Identity Comparison and Member Commitment to Agricultural Cooperatives: *A Renewed Analysis Comparing Two Estimation Techniques*

Jason Scott Entsminger
Research Associate and Ph.D. Candidate,
McQuinn Center for Entrepreneurial Leadership,
Division of Applied Social Sciences, University of Missouri
jse9t5@missouri.edu

Selected Paper prepared for presentation at the
2017 Agricultural & Applied Economics Association Annual Meeting
Chicago, Illinois
July 30 - August 1, 2017

Abstract

Agricultural cooperatives have long been identified within as a seminal organizational form enabling collective action, thus playing a key role in rural economic success. Simultaneously, these organizations hold social meaning for adherent members, playing a part in rural socialization processes. Through these distinct roles cooperatives have gained prominence as drivers of rural community development. However, recent trends show that, while patronage of these organizations has been increasing, total membership and number of organizations have been in decline. Various models have been proposed to explain such behavioral outcomes by members, including those which examine the cognitive antecedents to such behaviors, such as commitment. This article investigates the validity of one such model which posits that organizational members' commitment is driven by their identification with the organization, and that such identification is a cognitive process comparing expectations about what the organization's identity should be like with perceptions of it as enacted. The model includes multiple forms of commitment and accounts for the hybrid nature of the agricultural cooperative's identity as both an economic and social institution. Validity of the model is tested using Structural Equation Modelling procedures applied to a data set garnered from surveys of agricultural cooperative members in three countries. Estimation of the SEM procedures is conducted using both Maximum Likelihood and Weighted Least Squares with Mean- and Variance-Adjustment. Results under both estimation techniques generally support acceptance of the model, but raise both new questions about the strength of accepting cross-national validity and disparities in path coefficients between estimation techniques.

Acknowledgements

The author makes the following acknowledgements: to David Whetten, Peter Foreman, and Randall Westgren for sharing the underlying data set, and to the latter for their commentary and tutelage on this project as doctoral committee members; to Ze Wang for her commentary on this article and instruction in SEM; and to Harvey James for his commentary on this article as a doctoral committee member.

This research was supported financially by the McQuinn Chair in Entrepreneurial Leadership, an endowment of the University of Missouri.

Keywords: Agricultural cooperatives; Organizational identification; Hybrid identity; Commitment; Organizational theory; Membership; Structural Equation Modelling; Maximum Likelihood; Weighted Least Squares

Introduction

Tradition – at least that of the last century-and-a-half – has placed the agricultural cooperative, in some form or another, in a storied position within the ethos of the rural economy and agrarian culture of the Western nations. Despite the pride-of-place gained in its ascendancy during the first-half of the 20th century, recent decades have seen a relative decline in the quantity, capacity, and legitimacy of this organizational form. This trend of stagnation – if not outright decline – has been a cause for concern by many, and of great interest among rural policy makers and scholars alike. Agricultural cooperatives have, throughout their lifespan, presented an organizational form which achieves both economic prosperity and social cohesion within rural communities. Given these concerns, researchers from various fields – including economics, strategic management, organizational sociology, and others – have begun to apply various tools to examine what drives the trends in agricultural cooperative organizations, including defection, of various forms, by their members.

One line of inquiry centers on investigating the commitment by individuals to an organization, positing that such commitment is an antecedent of behavioral outcomes. In other words, decisions on the level of patronage or maintaining membership status at all – versus seeking alternatives and defecting, in whole or in part, from the organization – are predicated on and driven by the level of commitment to the organization a given member holds. Commitment, however, is not monolithic; it is multifaceted, presenting multiple modalities. Further, commitment by a member has been shown to be impacted by the match between the identity of that individual and the *organizational identity* of the social object to which they are an adherent. This matching of identities has been conceptualized and operationalized in various ways. Foreman and Whetten (2002) present one such model, in which the individual makes a cognitive comparison between what they expect the organization's identity to be and how they actually perceive it as enacted.[1] Additional complexity arises in that many organizational identities have several facets because the organization has a hybrid identity. In the case of agricultural cooperatives, which play both social and economic roles, these organizations have two central facets of their identities: a normative facet and a utilitarian facet.

This study focuses on validating one model of this commitment as an ***antecedent*** to behavioral outcomes, a necessary first step in later developing robust explanations for trends in agricultural cooperative membership. It analyzes a set of data gleaned from surveys in three countries of agricultural cooperative members first compiled by Foreman, Whetten, and Westgren, thereby providing support for the generalizability of such a model across geographic and cultural space. It builds on previous work by them and colleagues conducted using this same base data set; work that has to date remained unpublished within the literature. Those preliminary works also examined the validity of organizational identification-commitment framework and its generalizability across different geographic contexts. Both were found generally to be supported by the analyses preceding this one. However, those works relied on a linear regression basis of analysis, applying hierarchical Ordinary Least Squares (OLS) and Maximum Likelihood (ML) Structural Equation Modeling estimation techniques. Further, the data sets used in these have been further refined, now consisting of only observations from members of *agricultural* cooperatives. Therefore, I append the previous work by applying SEM techniques to compare the validity of the model under linear regression-based Maximum Likelihood and probit regression-based Mean- and Variance-adjusted Weighted Least Squares (WLSMV) estimation techniques.

[1] i.e. the individual compares what they believe the organizational identity *should* be to what they perceive it to *actually* be.

Background

Review much of the recent literature on agricultural cooperative trends – say, that within the last three decades - and one is likely to find language signaling some alarm that the organizational form is on the decline. This is, at least, in terms of total numbers of organizations and members. Consider, as a primary example, the United States, where annual reports on agricultural cooperatives from the USDA's Rural Development Service show a continuous downward trend for both of these measures. Of course, organization numbers and total membership is not a comprehensive picture of agricultural cooperatives. Many may try to hedge these figures by pointing out negative historical trends in the total number of U.S. farmers and ranchers. However, the same series of reports on U.S. agricultural cooperatives provides evidence that such attempts are overstated. ConsiderFigure 1, taken from the 2013 annual USDA report of cooperatives data, which shows that while the number of farms has remained relatively stable over the preceding 35 years, the total number of cooperative memberships dramatically declined; the two roughly match, when once memberships were nearly double the total number of farms. Interestingly, economic performance of these organizations, such as the total business volume (in dollars), has simultaneously been on the rise. In fact the most recent USDA data report, covering 2015, set a new record high for net operating margins. Trends for other nations, such as Canada or France, are not as easily identified due to reporting issues. However, there is some indication from what was available in published records that the stories elsewhere are similar to that of the U.S.

This context provides a conundrum, one which has not been ubiquitously examined by researchers. Only nascent work has been completed in empirically analyzing and explaining these observed phenomena, and it has been done in fits and starts. On such piece is Westgren and Foreman (1998), who consider the historical data for U.S. cooperatives from an organizational ecology perspective and examine the nature of the legitimation of this organizational form. Their concluding discussion lays the keystone pertinent to this current endeavor as such:

Even though pressure existed on the pragmatic[2] legitimacy of the cooperative form of enterprise, as farmers and their cooperatives were constrained by the routines (equity financing from patrons, limited strategic scope) and the norms of operation (one patron-one vote) that were required by business charter and regulations at the State and Federal level, farmers continued to patronize their cooperatives rather than non-cooperative firms. […] If, as Nourse (1942) proposed, agricultural cooperatives should only exist to serve a pragmatic purpose as a "competitive yardstick" to discipline non-cooperative firms, we should not see the increase in patronage over time, as measured by market share and business volume. The local, immediate forces of resource dependence that are built on the complex, costly, and inefficient exchange relationships between farmers and their cooperatives should militate against such growth, given the existence of both competing non-cooperative firms and the successful "yardstick". We infer that cognitive legitimacy sustains the institution into the 1980s, but we cannot find proof of the diminished salience of normative legitimacy. In fact, as Foreman and Whetten (1998) find in surveys of cooperative members in the Midwest[3], farmers support the normative nature of cooperatives as an organizational form, though they wish for increased organizational efficiency in the coops to which they belong. (p. 19)

[2] Here, "pragmatic" is another term for "utilitarian".

[3] Data which forms the basis for the project at hand herein.

The salient point is this: there is clearly some feature that attenuates the utilitarian motive for adherence to agricultural cooperatives. That adherence, of course, takes the dual forms of membership (a discrete outcome) and patronage (a continuous outcome). While the former is in decline, the latter is ascendant, and thus exploring a model which might later explain the two forms of the adherence decision is required. Clearly then the matter of eventual import is the prediction of a behavioral outcome[4] (adherence) which can manifest itself along a scale or continuum that stretches from total defection (termination of membership), through maintaining membership but with diminished patronage, up to increased patronage. But this adherence behavior must have some antecedent cause.

