Assessing the relationships between Nationalism, Ethnocentrism, and Individualism in Flanders using Bergstrom's approximate discrete model

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Although Nationalism, Ethnocentrism, and Individualism in Flanders have been the subject of several studies before, a longitudinal analysis has not been performed on all three concepts simultaneously nor have their relationships and the direction of their relationships been studied in continuous time. In this study we performed a continuous-time state-space analysis on panel data collected from 1274 subjects, in the years 1991, 1995 and 1999. The LISREL program is used for estimating the approximate discrete model (ADM), and for comparison, also the exact discrete model (EDM) is estimated by means of the Mx program. Details of continuous time modeling, especially the EDM and ADM, are dealt with. Individualism and Ethnocentrism turn out to be connected in a moderately strong feedback relationship with the effect from Individualism towards Ethnocentrism somewhat stronger than that in the opposite direction. Both Individualism and Ethnocentrism have small effects on Nationalism. The autoregression functions, cross-lagged effect functions, and mean predictions are shown.

Keywords and Phrases: state-space model, structural equation modeling, exact discrete model, feedback relationship, cross-lagged effect function, prediction.

1 Introduction

Many observers get the impression that in the wake of repeated constitutional reforms, Belgium is in the process of falling apart as a nation. Identification with Belgium as a nation has always been relatively weak, even before the start of the

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federalization process. As a result of the successive constitutional reforms, however, the Belgian nation has met competition from the Walloon and Flemish entities, which also appeal to the citizens' sense of identity. The Flemish government, in particular, pursues a genuine policy of nation building, aimed at creating a Flemish national consciousness. In this study Nationalism is understood as the degree to which Flemish individuals identify with Flanders as a nation to the detriment of Belgium as a whole.

In a previous longitudinal study (BILLIET, COFFÉ and MADDENS, 2005), Nationalism was related to Ethnocentrism or a negative attitude towards foreigners and immigrants. The background of relating both concepts is the voting behavior in Flanders in favor of the extreme right-wing party Vlaams Blok. In the 1991 General Elections for the Federal Parliament, Vlaams Blok obtained 9.3% of the Flemish vote. This number rose to 11.3% in 1995, 14.7% in 1999, and 17.1% in the 2003 General Elections. The party even obtained 22.8% of the Flemish vote in the 2004 elections for the Flemish Parliament, and became the largest political party in Flanders (FRAEYS, 2004). Vlaams Blok has been convicted for racism by a Belgian court in 2004. A core issue in the ideology of the Vlaams Blok is the preference for an ethnic national state, in which 'nation' is conceived as a 'biologically-defined ethnic community' (SPRUYT, 1995). The party also stresses that this ethnic state should be mono-cultural and mono-racial. BILLIET *et al.* (2005) found a moderate and rather constant correlation across time between Nationalism and Ethnocentrism (± 0.31) among the Flemish. Although they supposed that 'citizens who strongly identify with their nation develop a negative attitude towards foreigners' (p. 3), they did not try to answer on the basis of the data whether indeed Nationalism leads to Ethnocentrism, or Ethnocentrism leads to Nationalism, or both effects operate simultaneously in a reciprocal causal relationship.

In another study by BILLIET (1995) on the relationships between Church Involvement, Individualism, and Ethnocentrism among Flemish Roman Catholics, it was found that Individualism, defined as 'unrestrained striving for personal interests', had a big direct effect on Ethnocentrism, while Church Involvement had only a small direct effect on Ethnocentrism. These results were obtained in cross-sectional research with the data collected on one measurement occasion only. Disadvantages of cross-sectional research are that the direction of cross-effects between the variables (e.g. whether the effect is from Individualism towards Ethnocentrism, or in the opposite direction, or both) is even more difficult to assess empirically than in longitudinal research and that there is no control over the autoregressions of the variables in assessing these cross-effects.

Characteristic for the cross-lagged panel design is that measurements of the same variables are obtained from the same subjects at two or more occasions. The data of the General Election Study (INTERUNIVERSITAIR STEUNPUNT POLITIEKE-OPINIEONDERZOEK, 1991, 1995, 1999) have this form and allow to solve the problems described above in discrete as well as in continuous time. Repeating measurements of the same variables at different points in time (1991, 1995 and 1999)

makes it possible to evaluate opposite causal directions separately in one and the same model. The effects of $x(t_1)$ on $y(t_2)$ and of $y(t_1)$ on $x(t_2)$ in opposite directions (cross-lagged effects) involve different data and the autoregressions of $x(t_2)$ on $x(t_1)$ and of $y(t_2)$ on $y(t_1)$ as well as the initial correlation between $x(t_1)$ and $y(t_1)$ can be controlled for. In the present study the reciprocal relationships between the latent variables Individualism (I), Nationalism (N), and Ethnocentrism (E) will be studied in a cross-lagged panel analysis for all three latent variables simultaneously. In total, there are nine effects that can be estimated for the three variables: Three pairs of reciprocal effects between I and N, N and E, and I and E, and the three autoregressions for I, N, and E, respectively. We hypothesize strong autoregressions for I, N, and E. Partly based on the theoretical considerations in BILLIET (1995) and BILLIET *et al.* (2005), we hypothesize a recursive causal chain structure between I, N, and E: I influencing N, N influencing E, and I having also a direct effect on E. As a starting point, therefore, we do not expect reciprocal effects between the variables. One or more of the implied null hypotheses (no effect of N on I, E on N, and E on I) could be rejected, however, leading to the acceptance of reciprocities.

The basic arguments for continuous time modeling were expounded by its pioneers in econometrics. Bergstrom (PHILLIPS, 1993, p. 23) emphasized that the economy does not cease to exist in between observations nor functions only at quarterly or annual intervals corresponding to the observations. GANDOLFO (1993, pp. 2–3) added that the results of a discrete time model should not depend on the length of the observation interval and must remain the same when the interval is, say doubled or halved. If the results should not depend on the period length, he concluded, they should remain valid when this length tends to zero (that is, when one switches over from discrete-time to continuous-time analysis). OUD (2007) explained troublesome paradoxes in the analysis of the popular cross-lagged panel design in discrete time and how to resolve these paradoxes through a continuous-time approach. Different researchers, studying the same causal effect in different discrete-time intervals, are unable to compare the strength of the effects found. The strength and order of magnitude of effects vary with the discrete-time interval chosen by the researcher, and even the sign of the effects may reverse when passing from one interval to the other or from discrete to continuous time. Furthermore, a cross-lagged panel analysis offers two sets of coefficients for reciprocal effects between variables, lagged and instantaneous coefficients. From a causal standpoint, the specification of instantaneous coefficients does not make sense, however. Instead, in continuous time, infinitesimal change coefficients are specified by a differential equation model, that is solved for the discrete measurement time points in the exact discrete model (EDM; see SINGER, 1992, pp. 11–12).

