A General Approach to Panel Data Set-Theoretic Research

Roberto Garcia-Castro[1,*] and Miguel A. Ariño[2]

[1]IESE Business School, Camino del Cerro del Águila, 3, 28023 Madrid, Spain

[2]IESE Business School, Avda. Pearson 21, 08034 Barcelona, Spain

Abstract: Academic research based on general linear statistical models has been rapidly moving toward a greater and richer use of longitudinal and panel data econometric methods. By contrast, set-theoretic empirical research, despite its growing diffusion, has been mainly focused on cross-sectional analysis to date. This article covers this void in panel data set-theoretic research. We provide some diagnostic tools to assess a set-theoretic consistency and coverage both cross-sectionally and across time. The suggested approach is based on the distinction between *pooled*, *between* and *within* consistency and coverage, which can be computed using panel data. We use KLD's panel (1991–2005) to illustrate how the proposed approach can be applied in the context of set-theoretic longitudinal research.

Keywords: Set-theoretic methods, Fuzzy sets, Longitudinal research, Panel data, Stakeholders.

1. INTRODUCTION

In the last few years, researchers from various fields have increasingly adopted set-theoretic methods (STM) to test their theories (Fiss 2007 [1]; Garcia-Castro, Aguilera and Ariño 2013 [2]; Grandori and Furnari 2008 [3]; Greckhamer, Misangyi, Elms *et al*. 2008 [4]; Kogut, Macduffie and Ragin 2004 [5]; Pajunen 2008 [6]; Schneider, Schulze-Bentrop and Paunescu 2010 [7])[1]. Thiem and Dusa (2013) [8] identified 276 academic articles using STM from 1984-2012, mainly in the fields of management and organization, sociology, economics and political science. The exponential adoption of STM can be partly attributed to the influential work of Ragin (2008 [9]) and the rapid proliferation of statistical packages in STATA (Longest and Vaisey 2008 [10]) or R (Thiem and Dusa 2013 [8]) in addition to the original program *fs/QCA* developed by Ragin and colleagues.

STM is one of the many attempts to address the recent calls to build better causal theories and use more varied methods in academic research (Fiss 2007 [1]; Venkatraman 2008 [11]). The use of STM has been argued to contribute to developing better causal theories by clearly distinguishing between the necessary and sufficient conditions leading to an outcome, and by partially overcoming some of the limitations associated with correlational methods (Greckhamer *et al*. 2008 [4]; Ragin 2000 [12]). In addition, set-theoretic research allows us to explore important issues such as causal complexity, equifinality and causal asymmetry in radically new ways (Fiss 2011 [13]; Ragin 2008 [9]; Smithson and Verkuilen 2006 [14]), complementing the findings yielded by traditional correlational methods such as regression analyses and other multivariate econometric techniques.

At the same time, STM present some limitations of their own—see Ragin (2008) [9]. One main limitation of set-theoretic research to date has been the lack of generally applicable longitudinal approaches, and in particular the lack of specific instruments to deal with panel data. There have been some noteworthy contributions in the last years seeking to incorporate temporality to STM using both informal and formal approaches (Caren and Panofsky 2005 [15]; Hino 2009 [16]; Kvist 2007 [17]; Ragin and Strand 2008 [18]; Schneider and Wagemann 2012 [19]). These approaches include, among others, the pooling of datasets over time, the introduction of new sets accounting for the sequence and speed of the events analyzed or the use of the temporal operator ('/') in addition to the traditional Boolean operators OR ('+'), AND ('*') and NEGATION ('~'). However, these previous works do not specifically deal with a panel data structure. As a result, most previous STM research is limited to cross-sectional analyses or ad-hoc analysis of temporal data, missing the potential insights that panel data analysis typically offers, such as the possibility to check for temporal dynamic effects or reverse causality issues.

This article deals with this important void in STM by proposing a general method for applying set-theoretic analysis to panel data. The method revolves around a

*Address correspondence to this author at the IESE Business School, Camino del Cerro del Águila, 3, 28023 Madrid, Spain; Tel: (34) 91 211 30 00; E-mail: rgarcia@iese.edu

[1]Set-theoretic methods (STM) are also known as Qualitative Comparative Analysis (QCA) and fuzzy-sets analysis.

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basic distinction, developed in the next section, between *cross-sectional* consistency and coverage and *across-time* consistency and coverage. The analysis of consistency and coverage is at the core of fuzzy set methods (Ragin 2008) [9]. By analyzing how consistency and coverage are distributed both across cases and over time, we can infer sufficient and necessary causal conditions that are likely to remain hidden when researchers look at the data in a purely cross-sectional fashion. Further, across-time consistencies can be used as robustness checks in empirical studies. The robustness of set-theoretic results is an issue that has received substantial attention in set-theoretic-based research and it is currently one of its main limitations (Greckhamer *et al*. 2008 [4]; Kogut 2009 [20]).

In this article, we advance an analytical procedure for assessing the different consistencies and coverages that emerge once a longitudinal research design has been considered, and we propose precise guidelines for evaluating how stable these consistencies and coverages are across cases and over time. As such, our work extends current STM, making them more directly applicable to research questions that embrace a temporal dimension.

The paper is organized as follows. First, after reviewing some of the basics of STM, we introduce the notion of pooled, between and within consistency in the context of panel data research and suggest how these measures can be analyzed and used in empirical research. Next, we extend the analysis to measures of coverage. Then, we apply the proposed method to a panel data of 489 U.S. firms from 1991–2005, and we investigate the set-subset relationship between stakeholder management investments and firm performance using KLD data.[2] Finally, we discuss the main implications of the proposed methodology for set-theoretic research, as well as some of its main limitations.