A well-established body of literature from the management and organizational science fields posits that antecedent root of such a behavior as the commitment of the individual to the organization. (See as examples Steers (1977), Mathieu and Zajac (1990), Balfour and Wechsler (1996), and Meyer et al. (2002)) Commitment is a preference for maintaining relationships, in this case doing business with, participating in the activities and governance of, and holding membership within the agricultural cooperative. (Fulton M. , 1999) As Cechin et al. (2013) note, there is a growing understanding that commitment is an attitude distinct from the behavioral outcomes which it may influence, such as adherence. The treatment of member commitment is by no means new subject matter within the literature on agricultural cooperatives, stretching beyond the Fulton (1999) work. Consider, for example, a Principal Paper Session of the *American Journal of Agricultural Economics* in 2001, refereed by Richard Sexton, which presented a triptych of papers on “Cooperatives and Membership Commitment”. (See Cotterill (2001) for a summary discussion of the three articles.) The works in that series arguably focused narrowly on economic rationales underlying the utilitarian role of cooperative organizations, through

[4] Explicitly, adherence can be conceptualized as a behavioral expression, by the actions of membership and contribution, of an intent or desire to continue affiliation.

examinations of the incentive problems (Sykuta & Cook, 2001), an oligopolistic market equilibrium model (Fulton & Giannakas, 2001), and a duopsonistic selection model (Karantininis & Zago, 2001). Earlier work by Fulton and Adamowicz (1993) and the later endeavor by Pascucci and Gardebroek (2010) are similarly narrow. Moreover none of the aforementioned can be said as truly measuring commitment as a cognitive, attitudinal construct.

Numerous approaches to commitment as such a construct have been proposed. (Becker T. , 1992; Meyer & Allen, 1984; Mathieu & Zajac, 1990; Randall, 1990; Becker H. , 1960; Mottaz, 1989; Mowday, Porter, & Steers, 1982; O'Reilly & Chatman, 1986; Reichers, 1985; Wiener, 1982) In the organizational commitment literature, there is a growing consensus that the construct should be multi-dimensional; commitment has both an affective, emotional component (the individual *wants* to be an adherent) and a calculative, instrumental component (the individual *needs* to be an adherent). (Becker T. , 1992; Mathieu & Zajac, 1990; Meyer & Allen, 1997) Following this literature, we implement the widely-applied construct first developed by Meyer and Allen which is comprised of measurement scales for both emotional and instrumental elements: Affective and Continuance Commitment. (Allen & Meyer, 1990; McGee & Ford, 1987; Meyer & Allen, 1984) The application of this dual-commitment approach to cooperatives is not new. (Foreman & Whetten, 2002; Jussila, Byrne, & Tuominen, 2012; Jussila, Goel, & Tuominen, 2012)

However, the story continues. What drives an individual to feel committed to an organization? Early work by Whetten, Lewis, and Mischel (1992) points towards the degree to which an individual sees alignment between with the identity of the organization, termed *identification.* Others within the literature have proposed that concepts similar to commitment, such as cooperation and citizenship (Dutton, Dukerich, & Harquail, 1994) and the loyalty of alumni (Mael & Ashforth, 1992), are also tied to notions of identification. As can be deduced from the description, identification is a cognitive process in which alignment is assessed by the individual. Two main conceptualizations of this process exist. The first is present within the aforementioned works by Dutton, Dukerich, and Harquail (1994) and Mael and Ashforth (1992). In this conception the individual compares their perceptions of the organization's identity with their own intrinsically-determined self-identity. In the second conceptualization, individuals evaluate their perception of the organization's identity with the expectations they hold about what that organizational identity should be. In this approach, the individual projects an identity (their expectations) onto the organization and cognitively compares this to the identity their see as being actually enacted by the organization. This projection is thus necessarily rooted in their self-concept and thus, it is argued, is an extension of pertinent elements of their self-identity. This latter approach is employed in work by Whetten, Lewis, and Mischel (1992), Reger et al. (1994), Foreman and Whetten (2002), and others.

It must be emphasized, of course, that many organizational forms – just like the individuals that constitute them – have multiple identity facets. The literature on agricultural cooperatives makes it abundantly clear that this is the case for the organizational form of interest here. Two central facets emerge, one a normative, social element and the other a pragmatic, utilitarian, instrumental element. (Westgren & Foreman, 1998; Groves, 1985; Ortmann & King, 2007) This exact dichotomous structure has been treated before within the organizational literature, most poignantly by Albert and Whetten's seminal 1985 paper. It is important to note that hybrid identity organizations, as they have come to be termed, are "not simply an organization with multiple components, but [that] it considers itself (and other consider it), alternatively, or even simultaneously, to be two different types of organizations". (Albert & Whetten, 1985, p. 270) These two facets can originate from value systems that otherwise may seem incompatible (Parsons, 1956; Etzioni, 1960), and, as intimated by the results of Westgren and Foreman (1998), may have an effect of attenuating adherence behavioral outcomes.

Conceptual Framework

Given the preceding discussion, a conceptual framework for analyzing member commitment to an agricultural cooperative is developed, which I represent graphically in Figure 1. Here individuals have expectations about what the organization's identity should be. They also make assessments about how the organization enacts that identity, forming perceptions. Perceptions and expectations are both cognitive constructs of the individual. These are compared via an additional cognitive process that seeks to determine the level of congruence between the two. When incongruent there is a cognitive distance, misalignment, or gap between perceptions and expectations. This comparison is the measure of the individual's identification with the organization. This is in-line with the conceptualizations of Reger, Gustafson, DeMarie, & Mullane (1994) and Whetten, Lewis, & Mischel (1992), among others.

When this comparison yields no gap (i.e. there is perfect congruence or alignment between perceptions and expectations), then the individual perfectly identifies with the organization. Thus, the small the gap the greater the identification with the organization, and the larger the gap the less the individual identifies with the organization. This brings us to the second "stage" of the framework. The larger the gap (i.e. the less the individual identifies with the organization), the less committed that individual will be. Thus, there is hypothesized a negative relationship between the comparison and commitment[5]. However, the conceptual framework in Figure 2 is a simplified one. One must recall that there is sufficient evidence to conclude that agricultural cooperatives have hybrid organizational identities, akin to the concept of Albert & Whetten (1985). Thus cooperative members will engage in cognitive comparisons of the Normative and the Utilitarian identity facets; they may identify with the

[5] As indicated in the previous section, the approach adopted allows the researcher to eschew the problematic behavioral aspect by addressing its antecedent, commitment. Thus, behaviors are included in the diagrammatic representation of the conceptual framework only as a reminder of this connection.

cooperative on both, one, or neither facet. Likewise, commitment has two aspects, Affective and Continuance, both of which may be impacted by the identification of the individual with the organization. Thus, the simplified conceptual framework doubles in all dimensions.

Data

The data utilized in this analysis was obtained by surveys of members of rural cooperative organizations in three different countries. The initial sample was from a survey of members in the Midwest U.S. The specific items utilized to assess the normative and utilitarian identity of responding cooperative members was developed prior to survey implementation via focus groups and interviews with managers and directors of cooperatives in the region. This initial phase was implemented by PEOPLE. That survey was then replicated among cooperative members in Alberta, Canada and Ouest France (Bretagne and Pays de la Loire), France. Although there were some differences in the characteristics of the three samples, great care was taken to ensure that the surveys were nearly identical and the sample groups were as similar as possible. Specific elements of sampling for each of the three groups follows.

Midwest, U.S.

A survey was conducted of 1900 members of rural cooperatives in a midwestern state whose names and contacts were drawn from the list of customers served by a rural electric utility cooperative. That utility cooperative provided at the time of sampling electric services for over 90% of rural residents in a five-county region. The sampling frame was chosen for several theoretical and methodological reasons. Because of the overwhelming percentage of rural residents served by the electric coop, it was expected that researchers would garner a fairly representative sample of the members of the various agricultural coops in the region. Furthermore, because much of the meaning and significance of rural cooperatives in America is tied to agriculture, the original researchers wanted to obtain a sample that included both farmers and non-farmers that held a range of support for and involvement in coops. Using membership lists of farm-related coops only would obviously have given a censored sample, excluding non-farmers and those farmers that do not actively support cooperatives. However, using the electric coop's customer base as a sampling frame provided the best opportunity to capture a full range of views and experiences across a variety of coops.

Approximately 800 surveys were returned after two mailings, for an overall response rate of 42%. After removing surveys with significant amounts of incomplete information through pairwise deletion there were 670 useable surveys, for an initial 37% effective response rate. Although this is a respectable response rate, especially given the nature of the survey and the sample, it leaves open the possibility of sample bias and non-response bias. Several comparison tests were performed to check for these biases. First, using current agricultural census data, the data compilers were able to check for demographic differences between those survey respondents who were active farmers (45 % of the sample) and the overall population of farmers in the state. In sum, farmer-respondents were fairly representative of the population at large, thus reducing the possibility of sample bias.