Perhaps the most compelling reason for analyzing cross-effects in continuous time is that equal effects found in discrete time do not guarantee at all that the underlying continuous-time effects are equal. The cross-lagged effects found in discrete time in fact are part of an ongoing process. Equality at a single point in time may be

consistent with quite different cross-lagged effect functions across time. For example, the cross-lagged effect functions of a pair of reciprocal effects, although having equal values at one specific point in time, may have quite different forms across time and different maxima found at different points in time. In particular, for the observation interval of 4 years in the General Election Study, the cross-lagged effects from I to E and from E to I could be found to be equal, but the cross-lagged effect functions, estimated on the basis of this same interval in continuous time, could show for a shorter (longer) interval the effect of I on E to be larger than of E on I and for a longer (shorter) interval the converse to be true.

Continuous-time analysis of reciprocal relations in the cross-lagged panel design can be performed in several ways (OUD, 2007). One possibility is to use the EDM for estimating the parameters of the underlying differential equation model. The EDM, introduced in 1961–1962 by BERGSTROM (1988), links in an exact way the discrete-time model parameters to the underlying continuous-time model parameters by means of nonlinear restrictions. The nonlinear restrictions can be implemented, for example, by means of the nonlinear SEM program Mx (NEALE *et al.*, 1999) as shown by OUD and JANSEN (2000). Another possibility is to use the approximate discrete model (ADM). Just as the EDM, the ADM was introduced by BERGSTROM (1966, 1984). An advantage of the ADM is that it allows less nonlinearly oriented SEM programs like LISREL (JÖRESKOG and SÖRBOM, 1996) to be used also in parameter estimation. In fact, the ADM utilizes only simple linear restrictions to approximate the differential equation model. In the present article, the ADM will be used to find the approximate parameter estimates, but these will be compared with the exact EDM parameter estimates.

The paper is organized as follows. Section 2 deals with some details of continuous-time modeling, especially the EDM and ADM. Section 3 has more details regarding the respondents and measurement model of the three latent variables I, N, and E in the study. In section 4 the main results are presented, whereas in section 5 the auto-regression functions, cross-lagged effect functions, and mean predictions are shown. Finally, section 6 contains the conclusions.

2 Continuous-time modeling by means of the approximate discrete model

2.1 Continuous-time model

To describe the development in continuous time of the latent state variables in $\mathbf{x}(t)$ (I, N, and E in the present study), we use the following quite general stochastic differential equation model

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}(t)\mathbf{u}(t) + \boldsymbol{\kappa} + \mathbf{G}(t)\frac{d\mathbf{W}(t)}{dt}, \quad (1)$$

$$\mathbf{y}_{t_i} = \mathbf{C}_{t_i}\mathbf{x}(t_i) + \mathbf{D}_{t_i}\mathbf{u}(t_i) + \mathbf{v}_{t_i}. \quad (2)$$

The observed variables are in $\mathbf{y}_{t_i}$, observed at discrete-time points t_i ($i = 1, \dots, T$) with measurement errors in $\mathbf{v}_{t_i}$. The elements of $\mathbf{W}(t)$ contain the Wiener process (see, e.g. JAZWINSKI, 1970; ARNOLD, 1974). In addition to the Wiener process, which by definition is normally distributed, the initial state variables in $\mathbf{x}(t_0)$ are assumed to be normally distributed, $\mathbf{x}(t_0) \sim N(\boldsymbol{\mu}_{x_{t_0}}, \boldsymbol{\Phi}_{x_{t_0}})$, as well as the measurement errors, $\mathbf{v}_{t_i} \sim N(\mathbf{0}, \mathbf{R}_{t_i})$.

Drift matrix $\mathbf{A}(t)$ is analogous to the autoregression matrix in discrete time. In fact, in the EDM and ADM, the autoregression matrix is derived as a functional of the drift matrix (SINGER, 1998). Important properties of the model depend on the drift matrix. For example, if all eigenvalues of all $\mathbf{A}(t)$ have a negative real part, the model is asymptotically stable.

By means of matrix $\mathbf{G}(t)$, Cholesky factor of diffusion matrix $\mathbf{G}(t)\mathbf{G}(t)'$, the standard multivariate Wiener process $\mathbf{W}(t)$, having covariance matrix $\mathbf{I}$ for $t = 1$, is transformed into general Wiener process with arbitrary covariance matrix (RUYMGAART and SOONG, 1985, pp. 68–75). Analogous to the relation between autoregression matrix and drift matrix, the discrete-time error covariance matrix is derived as a functional of the diffusion matrix.

Effects $\mathbf{B}(t)\mathbf{u}(t) \neq \mathbf{0}$ and $\mathbf{D}_{t_i}\mathbf{u}(t_i) \neq \mathbf{0}$ for fixed input variables in $\mathbf{u}(t)$ accommodate for nonzero and nonconstant mean trajectories $E[\mathbf{x}(t)]$ and $E(\mathbf{y}_{t_i})$ that are frequently observed even in the case of an asymptotically stable model. By means of vector $\boldsymbol{\kappa}$, state equation (1) introduces constant (over time) random-subject effects $\boldsymbol{\kappa} \sim N(\mathbf{0}, \boldsymbol{\Phi}_{\kappa})$. To distinguish from the changing state variables, we call them ‘trait’ variables. An important advantage of the state-trait model is that it distinguishes trait variance (unobserved heterogeneity between subjects) clearly from stability. Because in a pure state model ($\boldsymbol{\kappa} = \mathbf{0}$ for all subjects) all subject-specific mean trajectories coincide with the overall mean trajectory, trait variance and stability are confounded, an actually nonzero trait variance spuriously leading to a less stable model (little or no exponential decay) as a substitute to keep the subject-specific mean trajectories apart. By contrast, in a state-trait model, trait variance and stability are disentangled. Note that the covariance matrix $\boldsymbol{\Phi}_{\kappa, x_{t_0}}$ between trait and initial state cannot, in general, be assumed zero, because the trait $\boldsymbol{\kappa}$ is modeled to influence $\mathbf{x}(t)$ continuously, not only after but also before t_0 .

Preferable for interpretation is that the state equation matrices are taken to be time-invariant: $\mathbf{A}(t) = \mathbf{A}$, $\mathbf{B}(t) = \mathbf{B}$, $\mathbf{G}(t) = \mathbf{G}$, leading to the time-invariant version (3) of (1), to be used in this paper:

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \boldsymbol{\kappa} + \mathbf{G} \frac{d\mathbf{W}(t)}{dt}. \quad (3)$$

Time-invariant measurement equation matrices ($\mathbf{C}_{t_i} = \mathbf{C}$, $\mathbf{D}_{t_i} = \mathbf{D}$, $\mathbf{R}_{t_i} = \mathbf{R}$) are also preferable. Time invariance for the measurement equation is called measurement invariance in behavioral science. Taking the loading matrix equal across time ($\mathbf{C}_{t_i} = \mathbf{C}$) is considered a minimum requirement for making sure that the latent state variables measure the same thing across time and become meaningfully interpretable.

