
50		0.8183	0.8233	0.8097	0.8219	0.8496
100		0.8271	0.8319	0.8259	0.8377	0.8552
200		0.8360	0.8406	0.8424	0.8439	0.8711
500		0.8449	0.8594	0.8508	0.8521	0.8992
1000		0.8630	0.8683	0.8593	0.8687	0.9056
2000		0.8723	0.8763	0.8679	0.8857	0.9223
5000		0.8909	0.8846	0.8853	0.9044	0.9308
10000		0.9004	0.9033	0.8941	0.9231	0.9494

Source: Own calculations.

Finally, with longer time series, the performance of the 2SLS-EMIMIC as compared to 2SLS-MIMIC is not so good anymore. While it outperforms the latter in terms of error criteria, it lags behind in fit index which might show some problems with cointegration properties for longer

time series of the proposed 2SLS-EMIMIC estimation.

**Table 4:** Simulation study, scenario 3

	RMSEA	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
	50	0.1595	0.1431	0.1543	0.1281	0.0796
	100	0.1296	0.0747	0.0932	0.0792	0.0992
	200	0.1143	0.0697	0.0621	0.0967	0.0745
	500	0.0549	0.0583	0.0614	0.0586	0.0452
	1000	0.0573	0.0415	0.0335	0.0577	0.0350
	2000	0.0297	0.0349	0.0288	0.0352	0.0281
	5000	0.0366	0.0412	0.0289	0.0206	0.0308
	10000	0.0300	0.0242	0.0257	0.0255	0.0154

	SRMR	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
	50	0.1821	0.2001	0.2416	0.1820	0.1968
	100	0.1620	0.1400	0.1198	0.1727	0.1391
	200	0.1073	0.1259	0.1337	0.0618	0.0786
	500	0.0969	0.0923	0.0630	0.0661	0.0963
	1000	0.0826	0.0810	0.0757	0.0630	0.0775
	2000	0.0762	0.0529	0.0457	0.0528	0.0340
	5000	0.0516	0.0331	0.0441	0.0629	0.0251
	10000	0.0495	0.0306	0.0286	0.0335	0.0197

	CFI	MIMIC	DMIMIC	EMIMIC	2SLS-MIMIC	2SLS-EMIMIC
	50	0.8168	0.8392	0.8178	0.8869	0.8836
	100	0.8250	0.8470	0.8260	0.8958	0.8925
	200	0.8333	0.8551	0.8342	0.9137	0.9014
	500	0.8416	0.8736	0.8509	0.9228	0.9194
	1000	0.8584	0.8830	0.8679	0.9413	0.9286
	2000	0.8670	0.8926	0.8766	0.9601	0.9379
	5000	0.8757	0.9022	0.8941	0.9697	0.9567
	10000	0.8844	0.9116	0.9120	0.9891	0.9662

Source: Own calculations.

### 3.3. Dataset

We apply the novel estimation approach using data from Survey of Health, Ageing and Retirement in Europe (SHARE), a multidisciplinary and cross-national panel database of micro data on health, socio-economic status and social and family networks of about 140,000 individuals aged 50 or older (around 380,000 interviews), covering 27 European countries and Israel. So far, eight waves of the study have been conducted. Information is collected by means of Computer-Assisted Personal Interview (CAPI) questionnaires, physical measurements and fill-in questionnaires across several modules containing demographic, health, psychological and socio-economic information (see Börsch-Supan et al., 2013). The third and seventh wave of the study adopted a retrospective perspective and recorded life histories. In our empirical analysis we refer also to excellent previous methodological work in SHARE, for example Malter et al. (2016) and Malter and Börsch-Supan (eds., 2017), as well as empirical results from Wave 6 and 7 SHARE datasets, composed and edited in the monograph *First Results from SHARE Waves 6 and 7* (Börsch-Supan, Bristle et al., 2019; for additional results from SHARE see also Börsch-Supan et al., 2005; 2011; 2013; 2015).

In this preliminary analysis, we present results using only dataset from Wave 6 of SHARE survey (Börsch-Supan, 2020; see also Börsch-Supan et al., 2013; Malter and Börsch-Supan, 2017). Once the complete cases were identified in function of the chosen variables, 5594 observations in total were retained.