All of the respondent households were members of the rural electric coop, and 74% of the respondents were members of at least one additional coop. These other co-ops were all agriculturally related, either for marketing grain, supplying seeds and chemicals, or providing financial credit to farmers and rural businesses. Over half (52%) of the respondents were active in farming, and almost 80% had farmed at one point in their lives and were receiving income from farm-related activities. For the purposes of this analysis we deleted all respondents who were solely members of the electrification cooperative (and did not farm) and used only responses without missing data from the twenty four variables which are used in this model. This left a sample of 364 cases for analysis, with a final effective rate of 19%.

Alberta, Canada

Similar to the U.S. sample, a survey was conducted among 2000 members of several agricultural cooperatives in Alberta, Canada. These members were randomly drawn from the membership roles of

20 major cooperatives in the province, including the dominant Alberta Wheat Pool. After two mailings, over 820 responses were returned, for a 41% response rate. After deleting surveys in a listwise manner with incomplete information and from self-described non-farmers, 688 cases remained, resulting in an effective response rate of 34%. No response bias was identified in comparing demographic data with Canadian census data.

Ouest France

In contrast to the sample sizes of approximately 2000 in the U.S. and Canada, a smaller sample of 1000 was drawn of farmers in western France. The sample of cooperative members was drawn randomly from membership lists of eight agricultural cooperatives that belong to the Confederation of Agricultural Cooperatives of the West of France (CCAOF). Staff members of the CCAOF chose four cooperatives from the Bretagne region and four from the Pays de la Loire region and mailed 1000 forms to the sample population. Nonrespondents were contacted by telephone four weeks after the mailing. The final response was 336 surveys, for a response rate of 34%. Interestingly, only a few responses were discarded due to incomplete information. I have retained 311 complete cases for further analysis.

The CCAOF staff compared the respondent profiles to the General Agricultural Census data for the country and determined that the respondents were better educated than the population of farmers (33% had completed the baccalaureate, compared to 2% of the general population) and younger than the general population (mean age of 41 years for respondents vs. 55 years for census). The differences reflect, in part, the nature of the more industrialized, modern production in the West of France compared to the national demographics.

The questionnaire was translated from the English version into French by a francophone student in France, and this translation was corroborated by two French-speaking American faculty. The resultant French translation was then back-translated into English by an anglophone student in France and was corroborated by an American language (French) instructor. The authors and the CCAOF staff resolved disparities. The translated document was pre-tested by CCAOF staff with ten farmer/cooperators drawn randomly from the membership list from a nonsampled cooperative in the Bretagne region.

Variables

Twenty four of the 146 items from the survey design are used in this analysis. The twenty four variables are coded on a 7-point Likert scale. There are four indicator/measurement variables for each of six latent variables. Table 1 lists the variables from the x vector, the observable variables associated with the exogenous measurement model for identity. The wording of the questions is given in the table. The questions were pretested to (a) assure that the underlying latent variables had multiple indicators and (b) highlight the distinction between expected identity and perceived identity in both a normative and utilitarian domain. Table 2 lists the variables from the y vector, the observable variables associated with the endogenous measurement model for commitment. The wording of the questions to which the respondents scored 1 (strongly disagree) to 7 (strongly agree) is given in the table. These items are derivatives of Meyer and Allen's (1984; 1997) well validated affective and continuance commitment scales. We selected four of the eight items in their affective commitment scale, particularly intending to capture effects of the member's identification with and attachment to their local cooperative. The four items selected to measure continuance commitment were intended to assess the twin effects of availability of alternatives and personal disruption on a member's decision to stay with their cooperative.

Table 5 reports the descriptive statistics for each of the observed variables denoted above, including the SPSS-calculated measures for skewness and kurtosis. For the purposes of investigating the data at this level, I do not report disaggregation by country. Histograms for each of the 24 variables, using the combined data for all countries, as well as Shapiro-Wilk and Kolomogorov-Smirnov tests of normality, both for combined data and disaggregated by country were also calculated, but are not reported herein. The results of Table 5 indicate that there is substantial skewness within the observed responses for most of the variables. Non-normality is further confirmed by both the graphical and statistical analyses conducted but not reported here. Within the data, skewness of variables is almost uniformly[6] biased leftward, toward lower values (i.e. favoring "agree"), an unsurprising feature given the long line of literature on yea-saying in Likert scale responses.

Methodological Approach

Maintaining consistency with the majority of the preceding work on organizational identification and commitment, I apply commonly accepted SEM procedures[7] to analyze the conceptual model with the newly refined data. First, a measurement model is estimated and its fit evaluated. Using the modification indices tool of the software program, recommendations for altering this model are considered when fit is poor. Any alterations made must follow from a theoretical basis. After selection of a final measurement model, a theorized structural/path model is estimated and its fit assessed. The modification indices procedure is also run to determine if there are any alterations which would improve a poorly-fitting model. The χ^2 Difference Test is performed to compare structural models to the final measurement model.

Here I adopt the general form of the theorized structural relationship presented in Westgren, Foreman, and Whetten (2009). Organizational identification is captured through the comparative cognitive process outlined by Foreman and Whetten (2002) in which the perceptions a member holds about how the organization enacts an identity facet are measured against what the member expects that element to have. This is operationalized within the SEM as an "induced variable", as discussed in Klem (2000). The initial weightings for the paths to comparison variables are set to be opposite signed

[6] The notable exceptions being Affective Commitment Scale factors "belonging" (y5) and "family" (y6).

[7] The primary reference are the procedures and recommendations presented in Kline (2016).

(i.e. perceptions to comparisons are set to -1, while expectations are set to +1). Latent constructs have four indicators each, replicating those of Westgren, Foreman, and Whetten (2009).

Analysis is conducted using the raw dataset (as opposed to a polychoric correlation matrix or covariance and means set), which enables the use of Robust ML and WLSMV estimation techniques[8] in addition to standard ML. Notably, while the latter offers certain attractive properties including asymptotic unbiasedness, consistency, and maximal efficiency in the estimation of parameters, it also requires the assumption that variables – at least observed ones – have a continuous and normal underlying multivariate distribution. CITES. Thus, as Li (2016) notes, "ML is not, strictly speaking, appropriate for ordinal variables" as this assumed normality is "severely violated when the analyzed data have only a few response categories (Lubke & Muthén, 2004)". (ibid., pp. 936 – 937) Robust ML (MLR) offers one alternative in the face of such a likely violation, preserving the asymptotic unbiasedness in parameter estimates featured in standard ML, but correcting standard errors and chi-square statistics. Going a step farther, however, are the class of diagonally-weighted least squares techniques, which includes *MPlus*' WLSMV procedure, which were developed explicitly for use with categorical data. As Li (2016) explains "WLSMV makes no distributional assumptions about *observed* variables" instead assuming a "normal *latent* distribution underlying each observed categorical variable". (ibid., p. 937; emphasis in original) Importantly, WLSMV still holds ML and MLR components at its core:

> *The WLSMV estimation proceeds by first estimating thresholds and polychoric correlations using ML. The parameter estimates are then obtained from the estimated asymptotic variances of the polychoric correlation and threshold estimates*

[8] See Li (2016) for a concise, but detailed, comparative discussion of the three estimation techniques, as well as an empirical investigation of their outcomes under simulated Likert-scale data.

> *used in a diagonal weight matrix [...]. Using the same sandwich-type matrix form as for MLR, the obtained standard error estimates are given by the square roots of the diagonals of the estimated asymptotic covariance matrix of the estimated parameter vector [...] It is worth noting that the aim of statistical corrections to standard errors in WLSMV is to compensate for the loss of efficiency when the full weight matrix is not calculated, and the mean and variance adjustments for test statistics in WLSMV are targeted to make the shapes of the test statistics be approximately close to the reference chi-square distribution with the associated degrees of freedom. (Li, 2016; p. 938)*

The underlying data to be used in validating the organizational identification-commitment model herein described is exclusively comprised on responses on Likert-scaled items. As such this analysis becomes subject to the well-known debate over whether to treat such data as continuous or categorical. Preceding works aiming to validate the model have adopted ML, with its attendant assumption of normality. Instead, I specifically adopt an approach of agnosticism to the competing sides in the debate over Likert-scaled data, performing a comparative analysis to facilitate evaluation.

Unlike prior studies using this data set, here M*plus* software is utilized for the analysis in place of AMOS[9]. Further differentiating this work from its predecessors is the approach to validating measurement models. Here an “integrated” measurement model is formulated in the first stage of analysis where all latent factors – those for both identity and commitment – are included to covary.

[9] See Narayanan (2012) for a comparative review of available software packages. There M*plus’* strength is identified as its capabilities in dealing with both continuous and categorical variables, observed data, and latent factors, all of which are critically important to the data set involved in this analysis.

Previous works performed Confirmatory Factor Analysis (CFA) on the latent constructs for these two "sides" of the path diagram independently. Best practices, including those proposed by Anderson and Gerbing (1988), prescribe the integrated approach utilized here. It must be cautioned, however, that the "integrated" measurement models here are still not complete; by their nature, the two induced variable constructs (compnorm and computil), cannot be included within the measurement model, as they are constructed, at least as required by M*plus* coding language, solely by regressive relationships (i.e. causal paths) to the constituent latent factors.