2.2 Exact discrete model

The EDM solves state equation (3) in discrete-time equation (4) for discrete-time interval Δt . In the time-invariant case, the solution depends on the time interval only and not on time itself.

$$\mathbf{x}_t = \mathbf{A}_{\Delta t} \mathbf{x}_{t-\Delta t} + \mathbf{B}_{\Delta t} \mathbf{u}_{t-\Delta t} + \mathbf{H}_{\Delta t} \boldsymbol{\kappa} + \mathbf{w}_{t-\Delta t} \quad \text{with } \text{cov}(\mathbf{w}_{t-\Delta t}) = \mathbf{Q}_{\Delta t}. \quad (4)$$

The following nonlinear relationships are derived between the continuous-time matrices in (3) and discrete-time matrices in (4) (HAMERLE, NAGL and SINGER, 1991; HAMERLE, SINGER and NAGL, 1993; OUD and JANSEN, 2000):

$$\begin{aligned} \mathbf{A}_{\Delta t} &= e^{\mathbf{A}\Delta t}, \\ \mathbf{B}_{\Delta t} &= \mathbf{A}^{-1}(\mathbf{A}_{\Delta t} - \mathbf{I})\mathbf{B}, \\ \mathbf{H}_{\Delta t} &= \mathbf{A}^{-1}(\mathbf{A}_{\Delta t} - \mathbf{I}), \\ \boldsymbol{\Phi}_{\kappa_{\Delta t}} &= \mathbf{H}_{\Delta t} \boldsymbol{\Phi}_{\kappa} \mathbf{H}_{\Delta t}', \\ \boldsymbol{\Phi}_{\kappa_{\Delta t}, x_{i_0}} &= \mathbf{H}_{\Delta t} \boldsymbol{\Phi}_{\kappa, x_{i_0}}, \\ \mathbf{Q}_{\Delta t} &= \text{irow}[(\mathbf{A} \otimes \mathbf{I} + \mathbf{I} \otimes \mathbf{A})^{-1}(\mathbf{A}_{\Delta t} \otimes \mathbf{A}_{\Delta t} - \mathbf{I} \otimes \mathbf{I})\text{row}(\mathbf{G}\mathbf{G}')]. \end{aligned} \quad (5)$$

Note that all the expressions in (5) involve the nonlinear matrix exponential

$$e^{\mathbf{A}\Delta t} = \sum_{k=0}^{\infty} \frac{(\mathbf{A}\Delta t)^k}{k!} = \mathbf{I} + \mathbf{A}\Delta t + \frac{1}{2}\mathbf{A}^2\Delta t^2 + \frac{1}{6}\mathbf{A}^3\Delta t^3 + \dots \quad (6)$$

Furthermore, $\boldsymbol{\kappa}_{\Delta t} = \mathbf{H}_{\Delta t} \boldsymbol{\kappa}$ is the discrete-time trait vector, $\boldsymbol{\Phi}_{\kappa_{\Delta t}}$ the covariance matrix of the discrete-time trait, and $\boldsymbol{\Phi}_{\kappa_{\Delta t}, x_{i_0}}$ the covariance matrix of the discrete-time trait and the initial state. ' $\otimes$ ' denotes the Kronecker product, 'row' the rowvec operation, putting the elements of a matrix rowwise in a column vector, and 'irow' the inverse operation.

The expression for $\mathbf{B}_{\Delta t}$ assumes the input variables $\mathbf{u}(t)$ to be piecewise constant between measurements. This indeed is a rather coarse approximation of the input. How to proceed when choosing a linear or even more complicated approximations for the input segments is explained by OUD and JANSEN (2000). The general procedure is extending the input with new variables that, in addition to the value at the segment start, contain further information about the form of the input segment: For example, in the linear case, the segment slope is added as a new variable.

2.3 Approximate discrete model

Still assuming the input to be piecewise constant between measurements, one derives from (3)

$$\int_{t-\Delta t}^t d\mathbf{x}(s) = \mathbf{A} \int_{t-\Delta t}^t \mathbf{x}(s)ds + \mathbf{B} \int_{t-\Delta t}^t \mathbf{u}(t-\Delta t)ds + \int_{t-\Delta t}^t \boldsymbol{\kappa}ds + \mathbf{G} \int_{t-\Delta t}^t d\mathbf{W}(s). \quad (7)$$

This gives rise to the approximation

$$\mathbf{x}_t - \mathbf{x}_{t-\Delta t} = \tilde{\mathbf{A}} \left[\frac{1}{2}(\mathbf{x}_t + \mathbf{x}_{t-\Delta t}) \right] \Delta t + \tilde{\mathbf{B}}\mathbf{u}_{t-\Delta t}\Delta t + \boldsymbol{\kappa}\Delta t + \tilde{\mathbf{G}}\Delta\mathbf{W}_t \quad (8)$$

with the integral $\int_{t-\Delta t}^t \mathbf{x}(s)ds$ in (7) replaced by the trapezoid approximation $[\frac{1}{2}(\mathbf{x}_t + \mathbf{x}_{t-\Delta t})]\Delta t$ and, consequently, $\mathbf{A}$, $\mathbf{B}$, $\boldsymbol{\Phi}_\kappa$, $\boldsymbol{\Phi}_{\kappa, x_{t_0}}$, and $\mathbf{G}$ by approximate $\tilde{\mathbf{A}}$, $\tilde{\mathbf{B}}$, $\tilde{\boldsymbol{\Phi}}_\kappa$, $\tilde{\boldsymbol{\Phi}}_{\kappa, x_{t_0}}$, and $\tilde{\mathbf{G}}$, respectively. A somewhat better approximation would result from using the trapezoid approximation simultaneously also for the input, that is, by simply replacing the values $\mathbf{u}_{t-\Delta t}$ at the input segment start in (8) and in the dataset during the estimation procedure by $\frac{1}{2}(\mathbf{u}_t + \mathbf{u}_{t-\Delta t})$.

As explained by BERGSTROM (1966, 1984, pp. 1172–1173), equation (8) takes the form of an econometric structural form equation (THEIL, 1971; JÖRESKOG, 1978)

$$\mathbf{x}_t = \mathbf{A}^* \mathbf{x}_t + \mathbf{A}_{\Delta t}^* \mathbf{x}_{t-\Delta t} + \mathbf{B}_{\Delta t}^* \mathbf{u}_{t-\Delta t} + \mathbf{H}_{\Delta t}^* \boldsymbol{\kappa} + \mathbf{w}_{t-\Delta t}^* \quad \text{with } \text{cov}(\mathbf{w}_{t-\Delta t}^*) = \mathbf{Q}_{\Delta t}^*, \quad (9)$$

if the following simple linear constraints in terms of the approximate matrices are imposed on the structural form matrices