#### 4. Calculation of index of precarious work of the elderly

The operationalization started by translating Kalleberg's (2009) definition of precarious work as "uncertain, unpredictable and risky" into several dimensions, i.e. employment stability, income and working conditions.

In order to define those dimensions, we took two steps. We first looked at the existing indices and at the same time we pre-selected all the questions dealing with the working life of the SHARE respondents from wave 6. 423 questions (including loops and question from different modules of Wave 6 of SHARE data) were selected, among which several instrumental questions (e.g. bracket values used to estimate income amounts) and looped questions (e.g. relating to each of the respondent's income sources or former jobs). Then only the questions were retained that related to the respondents' present job. Then the questions were labelled following the dimensions defined by Tangian (2007) and Olsthoorn (2014) and the best-fitting approach was selected and amended.

Olsthoorn was selected because the logics on which his operationalization is built take into account the substitutability-additionality continuum (cf. supra). Tangian's dimensions were selected because of three main reasons. First, his dimensions and sub-dimensions cover a broad spectrum of the employment relationship as opposed to, for instance, Cranford and colleagues (2003), who focus on regulatory aspects. Second, his dimensions are far enough from the indicator level (i.e. abstract enough) as to be applied to different data. Conversely, other indices such as Clark (2005) and Böckermann (2004) are very closely tailored to the data collection. Other, such as Greenhalgh and Rosenblatt (1984) and Loughlin and Murray (2013) are difficult to operationalize by proxy. Third, he uses European surveys in order to construct his indicators, as is the case in the present analysis.

In practice, the coding largely overlapped: Olsthoorn's deprivation dimension was similar to Tangian's income, and insecurity and employment instability were more or less the same as well. Tangian's "employability" has however no counterpart in Olsthoorn's classification.

In a second step, the subdimensions were amended on the basis of the available data. A new dimension ("subjective appreciation") was introduced, which echoes the subjective perspective of several of the indices mentioned above. The final result included thus five dimensions: income, stability, employability, integration in social security, and subjective appreciation.

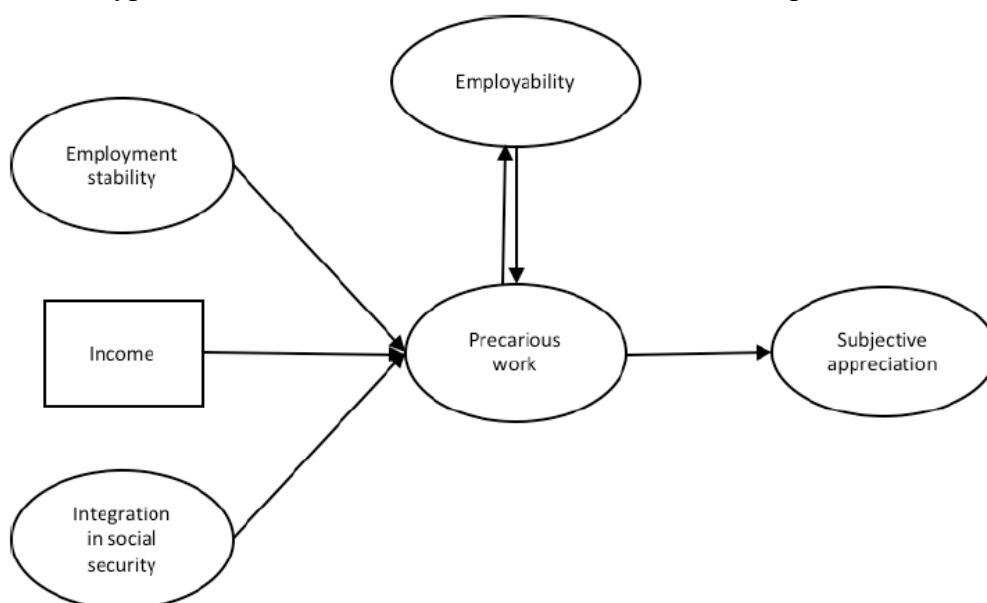
The definition of the dimensions and subdimensions was finished with the definition of the causal relationships between the dimensions which, as it has been said above, has not been problematized by the literature.