2. PANEL DATA SET-THEORETIC METHODS

Research based on general linear statistical models has been rapidly moving toward a greater and richer use of new longitudinal and panel data econometric methods that can cope with critical issues such as endogeneity and reverse causality concerns (see, Hamilton and Nickerson 2003 [21]). The advantages of using a longitudinal research design and panel data are well known and have been discussed extensively elsewhere (Greene 1993 [22]; Ployhart and Vandenberg 2010 [23]; Wooldridge 2002 [24]).

By contrast, set-theoretic empirical research has tended to be focused mainly on cross-sectional analysis to date (e.g., Fiss 2011 [13]; Greckhamer *et al*. 2008 [4]; Kogut *et al*. 2004 [5]). In order to address this important void, in this section we propose some general descriptive measures for evaluating set theoretic relations in the context of panel data.

2.1. Pooled, Between and Within Consistency

Our analysis starts from the seminal work of Ragin (2000 [12], 2008 [9])[3]. In particular, we deal with the familiar notions of *fuzzy sets* (Zadeh 1965) [25] and the measures of *consistency* and *coverage* (Ragin 2006) [26]. While there are some important differences between 'crisp' and 'fuzzy' sets—see Ragin (2008) [9]—, the discussion in this article generally applies to these two types of sets.

Ragin (2006) [26] provides a general standard to measure set-theoretic consistency, or the degree of inclusion between two sets (set-subset relationship):

$$Consistency\ (X_i \leq Y_i) = \frac{\sum_{i=1}^{N} \min(X_i, Y_i)}{\sum_{i=1}^{N} X_i}$$

where X_i is the degree of membership of an individual i in set X, and Y_i is its degree of membership in set Y.

The introduction of time gives way, however, to three different types of consistency. If we define i as the number of cross-sectional observations and t as the number of periods in the panel data, then we can compute the overall panel consistency taking all i=1,…N and t =1,…T. We refer to this consistency as *pooled consistency* (POCONS) and it is defined as:

$$Pooled\ Consistency\ (X_{it} \leq Y_{it}) = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} \min(X_{it}, Y_{it})}{\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}}$$

[2]Kinder, Lydenberg, Domini & Co. Inc., 129 Mt. Auburn St, Cambridge, MA 02138, USA. http://www.sustainalytics.com/

[3]Our approach to panel data STM builds on the large existing literature on STM (Fiss 2007, 2011; Kogut *et al*. 2004; Ragin 2000, 2008; Schneider and Wagemann 2012; Smithson and Verkuilen 2006). Thus, given the vast literature available on STM we will not provide an extensive review in here. For the purpose of this paper, it suffices to say that STM are based on set-subset connections using Boolean algebra instead of correlations between the variables—therefore, common notions such as fixed effects or random effects models often used in correlational panel data methods are not relevant in this context.

where X_{it} is the degree of membership of the individual *i* in the time *t* in set X, and Y_{it} is its degree of membership in set Y. The pooled consistency indicates the overall consistency observed in the sample when time and individual effects are not taken into account, and it is equivalent to pooling all the cross-sectional consistencies as defined by Ragin (2008) [9]. Alternatively, we can compute the consistency for each single year *t* in the panel:

$$Between\ Consistency\ (X_{it} \leq Y_{it}) = \frac{\sum_{i=1}^{N} \min(X_{it}, Y_{it})}{\sum_{i=1}^{N} X_{it}}$$

for each *t* = 1,…T.

The *between consistency* (BECONS) is a measure of the cross-sectional consistency for each year *t* in the panel. The BECONS is the most common measure of consistency in the literature and it is often simply referred to as 'consistency' in set-theoretic research (Ragin 2000) [12].

Finally, it is also possible to measure whether the hypothesized subsetness connection between X_{it} and Y_{it} is consistent not across cases but over time:

$$Within\ Consistency\ (X_{it} \leq Y_{it}) = \frac{\sum_{t=1}^{T} \min(X_{it}, Y_{it})}{\sum_{t=1}^{T} X_{it}}$$

for each *i* = 1,…N.

The *within consistency* (WICONS) measures the longitudinal consistency of the set-subset connection for each individual *i* in the panel over time. In other words, the WICONS is a measure of how consistent the set-subset relationship is across time for each particular case in the sample.

In any real panel data there are T different BECONS, N different WICONS and one single POCONS (Table **1**). Since the BECONS, WICONS and POCONS are likely to be different in empirical research, the three should be considered in order to more fully understand the set-subset relations between the causal conditions and the outcome.

Assume that a researcher finds a high overall consistency (POCONS) between X_{it} and Y_{it}. No matter how high this consistency is, unless the POCONS is 1, there will always be some inconsistent cases—i.e., cases violating the hypothesized subsetness relationship between X_{it} and Y_{it}. An inspection of Table **1** reveals that the inconsistencies found in the data may be randomly spread over the entire matrix or they may be concentrated in particular years or firms (see Appendix). In the case these inconsistencies are randomly spread, the researcher may conclude that they are relatively benign deviations resulting from particular cases, unimportant outliers or measurement errors. In this case, the panel structure of the data is not relevant. However, if these inconsistent cases are persistently concentrated in particular years or firms, then they represent significant violations of the theory. For instance, if only one particular year displays inconsistent scores, it is a signal of panel structure; in that case, ideally, the theory should include temporal effects that seek to explain why the hypothesized set-subset relationship does not hold in that particular year. These violations of the theory can then be used by the researcher to refine her arguments or to build a new