$$\begin{aligned} \mathbf{A}^* &= \frac{1}{2} \tilde{\mathbf{A}} \Delta t, \\ \mathbf{A}_{\Delta t}^* &= \mathbf{I} + \frac{1}{2} \tilde{\mathbf{A}} \Delta t, \\ \mathbf{B}_{\Delta t}^* &= \tilde{\mathbf{B}} \Delta t, \\ \mathbf{H}_{\Delta t}^* &= \mathbf{I} \Delta t, \\ \boldsymbol{\Phi}_{\kappa \Delta t}^* &= \mathbf{H}_{\Delta t}^* \tilde{\boldsymbol{\Phi}}_\kappa \mathbf{H}_{\Delta t}^{*'} = \tilde{\boldsymbol{\Phi}}_\kappa \Delta t^2, \\ \boldsymbol{\Phi}_{\kappa \Delta t, x_{t_0}}^* &= \mathbf{H}_{\Delta t}^* \tilde{\boldsymbol{\Phi}}_{\kappa, x_{t_0}} = \tilde{\boldsymbol{\Phi}}_{\kappa, x_{t_0}} \Delta t, \\ \mathbf{Q}_{\Delta t}^* &= \tilde{\mathbf{Q}} \Delta t = \tilde{\mathbf{G}} \tilde{\mathbf{G}}' \Delta t, \end{aligned} \quad (10)$$

leading to reduced form (4) with reduced form matrices

$$\begin{aligned} \mathbf{A}_{\Delta t} &= (\mathbf{I} - \mathbf{A}^*)^{-1} \mathbf{A}_{\Delta t}^*, \\ \mathbf{B}_{\Delta t} &= (\mathbf{I} - \mathbf{A}^*)^{-1} \mathbf{B}_{\Delta t}^*, \\ \mathbf{H}_{\Delta t} &= (\mathbf{I} - \mathbf{A}^*)^{-1} \mathbf{H}_{\Delta t}^*, \\ \boldsymbol{\Phi}_{\kappa \Delta t} &= (\mathbf{I} - \mathbf{A}^*)^{-1} \boldsymbol{\Phi}_{\kappa \Delta t}^* (\mathbf{I} - \mathbf{A}^{*'})^{-1}, \\ \boldsymbol{\Phi}_{\kappa \Delta t, x_{t_0}} &= (\mathbf{I} - \mathbf{A}^*)^{-1} \boldsymbol{\Phi}_{\kappa \Delta t, x_{t_0}}^*, \\ \mathbf{Q}_{\Delta t} &= (\mathbf{I} - \mathbf{A}^*)^{-1} \mathbf{Q}_{\Delta t}^* (\mathbf{I} - \mathbf{A}^{*'})^{-1}. \end{aligned} \quad (11)$$

It is interesting to observe that (9), in addition to the lagged coefficients in $\mathbf{A}_{\Delta t}^*$, also includes instantaneous coefficients in $\mathbf{A}^*$. However, this is no true case of instantaneous effects such as in cross-sectional research, because via (11) the coefficients in $\mathbf{A}^*$ are constrained by the lagged ones.

Comparing (5) of the EDM with (11) of the ADM one observes that for the EDM one does not need to put constraints on the structural form, because in (5) the constraints are put directly and exactly on the reduced form, but the ADM has the advantage of offering simple linear constraints with a quite reasonable approximation.

Whereas in the popular but crude rectangle approximation $\tilde{\mathbf{A}}$ in $\mathbf{A}_{\Delta t} = \mathbf{I} + \tilde{\mathbf{A}}\Delta t$ only the value at the start of the integration interval is taken into account,

$$\mathbf{x}_t = \mathbf{A}_{\Delta t} \mathbf{x}_{t-\Delta t} \quad \text{or} \quad \frac{\Delta \mathbf{x}_t}{\Delta t} = \tilde{\mathbf{A}} \mathbf{x}_{t-\Delta t},$$

the trapezoid approximation $\tilde{\mathbf{A}}$ in $\mathbf{A}_{\Delta t} = (\mathbf{I} - \frac{1}{2}\tilde{\mathbf{A}}\Delta t)^{-1}(\mathbf{I} + \frac{1}{2}\tilde{\mathbf{A}}\Delta t)$ averages the values at the start and end point of the interval:

$$\mathbf{x}_t = \mathbf{A}_{\Delta t} \mathbf{x}_{t-\Delta t} \quad \text{or} \quad \frac{\Delta \mathbf{x}_t}{\Delta t} = \tilde{\mathbf{A}}[\frac{1}{2}(\mathbf{x}_t + \mathbf{x}_{t-\Delta t})]$$

(GARD, 1988, p. 192). The improvement is easily observed by putting both the exact nonlinear matrix exponential form and the approximate linear constraint forms of $\mathbf{A}_{\Delta t}$ in power series expansion:

$$\begin{aligned} \mathbf{A}_{\Delta t} &= e^{\mathbf{A}\Delta t} \\ &= \mathbf{I} + \mathbf{A}\Delta t + \frac{1}{2}\mathbf{A}^2\Delta t^2 + \frac{1}{6}\mathbf{A}^3\Delta t^3 + \frac{1}{24}\mathbf{A}^4\Delta t^4 + \dots \text{(exact)} \\ \mathbf{A}_{\Delta t} &= (\mathbf{I} - \frac{1}{2}\tilde{\mathbf{A}}\Delta t)^{-1}(\mathbf{I} + \frac{1}{2}\tilde{\mathbf{A}}\Delta t) \\ &= \mathbf{I} + \tilde{\mathbf{A}}\Delta t + \frac{1}{2}\tilde{\mathbf{A}}^2\Delta t^2 + \frac{1}{4}\tilde{\mathbf{A}}^3\Delta t^3 + \frac{1}{8}\tilde{\mathbf{A}}^4\Delta t^4 + \dots \text{(trapezoid)} \\ \mathbf{A}_{\Delta t} &= \mathbf{I} + \tilde{\mathbf{A}}\Delta t \quad \text{(rectangle)}. \end{aligned} \tag{12}$$

Whereas the rectangle approximation truncates the exact series, the weights in the trapezoid approximation are seen to go down only less quickly than in the exact series.

2.4 Application of the ADM in SEM

Although the EDM can be implemented in a nonlinear SEM program like Mx, less nonlinearly oriented but more user-friendly SEM programs like LISREL allow the use of the ADM instead of the EDM. In one estimation procedure (MÖBUS and NAGL, 1983) equation (8) is directly tackled by using the transformed data $\mathbf{x}_t - \mathbf{x}_{t-\Delta t}$ and $\frac{1}{2}(\mathbf{x}_t + \mathbf{x}_{t-\Delta t})$. Here we will use LISREL to estimate the structural form (9) with the simple linear constraints (10). LISREL and similar programs are specially valuable in the modeling process, because they provide plenty of information about model fit, about standard errors and modification results of individual parameters by means of so-called modification indices (JÖRESKOG and SÖRBOM, 1996). A detailed description of the specification and estimation of the ADM parameter matrices by means of LISREL is given by OUD (2007). Obviously, by means of a nonlinear SEM program one could also estimate the ADM on the basis of the reduced form matrices (11).