A first step in defining the (potential) causal relationships between the dimensions was to identify the analytical level at which they are located. Income, integration in social security and employment stability are located at the level of the work, and some of their features may arguably be located at the institutional regime. Subjective appreciation, on the other hand, as well as employability, are located at the analytical level of the worker. The possible correlations between the different dimensions or levels have not been hypothesized, and those authors who incorporate both objective and subjective dimensions into their indices (Tangian, 2007; Vives et al., 2010) do not elaborate on the possible relations between them, and regard them both simply as components of precarious work. This overlooks two possible causal relationships:

1. The subjective appreciation of the worker is influenced by the objective components at the job level: workers with unstable employment, a low income and a low degree of integration in social security are more likely to be overall less satisfied with their jobs than workers in a less precarious situation.
2. Employability is both a function and a determinant of the objective dimensions: a worker with scarce training and career advancement opportunities is more likely to have low stability, low income and a low degree of integration in social security, and jobs with those characteristics are more likely to foster low employability than otherwise.

Whereas the case can be made for subjective appreciation as being a part of precarious work as such, it is difficult to ignore the causal links hypothesized above. Therefore, the causal model used for the index incorporates them both. In this model, precarious work is regarded as a latent variable defined by the three objective dimensions and employability, which in turn affects the subjective appreciation of the worker. In other words, subjective appreciation does not strictly belong to the “precarious work” construct. The result of the exercise is portrayed in the figure below.

**Figure 2:** The hypothesized relations between the dimensions of the precarious work concept



Source: Own elaboration.

Once the indicators were all labelled, those related to the respondents’ current job were selected. All variables relating to either his whole career or his former job were dropped. In addition, missing values were assessed. An arbitrary cutoff value was set at 60%, due mainly to looped variables. Questions where information was missing for more than 50% of the population, and which were not part of any specific if-loops, were dismissed. Variables related to loops in main variables (such as in the case of persons having more than one job), or lists (such as income sources) for which missing values are higher than 60% were included, as they relate to specific sub-populations within the main group.

The final selection includes 25 variables constructed from the Employment and Pensions module of the survey and one variable (income) imported from the Generated Variables

module. One looped variable (i.e. pensions) was summarized in a single indicator. All variables were recoded so they would point in the same direction, i.e. low values coincide with low precarity, high values coincide with high precarity.

The selected indicators, as recoded for the analysis, are described in Table 5 below. Table 6 provides some basic statistics.

**Table 5:** List of used variables

Variable name	Description	Dimension	Type
income_decile	Income deciles	Income	Discrete
job_number	Number of jobs	Employment stability	Dichotomous
job_self	Self employment	Employment stability	Dichotomous
job_satisfaction	Satisfied with (main) job	Subjective appreciation	Ordinal
job_phdeman	(Main) job physically demanding	Subjective appreciation	Ordinal
job_timepress	Time pressure due to a heavy workload in (main) job	Subjective appreciation	Ordinal
job_freedom	Little freedom to decide how I do my work in (main) job	Subjective appreciation	Ordinal
job_newskills	Opportunity to develop new skills in (main) job	Employability	Ordinal
job_support	Receive support in difficult situations in (main) job	Subjective appreciation	Ordinal
job_recognition	Receive recognition for work in (main) job	Subjective appreciation	Ordinal
job_sat_salary	Salary or earnings are adequate in (main) job	Subjective appreciation	Ordinal
job_promotion	Poor prospects for (main) job advancement	Employability	Ordinal
job_security	Poor (main) job security	Subjective appreciation	Ordinal
pensions_future	Number of pensions claimed in the future	Integration in social security	Discrete
pensions_benefit	Amount of benefits in the future	Integration in social security	Continuous
tenure	Number of years in current job as percentage of age	Employment stability	Continuous
job_term	Type of contract	Employment stability	Ordinal
pensions_years_ratio	Number of years the respondent has been contributing to pensions as a ratio of tenure	Integration in social security	Continuous
pensions_comp_ratio	compulsory pensions as a ratio of the total number of of pensions	Integration in social security	Continuous
job_hours	Total hours usually working per week	Employment stability	Continuous

Source: SHARE Wave 6, own modifications.