Table 1: Pooled, Between and Within Consistency

	Year$_1$	**Year$_2$**	**Year$_3$**	**…**	**Year$_T$**	**Within Consistency** $\frac{\sum_{t=1}^{T} \min(X_{it}, Y_{it})}{\sum_{t=1}^{T} X_{it}}$
Firm$_1$	X_{11},Y_{11}	X_{12},Y_{12}	X_{13},Y_{13}	…	X_{1T},Y_{1T}	*WICONS$_1$*
Firm$_2$	X_{21},Y_{21}	X_{22},Y_{22}	X_{23},Y_{23}	…	X_{2T},Y_{2T}	*WICONS$_2$*
Firm$_3$	X_{31},Y_{31}	X_{32},Y_{32}	X_{33},Y_{33}	…	X_{3T},Y_{3T}	*WICONS$_3$*
…	…	…	…	…	…	…
Firm$_N$	X_{N1},Y_{n1}	X_{N2},Y_{N2}	X_{N3},Y_{N3}	…	X_{NT},Y_{NT}	*WICONS$_N$*
Between Consistency $\frac{\sum_{i=1}^{N} \min(X_{it}, Y_{it})}{\sum_{i=1}^{N} X_{it}}$	*BECONS$_1$*	*BECONS$_2$*	*BECONS$_3$*	…	*BECONS$_T$*	**Pooled Consistency** $\frac{\sum_{i=1}^{N} \sum_{t=1}^{T} \min(X_{it}, Y_{it})}{\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}}$

theory. The question is, of course, determining when these violations are severe enough and when they are relatively unimportant in a panel. To answer this question, it is necessary to analyze not only the overall consistency (POCONS) but also the between and within consistencies, as well as how stable they are over time and across cases.

The POCONS, BECONS and WICONS may each display patterns of their own, within some limits. Given a constant POCONS, the T different BECONS may be stable over time or they may display a clearly temporal pattern, depending on the economic cycle or on time-dependent trends. The same applies to the N different WICONS; they may be homogenous across firms or they may be highly dispersed. Yet the POCONS, BECONS and WICONS are interrelated. It can be observed that the relationship between POCONS and BECONS is given by:

$$POCONS = \sum_{t=1}^{T}\left(\frac{\sum_{i=1}^{N} X_{it}}{\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}}\right) * BECONS_t$$

Likewise, the relationship between POCONS and WICONS is given by:

$$POCONS = \sum_{i=1}^{N}\left(\frac{\sum_{t=1}^{T} X_{it}}{\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}}\right) * WICONS_i$$

The above two equations show that the POCONS can be expressed as a weighted average of $BECONS_t$ and $WICONS_i$ respectively. Note that the weights depend solely on the degree of membership in X_{it}. If the sum across firms of the degree of membership in X_{it} is constant over time, then the POCONS is simply equal to the average of all BECONS in the panel. Likewise, if the sum over time of the degree of membership in X_{it} is constant across firms, then the POCONS is equal to the average of all WICONS in the panel. If, however, those weights are quite different, then the difference between the POCONS and each of the BECONS or the WICONS may be very large.

We have shown that the POCONS, BECONS and WICONS are interrelated, but, at the same time, they can exhibit different patterns over time and across firms. As such, we need to assess how stable these consistencies are in these two dimensions. In order to do so, we next suggest some measures based on euclidean distances.

2.2. BECONS and WICONS Distance

One straightforward way to analyze how the consistencies vary over time and across firms is to observe how far the BECONS and WICONS observed vectors are from the respective T and N dimensional vectors with all their elements equal to POCONS. This is identical to measuring how far the BECONS and WICONS vectors are from an evenly distributed vector of consistencies. For example, the BECONS vector (0.8, 0.8, 0.8) has a zero distance, since all the consistencies are identical for the three years and equal to 0.8. In practice, this means that the consistency of 0.8 is very stable over time and, hence, there is no time effect on the relationship between the causal condition and the outcome. By contrast, the BECONS vector (0.1, 0.1, 0.9) exhibits an extreme distance indicating that the subsetness relationship between the causal condition and the outcome is time dependent—i.e., it is highly consistent in the third year, but not in the first two.

We formalize this argument using euclidean distances. We define the between distance as the euclidean distance between the normalized T-dimensional vector of BECONS

$$\left(\frac{BECONS_t}{\sum_{t=1}^{T} BECONS_t}\right)_{t=1}^{T}$$

and the T-dimensional vector (1/T,…,1/T), that is

$$BECONS\ Distance = d(BECONS, POCONS) = \sqrt{\sum_{t=1}^{T}\left(\frac{BECONS_t}{\sum_{t=1}^{T} BECONS_t} - \frac{1}{T}\right)^2}$$

When all BECONS are equal, the BECONS distance becomes zero and then all $\frac{BECONS_t}{\sum_{t=1}^{T} BECONS_t}$ are equal to 1/T. The maximum distance is $\sqrt{1-\frac{1}{T}}$, which is obtained when just one of the BECONS is different from zero. If we now standardize the BECONS distance dividing by $\sqrt{1-\frac{1}{T}}$, then the resulting distance will range from 0 to 1, with zero as the lowest possible distance between all the BECONS values and with one as the maximum. Hereafter, we refer to this *standardized* distance as the BECONS distance. The smaller the distance, the more stable the BECONS are over time and the closer the T-dimensional vector

BECONS will be to the T-dimensional vector with all its elements equal to POCONS.