Results

Following the procedures outlined above final forms of both the measurement and structural models were derived under both ML and WLSMV. Note that this is standard ML throughout. Robust ML (MLR in *MPlus*) was also performed but the results under this technique were not meaningfully differentiable from those of standard ML. Thus, the choice was made to report and compare only the two. This has the added benefit of enabling better comparison with previous works which relied solely on standard ML. It is also worthwhile to mention that an ML estimation of was conducted using the "clusters" feature of *MPlus* to specifically test/account for the possibility of correlation among standard errors along national lines. The results of this test model showed no statistically significant effect and no meaningful divergence in results over estimation without the added step.

As it happens, the forms which offer the best fit under both estimation techniques are identical. The final ***structural*** form is reported in Figure 3, following the commonly accepted standards for graphical representation of latent factors, observed variables, covariances, structural paths, and disturbances/residuals. Pattern coefficients (a.k.a. factor loadings[10]) for both the measurement and

[10] Kline (2016) advocates against the use of this term, calling it ambiguous. However, for the rest of this article it is retained, if only as a matter of convenience to clearly distinguish for the reader between the paths from latent factors to the indicators by which they are measured and those between latent factors which represent the structural portion of the model.

structural models under both estimation techniques are reported in Table 6. Path coefficients of the structural models are similarly reported in Table 7. Here, only those results for the combined data (all countries estimated as a singular set) are reported. In all models, all factor loadings and path coefficients were statistically significant beyond the 0.001 level. Table 8 reports the fit statistics for all final models estimated, including the estimation of group-only models.[11] Covariance estimates are not reported here in detail. However, when pertinent select covariance results are discussed within the sections that follow. All results reported here are standardized (STDYX), and thus are to be interpreted as the coefficient resulting for a change of one standard deviation.

Measurement Model Coefficients

The final[12] form measurement model here, as noted in previous sections, differs from the approach adopted in preceding work using this data set. Here, the measurement model estimates both the identity and commitment components together, with all latent factors allowed to co-vary. Further, to achieve acceptable fit, a number of covariances between indicators had to be included which were not present in the final models of previous work. For example, the final CFA models reported in Westgren, Foreman, and Whetten (2009) included only the covariance y_5 with y_6.

[11] It should be noted that more robust group analysis techniques could not be performed under WLSMV because the data does not have observations across all points (1 to 7) for all items in the Likert-scales, causing a run error. Since such robust techniques could not be performed for comparison across the two estimation methods, results for ML estimation are not reported or discussed in this paper.

[12] i.e. the best-fitting model that is theoretically justified.

Results of this measurement model for both ML and WLSMV indicate that standardized factor loadings are well in line with the general rule of thumb of being greater than 0.40[13]. (Walker & Maddan, 2009) One also notes that the magnitudes of these loadings appear to be consistent between the linear- and probit-regression based estimation techniques, with those for the latter being slightly higher in all but one instance[14]. Notably, some of the lowest factor loadings under both methods are those for the two sets of commitment indicators which are set to co-vary, y_1 with y_2 and y_5 with y_6.

In terms of covariances, only two showed no or low significance: Utilitarian Expectation with Continuance and Affective commitment under both ML ($p=0.097$ and 0.312, respectively) and WLSMV ($p=0.039$ and 0.302, respectively). The sign on each was positive and magnitudes were low in comparison to other covariance measures between latent factors. The covariances between indicator variables were all of the same relative magnitudes and following an inflation pattern similar to that of the factor loadings between the estimation techniques, with one exception. Under ML the covariance between x_1 and x_5 was 0.250, while under WLSMV it was 0.128.

Structural Model Coefficients

Based on the final form of the measurement model, structural models were calculated. As a starting point, I attempted to replicate exactly the structural model of Westgren, Foreman, and Whetten (2009), which allowed for two covariances between latent factors (utilper with normper and utilexp with utilper). Under the newly refined data set and within M*plus*, this model could not be estimated at all; the model would not converge, even under considerable relaxation of convergence criteria. It is

---

[13] Some practitioners strongly dissuade from using such rules of thumb, encouraging that assessment of results be based on expectations of theory. In this line, I also conclude that the magnitudes of standardized factor loadings are in line with expectations.

[14] y_8 is 0.002 less under WLSMV than under ML

suspected that the cause is linear dependence between the comparison induced variables and the commitment latent factors. Once covariance was allowed between the affective and continuance commitment latent factors, the model could converge. However, this still had poor fit and modification indices procedures indicated significant improvements would be made by allowing the additional covariances between all identity perception and expectation latent factors. This is the final model reported graphically in Figure 3.

As seen in Table 6, factor loadings remain essentially consistent with those of the measurement model. Consistency is also maintained between the ML and WLSMV estimations for these results. In terms of structural paths, reported in Table 7, the signs of results are exactly consistent with those found in Westgren, Foreman, and Whetten (2009). Those authors present a detailed interpretation and dissection of those results, which is reproduced here in the appendix. One should note that the path coefficients of the structural model components (in Table 7) for both the ML and WLSMV estimations are interpreted in the same manner: as simple linear regression coefficients. This is because the dependent variables are latent constructs, and thus continuous, meaning that these particular elements are estimated using straightforward linear regressions[15]. The coefficients reported are *MPlus'* STDYX standardizations, which use both the variances of the continuous latent variables as well as those of the background variables for correction. These are interpreted based on a one-standard-deviation change. Thus as an example, a one standard deviation widening in the gap between perceptions and expectations on the organization's normative identity (i.e. less identification with the organization by the average member along normative lines) causes a *decrease* of 0.187 in the continuance commitment

[15] The difference between the techniques comes in their treatment of dependent variables which are categorical (and by construct, observed). Under ML such outcomes are estimated under logistic or log-odds, while under WLSMV these are treated with probit applications.

Similar to the factor loadings, there is consistency in magnitude between the two estimation techniques for the path coefficients *within the identification component* of the model (paths A, B, C, and D). However, this consistency between estimation techniques is not present across the all features of the structural model. First, several covariances have divergent magnitudes between the techniques. These are utilitarian expectations with normative expectations (.360 and .544), utilitarian expectations with utilitarian perceptions (0.426 and 0.545), affective with continuance commitment (0.407 and 0.299), and x_1 with x_5 (0.239 and 0.095). [For ML and WLSMV estimations respectively.] Second, and perhaps more pronounced, there are divergences in magnitude between the two estimation techniques for the path coefficients for the effects of identification on commitment (paths E, F, G, and H). By example, the coefficient for Path F (the affect of low normative identification on affective commitment) is -0.322 under ML, but -1.368 under WLSMV. As a basis of understanding the magnitude of these differences on the whole, I calculated the absolute *differences* between the two estimation techniques for all estimated coefficients (both measurement model and structural model factor loadings, and the structural path coefficients). Then using this information calculated differences as a percent of the average results. The average difference percentage for factor loadings is 6.64% and 6.72% for measurement and structural models, respectively. For the four identity paths (A – D) it is 15.41%. But for the effects on commitment paths (E – H) it is 106.1%.

Model Fit Statistics

As a preliminary matter, one should note the large sample size for both the combined data (n=1363) and the groups (see Table 4). It is well know that such large sample sizes lead to concern in interpreting the results certain goodness of fit measures such as χ^2 and Weighted Root-mean-square Residual (WMRM).

For the sake of thoroughness, I do, however, report those results[16] in Table 8. Following the recommendations of Hu and Bentler (1998; 1999), I focus on a multi-measure approach to evaluating model fit using SRMR (and, for WLSMV, its quasi-equivalent, WRMR) supplemented with RMSEA, CFI, and/or TLI. First I discuss the fit statistics for the combined data (all groups) estimations, which have had their coefficient results reported and discussed in this paper. Then I will turn to a brief commentary on the fit of the models for group data, whose coefficient results are omitted here.

With the combined data, the final measurement model estimated under ML has exceptionally good fit, with an SRMR of 0.035 (standard cutoff is <0.05), an RMSEA value of 0.040, and the probability of the RMSEA being less than the cutoff (0.05) at 100%. Comparatively, fit under the WLSMV estimation is acceptable, but not to the same degree – in absolute terms – as that for ML. The WRMR for the combined data is 1.323, which exceeds the preferred cut-off value of 1.000. However, unlike SRMR, we temper this result by considering the sample size. RMSEA under WLSMV is 0.048, just within the critical range, and the probability of the actual value being within the critical region is 88.5%. The acceptability of the structural models are more ambiguous. SRMR for this model worsens, to 0.051, above the cut-off for "good" fit but within the range for a conclusion of "acceptable" fit. The WRMR also increases, to 1.447. The RMSEA values increase, but are within the cut-off range for both estimation techniques (ML=0.045 and WLSMV=0.050). However, while the probability of the RMSEA being less than 0.05 remains high for ML estimation (99.0%), for WLSMV it drops considerably, to 48.3%. I also perform χ^2 Difference Tests[17] to compare the structural model to the measurement model in which it is nested,

---

[16] All χ^2 results were statistically significant beyond the 0.001 level. Under smaller sample sizes this would be a cause for concern, but under the sizes here will be ignored.