**Table 6:** Descriptive statistics of the used variables

Variable name	Median	Mean	Std dev	Minimum	Maximum
income_decile	40000.00	47311.00	26405.00	10000.00	100000.00
job_number	0.00	0.07	0.26	0.00	10000.00
job_self	0.00	0.03	0.18	0.00	10000.00
pensions_future	-10000.00	-11113.00	0.83	-50000.00	0.00
pensions_benefit	8800000.00	7089680.00	4938989.00	0.00	11889230.00
tenure	0.66	0.65	0.22	0.20	10000.00
job_term	0.00	0.09	0.28	0.00	10000.00
pensions_years	-360000.00	-290637.00	177777.00	-460000.00	0.00
pensions_comp_ratio	-10000.00	-0.68	0.45	-10000.00	0.00
job_hours	400000.00	367460.00	60987.00	250000.00	430000.00
job_satisfaction	20000.00	23349.00	0.67	0.00	30000.00
job_phdeman	10000.00	13845.00	10578.00	0.00	30000.00
job_timepress	10000.00	14478.00	0.92	0.00	30000.00
job_freedom	10000.00	11547.00	0.94	0.00	30000.00
job_newskills	20000.00	18063.00	0.88	0.00	30000.00
job_support	20000.00	19261.00	0.81	0.00	30000.00
job_recognition	20000.00	18388.00	0.83	0.00	30000.00
job_sat_salary	20000.00	15995.00	0.87	0.00	30000.00
job_promotion	20000.00	19854.00	0.92	0.00	60000.00
job_security	10000.00	0.89	0.89	0.00	30000.00

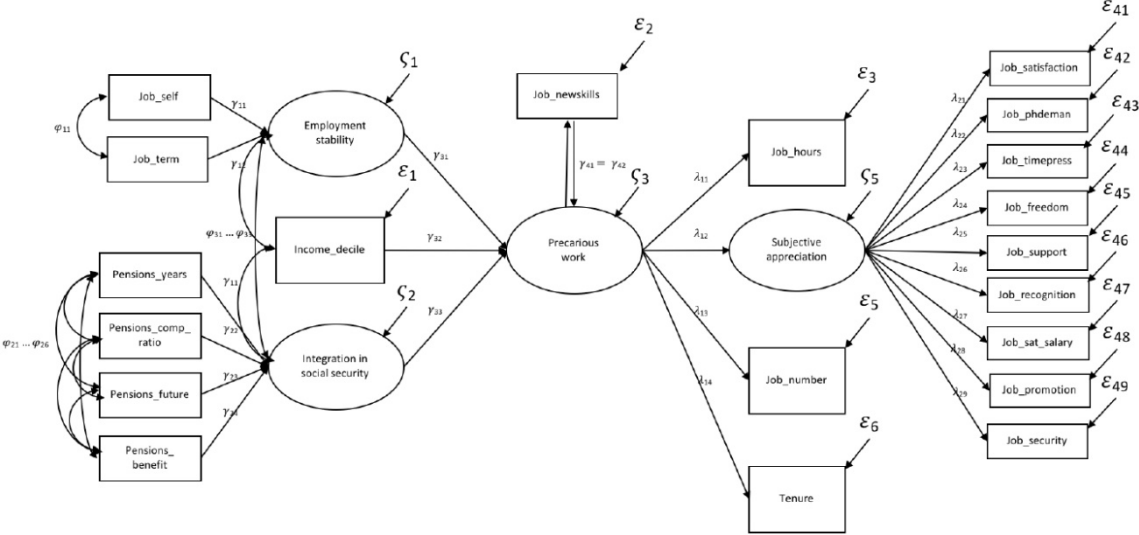
Source: SHARE Wave 6, own modifications.

The calculation of the index's values was conducted, following the recommendation in OECD (2008), using regression techniques, *in casu* Multiple Indicator Multiple Cause (MIMIC) analysis, which is part of the larger family of Structural Equation Modelling (SEM). It was conducted using library lavaan from the R software package ("The lavaan Project," n.d.), and comprised three steps: the definition of precarious work as a latent variable in a MIMIC model, the introduction of an instrumental variable to correct for the causal loop of employability and

precarious work, and the calculation of the index on the basis of the predicted values of the latent variable. The three steps are set out below.

