Limited diversity as overspecification

Assessing the explanatory power of single conditions in QCA.

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Abstract. Limited diversity has long been seen as a source of threats to the credibility of causal ascription in Qualitative Comparative Analysis. To rule out such threats, strategies have been developed that question the counterfactual nature of unobserved configurations, their explanatory merit, and the causal structure entailed in the algorithm for ascription. A lesser explored line considers limited diversity to be the consequence of model overspecification. In contributing to this latter line, this article builds on the established theoretical criteria that a distribution must meet for an explanatory claim to be held true, and it advances two gauges – "import" and "essentiality" – to assess the difference-making power of single conditions and mold proper models before analysis. Their application in prominent studies suggest solutions from Standard Analysis may be more sound than is often conceded.

Keywords. Causal ascription, Unobserved diversity, Model specification, Qualitative Comparative Analysis, Quine-McCluskey.

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Introduction

Capital accumulation, industrialization, urbanization, and education are the steps of the path along which democracies have been historically proven to thrive. Alone, however, these "social requisites" of democracies (Lipset 1959) cannot warrant their survival. As the case of interwar Germany showed, endurance also requires stable institutions. The hypothesis, by nature, is configurational and justifies a Boolean treatment. An established adaptation of Lipset's theory to interwar Europe (Berg-Schlosser and De Meur 1994, Rihoux and De Meur 2009) thus expected the survival of democracy in wealthy (*W*), industrialized (*I*), urbanized (*U*), literate (*L*) social systems with stable (*S*) governments. However, the results brought forth a discomforting puzzle. Although **L** was shared by all the positive cases, the Boolean procedure minimized it away as irrelevant. Further applications confirmed that indeed, when running a Qualitative Comparative Analysis, conditions that are "empirically necessary" to the outcome may disappear from solutions (Schneider and Wagemann 2012; Ragin 2008; Ragin and Sonnett 2004). Moreover, conditions may enter solutions despite lacking a direct causal connection to the outcome (Baumgartner and Thiem 2015a).

These pitfalls have contributed to undermining the belief that the technique can correctly ascribe causation. Configurational scholars have long diagnosed these issues as a consequence of limited diversity. When the mismatch between observed and possible configurations in a truth table is large, the solutions from minimizations with and without "logical remainders" can diverge. To improve the credibility of such results, strategies along four separate lines have been advanced over time: two of them focus on the counterfactual use of unobserved configurations (Ragin and Sonnett 2004; Schneider and Wagemann 2012, 2013; Baumgartner 2008, 2009; Baumgartner and Thiem 2015b); the other two instead question the complexity of the model (Schneider and Wagemann 2006, 2012; Baumgartner 2012; Baumgartner and Thiem 2015a; De Meur and Berg-Schlosser 2009; Goertz 2006).

This article advances the fourth line. With Goertz (2006), it maintains theoretical relevance or previous knowledge can lead to overly complex explanatory models: conditions may be included that have no actual import nor are essential to the explanation. It reasons that conditions' import and essentiality instead depend on their empirical relationship with the cases at hand and with the other conditions in the model and that they may not be properly assessed by Quine-McCluskey minimizations. It therefore introduces two gauges to test the importance and essentiality of single conditions and, on this basis, to determine whether to include them in the model before running the Standard Analysis. The expectation is that "correct" models provide evidence for adjudicating on the actual capacity of Standard Analysis to yield credible findings and, eventually, for fixing it.

The structure of the article is simple. Section 1 discusses the four main strategies for confronting limited diversity and highlights the diagnoses and prescriptions that they entail for better QCA solutions. Section 2 narrows in on the understanding of limited diversity as overspecification, building on the requisites of set-theoretical causation to elaborate two indexes, "import" and "essentiality", that allow the explanatory power of single conditions to be ascertained and the model to be fine-tuned to the cases at hand. Section 3 applies these new gauges to models from recognized empirical studies and investigate how correct models lead to different results. Section 4 discusses the replications and outlines provisional considerations about the credibility of the findings of Standard Analysis.