[17] For ML these are conducted manually in the standard manner. For WLSMV the DIFFTEST operations procedure within M*plus* is used by necessity.

theoretically. For both ML and WLSMV the Difference Tests are statistically significant. Under other circumstances this would lead to rejecting the structural model and accepting the measurement model. However, as noted previously the measurement model lacks the induced variables by necessity. Therefore, the result of these tests should be considered suspect until further investigation can inform the author's understanding of the methodological limitations.

Although robust group analysis techniques could not be applied comparatively between the two estimation techniques, there is still a need to examine what evidence can be offered – despite its limited nature – on the performance of the models across the three groups. Previous work by Foreman, Sheep, Whetten, and Westgren used the original, less-refined data set to examine the cross-national (i.e. inter-group) generalizability of the constructs. They applied robust group analysis techniques, but only under ML estimation, and concluded that there was "strong support for the cross-national validity of both the model of identification and the measures of identity" for the three regional samples in the data set. (p.25) Here, I only report the fit statistics for the estimations of the models run for the separated group samples. These results are consistent with those discussed above for the combined data estimations in terms of comparisons between measurement and structural models and ML and WLSMV estimation techniques.

Of particular note is that the estimations of the French data have consistently poorer fit across all dimensions compared to those of the U.S. and Canadian samples. Under ML estimation, both the French measurement and structural models had SRMR and RMSEA values that were the highest of any group. Values were exceeding the "good" cut-off at 0.052 and 0.062, respectively, for SRMR and 0.050 and 0.054, respectively, for the RMSEA. The probability of RMSEA being within the "good" range was 52.2% and 17.4%, respectively. WLSMV results were similar, with WRMR values for measurement and structural models, respectively, of 1.015 and 1.088. This is in comparison to most[18] of the estimations

[18] The U.S. and Canadian measurement models and the U.S. structural model

for the other two national sub-samples, whose WRMR were below the cut-off value, in the acceptance range. RMSEA for French WLSMV estimations was acceptable, but not “good”. Notably, the probability that the actual RMSEA for the measurement and structural model for this group being within the acceptance range was essentially 0% for both, making a determination of good-fitting models along this measure unlikely.

Results for goodness of fit in the U.S. and Canadian models are more ambiguous than for the French. SRMR for these measurement models under ML estimation indicates good fit, (U.S.=0.044 and CAN=0.038), but this is not the case for the related structural models (U.S.=0.056 and CAN=0.060). RMSEA for ML estimations fares better, with all values being below the cut-off and relatively high probabilities of the actual values being the same. For WLSMV the picture is more muddied. WRMR values are below – or very near, in the case of the Canadian structural model – the cut-off value, indicating acceptable model fit when accounting qualitatively for sample size. RMSEA values are also within the acceptable range for the Canadian models, and the relevant probabilities of this being the case for the actual values are also high. However, this is not true for the U.S. models.

Conclusion

From the preceding discussion, a number of new aspects come to light. First, the analysis conducted here indicates that there may be some underlying construct, such as a cognitive feature, influencing the evaluation of normative identity facet of the organization. This is extrapolated from the finding that the best fitting measurement models here were arrived at after modification indices procedures consistently indicated larger fit improvement values for the imposition of covariances among normative indicators than those for utilitarian indicators. For the same reason applied to the structural model estimations, I theorized that there may be a “permeability” in the cognitive processes employed to conduct comparative evaluation between perceptions and expectations, and even perhaps within the constructs of affective and continuance commitment. These are substantive departures from the assumptions and findings of previous work on this model. I interpret these observations as being potentially indicative of a stronger role for cognition than previously expected.

While this finding is a departure from prior estimations of this model, the analysis here does verify some central findings of preceding work with this data set and with others. This includes continued support for the views that (1) within an organization of hybrid identity, such as an agricultural cooperative, there is conflict or competition between the normative and utilitarian identities, (2) members' identification with the cooperative affects their commitment to it at some level, and (3) a greater emphasis on the utilitarian identity of the coop (i.e. it acts more like a business, and thus is less differentiated from an Investor-owned Firm alternative) lowers the commitment by members. Further, evidence from this project as to the applicability of the model across discrete national groups is mixed, but also limited. Aspects of model fit across separated group estimations begin to question prior conclusions asserting cross-national generalizability of the model and its underlying scales. This should be revisited under more robust circumstances. Unfortunately, confident conclusions cannot be made here since data constraints preclude the use of *MPlus'* robust group analysis tools under WLSMV.

What is not clear from this analysis is the general acceptability of one estimation technique over another (or the acceptance of both). The results reported above provide a conundrum, one which will require study and evaluation beyond the scope of this project to fully disentangle. The analysis here showed divergence between the results of ML and WSLMV estimations. Given conclusions by recent methodological advancements, such as Li's (2016) comparative investigation, this is not a complete surprise. The results here mimic Li's in meaningful ways, notably that ML results are consistently lower than those of WLSMV. In my results divergence does not appear to be uniform; some elements offer comparable magnitudes between the two techniques, while others are not. Answers as to why this is are not yet fully apparent, nor is a clear answer to which method should justly be employed. Thus, I have explicitly chosen to report both here. The conundrum further extends beyond the balancing of direct factors like estimate unbiasedness (where WLSMV is favored) or standard error bias and interfactor correlations (where robust ML is favored); one also must balance what the two techniques can accomplish in examining and validating other aspects of theoretical models. Here, for example, the cost of WLSMV's stringent demands precluding the use of robust inter-group validation tools may strongly outweigh the underestimation of model parameters by ML, favoring the latter in cases where such validation (or rejection) is a more pressing research need than highly accurate coefficient results.

The immediately preceding discussion is not frivolity when one considers the implications for the central objective at hand: forming a model of the antecedents to adherence behavior. Having an acceptable model of this stage is a necessary first step in effectively investigating the dualistic behavioral outcomes of membership and patronage decisions. My investigations here confirm the validity of the Foreman and Whetten construction of such a model, but also identify new concerns worthy of explicit empirical investigation. This investigation cannot be done with the current data set, and will require direct attention of researchers to suss out whether there are underlying cognitive processes that must be distinctly accounted for within the identification-commitment model. That said, I also contend that it is time the model is extended to include direct application to behavioral outcomes data; there is growing support that the antecedent model examined here "works" to explain commitment, now let us begin delineating the strength of commitment's effect on member behaviors.

References

Albert, S., & Whetten, D. (1985). Organizational Identity. In B. Staw, & L. Cummings (Eds.), *Research on Organizational Behavior* (Vol. 7, pp. 263-295). Greenwich, CT: JAI Press.

Allen, N., & Meyer, J. (1990). The Measurement and Antecedents of Affective, Normative, and Continuance Commitment to the Organization. *Journal of Occupational Psychology*, 1-18.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 411-423.

Balfour, D. L., & Wechsler, B. (1996). Organizational Commitment: Antecedents and Outcomes in Public Organizations. *Public Productivity & Management Review, 19*(3), 256 - 277.

Becker, H. (1960). Notes on the Concept of Commitment. *American Journal of Sociology*, 32-42.

Becker, T. (1992). Foci and Bases of Commitment: Are They Distinctions Worth Making? *Academy of Management Journal*, 232-244.

Cechin, A., Bijman, J., Pascucci, S., & Omta, O. (2013). Decomposing the Member Relationship in Agricultural Cooperatives: Implications for Commitment. *Agribusiness, 29*(1), 39 - 61.

Cotterill, R. W. (2001). Cooperative and Membership Commitment: Discussion. *American Journal of Agricultural Economics*, 1280-1281.

Dutton, J., Dukerich, J., & Harquail, C. (1994). Organizational Images and Member Identification. *Administrative Science Quarterly*, 239-263.

Etzioni, A. (1960). *A Comparative Analysis of Organizations.* New York: Free Press.

Foreman, P., & Whetten, D. (2002). Members' Identification with Multiple-Identity Organizations. *Organization Science*, 618-635.

Fulton, J., & Adamowicz, W. L. (1993). Factors That Influence the Commitment of Members to their Cooperative Organization. *Journal of Agricultural Cooperation*, 39 -53.

Fulton, M. (1999). Cooperatives and Member Commitment. *LTA*, 418-437.

Fulton, M., & Giannakas, K. (2001). Organizational Commitment in a Mixed Oligopoly: Agricultural Cooperatives and Investor-Owned Firms. *American Journal of Agricultural Economics*, 1258 - 1265.

Groves, F. (1985). *What is Cooperation?* Madison, WI: University Center for Cooperatives.

Hu, L.-t., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, 424-453.

Hu, L.-t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal* , 1-55.

Jussila, I., Byrne, N., & Tuominen, H. (2012). Affective Commitment in Co-operative Organizations: What Makes Members Want to Stay? *International Business Research, 5*(10).