The graphic representation of the model following the MIMIC conventions is depicted in the next page. It is clear from the figure that the model corresponds largely to the causal model depicted in Figure 1. However, some adaptations require clarifications. First, the employability dimension (portrayed as a latent variable in the model above) has been replaced by a proxy, Job\_new\_skills. Second, the regression coefficients from and to employability were set to be equal in order to obtain an identified model (otherwise the software is unable to estimate the standard error terms, cf. infra). Third, some of the variables belonging to employment stability (tenure, job\_number and job\_hours) are regarded as reflective rather than formative indicators following our causal model: the number of hours someone works, the number of years they stay in their job and the number of jobs they do besides their first job do not *cause* precarious work, but are rather hypothesized to be the effect of the employment stability linked to the formal status of the worker.

**Figure 3:** MIMIC model for precarious work



Source: Own elaboration.

Our first stage used latent variable regression where instruments were chosen using Bollen's procedure described above where the dependent variable was our proxy for employability (job\_newskills).

The final step in the construction of the index was the (2SLS-based) MIMIC analysis, from which the index values were obtained. The results from the analysis (using maximum likelihood approach described in the theoretical part of the paper) are summarized in Table 7. Results are provided for two models, with (Model 1) and without (Model 2) the instrumental variable-correction.

**Table 7:** Results of the MIMIC regression

	Model 1		Model 2	
	Coef. (standardized)	Sig.	Coef. (standardized)	Sig.
<i>Latent variables</i>				
Precar				

Pensions	1.00		1.00	
Income	5061.00	***	3039.00	***
Job_newskills	0.67	***		***
Est_job_skills			0.47	
Stability	0.30	***	0.13	***
<b>Subjective</b>				
job_satisfaction	1.00		1.00	
job_phdeman	0,738	***	0,758	***
job_timepress	0,724	***	0,741	***
job_freedom	0,901	***	0,897	***
job_support	1220.00	***	1216.00	***
job_recognition	1496.00	***	1502.00	***
job_sat_salary	1160.00	***	1168.00	***
job_promotion	0.52	***	-0.51	***
job_security	0.63	***	0.62	***
<b>Pensions</b>				
Pensions_future	1.00		1.00	
Pensions_compulsory	-0.84	***	-0.83	***
Pensions_years	18970.00	***	18785.00	***
<b>Stability</b>				
Job_term	1.00		1.00	
Job_self	0.09	*	0.08	
-----				
<b>Regressions</b>				
-----				
Job_newskills – precar	0.00		0.00	
Subj – precar	0.64	***	0.41	***
Tenure - precar	0.24	***	-0.01	
Job_number -	-0.11	***	-0.12	***
-----				
Nr. of observations	5560		5560	

Note: Significance: \* <0.1; \*\* < 0.01; \*\*\* <0.001.

Source: SHARE, Wave 6 (own modifications).

Some preliminary conclusions can be made from the model. First, the largest single predictor for precarious work seems to be income: a low income is associated with high precarity. Employability seems to exert some influence as well, though much smaller. Second, most of the effects go in the hypothesized direction (i.e. high values of the variable are associated with high values of precarious work) with some exceptions: the number of jobs (more precarity is associated with people who have only one job as opposed to people with two jobs) and the perception of promotion opportunities in the model with the employability estimates.

On the basis of the model above, the estimated scores for the variable “precar” were averaged by country, rescaled (0-1) and used as the precarious work index. The results can be seen in the table and graph below.