In a similar way, the WICONS distance can be defined as the euclidean distance between the normalized N-dimensional vector of WICONS $\frac{WICONS_i}{\sum_{i=1}^{N} WICONS_i}$ and the N-dimensional vector (1/N,…,1/N):

$$WICONS\ Distance = d(WICONS, POCONS) = \sqrt{\sum_{i=1}^{N}\left(\frac{WICONS_i}{\sum_{i=1}^{N} WICONS_i} - \frac{1}{N}\right)^2}$$

Low BECONS and WICONS distances indicate highly stable solutions both over time and across cases. In these situations, the BECONS, WICONS and POCONS all will have similar values and the three give the same information to the researcher. By contrast, high distances indicate that there is information in the panel that is not fully captured by the POCONS. There are four broad possibilities when one compares the BECONS and the WICONS distances:

- *BECONS distance = WICONS distance = 0*. This implies that POCONS = $BECONS_t$ = $WICONS_i$. This case corresponds to a balanced panel data where there are no time or firm effects.
- *BECONS distance = WICONS distance ≠ 0.* There is some evidence of both time and firm effects if the BECONS and WICONS distances are sufficiently large, according to the criteria we advance below.
- *BECONS distance > WICONS distance.* This implies that the time effects dominate over the cross-sectional effects. If the BECONS distance is large, there are likely severe time effects with an impact on the subsetness relation between X_{it} and Y_{it}.
- *WICONS distance > BECONS distance.* This implies that the cross-sectional effects dominate over the time effects. If the WICONS distance is large, there are likely severe cross-sectional patterns—e.g., clusters of firms—affecting the subsetness relation between X_{it} and Y_{it}.

The evaluation of the BECONS and WICONS distances must be done carefully, mainly because they are sensitive to the number of periods and individuals in the panel, respectively[4]. To address this issue we advocate using the following *adjusted distance:*

$$BECONS\ adjusted\ distance = \frac{BECONS\ distance}{\sqrt{\frac{n}{n^2+3n+2}}}$$

$$WICONS\ adjusted\ distance = \frac{WICONS\ distance}{\sqrt{\frac{n}{n^2+3n+2}}}$$

The BECONS (WICONS) adjusted distance can be readily applied to any panel of any T, N size. While theoretically the adjusted BECONS(WICONS) distance can be higher than 1, in practice it will be between 0 and 1 when applied to a real dataset. While the relevant threshold to be considered between 0 and 1 in a particular research context will have to be determined by researchers in subsequent empirical studies, our Monte Carlo simulations with samples size of 10, 15, 50, 100, 500, 1,000 and 10,000 shows that an adjusted distance of .1 indicates that approximately 95% of the consistencies lie within an interval of +/- .1 around the average of the consistencies. Similarly, an adjusted distance of .2 indicates that approximately 95% of the consistencies lie within an interval of +/- .2 around the average. Adjusted distances above these thresholds signal some sort of panel data structure in the data.

A high BECONS adj-distance indicates that the time effects (e.g., economic cycle effects) are severe. Similarly, a high WICONS adj-distance indicates that the population of firms being studied is not homogenous, but that there is some sort of stratification in the data—some clusters of firms are persistently consistent over time while other clusters of firms are clearly inconsistent. It is obvious that if the BECONS or WICONS adj-distances are far from zero, the POCONS is a very imprecise measure of consistency for the whole panel. By contrast, if both the BECONS and WICONS adj-distances are close to zero, then the POCONS provides an accurate measure of the overall consistency between X_{it} and Y_{it}.

In addition to their application as useful robustness checks, a deep understanding of the BECONS and the

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[4]The average BECONS and WICONS distances decrease as sample size (T, N) increases. The average euclidean distance of a random vector T or N dimensional vector whose elements are no negative and sum one can be calculated to be $\sqrt{\frac{n}{n^2+3n+2}}$ where n is equal to the number of elements in the vector. We use this latter average distance to standardize the WICONS and BECONS distances.

WICONS and their adj-distances may lead to important theoretical advancements. It is quite possible that clusters of firms, whether they are highly consistent or inconsistent, will display some common features (size, strategy, organizational traits and so on), which can lead to refinement and further development of the hypotheses being tested.

2.3. Pooled, Between and Within Coverage

In addition to consistency, researchers need to assess whether the set-theoretic relations they find are empirically relevant or not—i.e., *coverage*. Our analysis of panel data coverage starts from Ragin's (2008) [9] widely used definition of coverage:

$$Coverage(X_i \le Y_i) = \frac{\sum_{i=1}^{N} \min(X_i, Y_i)}{\sum_{i=1}^{N} Y_i}$$

We can now compute the pooled coverage (POCOV) for a panel in a similar way as with pooled consistency:

$$Pooled\ Coverage(X_{it} \le Y_{it}) = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} \min(X_{it}, Y_{it})}{\sum_{i=1}^{N} \sum_{t=1}^{T} Y_{it}}$$

The POCOV indicates the overall coverage observed in the sample when the time and individual specific effects are not taken into account. Alternatively, we can compute a specific coverage for every single year in the panel:

$$Between\ Coverage\ (X_{it} \le Y_{it}) = \frac{\sum_{i=1}^{N} \min(X_{it}, Y_{it})}{\sum_{i=1}^{N} Y_{it}}$$

for each t = 1,…T.

The between coverage (BECOV) is a measure of the cross-sectional coverage for each year *t* in the panel. The BECOV is simply referred to as 'coverage' for a given year in set-theoretic research (Ragin 2008) [9]. Lastly, we compute the coverage for each cross-section in the panel over time:

$$Within\ Coverage\ (X_{it} \le Y_{it}) = \frac{\sum_{t=1}^{T} \min(X_{it}, Y_{it})}{\sum_{t=1}^{T} Y_{it}}$$

for each i = 1,…N.

The within coverage (WICOV) measures the coverage of the set-subset connection across time for each individual *i* in the panel. Put another way, the coverage for a given individual indicates whether the consistent relationship found between X and Y for this individual across time is empirically relevant or not. Ragin (2008) [9] further distinguishes between raw and unique coverage and the formulas shown above for pooled, between and within coverage can be used to compute these two types of coverage indistinctly.