Jussila, I., Goel, S., & Tuominen, H. (2012). Member Commitment in Co-operatives: The Utilitarian Approach. *Business and Management Research, 1*(3).

Karantininis, K., & Zago, A. (2001). Endogenous Membership in Mixed Duopsonies. *American Journal of Agriclutural Economics*, 1266 - 1272.

Klem, L. (2000). Structural equation modeling. In L. G. Grimm, & P. R. Yarnold (Eds.), *Reasing and understanding more multivariate statistics* (pp. 227-260). Washington, DC: American Psychological Association.

Kline, R. B. (2016). *Principles and Practice of Structural Equation Modeling* (Fourth ed.). New York: The Gulford Press.

Li, C.-H. (2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavioral Research*, 936 - 949.

Mael, F., & Ashforth, B. (1992). Alumni and their Alma Maters: A Partial Test of the Reformulated Model of Organizational Identification. *Journal of Organizational Behavior*, 103-123.

Mathieu, J. E., & Zajac, D. M. (1990). A Review and Meta-Analysis of the Antecedents, Correlates, and Consequences of Organizational Commitment. *Psychological Bulletin, 108*(2), 171 - 194.

Mathieu, J., & Zajac, D. (1990). A Review and Meta-analysis of the Antecedents, Correlates, and Consequences of Organizational Commitment . *Psychological Bulletin*, 171-194.

McGee, G., & Ford, R. (1987). Two (or More?) Dimensions of Organizational Commitment: Reexamination of the Affective and Continuance Commitment Scales. *Journal of Applied Psychology*, 299-317.

Meyer, J. P., Stanley, D. J., Herscovitch, L., & Topolnytsky, L. (2002). Affective, Continuance, and Normative Commitment to the Organization: A Meta-analysis of Antecedents, Correlates, and Consequences. *Journal of Vocational Behavior*, 20 - 52.

Meyer, J., & Allen, N. (1984). Testing the 'Side-bet Theory' of Organizational Commitment: Some Methodological Considerations. *Journal of Applied Psychology*, 372-378.

Meyer, J., & Allen, N. (1997). *Commitment in the Workplace: Theory, Research, and Application.* Thousand Oaks, CA: Sage Publications.

Mottaz, C. (1989). An Analysis of the Relationship Between Attitudinal Commitment and Behavioral Commitment. *Sociological Quarterly*, 143-158.

Mowday, R., Porter, L., & Steers, R. (1982). *Employee-organization Linkages: The Psychology of Commitment, Absenteeism, and Turnover.* New York: Academic Press.

Narayanan, A. (2012). A Review of Eight Software Packages for Structural Equation Modeling. *The American Statistician*, 129-138.

O'Reilly, C., & Chatman, J. (1986). Organizational Commitment and Psychological Attachment: The Effects of Compliance, Identification, and Internalization on Prosocial Behavior. *Journal of Applied Psychology*, 492-499.

Ortmann, G., & King, R. (2007). Agricultural Cooperatives I: History, Theory and Problems. *Agrekon*, 18-46.

Parsons, T. (1956). Suggestions for a Sociological Approach to the Theory of Organizations - I. *Administrative Science Quarterly*, 63-85.

Pascucci, S., & Gardebroek, C. (2010). Some Like to Join, Others to Deliver. An Econometric Analysis of Farmers' Relationships with Agricultural Co-operatives. *Proceedings of the 114th EAAE Seminar "Structural Change in Agriculture".* Berlin, Germany: EAAE.

Randall, D. (1990). The Consequences of Organizational Commitment: Methodological Investigation. *Journal of Organizational Behavior*, 361-378.

Reger, R., Gustafson, L., DeMarie, S., & Mullane, J. (1994). Reframing the Organization: Why Implementing Total Quality is Easier Said Than Done. *Academy of Management Review*, 565-584.

Reichers, A. (1985). A Review and Reconceptualization of Organizational Commitment. *Academy of Management Review*, 465-476.

Rural Development Service. (2014). *Cooperative Statistics 2013.* Washington, D.C.: United States Department of Agriculture.

Rural Development Service. (2016). *Agricultural Cooperative Statistics 2014.* Washington, DC: United States Department of Agriculture.

Steers, R. M. (1977). Antecedents and Outcomes of Organizational Commitment. *Administrative Science Quarterly, 22*(1), 46 - 56.

Sykuta, M. E., & Cook, M. L. (2001). A New Institutional Economics Approach to Contracts and Cooperatives. *American Journal of Agricultural Economics*, 1273 - 1279.

Walker, J. T., & Maddan, S. (2009). *Statistics in Criminology and Criminal Justice: Analysis and Interpretation* (Third ed.). Burlington, MA: Jones & Bartlett Learning, LLC.

Westgren, R., & Foreman, P. (1998). Legitimacy and The Institutionalization Of Agricultural Cooperatives as An Organizational Form. *Academy of Management Annual Meeting.* San Diego, CA: Academy of Management.

Whetten, D., Lewis, D., & Mischel, L. (1992). Towards and Integrated Model of Organizational Identity and Member Commitment. *Academy of Management Annual Meeting.* Las Vegas, NV: Academy of Management.

Wiener, Y. (1982). Commitment in Organizations: A Normative View. *Academy of Management Review*, 418-428.

Figure 1 Reproduction of Figure 2 from USDA Cooperative Statistics 2013, U.S. Farms and Cooperative Memberships, 1979-2013

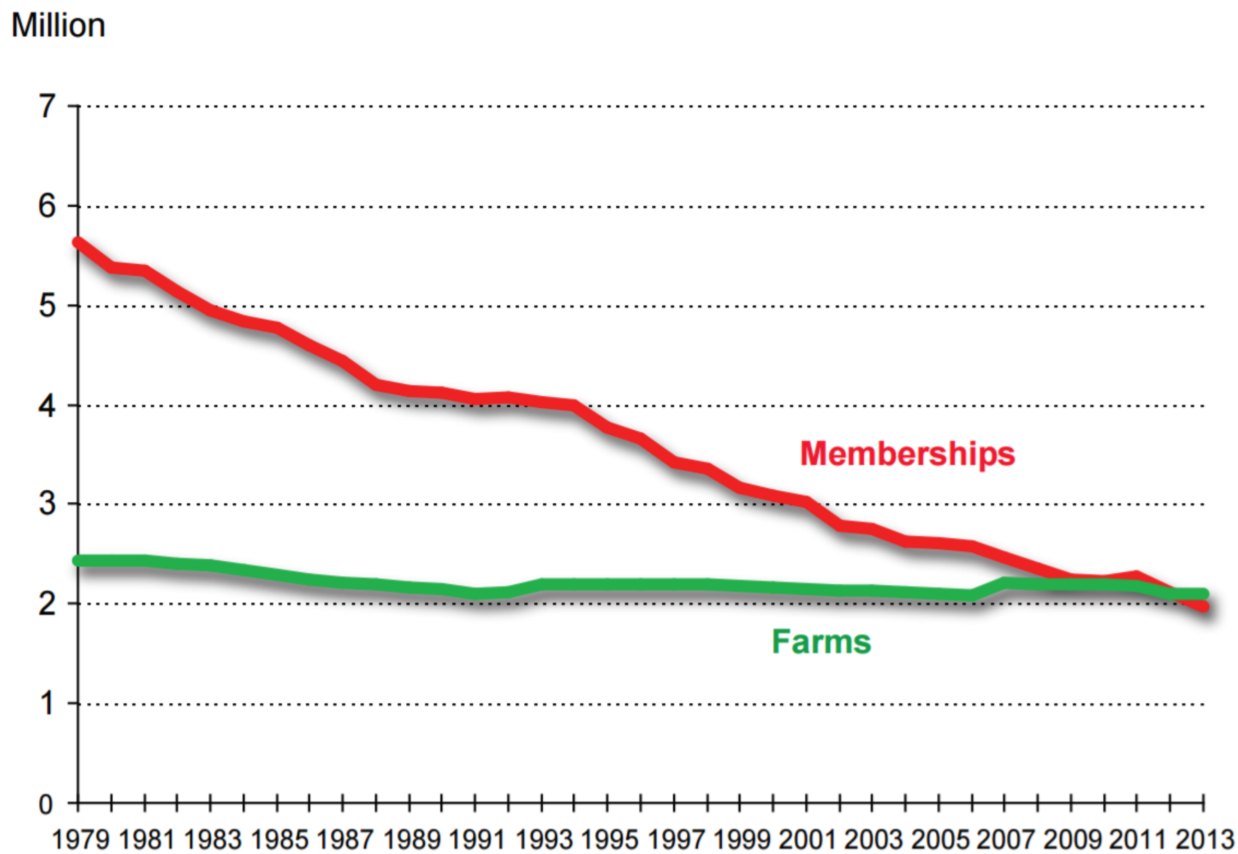

Figure 2 Conceptual framework (based on Foreman and Whetten, 2002)