3 Respondents and measurement model

3.1 Respondents

In the General Election Study in Belgium (INTERUNIVERSITAIR STEUNPUNT POLITIEKE-OPINIEONDERZOEK, 1991, 1995, 1999), survey data were collected in 1991, 1995 and 1999 by the Inter-University Centre ISPO-PIOP (Universities of Leuven and Louvain-La-Neuve). The sample contained two types of respondents, Flemish respondents and Dutch-speaking respondents of the Brussels-Capital Region. The sample of the Flemish was selected as a two-stage sample with equal probabilities of the secondary units. In the first stage, equal-sized sets of secondary sampling units were randomly assigned to municipalities (primary sampling units) with probabilities proportional to size of registered voters within the municipalities. In the second stage, the secondary sampling units (respondents) were randomly selected within the municipalities from population registers.

After the election of 1991, 2691 selected Flemish respondents were interviewed for the first time for the Election Study 1991. In 1995, following the election of 1995, a subsample of 2050 respondents was taken from the original 2691 first-wave respondents. From these 2050 panel respondents only 1762 could be re-interviewed in 1995. Only 1239 respondents of the 1762 could be interviewed a third time in 1999. Details about the sampling procedure can be found in INTERUNIVERSITAIR STEUNPUNT POLITIEKE-OPINIEONDERZOEK (1991, 1995, 1999).

For practical reasons, the procedure followed in the Brussels-Capital Region was somewhat different from that followed in the Flemish (and Walloon) regions. Most of the 19 municipalities (communes) refused to give their authorization to draw a sample from the National Register. In addition, and this for political reasons (the political situation with regard to the language communities), it was (and is) illegal to have official lists of the Flemish and French-speaking inhabitants of Brussels. Details are again presented in INTERUNIVERSITAIR STEUNPUNT POLITIEKE-OPINIEONDERZOEK (1991, 1995, 1999). During the first wave of the Election Study 1991, 281 Dutch-speaking respondents of the Brussels-Capital Region were interviewed. From these 281 respondents, 75 also cooperated in the 1995 survey and 35 respondents could be interviewed for the third time in 1999. The total number of Flemish and Dutch-speaking respondents of the Brussels Capital Region, who have been interviewed three times, is therefore 1274. It is on this panel of $N = 1274$ respondents that all analyses in the sequel have been performed. The geographical distribution of these respondents over provinces in Flanders and Brussels is given in Table 1.

3.2 Measurement model

The LISREL model to be presented consists of two parts that are simultaneously estimated. The latent structural part, which contains the relationships between the latent variables, will be presented in the next section, the measurement part in this

Table 1. Geographical distribution of panel respondents in Flanders and Brussels: respondents interviewed in 1991, 1995 as well as 1999.

Province	Respondents
Antwerp	331
Flemish Brabant	187
Limburg	187
East Flanders	311
West Flanders	223
Brussels	35
Total	1274

section. The measurement part uses the following measurement equations for the observation time points $t_i = 1991, 1995, 1999$.

$$\mathbf{y}_{t_i} = \mathbf{C}_{t_i} \mathbf{x}(t_i) + \mathbf{d}_{t_i} + \mathbf{v}_{t_i} \quad \text{with } \text{cov}(\mathbf{v}_{t_i}) = \mathbf{R}_{t_i}. \quad (13)$$

Matrices $\mathbf{C}_{t_i}$ contain the loadings (measurement units) of the observed variables on the latent variables, vectors $\mathbf{d}_{t_i}$ the measurement origins, and matrices $\mathbf{R}_{t_i}$ the measurement error variances. As the observed variables are assumed to be unifactorial, each row in $\mathbf{C}_{t_i}$ has only one nonzero element. The measurement errors are assumed to be uncorrelated, implying the matrices $\mathbf{R}_{t_i}$ to be diagonal.

The three latent variables in the model were measured as follows. Individualism (unrestrained striving for personal interests) was measured by five 5-point-scale items and Ethnocentrism (negative attitude toward outgroups) by eight 5-point-scale items. Translated into English, the items read:

Individualism (I)

- (1) Everybody has to take care of himself first.
- (2) What counts is money and power.
- (3) Striving for personal success is important.
- (4) Always pursue personal pleasure.
- (5) Best not to deal too much with others.

Ethnocentrism (E)

- (1) Belgium should not have allowed in guest workers.
- (2) Immigrants cannot be trusted.
- (3) Guest workers threaten the employment of Belgians.
- (4) Guest workers exploit the social security system.
- (5) Muslims are a threat to our culture and customs.
- (6) Presence of different cultures enriches society.
- (7) Repatriate guest workers when number of jobs decreases.
- (8) No political activities for immigrants.

In contrast to the other items, item (6) under Ethnocentrism was positively formulated and its answers therefore reversely scaled.

The third latent variable, Nationalism (identification with the subnational Flemish community), was measured in a somewhat more complicated fashion.

Nationalism (N)

- (1) First place membership group: Flemish (2), Belgium (0), Rest (1) + Differences Flemish/Walloons: Major (2), Minor (0), Middle (1).
- (2) Flanders/Belgium must decide (10-0).
- (3) Belgium has to disappear/strengthened (5-1).
- (4) Split up/federalize social security (5-1).

The 5-point-scale item (1) with range (4-0) was formed by adding up two other three-point-scale items. The formulation of the latter items as well as of items (3) and (4) in 1991 was slightly changed in the later election years 1995 and 1999. The 11-point-scale item (2) was the only item for Nationalism having exactly the same formulation in 1991 as in subsequent election years. A formal test of measurement invariance (time invariance) over election years by means of the popular χ^2 -difference test (e.g. see JÖRESKOG and SÖRBOM, 1996, p. 138) was performed, in which the loadings, measurement origins, and measurement error variances in 1991 (in $\mathbf{C}_{1991}$, $\mathbf{d}_{1991}$, and $\mathbf{R}_{1991}$, respectively) on the one hand were compared with those in 1995 and 1999 (in $\mathbf{C}_{1995} = \mathbf{C}_{1999}$, $\mathbf{d}_{1995} = \mathbf{d}_{1999}$, and $\mathbf{R}_{1995} = \mathbf{R}_{1999}$, respectively) on the other hand. It turned out that only for item (4) under Nationalism time invariance had to be rejected. The same conclusion was drawn by BILLIET *et al.* (2005, p. 10). Therefore, in the sequel all measurement parameters under Nationalism will be specified to be time-invariant, except for item (4) having a deviating loading, measurement origin and measurement error variance in 1991.

Only one more deviation from time invariance was allowed in the measurement model by freeing the measurement origin of item (5) for Individualism in 1999. Freeing this single parameter, which increased its value from 2.456 to 3.286, had two additional effects. First the model χ^2 went down by the huge amount of 1209, implying a considerable improvement in model fit. But it also led to two of the three reliability estimates $R^2 = 1 - (\text{measurement error variance})/(\text{total item variance})$, which were negative caused by the estimated time-invariant measurement error variance being larger than the total item variance in 1991 and 1995, to turn positive. Evidently, the big increase in the mean of item (5) at time point 1999 is not in accordance with the mean development of other items. Freeing this parameter prevents it from unduly influencing the latent mean development at time point 1999.