As a matter of clarification, the article adopts a conventional QCA lexicon and notation with minimal adjustments. Explanatory conditions and outcomes are each a single property-set, of which cases are observed instances from a given population $\boldsymbol{\mathcal{P}}$. $\boldsymbol{\mathcal{M}}$ indicates a model-set, of which whole conditions are elements. Bold standard letters indicate conditions independent of their gauge and state. When the gauge is relevant, slanted uppercase signifies presence and slanted lowercase signifies absence unless otherwise specified. Subscript *i* means that the condition is instantiated by the *i*-th observation from $\mathcal{P}$. A dot or no sign signals set intersection and Boolean conjunction; a plus sign indicates set union and disjunction; and a backslash is for set difference and complement in disjuncts. Configurations are intersections and conjunctions; those listed in a truth table are "primitives." Stars are for unobserved configurations in $\mathcal{P}$. Arrows indicate a set relationship and always point toward the super-set. Double headed arrows are for overlapping sets. Finally, "N-cons" and "S-cons" are used as short labels for the Standard parameters of consistency of, respectively, necessity and sufficiency, respectively.

1. One problem, four strategies

Scarcely populated truth tables arise from the gap between hypothesized diversity and observed diversity in a population. At the description level, this gap exposes the special ordering imparted by causation to diversity while unfolding in the real world. Inference, however, weakens if unobserved heterogeneity is not treated properly (Ragin 2008). Over time, the issue has been given four different solutions. Each entails specific and occasionally diverging recommendations for sounder results, and their arguments are summarized below.

Strategy #1. Sound counterfactuals only

The first solution addresses limited diversity as the source of disappearing conditions. It stipulates that models themselves are given and explanatory and that unobserved heterogeneity improves minimizations' leverage when used for counterfactual reasoning. Accordingly, results' pitfalls must depend on their usage in Standard minimizations.

Ragin and Sonnett (2004; Ragin 2008, Schneider and Wagemann 2012) focused on the nature and purpose of unobserved configurations and maintained that sound results could only follow "plausible" counterfactuals. Plausibility, however, has a special meaning in QCA due to the particular rationale of the algorithm used for ascription. Indeed, the Quine-McCluskey reverses the mainstream statistical understanding of counterfactual. Its minimizations do not ascertain the *ceteris paribus* covariation of a factor and an outcome in a causally homogeneous sample; instead, they pinpoint the invariant parts of explanatory complexes across dissimilar cases sharing outcome within a scope condition. The technique still entails the falsifiability of the starting hypothesis by testing whether the factor "makes a difference" to the strength of the causal relationship (Lewis 2001). However, given its focus on invariance, it defines as plausible counterfactual the unobserved configuration that *would* have led to the outcome if observed. Consistent with the theory-driven nature of the method, Ragin and Sonnett (2004) make plausibility claims resting on "directional expectations". Before running the analysis of sufficiency, the researcher defines the state under which a condition is expected to contribute to the outcome. Thus, if the theory states that *A* contributes to *Y*, then the unobserved configuration *aBC** is an implausible match with the observed configuration *ABC* because it implies, against theory, that in a hypothetical twin world *BC* could have generated *Y* despite *a*.

Barring implausible counterfactuals from minimizations warrants unbiased results and restores disappearing necessary conditions in solutions (Ragin 2008). However, Wagemann and Schneider (2012, 2013) noted how plausible counterfactuals do not rule out all threats to credible results. To them, directional expectations cannot ensure that each and every counterfactual is used *(a)* non-contradictorily; *(b)* in a way that does not embody any logical impossibility; and *(c)* such that findings are perfectly true to observations. Given these many threats, their Enhanced Standard Analysis (ESA) identifies the different nature of each logical remainder and establishes consistent minimization rules for each type. Applications show the ESA yields different parsimonious solutions but the same intermediate solutions as the Standard Analysis (Schneider and Wagemann 2012). This conclusion has struck a blow for intermediate solutions with plausible counterfactuals as the robust and, therefore, credible finding to discuss.

Strategy #2. Changing the algorithm

The credibility of plausible minimizations has been fiercely questioned by Baumgartner (2008, 2009) and Baumgartner and Thiem (2015b), who developed a different epistemology of causal complexity and rejected the Quine-McCluskey as the proper minimization algorithm.