2.4. Research Strategy: Protocol for Assessing Consistency and Coverage in Longitudinal Studies

Researchers dealing with panel data set-theoretic research now have several measures to assess pooled, between and within consistency and coverage. In this section, we suggest some steps to follow when assessing the consistency and coverage between the causal conditions and the outcome. We summarize these steps in Table **2**. These steps need not be followed in exactly the same order as presented in Table **2**.

The first step is to evaluate the overall consistency of the panel. This can be done using the POCONS. Next, the yearly BECONS must be assessed. Even when overall consistency (POCONS) is low, if there is a large BECONS distance across years, it is possible to find a strong consistent set-theoretic relationship for particular years, indicating that such relationship is time dependent. Then, the WICONS and the WICONS distance can be assessed in a similar way as the BECONS. Lastly, if the POCONS, BECONS and/or WICONS prove to be consistent—for the entire dataset or for part of it—then researchers can assess the POCOV, BECOV and WICOV using the formulas provided above.

Finally, the protocol in Table **2** applies to the analysis of sufficient conditions—i.e. X_{it} is a subset of Y_{it}. Since the calculation of the consistency of a sufficiency relationship is identical to the calculation of the coverage of a necessity relationship, and the calculation of the coverage of a sufficiency relationship is identical to the calculation of the consistency of a necessity relationship (Ragin, 2008: 63) [9], then the protocol can be also followed to assess necessary conditions using the same formulas.

3. APPLICATION TO ORGANIZATIONAL RESEARCH: KLD PANEL DATA (1991-2005)

We use a panel containing KLD data, often used in management research (Hillman and Keim 2001 [27]; Margolis and Walsh 2003 [28]) to illustrate how the

Table 2: Protocol for Assessing POCONS(COV), BECONS(COV), WICONS(COV)

Procedure	Type of set-theoretic relation	
	Cause (X_{it}) is a subset of outcome (Y_{it}). Sufficient Condition	
Step 1	Assess **POCONS**	$\frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\min(X_{it},Y_{it})}{\sum_{i=1}^{N}\sum_{t=1}^{T}X_{it}}$
Step 2	Assess **BECONS** for each T	$\frac{\sum_{i=1}^{N}\min(X_{it},Y_{it})}{\sum_{i=1}^{N}X_{it}}$
Step 3	Assess **BECONS distance**. If the distance is high, then check for time effects in the panel	$\sqrt{\sum_{t=1}^{T}\left(\frac{BECONS_t}{\sum_{t=1}^{T}BECONS_t}-\frac{1}{T}\right)^2}$
Step 4	Assess **WICONS** for each N	$\frac{\sum_{t=1}^{T}\min(X_{it},Y_{it})}{\sum_{t=1}^{T}X_{it}}$
Step 5	Assess **WICONS distance**. If the distance is high, then check for firm effects in the panel	$\sqrt{\sum_{i=1}^{N}\left(\frac{WICONS_i}{\sum_{i=1}^{N}WICONS_i}-\frac{1}{N}\right)^2}$
Step 6	If POCONS, BECONS_t and/or WICONS_n are significant, then assess **POCOV**, **BECOV** and **WICOV**	$\frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\min(X_{it},Y_{it})}{\sum_{i=1}^{N}\sum_{t=1}^{T}Y_{it}}$ $\frac{\sum_{i=1}^{N}\min(X_{it},Y_{it})}{\sum_{i=1}^{N}X_{it}}$ $\frac{\sum_{t=1}^{T}\min(X_{it},Y_{it})}{\sum_{t=1}^{T}Y_{it}}$

pooled, between and within measures can be computed in practice. KLD data has been used to study the relationship between firms' investments in stakeholder management and financial performance (e.g., McWilliams and Siegel 2000 [29]; Waddock and Graves 1997 [30]).

The basic hypothesis is that investments in stakeholders will be positively associated with higher financial performance. Previous research has found that building better relationships with primary stakeholders generally leads to increased financial returns, because it helps firms develop intangible yet valuable assets which can become sources of competitive advantage (Hillman and Keim 2001 [27]). For instance, investing in stakeholder relations may lead to increased customer or supplier loyalty, reduced employee turnover, or improved firm reputation, which, in turn, have all been found to lead to improved financial performance (Graves and Waddock 2000 [31]; Ogden and Watson 1999 [32]; Waddock and Graves 1997 [30]).

We do not discuss the relative merits of this hypothesis here; we simply utilize this argumental line and KLD data to illustrate how panel data STM can provide new insights into this particular research question. The empirical evidence found to date, using general linear statistical methods, is mixed with studies reporting positive, negative and neutral relationships between stakeholder management and firm performance (Margolis and Walsh 2003 [28]; Orlizky, Schmidt and Rynes 2003 [33]).

3.1. Data and Measures

KLD is an independent rating agency specialized in the assessment of corporate social performance across a range of dimensions related to stakeholder concerns. In total, the panel covers 15 years (1991–2005), with a total of 6,009 firm-year observations. The KLD dataset is an unbalanced panel data where the firm is the primary stratification variable, so that there is a 489-item unbalanced panel with a time series of between one and 15 observations in each stratum. Not all firms are present for the whole period due to attrition, mergers, or changes in the universe of firms monitored by KLD. The general structure of the panel and the total number of firms monitored per year is roughly depicted in Table **3**.

The KLD rating is an aggregate measure of the level of investment of the firm in several stakeholder groups, such as customers, employees, suppliers and the like.[5] It ranges from -8 to +12, with an average value of .74. In order to transform a continuous variable like the KLD rating index into a fuzzy set, some sort of calibration is required. We calibrate this variable using the .25, .5 and .75 percentiles from its distribution. These percentile point anchors are often used in set-theoretic research to calibrate continuous variables (Fiss 2011) [13].