The estimates of the measurement model are displayed in Table 2. Only the unstandardized loadings are shown, but in this case of unifactorial items the standardized loadings are simply $\sqrt{R^2}$. As is customary for identification of the measurement model, one of the loadings under each of the latent variables was fixed at 1.000 and one of measurement origins at 0.000. The former means that the measurement unit of the item involved is taken over by its latent variable, whose variance becomes equal to the variance of the item minus the measurement error variance, whereas the latter means that the mean of the latent variable becomes equal to the item

Table 2. Loadings (unstandardized), measurement origins, measurement error variances, and reliabilites (R^2) for the items of the latent variables (*t*-values italic).

Latent variable	Individualism (I)	Ethnocentrism (E)	Nationalism (N)
<i>Loadings</i>			
Item (1)	1.000 —	1.000 —	0.325 <i>30.3</i>
Item (2)	0.765 <i>35.8</i>	1.070 <i>40.0</i>	1.000 —
Item (3)	0.771 <i>34.7</i>	1.072 <i>39.0</i>	0.329 <i>32.7</i>
Item (4)	0.641 <i>34.1</i>	1.211 <i>41.5</i>	0.496 (1991) <i>27.9</i> 0.290 (1995/1999) <i>28.0</i>
Item (5)	0.162 <i>8.3</i>	0.961 <i>34.3</i>	
Item (6)		0.811 <i>32.4</i>	
Item (7)		1.250 <i>41.8</i>	
Item (8)		1.215 <i>38.9</i>	
<i>Measurement origins</i>			
Item (1)	0.000 —	0.000 —	0.282 <i>5.4</i>
Item (2)	0.366 <i>6.7</i>	−0.371 <i>−4.7</i>	0.000 —
Item (3)	0.403 <i>7.1</i>	−0.220 <i>−2.7</i>	0.870 <i>17.9</i>
Item (4)	0.590 <i>12.2</i>	−0.147 <i>−1.7</i>	0.159 (1991) <i>1.9</i> 1.818 (1995/1999) <i>36.0</i>
Item (5)	2.043 (1991/1995) <i>39.5</i> 3.286 (1999) <i>60.1</i>	0.195 <i>2.3</i>	
Item (6)		0.254 <i>3.4</i>	
Item (7)		−0.582 <i>−6.6</i>	
Item (8)		−0.468 <i>−5.1</i>	
<i>Measurement error variances</i>			
Item (1)	0.587 <i>31.4</i>	0.725 <i>41.0</i>	1.371 <i>39.9</i>
	$R^2 = 0.596$	$R^2 = 0.417$	$R^2 = 0.289$
Item (2)	0.661 <i>37.4</i>	0.442 <i>38.6</i>	3.836 <i>30.2</i>
	$R^2 = 0.348$	$R^2 = 0.559$	$R^2 = 0.638$
Item (3)	0.747 <i>38.1</i>	0.508 <i>39.2</i>	1.130 <i>38.9</i>
	$R^2 = 0.474$	$R^2 = 0.534$	$R^2 = 0.351$
Item (4)	0.548 <i>38.4</i>	0.450 <i>37.3</i>	1.126 (1991) <i>18.8</i>
	$R^2 = 0.352$	$R^2 = 0.638$	$R^2 = 0.567$ 0.750 (1995/1999) <i>31.1</i> $R^2 = 0.366$

(continued)

Table 2. (continued)

Latent variable	Individualism (I)	Ethnocentrism (E)	Nationalism (N)
Item (5)	0.917 43.5 $R^2 = 0.040$	0.731 41.2 $R^2 = 0.427$	
Item (6)		0.642 41.7 $R^2 = 0.304$	
Item (7)		0.456 36.9 $R^2 = 0.643$	
Item (8)		0.665 39.3 $R^2 = 0.553$	

mean. All loadings and all measurement error variances in Table 2 turn out to be highly significant, indicating that every item contributes to the latent variable it is an indicator of and that none of the items is a perfect indicator of the latent variable involved. Most informative in this respect are the reliability estimates R^2 (computed with respect to the total item variances in 1991). Item (4) for Ethnocentrism and item (2) for Nationalism have the highest R^2 -value, both $R^2 = 0.638$, item (5) for Individualism has the lowest: $R^2 = 0.040$. The latter item has also the loading with the lowest t -value. So, the contribution of the latter item, although having a significant loading, is lowest.

With regard to the measurement origins, it can be observed that for Individualism all remaining items have higher means than expected in terms of item (1), especially item (5). For Nationalism all remaining items have higher means than expected in terms of item (2). For Ethnocentrism most items have lower means than expected in terms of item (1). Most important is that by entertaining time invariance for the measurement origins almost everywhere, the dynamics of the model, especially also growth and decline in the means, is described almost exclusively by the latent structural part of the model.

4 Results on the latent dynamic level

The special case of (3) for describing the development of the latent state variables I, E and N and their relationships in continuous time is

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{A}\mathbf{x}(t) + \mathbf{b} + \mathbf{G}\frac{d\mathbf{W}(t)}{dt}. \quad (14)$$

Although the continuous-time relationships between the I, E, and N are specified in drift matrix $\mathbf{A}$, the latent intercept vector $\mathbf{b}$ continuously feeds the latent mean trajectories and the Wiener process $\mathbf{W}$ the latent covariance process via diffusion matrix $\mathbf{G}\mathbf{G}'$. The diffusion matrix was specified to be diagonal, because the modification indices computed by the LISREL program for the off-diagonal elements were low and did not exceed in both 1995 and 1999 the value of 7.882 used by JÖRESKOG

and SÖRBOM (1993, p. 93). No trait variables were specified, as their specification invariably led to nonadmissible solutions (negative trait variances and a nonconjugate complex eigenvalue in **A**) and appropriately restricting the model to solutions at the boundary of admissibility. We concluded that the initial condition was sufficient to differentiate trajectories for individual subjects from the mean trajectory.

By means of the LISREL program the ADM solution for the approximate $\tilde{\mathbf{A}}, \tilde{\mathbf{b}},$ and $\tilde{\mathbf{Q}} = \tilde{\mathbf{G}}\tilde{\mathbf{G}}'$ was found and by means of Mx the EDM solution for **A**, **b**, and **Q** = **GG'**. Both are given in Table 3. Most striking is that the ADM comes very close to the EDM with small differences in the third decimal only. It means that the EDM can safely be evaluated by means of the ADM and its standard errors as estimated by LISREL. As the model contains 73 parameters to be estimated and the number of (nonidentical) elements in the observed covariance matrix is $1326 = (51 \times 52)/2$ and in the mean vector 51, the model degrees of freedom is $df = 1326 + 51 - 73 = 1304$. The LISREL model $\chi^2 = 7881.1$ with $df = 1304$ does not imply a particularly good fit. It should be noted, however, that the model with 51 observed variables is huge, the sample of $N = 1274$ big, and that the time invariance of the continuous-time state-space model puts a lot of specific restrictions on the model as, for example, with regard to the measurement origins. It is therefore no surprise

Table 3. ADM estimates by means of LISREL (in $\tilde{\mathbf{A}}, \tilde{\mathbf{b}},$ and $\tilde{\mathbf{Q}}$; *t*-values italic) and EDM estimates by means of Mx (in **A**, **b**, and **Q**); the values in $\tilde{\mathbf{A}}$ and **A** have been standardized.