Their understanding provides no room for counterfactual reasoning. To them, observed configurations are the only configurations to be analyzed, as they render those mechanisms that obtained in the real world; logical remainders are, "notwithstanding their truth, not amenable to a causal interpretation" (Baumgartner 2008:332, Baumgartner and Thiem 2015b). However, observed configurations are redundant portrayals such that correct causal ascription requires minimizations – but inevitably different from those in Standard Analysis. The latter ascribes causation through a backward falsifying strategy, as it disproves that a condition is essential by showing its removal does not affect the sufficiency of the configuration. In Baumgartner and Thiem's reversed epistemology, the strategy instead runs forward and confirms that a factor is a cause as far as it qualifies as an "INUS" condition (Mackie 1965) – that is, as an insufficient but necessary constituent of an unnecessary but sufficient configuration. The procedure for identification is, therefore, the mirror-image of the Quine-McCluskey: instead of sufficiency, it narrows on necessity; implicants are found by adding factors to increase the complexity of disjuncts, instead of pruning conjuncts, until the relationship vanishes. As it retrieves any structure that fits observations, this “super-/sub-set analysis” is also claimed to improve results upon the Quine-McCluskey. The latter’s minimizations treat each condition as it if has a direct causal connection to the outcome – i.e., as a “set-theoretically independent” element in a causal complex – and do not report implicants that are perfectly implied, or “dominated”, by other conditions. In so doing, Standard Analysis fails to recognize that causation may be structured and that “alternative causes of an outcome frequently correspond to dominated conditions” (Baumgartner and Thiem 2015b:11) – which the super-/sub-set analysis fully reports instead.

The super-/sub-set analysis dismisses any consideration of plausibility from inference, emphasizing only the requirement of formal correctness in ascription. As a consequence, it often retrieves a large number of implicants and leaves their adjudication to ex-post theorizing. The problem of credible causal ascription thus resurfaces as “too many fitting solutions.” However, Baumgartner and Thiem’s proposal unveils the limitation of Standard Analysis, suggesting it could not achieve correct results when the starting model includes conditions linked in dependency relationships.

Strategy #3. Layering explanatory complexity

That the Quine-McCluskey may mishandle hierarchical causation was first recognized by Schneider and Wagemann (2006, 2012). They consider explanations to be convincing when complete, and completeness often requires the inclusion of both “remote” structural factors and “proximate” efficient causes of an outcome. However, remote and proximate factors are chained, and the usual flat model misrepresents this structure while escalating unobserved diversity. They thus advance a “two-step” protocol that restrains complexity and better renders causal ontology. The protocol prescribes that the sufficiency analysis is run in step 1 on remote conditions to find the parsimonious solution, then in step 2 on proximate conditions, supplemented each time with a different remote term, to find the conservative results. A recognized limit of the two-step proposal lays in the classification of factors into remote and proximate causes, which is mainly left to the discretion of the researcher. Indeed, criteria have been advanced for identifying the factors' nature, such as the spatiotemporal contiguity to the occurrence of the outcome. However, these criteria cannot rely on empirical probation with Standard analysis: Schneider and Wagemann (2006:760, 2012) posit the remote-proximate classification cannot be expected to overlap the necessity-sufficiency distinction as gauged by consistency parameters.

The empirical probation of functional dependencies among explanatory conditions is the special aim of a different kind of configurational technique. Again developed by Baumgartner (2012), "coincidence analysis" (CNA) probes the existence of subset relationships between all factors in a model. As opposed to Schneider and Wagemann, this proposal is data-driven and again relies on a different algorithm than the Quine-McCluskey. The latter assumes a direction in causation, whereas in CNA each factor is in turn treated as it could be the outcome – the "endogenous" factor – of any other (Baumgartner and Thiem 2015a:177). The Quine-McCluskey only minimizes configurations that overlap on all but one term, while CNA intentionally relaxes this "one-different restriction" (Baumgartner 2012:6). Moreover, CNA compares configurations across outcomes, rather than within the same outcome, and establishes dependencies between any complex ϕ and one endogenous factor A whenever ϕ is not observed in conjunction with a. As a result, the researcher is provided with "causal structures" that can be arranged in chained models. However, again, the evidence is rarely final. The analysis does not tell whether the conditions unrelated to the outcome are a byproduct or an antecedent in a causal chain. Moreover, the analysis again generates multiple "complex solution formulas that fare equally well with respect to all parameters of model fit" (Baumgartner and Thiem 2015a: 180). Further, the analysis stems from the assumption that any observed truth table is saturated due to the dependencies among factors (Baumgartner 2012:11). The assumption may not be tenable, though, as it may mistake the effect of missing observations for that of a causal dependency.