Hillman and Keim (2001) [27] found some support for a hypothesized relationship between KLD investments and market value-added (MVA). Thus, we use this same metric to measure firm performance. MVA was calculated as: Market Value – Capital. Where market value is the firm's market value or market capitalization, and capital is the book value of equity and debt invested in the firm. All financial data was collected from Datastream. Similar to KLD calibration, we used the .25, .5 and .75 percentile points to transform the MVA variable into a fuzzy set. All calibrations and set-theoretic computations were done using the *fuzzy* commands recently implemented in STATA (Longest and Vaisey 2008) [10].

3.2. Results

Table **3** shows the POCONS for the whole panel (.661), BECONS, WICONS and their distances. The relatively low POCONS is hardly surprising, since our simple model only includes a single causal condition (i.e., KLD). The addition of more causal conditions may eventually lead to more complex configurations with higher consistencies. However, given the methodological nature of this article, we decided to test this simple relation between KLD and firm performance to keep the analysis as simple as possible.

While the POCONS indicates that X_{it} is not a consistent subset of Y_{it} when all the data is considered, the yearly BECONS tells a different story. The BECONS for the year 1991 (0.8) is significant according to set-theoretic standards.[6] Then, during the decade leading up to 2000, this consistency decreased and stabilized around the POCONS. One possible interpretation of the data is that investments in KLD were sufficient to profitably differentiate a firm from its competitors in 1991, at a time when few firms had significant KLD investments, but that this advantage was soon eroded by other companies investing in KLD. As a company increasingly invests in its stakeholders, the expectations of the agents involved in the transaction with the firm will also increase (Barnett 2007) [34]. Mohr, Webb and Harris (2001) [35] argue that as firms increase their CSR activities, their rivals feel pressure to increase theirs as well, since some consumers prefer to buy from the most socially responsible firm. As a result, if all competitors offer increased CSR standards, the differentiation provided by the CSR investment will be lower (Barnett 2007) [34]. Confirming this hypothesis, KLD membership scores increased for the majority of firms in the panel from 1991-2005, arguably diminishing its impact on MVA. However, the slight increase of the consistency again in 2004 and 2005 may cast some doubt on this interpretation.

The evolution of the BECONS over the period is depicted in Figure **1**, where the BECONS are compared against the POCONS (solid horizontal bar in the figure). The variation across years of the 15 BECONS is reflected in the BECONS adj-distance of .132 (> 0.1), which indicates some heterogeneity across years. An inspection of the BECONS in Figure **1** reveals some oscillation over time, with higher consistency peaks at the beginning and at the end of the period. In sum, if there are sound theoretical reasons to think that KLD investments were sufficient to lead to superior MVA in 1991 but not in other years due, for example, to increased competition, then the yearly BECONS analysis can be used to test this hypothesis. Further, new insights can be gained when consistencies are analyzed on a yearly basis such as the fact that consistencies show some cyclicality over time and the moderate increase in 2004 and 2005.

Table **3** also shows the WICONS for the first three firms (3Com Corporation, AGL Resources, Alltell Corporation) and the last firm in the panel (Xerox Corporation). The full vector comprising 489 WICONS

[5]KLD complete score system is available from the authors on request.

[6]A commonly used threshold for consistency is .75 (Ragin, 2008). Standard statistical tests can be used to find out if a consistency is statistically higher than this threshold (Longest and Vaisey 2008; Ragin 2000).

Table 3: KLD as a Sufficient Condition for High MVA: KLD Panel Data (1991–2005)

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	WICONS	WICOV
(1) 3Com Corp.						*	*	*	*	*	*	*	*	*	*	.973	.179
(2) AGL Resources		*	*	*	*	*	*	*	*	*	*	*	*	*	*	1	.001
(3) ALLTEL Corp.					*	*	*	*	*	*	*	*	*	*	*	1	.000
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
(489) Xerox Corp.	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	.082	.982
BECONS	.800	.599	.555	.593	.645	.711	.684	.701	.684	.625	.695	.503	.608	.719	.759		
BECOV	.032	.032	.035	.050	.070	.060	.066	.072	.077	.082	.081	.073	.070	.088	.120		
POCONS										.661							
POCOV										.068							
BECONS Adj-distance										.132							
WICONS Adj-distance										.422							
N	371	373	372	385	410	443	473	495	453	412	387	367	374	362	332		

*: Available data.

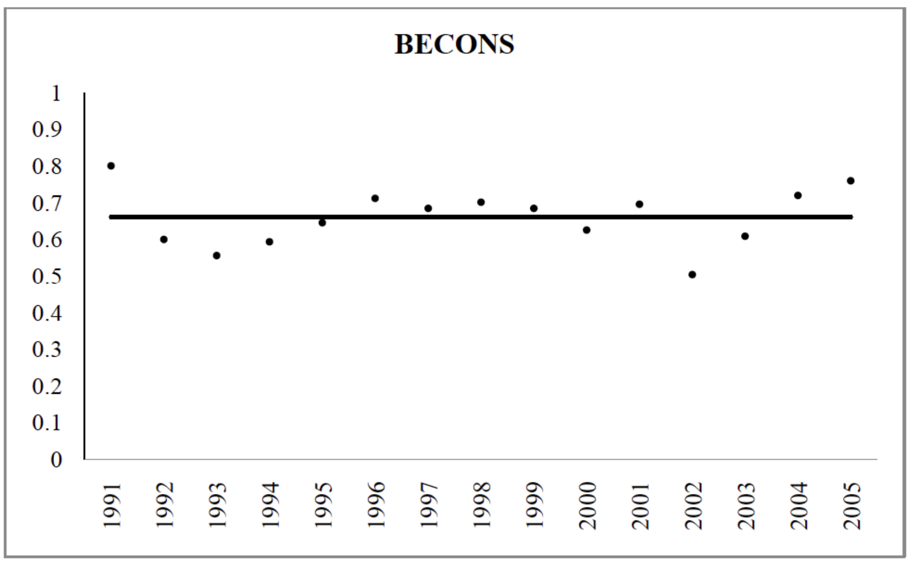

Figure 1: BECONS scores.

is not listed due to space constraints, but we do show its distribution against the POCONS (solid horizontal bar) in Figure **2**[7]. The WICONS has only been computed for those firms that were present for two or more years in the panel. We found 359 firms that were always consistent during the panel—i.e., membership in X_{it} was always lower than Y_{it}. The simultaneous presence of full WICONS (consistency = 1) together with low consistencies close to zero, suggests that there is some clustering in the data.