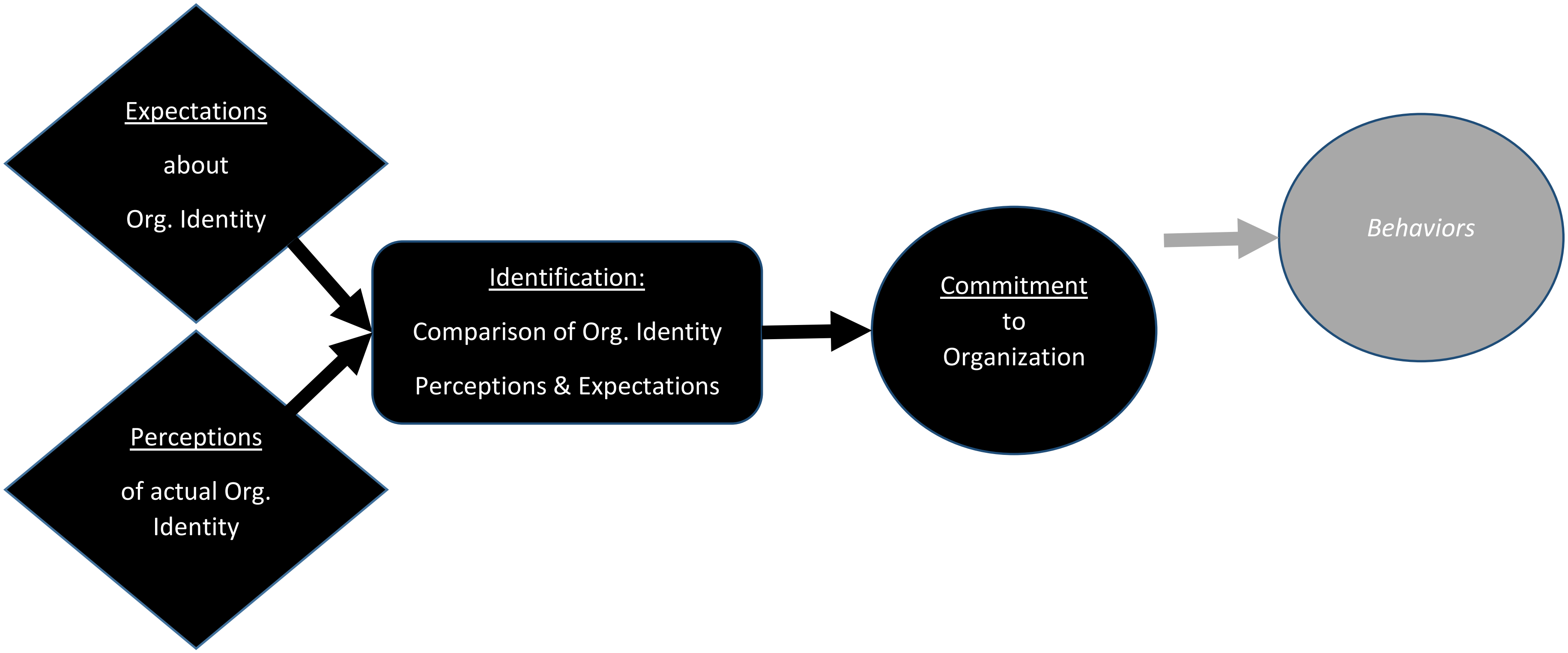

Table 1 Listing of Identity Indicator Variables

Identity Facet	**Scale Item**	**Perception**	**Expectation**
		Indicate your perception of the importance this coop places on each of the following items.	*Indicate how important you feel these items should be to the coop*
Normative	member ownership and control in the cooperative	x_1	x_5
	social relationships with other members	x_2	x_6
	community involvement	x_3	x_7
	commitment to traditional cooperative ideals	x_4	x_8
Utilitarian	price of products/ services	x_9	x_{13}
	customer service	x_{10}	x_{14}
	professionalism / expertise of staff	x_{11}	x_{15}
	quality of products / services	x_{12}	x_{16}

Table 2 Listing of Commitment Indicator Variables

Commitment Type	Scale Item	
Continuance (reverse scaled)	I feel I have too few options to consider leaving this coop	y_1
	One of the negative consequences of leaving this coop would be the scarcity of available alternatives	y_2
	It would be very hard for me to leave this coop now even if I wanted to	y_3
	Too much in my life would be disrupted if I decided I wanted to leave this coop now.	y_4
Affective	I feel a sense of belonging to this coop	y_5
	I feel like part of the family at this coop	y_6
	I feel emotionally attached to this coop	y_7
	This co-op has a great deal of personal meaning for me	y_8

Table 3 Listing of Latent Factor and Induced Variable Names

Identity Components			**Commitment Scale**	
	Normative	**Utilitarian**	**Continuance**	ccs
Perception	normper	utilper		
Expectation	normexp	utilexp	**Affective**	acs
Comparison	compnorm	computil		

Table 4 Summary of Data Sampling and Observations Used

Country	Region	Total Sample	Total Response	Response Rate	Obsrvs. Used	Effective Response Rate
United States	Mid-west	1900	798	42%	364	19%
Canada	Alberta	2000	820	41%	688	34%
France	Bretagne; Pays de la Loire	1000	336	34%	311	31%

Table 5 Descriptive Statistics, including Skewness and Kurtosis

	Mean	Median	Std. Deviation	Variance	Skewness	Kurtosis
x1	3.49	4.00	1.721	2.962	0.252	-0.707
x2	3.73	4.00	1.688	2.850	0.228	-0.664
x3	3.49	4.00	1.605	2.576	0.268	-0.507
x4	3.37	3.00	1.662	2.762	0.370	-0.538
x5	2.49	2.00	1.473	2.171	0.969	0.602
x6	3.36	3.00	1.809	3.274	0.423	-0.738
x7	3.03	3.00	1.579	2.492	0.567	-0.203
x8	2.75	2.00	1.709	2.922	0.834	-0.080
x9	2.62	2.00	1.547	2.392	0.890	0.203
x10	2.48	2.00	1.461	2.135	1.003	0.582
x11	2.63	2.00	1.437	2.066	0.854	0.367
x12	2.44	2.00	1.332	1.774	0.912	0.546
x13	1.51	1.00	0.908	0.824	2.390	7.290
x14	1.57	1.00	0.921	0.848	2.073	5.437
x15	1.70	1.00	0.997	0.993	1.726	3.488
x16	1.57	1.00	0.915	0.838	2.126	5.908
y1	3.62	4.00	1.933	3.738	0.211	-1.082
y2	3.65	3.00	2.096	4.393	0.230	-1.303
y3	3.02	2.00	2.059	4.240	0.689	-0.858
y4	2.81	2.00	1.975	3.902	0.871	-0.490
y5	4.15	4.00	1.910	3.649	-0.141	-1.051
y6	4.16	4.00	1.824	3.328	-0.141	-0.940
y7	3.35	3.00	1.946	3.787	0.348	-1.097
y8	3.45	3.00	1.894	3.588	0.300	-0.998