Strategy #4. Questioning the complexity of the model

A further array of methodological refinements has been inspired by the doubt that limited diversity stems from a model that faithfully renders the theoretical hypothesis but in so doing includes more conditions than the diversity of the population requires. Marx (2010) emphasizes how an overly rich truth table may entail a confirmatory bias in results due to the increased probability of consistent primitives. He considers that highly complex models tend to pigeonhole observations and allow consistency to be decided by single instances. To increase the results' credibility, he calls for truth tables in which the consistency of observed configurations is high, even if the ratio of instances to configurations makes their inconsistency possible. He therefore suggests two routes for securing sounder truth tables. The first recalls the solution to power issues in sampling for statistical analysis and requires increasing the number of instances. If this is unviable due to a strict scope condition, the starting model can be tailored to the cases at hand before ascription – which calls for criteria for dropping conditions.

Berg-Schlosser and De Meur (2009) suggest that the rows in a truth table can be reduced by using "superconditions" that synthesize two or more single factors that have been shown to correlate consistently. However, this method of reduction may only alleviate the problem if the number of conditions remains disproportionate to the number of cases. Goertz (2006) identifies "trivialness" as a criterion for selection and first develops the concept in relation to necessity. He defines as a trivial and necessary factor as one "that is present in all cases in the universe of analysis, both when the dependent variable is present and absent" (*ivi*:90). He also emphasizes that trivial conditions can be considered an operationalization of the scope condition (2006:94), so their inclusion in the model may be justified by a theoretical interest in the contribution of contexts to the production of the outcome. With the Quine-McCluskey, however, these conditions generate a truth table in which half the rows are counterfactuals without this background condition. This raises an interesting puzzle and compels considerations of the external validity of Standard minimizations. This argument becomes clearer through a fictional example in which a constant is added to a saturated distribution with known solution, as follows:

Let $\boldsymbol{\mathcal{P}}_1$ be a population of 8 instances *i* such that their distribution across the possible intersections of two conditions **A**, **B** generates the solutions *A*+*B* → *Y* and *ab* → *y*; and let **C** be a constant. $\boldsymbol{\mathcal{P}}_1$ is compatible with the dataset in Table 1.a, and with the truth table of Table 1.b.

-- TABLE 1 --

If we do not question the model, with a conventional inclusion cutoff at 0.80, the parsimonious solution explains *Y* with the disjunction *A*+*B*, whereas the complex and the intermediate minimizations alike find the disjunction *AC* + *BC* – the latter, under the directional expectations that **A**, **B** and **C** all contribute to *Y* when present. With the same inclusion cutoff, the complex solution to *y* overlaps with the only observed negative primitive, *abc*, whereas the parsimonious solution use the logical remainders and ascribes causation to *ab*. However, the intermediate solution changes depending on the directional assumptions about the contribution of **C** to *y* in this unobserved twin world. The intermediate solution overlaps the complex if we expect the twin world and the observed world to share the very same background conditions. Thus, *C* is always necessary, and contributes to *y*. However, intermediate minimizations find the parsimonious solution if we concede that in such a twin world **C** may variate and, hence, be sufficient to *y*. The ambiguity cannot be fully addressed by analyzing individual consistency scores. As Table 2 shows, observations suggest that C is fully necessary to both the outcome and its negation, but its sufficiency values are undetermined.

-- TABLE 2 --

This ambiguity shows how trivial conditions push the explanatory power of solutions beyond the validity limits of counterfactual thinking. Further, when the model includes the constant, the solutions display the same S-cons values as those solutions obtained from the model without it, which indicates that the constant does not add explanatory power to the results. These considerations support Goertz's recommendation that trivially necessary conditions are dropped before ascription.

As trivialness makes especially clear, QCA cannot claim external validity for its findings: the results hold true strictly within the scope condition, which provides the necessary yet untested background to the explanatory hypothesis engrained in the model. Its strength as a method lies instead in the internal validity of its causal ascription. Dismissing trivial conditions before minimizations contributes to better results, as it reduces the complexity of the explanatory models to primitives with knowable import in $\boldsymbol{\mathcal{P}}$. However, as Baumgartner suggests, trivial conditions may only be an extreme example of the wider category of empirically unjustified conditions. Some further testing is therefore required to establish whether all theoretical conditions have a local explanatory power.