The WICONS adj-distance is .422, well above the .1 and .2 thresholds, suggesting the existence of strong differences across groups of firms in the sample. In this case, the WICONS are highly polarized with a large subgroup of firms displaying very high consistencies (=1)—i.e., KLD is sufficient to high MVA and another subgroup of firm with extremely low ones (=0)—i.e., KLD is not sufficient for high MVA in this group. These results beg the question of why these large differences. While there might be several reasons why consistencies are polarized into different groups, a closer look at the data shows that firms with a consistency of 1 are, on average, smaller in terms of

[7]The full 489 WICONS scores are available from the authors on request.

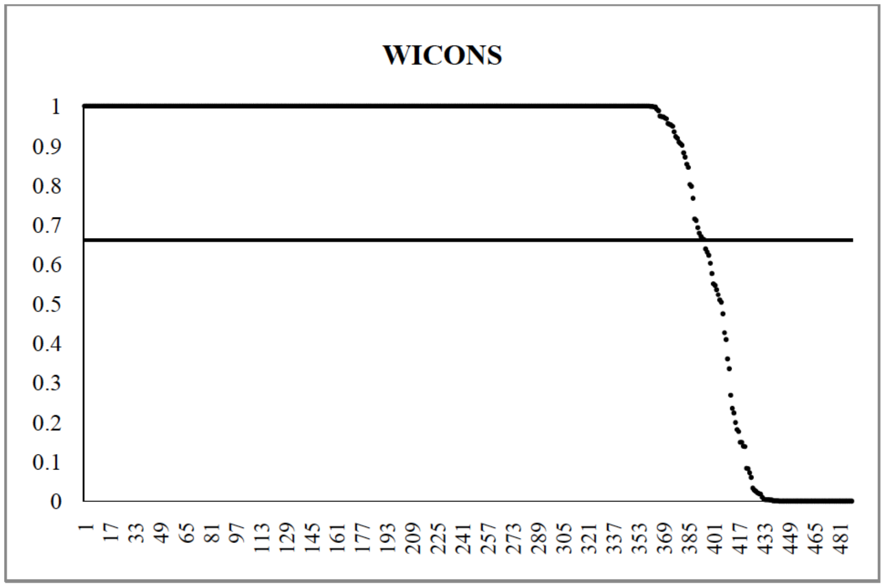

Figure 2: WICONS scores.

assets ($6.24 billion vs. $27.29 billion) and employees (23,379 vs. 42,717). Had the research focused on these smaller firms, for example, the overall POCONS would have been much higher as a result, indicating that investments in KLD are more statistically sufficient in smaller firms than in larger ones. These findings, if confirmed by further statistical analysis, would suggest the need to revise the initial theory, or at least to control for size in the empirical testing. Such analysis, however, given the methodological character of this article, is beyond the scope of this simple illustration.

In Table **3**, we also report the POCOV, BECOV and WICOV (first three firms and the last firm in the sample). Overall, the POCOV is relatively low, indicating that the empirical relevance of KLD in explaining high MVA is reduced—i.e., there are other variables to explain high MVA. The BECOV displays an upward trend from 1991 to 2005, suggesting that KLD investments became more important in explaining high MVA over time, probably due to the higher level of investments in KLD made by the firms in our sample during this period. Lastly, the WICOV indicates the empirical relevance of the WICONS for each firm. Consistent cases with a higher WICOV are more empirically relevant because their membership in X_{it} is higher than consistent cases with low WICOV.

Overall, the results suggest that the consistency is low for the panel taken as a whole (POCONS=0.661), but that there are significant differences over time and across individuals in terms of their consistency, which requires a more detailed analysis by subgroups. The coverages, in general, indicate that the explanatory power of KLD in regard to financial performance is relatively low, although its importance increased from 1991 to 2005.

3.3. Sensitivity Analysis and Robustness

We conducted several robustness checks to verify whether the results shown held under different calibrations of the sets and different performance measures. Previous research has shown that robustness tests are indispensable in set-theoretic research (Hug 2013 [36]; Schneider and Wagemann 2012 [19]; Skaaning 2011 [37]; Thiem 2013 [38]). First, we conducted sensitivity analyses to examine whether our findings were robust, given alternative set calibrations. Specifically, we varied the crossover points between +/- 10 percentile points for KLD and MVA. No substantive changes were observed in terms of the consistencies depicted in Table **3**. Second, in addition to MVA, we used ROA (return on assets), another performance metric often used to test the relationship between KLD and firm performance (Margolis and Walsh 2003) [28]. The results, albeit with small differences, do not differ much from the consistency and coverage scores shown in Table **3**, confirming the robustness of the POCONS(COV), BECONS(COV) and WICONS(COV).

4. DISCUSSION AND CONCLUSION

This article covers a void in longitudinal set-theoretic research. While STM are starting to be widely used in sociological, political and organizational studies, the lack of general approaches to dealing with panel data has limited their applicability. The analysis of panel data has been proven to be critical in academic research in recent years in addressing some critical methodological concerns such as endogeneity, reverse causality among others (Hamilton and Nickerson 2003) [21].