	I	E	N		I	E	N
I	$\begin{bmatrix} -0.069 \\ -9.41 \end{bmatrix}$	$\begin{bmatrix} 0.033 \\ 5.15 \end{bmatrix}$	$\begin{bmatrix} -0.007 \\ -1.39 \end{bmatrix}$		$\begin{bmatrix} -0.070 \\ 0.040 \end{bmatrix}$	$\begin{bmatrix} 0.033 \\ -0.063 \end{bmatrix}$	$\begin{bmatrix} -0.008 \\ 0.003 \end{bmatrix}$
E	$\begin{bmatrix} 0.039 \\ 7.48 \end{bmatrix}$	$\begin{bmatrix} -0.062 \\ -11.98 \end{bmatrix}$	$\begin{bmatrix} 0.003 \\ 0.80 \end{bmatrix}$		$\begin{bmatrix} 0.013 \\ 0.012 \end{bmatrix}$	$\begin{bmatrix} 0.012 \\ -0.061 \end{bmatrix}$	
N	$\begin{bmatrix} 0.013 \\ 2.31 \end{bmatrix}$	$\begin{bmatrix} 0.011 \\ 2.10 \end{bmatrix}$	$\begin{bmatrix} -0.061 \\ -10.79 \end{bmatrix}$				
	$\tilde{\mathbf{A}}$				A		
	I	$\begin{bmatrix} 0.061 \\ 3.28 \end{bmatrix}$			I	$\begin{bmatrix} 0.061 \\ 0.095 \end{bmatrix}$	
	E	$\begin{bmatrix} 0.094 \\ 7.58 \end{bmatrix}$			E	$\begin{bmatrix} 0.095 \\ 0.105 \end{bmatrix}$	
	N	$\begin{bmatrix} 0.105 \\ 2.21 \end{bmatrix}$			N	$\begin{bmatrix} 0.105 \end{bmatrix}$	
	$\tilde{\mathbf{b}}$				b		
	I	$\begin{bmatrix} 0.078 \\ 11.37 \end{bmatrix}$			I	$\begin{bmatrix} 0.079 \\ 0.045 \end{bmatrix}$	
	E	$\begin{bmatrix} 0.044 \\ 15.39 \end{bmatrix}$			E	$\begin{bmatrix} 0.045 \\ 0.469 \end{bmatrix}$	
	N	$\begin{bmatrix} 0.466 \\ 11.06 \end{bmatrix}$			N	$\begin{bmatrix} 0.469 \end{bmatrix}$	
	$\tilde{\mathbf{Q}} = \tilde{\mathbf{G}}\tilde{\mathbf{G}}'$				Q = GG'		

that the popular fit measure RMSEA (BROWNE and CUDECK, 1993) with value 0.068 indicates that the model fits ‘reasonably’.

With regard to the coefficients in drift matrices $\tilde{\mathbf{A}}$ and $\mathbf{A}$, an important difference in interpretability is between the auto-effects in the diagonal on the one hand and the cross-effects off-diagonally on the other hand. The auto-effects $\tilde{a}_{ii}$ and a_{ii} are scale free in the sense that they do not change under arbitrary linear transformations of I, E and N and so are directly interpretable. In particular, all three show significant negative feedback (-0.069 , -0.062 , -0.061 in $\tilde{\mathbf{A}}$; -0.070 , -0.063 , -0.061 in $\mathbf{A}$), implying stability or a long-term tendency for the individual trajectories to converge to the mean trajectories $E[\mathbf{x}(t)]$. These negative drift coefficients correspond to autoregressions of 0.763, 0.787, and 0.782, respectively, over the observation interval of $\Delta t=4$, and thus quite high as hypothesized. The differences between the autoregressions are small, but the autoregression or tendency to keep autonomously the same level across time is somewhat higher in E and N than in I.

To become comparable, the cross-effects $\tilde{a}_{ij}$ and a_{ij} , not being scale free, have been standardized by multiplying by the ratios of the initial standard deviations: $\sqrt{\phi_{x_i, t_0}} / \sqrt{\phi_{x_j, t_0}}$ (see Table 4). This is equivalent to choosing the essentially arbitrary variances of the latent variables to be equal at the start. In contrast to the hypothesized recursive (causal chain) structure (see Figure 1a), the empirical analysis results in Table 3 reveal clear reciprocal relationships between I and E and unidirectional influences of both I and E on N (see Figure 1b). The effect from I to E (0.039) is somewhat stronger than in the opposite direction from E to I (0.033). Although also significant, the effects from I and E on N are both small (0.013 and 0.011, respectively). The role of Nationalism N is totally different from what we expected and turns out not to influence Ethnocentrism E (both the effect of N on I and of N on E are nonsignificant), but to undergo weak influences from both I and E. The rather strong effect back from E to I is also different from expectation.

Table 3 further shows that all three latent variables have intercepts in $\tilde{\mathbf{b}}$ with a significantly positive contribution to latent development. Finally, all three latent variables have a significant diffusion coefficient in $\tilde{\mathbf{Q}}$, implying proportions of explained variance in I, E, and N of 0.591, 0.639, and 0.653 in 1995, and 0.588, 0.603, and 0.604 in 1999, respectively.

Table 4. Estimates of the initial state variances and covariances in $\Phi_{x_{t_0}}$ and the initial state means in $\mu_{x_{t_0}}$ by means of LISREL.

	I	E	N	
I	0.778 17.45			2.460 83.18
E	0.321 13.44	0.508 17.10		2.899 116.82
N	-0.183 -2.41	0.106 1.87	5.999 17.38	4.231 51.64
	$\Phi_{x_{t_0}}$			$\mu_{x_{t_0}}$

Fig. 1. Dynamic relationships between latent state variables Individualism (I), Ethnocentrism (E), and Nationalism (N) as hypothesized (a) and found in the empirical analysis (b).