**Table 8:** Precarious work index by country

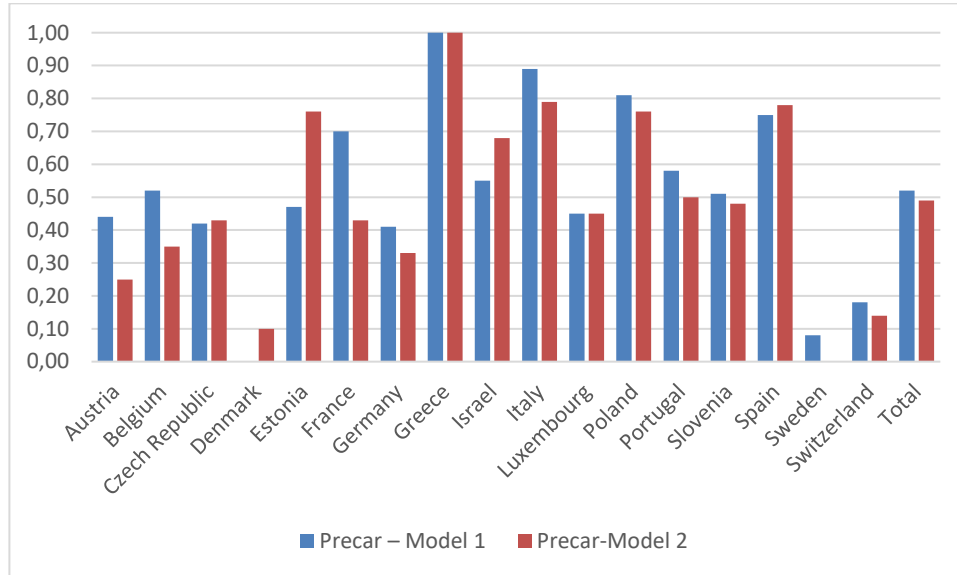
Country	Precar – Model 1	Precar-Model 2
Austria	0.44	0.25
Belgium	0.52	0.35
Czech Republic	0.42	0.43
Denmark	0.00	0.10
Estonia	0.47	0.76
France	0.70	0.43
Germany	0.41	0.33
Greece	1.00	1.00
Israel	0.55	0.68
Italy	0.89	0.79
Luxembourg	0.45	0.45
Poland	0.81	0.76
Portugal	0.58	0.50
Slovenia	0.51	0.48
Spain	0.75	0.78



Sweden	0.08	0.00
Switzerland	0.18	0.14
<b>Total</b>	<b>0.52</b>	<b>0.49</b>

Source: SHARE, Wave 6 (own modifications).

**Figure 4:** Precarious work index by country



Source: SHARE, Wave 6 (own modifications).

The results from Model 1 seem, in general terms, to echo the institutional differences among regimes (higher values of the index denote higher level of precarious work in the country and lower values lower level, the index is rescaled so that it ranges between 0 and 1): the lowest levels of precarious work can be found in Scandinavia (Denmark and Sweden), with Switzerland following closely. The highest levels are, by contrast, to be found in Southern Europe (Spain, Greece and Italy). The continental welfare regimes from Western and Central Europe (Austria, Belgium France, Germany and Luxembourg) are somewhere in the middle, whereas the post-communist states show no common denominator: Slovenia and Estonia are closer to central Europe, whereas Poland displays larger scores.

The results from Model 2 are largely similar, with two exceptions: Estonia displays a much higher degree of precariousness, as well as France and Austria and Belgium much lower levels as compared to Model 1.

#### 4. Concluding remarks

The article presented is to our knowledge the second one (first one being Tekwe et al., 2014 – their article addressed endogeneity in MIMIC in a very limited context related specifically to measurement error problems) which explicitly models reverse causality in MIMIC models which can arise very frequently. We present a novel estimation procedure, based on Bollen's 2SLS estimator and transformation into Jöreskog's general covariance structure analysis. We are able to derive three new estimation procedures and show their consistency and asymptotic normality (for 2SLS-MIMIC). While the task remains (we are working on this presently) to derive the asymptotics also for the 2SLS-EMIMIC estimator, the results of simulation studies confirm the validity of the procedure and desired properties of the new estimators.

In an empirical part of the analysis we conduct a preliminary analysis to construct index of precarious work of the elderly. As precarious work still largely lacks in empirical estimation and suffers from definitional problems, our approach which uses the multidimensional character of precarious work as well as its latent character is important for future work in the area. Our analysis constructs such an index for different countries included in SHARE and demonstrates the potential of the new approach.

We have to mention several limitations of the study. Firstly, there exist significant critiques of the method of MIMIC for estimating shadow economy and other concepts. As has been shown by e.g. Breusch (2016), MIMIC is not always a proper modelling technique to estimate the latent concepts under question. Also, the IV context could be developed in more depth, related to overidentification issues and including estimators such as LIML, FIML, 3SLS and different types of GMM approaches. Furthermore, we address only maximum likelihood MIMIC estimation and do not relate to other two approaches at hand: econometric and factor analytic one (mentioned already in the original article of Jöreskog and Goldberger, 1975). For future work it would be important to address also those points more properly.

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