In this article, we provide a general framework in which consistency and coverage can be assessed both across individuals and over time. The introduction of POCONS(COV), BECONS(COV) and WICONS(COV) measures allows for an analytical treatment of panel data, serving as a robustness check for purely cross-sectional results and facilitating that researchers can compare their different results by using a common language. In this sense, this work contributes to substantially refining pre-existing STM in ways that make them more directly applicable to current research questions.

The essence of our approach is the measurement and analysis of the BECONS and WICONS and their distances. In the absence of panel structure—e.g., the BECONS and WICONS adj-distances < .1—, the POCONS summarizes all relevant information in the data in one single measure of consistency. However, the larger the BECONS or WICONS adj-distances, the lower the reliability of the POCONS in assessing the consistency between the causal conditions and the outcome. The existence of a high BECONS or WICONS distance indicates that the relationship between the causal conditions and the outcome has changed over time, or that the relationship is different across clusters of firms respectively. As such, it is no longer sufficient to simply measure the overall POCONS in a dataset, because the BECONS and WICONS adj-distances may reveal stable patterns in the data. In some cases, these patterns represent major violations of the theory—whenever there are many null consistencies for a single year or group of individuals—which researchers should take into account. In other cases, a high BECONS (WICONS) distance is due to the presence of many full consistencies combined with null consistencies; this provides strong support for the hypothesis, but *only* for a reduced group of cases in the dataset. An identical analysis can be done for the POCOV, BECOV and WICOV.

In terms of the results shown in the empirical section, our analysis of the POCONS, BECONS and WICONS reveals that there is not a universal relationship between KLD investments in stakeholders and firm performance. However, we have shown that the consistency was not homogeneous across years and, in fact, the consistency was significant at the beginning of the analyzed period. Likewise, the analysis of the WICONS shows that some firms had a full consistency while in other firms this consistency was zero, suggesting that the impact of KLD on firm performance may be mediated or moderated by some attributes of the firms in the sample. Thus, our work is the first one to report cross-section and time varying differences in how KLD investments affect financial performance using QCA methods on a 15-year panel of firms.

While the analytical approach advanced in this article is general and flexible enough to deal with any conceivable panel data structure, it presents at least two main limitations. First, the evaluation of the BECONS and WICONS adj-distance requires a benchmark. The thresholds of 0.1 and 0.2 reported in this article have been validated using Monte Carlo simulations and they provide a first benchmark to be used in empirical studies, but more empirical research is needed in order to confidently assess the validity and generalizability of these thresholds in other contexts. The second limitation is related to the analysis of the BECONS and WICONS. While the BECONS and WICONS adj-distances developed here serve as a test for identifying panel structure in the data, they cannot tell us which particular structure better describes the data. Thus, researchers need to complement the analysis of distance with other analytical methods, such as factor analysis, and other conventional multivariate tools in order to describe and analyze such structure. For instance, a high WICONS distance can indicate a highly polarized panel of zeros and ones consistency scores, but it can also indicate a highly stratified population of firms clustered in many reduced homogenous groups in terms of their WICONS. The practical and theoretical implications are likely to be very different in these two scenarios.

In conclusion, the approach advanced in this article is sufficiently general to be applied to a wide range of longitudinal/panel data studies. It can be applied to the study of statistically necessary and sufficient conditions separately, with special emphasis on how these two types of conditions evolve over time. The notions of BECONS and WICONS may be equally useful in cross-sectional studies where countries can be divided in different regions or industries in sub-sectors. Finally, whereas we used a relatively simple empirical setting in this paper, with a single causal condition (KLD investments) and one outcome (MVA), the approach presented can easily be extended to the study of more complex organizational configurations (Fiss, 2007) [1], and their trajectories and path development (Fiss, 2011) [13], taking advantage of the temporal dimension that longitudinal and panel data research typically adds.

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Appendix: Theory Violation Matrix

Random effects												
	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	YT	
Firm1		⊗										Wicons1
Firm2												Wicons2
Firm3			⊗									Wicons3
Firm4						⊗						Wicons4
Firm5										⊗		Wicons5
Firm6												Wicons6
Firm7				⊗								Wicons7
Firm8												Wicons8
Firm9									⊗			Wicons9
Firm10	⊗											Wicons10
FirmN							⊗					WiconsN
	Becons1	Becons2	Becons3	Becons4	Becons5	Becons6	Becons7	Becons8	Becons9	Becons10	BeconsT	
⊗: inconsistent result												
Time effects												
	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	YT	
Firm1	⊗											Wicons1
Firm2	⊗											Wicons2
Firm3	⊗				⊗							Wicons3
Firm4	⊗											Wicons4
Firm5												Wicons5
Firm6	⊗											Wicons6
Firm7	⊗											Wicons7
Firm8	⊗											Wicons8
Firm9									⊗			Wicons9
Firm10	⊗											Wicons10
FirmN	⊗											WiconsN
	Becons1	Becons2	Becons3	Becons4	Becons5	Becons6	Becons7	Becons8	Becons9	Becons10	BeconsT	
⊗: inconsistent result												
Cross-section effects												
	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	YT	
Firm1	⊗	⊗	⊗		⊗	⊗	⊗		⊗	⊗	⊗	Wicons1
Firm2												Wicons2
Firm3												Wicons3
Firm4												Wicons4

Firm5												Wicons5
Firm6												Wicons6
Firm7				⊗								Wicons7
Firm8												Wicons8
Firm9									⊗			Wicons9
Firm10												Wicons10
FirmN												WiconsN
	Becons1	Becons2	Becons3	Becons4	Becons5	Becons6	Becons7	Becons8	Becons9	Becons10	BeconsT	
⊗: inconsistent result												

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