5 Autoregression functions, cross-lagged effect functions, and latent mean estimates and predictions

The autoregression and cross-lagged effect functions trace the autoregressions and cross-lagged effects through continuous time. That is, the effects are computed not only for the empirical observation intervals $\Delta t = 4$ and $\Delta t = 8$ but interpolated and predicted for arbitrary intervals also. This is done on the basis of the drift matrix $\mathbf{A}$ (see Table 3) by means of $\mathbf{A}_{\Delta t} = e^{\mathbf{A}\Delta t}$ in (5). $\mathbf{A}_{\Delta t}$ over arbitrary intervals Δt is also called the unit impulse-response, because it depicts in continuous time the effect of an isolated unit increase in one state variable at $\Delta t = 0$ on all state variables for all intervals $\Delta t \geq 0$. The first column of $\mathbf{A}_{\Delta t}$ is the impulse-response of $\mathbf{x}_0 = [1\ 0\ 0]'$, the second column of $\mathbf{x}_0 = [0\ 1\ 0]'$ and the third column of $\mathbf{x}_0 = [0\ 0\ 1]'$. As drift matrix $\mathbf{A}$ in Table 3 is standardized with the standard deviations at t_0 taken as the units, both Figure 2 (autoregression functions) and Figure 3 (cross-lagged effect functions for the significant cross-effects in Table 3) give the effect of a one standard deviation increase in the independent latent state variable on the dependent latent state variable. Because the model is asymptotically stable (the eigenvalues -0.103 , -0.060 , -0.031 of $\mathbf{A}$ are all strictly negative), both the autoregression functions and the cross-lagged effect functions go to 0. The cross-lagged effect functions start also from value 0, because over $\Delta t = 0$ there can be no effect between different variables. The autoregression functions, however, start from value 1, because in the same variable there is no change over $\Delta t = 0$.

It should be stressed in advance that, with the exceptions of the values for the empirical observation intervals $\Delta t = 4$ and $\Delta t = 8$, the curves in Figures 2 and 3 as well as in Figure 4 consist of interpolations and predictions, becoming less precise the more distant they are from the empirical observation intervals. However, it is

Fig. 2. Autoregression functions.

Fig. 3. Cross-lagged effect functions for the significant cross-effects in Table 3.

important to show results over a pretty long time period, because this gives a clear picture of the long-run implications and plausibility of the model.

Although the differences between the autoregression functions in Figure 2 are too small to be taken seriously, they nicely illustrate the problematic character of a discrete-time cross-lagged panel analysis and the advantages of analyzing in continuous-time. The set of autoregression functions turns out to be non-monotone in the sense that the order of magnitude is not the same for all intervals Δt . In fact, at both empirical observation intervals of $\Delta t = 4$ and $\Delta t = 8$ in discrete time, E has the highest autoregression values (0.787 and 0.632), N the next highest (0.782 and 0.611)

Fig. 4. Latent mean estimates and predictions.

and I the lowest (0.763 and 0.593). The results of the continuous-time analysis in Figure 2, however, reveal that from $\Delta t = 14.2$ onwards the order between N and I reverses with N becoming the variable with the lowest autoregression. This implies, that the discrete-time analyst working with, for example, $\Delta t = 16$ and $\Delta t = 24$, would come to totally different conclusions than his colleague working with $\Delta t = 4$ and $\Delta t = 8$. The continuous-time analysis, however, exactly describes how the result of the interplay between auto- and cross-effects in **A** develops according to the model over the whole range of increasing intervals Δt .

Turning now to Figure 3, one observes, in contrast to the autoregression functions in Figure 2, monotonicity. The order of magnitude of the four cross-lagged effect functions turns out to be for all other intervals the same as for the empirical observation intervals $\Delta t = 4$ and $\Delta t = 8$. Particularly, in the feedback loop between I and E, the effect of Individualism on Ethnocentrism ($I \rightarrow E$) exceeds everywhere the effect of E on I ($E \rightarrow I$) in the opposite direction. Moreover, for the relatively small effects of I and E on N, the effect of Individualism on Nationalism ($I \rightarrow N$) is everywhere slightly larger than the effect of Ethnocentrism on Nationalism ($E \rightarrow N$). However, the continuous-time analysis also shows that all four cross-lagged effects reach their maximum quite some time after the empirical observation intervals $\Delta t = 4$ and $\Delta t = 8$. The maximum of effect $I \rightarrow E$ (0.235) is reached somewhat later ($\Delta t = 17.0$) than the lower maximum (0.190) of $E \rightarrow I$ in the opposite direction ($\Delta t = 16.4$). The maximum of $I \rightarrow N$ (0.105) at $\Delta t = 22.0$ is reached 1.2 years before the maximum (0.099) of $E \rightarrow N$ at $\Delta t = 23.2$. Again, the latter differences are certainly too small to be taken seriously. However, the monotonicity of the cross-lagged effect functions also in the long run and the fact that the period needed for the maximum impacts to occur clearly exceeds the data collection period are important results.

Finally, Figure 4 shows how, on the basis of the parameter estimates in Table 3, the means of the latent variables develop over time. This is based on the following equation, derived from (4)–(5):

$$E[\mathbf{x}(t)] = e^{\mathbf{A}(t-t_0)} E[\mathbf{x}(t_0)] + \mathbf{A}^{-1} [e^{\mathbf{A}(t-t_0)} - \mathbf{I}] \mathbf{b}. \quad (15)$$

It is interesting that the mean values of I and E did hardly change in the period 1991–1999 and are hardly expected to change over the prediction period, whereas quite some increase in N is observed in the period 1991–1999 with a further moderate increase predicted until about 2019. As said before, predictions in the far future, say from 2007 onwards, become extremely uncertain and can only be done on the premise of the conditions during the data collection period remaining equal. However, extrapolating the curves to the far future clearly shows the implications and long-run plausibility of the model. At least in this case, even in the long run the curves do not reach impossible or extremely unlikely values (e.g. negative values or explosive behavior).

6 Conclusions

Relationships between Nationalism, Ethnocentrism, and Individualism have been studied on the same dataset before. However, this was done in a cross-sectional analysis (Individualism and Ethnocentrism), in a longitudinal analysis but without analyzing the direction of the effect (Nationalism and Ethnocentrism), nor were all three concepts analyzed simultaneously or in continuous time. In this paper a state-space analysis is performed with all three concepts handled simultaneously as latent state variables that influence each other continuously across time. The model analysis was performed by means of the LISREL program by estimating the ADM, and the EDM was also estimated. Differences between both were negligible. Individualism and Ethnocentrism turned out to be connected in a moderately strong feedback relationship with the effect from Individualism towards Ethnocentrism somewhat stronger than in the opposite direction from Ethnocentrism towards Individualism. Both Individualism and Ethnocentrism had small effects on Nationalism. The role of Nationalism was found to be dependent only with no significant effect on the two other latent variables.

Standardized cross-lagged effect functions (unit-impulse responses) revealed the maximum impact of Individualism on Ethnocentrism (0.235) expected to occur after 17 years and in the opposite direction (0.190) after 16.4 years. The smaller maximum impacts of Individualism on Nationalism (0.105) and Ethnocentrism on Nationalism (0.099) are expected to occur later, after 22.0 and 23.2 years, respectively. Predictions of the development of the latent variables showed no change in the mean values of Individualism and Ethnocentrism over the coming decades and the moderate increase in Nationalism between 1991 and 1999 to continue over the coming years and to fade away around 2019.

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