Figure 3 Final Structural Model with Indicator Variables Included

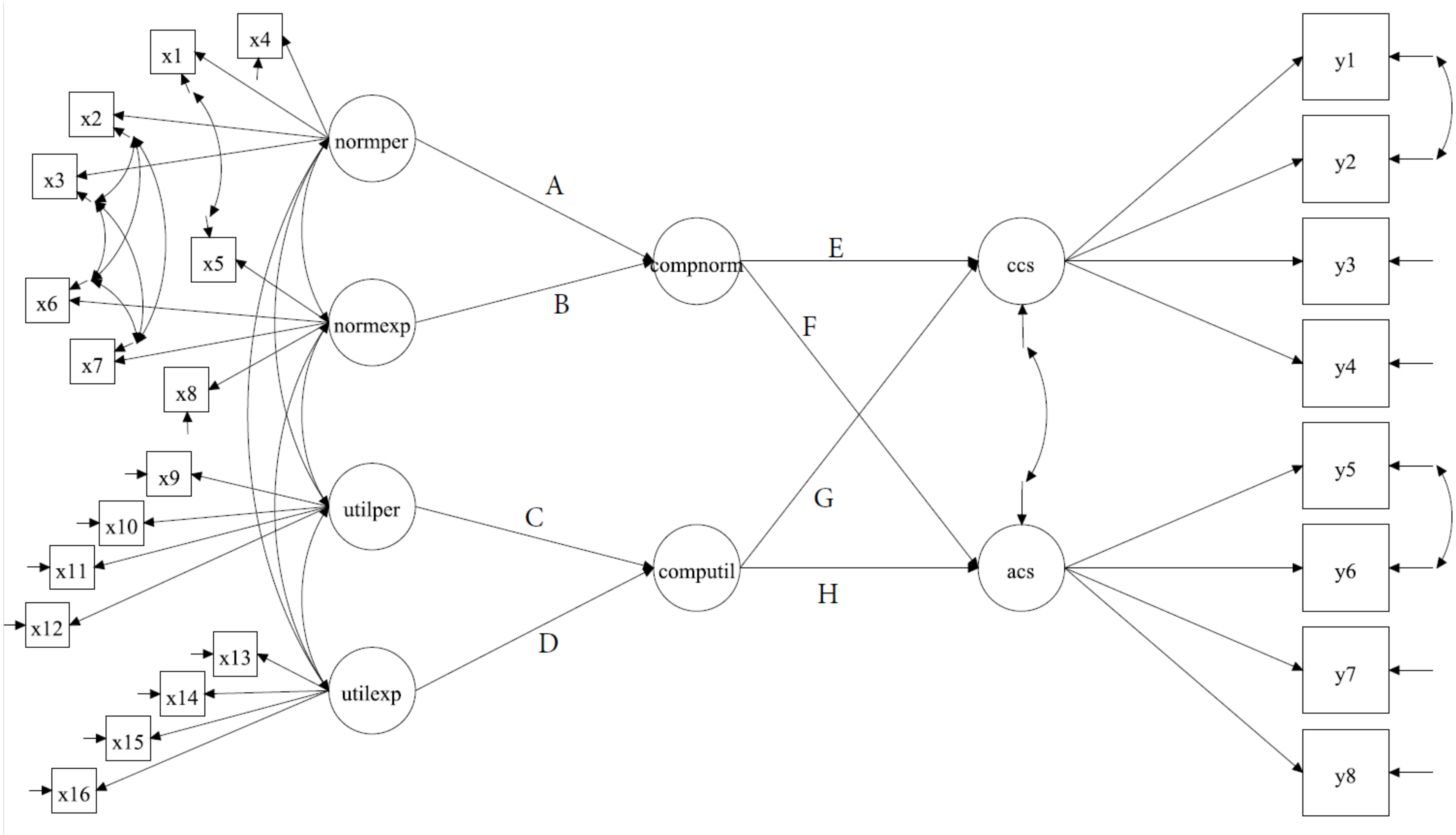

Table 6 Pattern Coefficients (Factor Loadings) Results for Combined (All-groups) Estimations

Latent Factor	**Variable**	**Measurement**		**Structural**	
		ML	**WLSMV**	**ML**	**WLSMV**
Normative Perception	x_1	0.744	0.788	0.719	0.772
	x_2	0.566	0.612	0.548	0.613
	x_3	0.649	0.681	0.647	0.682
	x_4	0.764	0.784	0.757	0.782
Normative Expectation	x_5	0.701	0.752	0.694	0.738
	x_6	0.657	0.724	0.647	0.705
	x_7	0.658	0.723	0.652	0.704
	x_8	0.812	0.832	0.831	0.834
Utilitarian Perception	x_9	0.692	0.745	0.690	0.742
	x_{10}	0.860	0.896	0.858	0.918
	x_{11}	0.826	0.859	0.822	0.854
	x_{12}	0.829	0.866	0.824	0.862
Utilitarian Expectation	x_{13}	0.745	0.821	0.747	0.818
	x_{14}	0.870	0.916	0.870	0.918
	x_{15}	0.868	0.917	0.868	0.921
	x_{16}	0.822	0.878	0.818	0.842
Continuance Commitment	y_1	0.465	0.519	0.466	0.520
	y_2	0.475	0.545	0.478	0.548
	y_3	0.801	0.827	0.803	0.828
	y_4	0.909	0.977	0.906	0.976
Affective Commitment	y_5	0.545	0.593	0.547	0.592
	y_6	0.498	0.558	0.496	0.557
	y_7	0.772	0.770	0.787	0.772
	y_8	0.813	0.881	0.800	0.880

Table 7 Path Coefficient Results for Combined (All-groups) Estimations

Path	ML	WLSMV
A	-1.014	-1.196
B	1.200	1.291
C	-1.075	-1.091
D	0.692	1.000
E	-0.187	-0.715
F	-0.322	-1.368
G	0.311	0.872
H	0.672	1.743

Table 8 Fit Statistics, All Models and All Groups

Est.	Model	Group	Free Param.	Chi-sqr.	D.F.	Chi-sqr Diff. Test Significance	RMSEA	RMSEA Lower	RMSEA Upper	Prob. RMSEA ≤0.5	CFI	TLI	S/W RMR
Maximum Likelihood	Measure.	Combined	96	737.666	228	N/A	0.040	0.037	0.044	1.000	0.969	0.962	0.035
		US		*403.837*			*0.046*	*0.039*	*0.053*	*0.810*	*0.968*	*0.961*	*0.044*
		CAN		*482.092*			*0.040*	*0.035*	*0.045*	*0.999*	*0.966*	*0.959*	*0.038*
		FRA		*402.479*			*0.050*	*0.042*	*0.057*	*0.522*	*0.953*	*0.943*	*0.052*
	Structural	Combined	92	885.903	232	0.000	0.045	0.042	0.049	0.990	0.960	0.952	0.051
		US		*423.885*		*0.000*	*0.048*	*0.040*	*0.055*	*0.696*	*0.965*	*0.958*	*0.056*
		CAN		*616.408*		*0.000*	*0.049*	*0.044*	*0.054*	*0.619*	*0.949*	*0.939*	*0.060*
		FRA		*444.495*		*0.000*	*0.054*	*0.047*	*0.062*	*0.174*	*0.942*	*0.932*	*0.062*
WLSMV	Measure.	Combined	192	933.818	228	N/A	0.048	0.044	0.051	0.885	0.982	0.979	1.323
		US	*192*	*478.687*			*0.055*	*0.048*	*0.062*	*0.116*	*0.983*	*0.979*	*0.907*
		CAN	*190*	*513.981*			*0.043*	*0.038*	*0.048*	*0.993*	*0.985*	*0.982*	*0.993*
		FRA	*188*	*521.143*			*0.064*	*0.057*	*0.072*	*0.001*	*0.968*	*0.962*	*1.015*
	Structural	Combined	188	1024.182	232	0.000	0.500	0.047	0.053	0.483	0.980	0.976	1.447
		US	*188*	*497.361*		*0.001*	*0.056*	*0.049*	*0.063*	*0.071*	*0.982*	*0.978*	*0.964*
		CAN	*186*	*578.082*		*0.000*	*0.047*	*0.042*	*0.051*	*0.880*	*0.982*	*0.979*	*1.093*
		FRA	*184*	*567.529*		*0.000*	*0.068*	*0.061*	*0.075*	*0.000*	*0.964*	*0.957*	*1.088*

APPENDIX: Excerpt from Westgren, Foreman, and Whetten (2009)

The interpretation of the induced variable model is as follows. If the gap between normative expectations and normative perceptions of cooperative identity decreases (more coherence in this identity construct), then both affective and continuance commitment increase. If the gap between utilitarian perceptions and expectations decreases, then both affective and continuance commitment decrease. That is, if either utilitarian identity expectations drop relative to the perceived level, or if the perceived level of utilitarian identity rises relative to expectations, then the member is less committed to stay with the cooperative, ceteris paribus.

How does one evaluate the foregoing interpretation? The key is to follow Pearl's interpretations of SEM parameters, wherein the coefficient for a given arc in a path model does not determine either the total effect or the direct effect of one exogenous variable on an endogenous variable. Rather, the total effect of one variable on another is measured by holding that variable constant and letting all other variables in the model run their course. This reasoning takes into account that there are antecedent variables in the causal (path) model that are expressed through intervening variables, including those that are connected by nondirected arcs. Thus, we need to interpret the B_{ij} *– the effects of the identity comparison variables on the commitment variables in light of what is antecedent. An increase in normative perception? A decrease in normative expectations? How would a change in either exogenous variable causally affect all other exogenous variables through their covariances, then through the induced variables to the commitment variables, a long string of partial effects.*

The interesting result is that it appears that normative identity and utilitarian identity appear to conflict in the cooperative organization. A positive change in normative perceptions lowers the identity gap and increases commitment. A positive change in utilitarian perceptions has the opposite effect. This implies that, ceteris paribus, a rise in the utilitarian identity makes the cooperative appear to be more like a business and the member may defect to a non-cooperative competitor. The indirect effect may be that that the perceived increase in the utilitarian identity causes a decrease in the perceived normative identity, which will also cause defection from the cooperative. This interpretation means that the original definition of a hybrid-identity organization by Albert and Whetten is borne out in agricultural cooperatives. Albert and Whetten define these to have inherently incompatible value systems which are linked in the organization but in conflict. One can interpret this to mean that movement toward a higher perceived normative identity necessarily moves one towards a lower perceived utilitarian identity. Normative and utilitarian identity are thus captured on a unidimensional scale, rather than in two-dimensional space.

This interpretation is consistent with the duopoly/duopsony models of Fulton, Fulton and Giannakas, and Karantininis and Zago. In their models, there is some dimension of behavior that distinguishes cooperatives from investor-owned firms besides transaction prices. We see this dimension as the normative – utilitarian identity continuum. Cooperative members place positive value on locating themselves in a cooperative where they find congruence with their normative identity expectations. To the degree those expectations are not met, cooperative members will defect.