2. Gauging *import* and *essentiality*

QCA understands the explanatory relevance of single conditions as their set-theoretical relationship of necessity and sufficiency to the outcome. In its popular version, a factor has import in $\boldsymbol{\mathcal{P}}$ when it impresses a "triangular" shape into the distribution of its instances against the outcome in contingency tables or XY-plots. Standard parameters assess the fit to this shape by gauging the consistency and coverage of sufficiency and necessity (Ragin 2006, 2008; Schneider and Wagemann 2012). The parameters convey clear information about the conditions' shaping power when the values are extreme – that is, when individual conditions display a fully in/consistent set-relation to the outcome or an undetermined one. Apart from such revealing boundaries, the ambiguity of their information increases as different meaningful shapes become compatible with the same consistency value. This special weakness affects the analysis with fuzzy scores more than that with crisp scores (Schneider and Grofman 2006; Schneider and Wagemann 2012). Fuzzy scores allow subset and superset relationships to be understood as inequalities: sufficiency occurs when $w_i < y_i$, and necessity occurs when $w_i > y_i$ -- w_i being the fuzzy membership scores of *i* to the explanatory property-set; and y_i the fuzzy membership scores of *i* to the *explanandum*. As a consequence, fuzzy scores are understood to rotate the key axes of the analytic space: misfitting to sufficiency are those distributions whose instances fall below $y_i = w_i$; trivial distributions are those whose instances fall in the regions where $\sim w_i > y_i > w_i$, ~ reading 'not' and indicating the complement. However, the rotation blurs the original requisites underlying the triangular shape, which instead makes sense in an analytic space where the origin is translated to the (0.5; 0.5) point.

Recall from Ragin (1987, 2008) that the basic set-theoretic approach to necessity and sufficiency confines the distribution of instances by an *explanans* **W** and an outcome **Y** within four intersections in a non-rotated analytic space – namely, W_iY_i, W_iy_i, w_iy_i, and w_iY_i. The distribution establishes that, in $\boldsymbol{\mathcal{P}}$, W_i is

- *sufficient* to the outcome Y_i when $W_i \rightarrow Y_i$, and the requisites [R.] hold that

  $W_iY_i \neq \emptyset$ [R.1], $W_iy_i = \emptyset$ [R.2];

- *necessary* to the outcome Y_i when $W_i \leftarrow Y_i$, and the requisites [R.] hold that

  $W_iY_i \neq \emptyset$ [R.1], $w_iY_i = \emptyset$ [R.3];

- *necessary* and *sufficient* to Y_i when $W_i \leftrightarrow Y_i$, and the requisites [R.] hold that

  $W_iY_i \neq \emptyset$ [R.1], $w_iY_i = \emptyset$ [R.3], $W_iy_i = \emptyset$ [R.2].

Goertz adds that *non-trivial* necessity and sufficiency follows when

$w_iy_i \neq \emptyset$ [R.4].

Each of these requisites plays a unique role in establishing a causal relation. [R.1] demands the joint observation of cause and effect. [R.4] imposes certainty of variation in the outcome. [R.3] and [R.2] establish the direction of the causal relation.

Of them, however, [R.2] is especially crucial. The requisite entails that a factor is sufficient when contradictions do not occur. When met, this claim holds that the condition is a "difference-maker" and can thus be ascribed causal power. [R.2] provides Marx (2010) with the basis for his standards to assess the risk that a particular distribution is due to chance. Baumgartner and Thiem (2015a, 2015b) rely on this "negative existential claim" for pinpointing chained conditions, and their algorithm ascertains causation as the non-contradictory relationship of any single factor or complex to another. Yamasaki and Rihoux (2009) and Schneider and Wagemann (2012, 2013) maintain that its violation makes inconsistent the use of counterfactuals. The very same distinction of hard and easy counterfactuals introduced by Ragin and Sonnett (2004) is only possible under assumption of non-contradictoriness. Rihoux and de Meur (2009) treat contradictions as unequivocal signals that the model is underspecified – or wrong. In a nutshell, non-contradictoriness is the key proof of causal set-theoretic power. By extension, the capacity of unraveling contradictions in $\mathcal{P}$ can be seen as evidence that a condition has an ordering effect on the population.

When calculated based on single conditions, the Standard parameters of consistency provide a proxy of such "unraveling power." N-cons is high when a condition isolates negative instances from the remaining population, and S-cons is high when it pinpoints positive instances. These “told apart” instances contribute to the group of “better instances” that support the claim of the factor’s causal power and are particularly rewarded in consistency formulas (Ragin 2006). However, as already noted, the parameters become less precise as their scores come closer to 0.5. The difference-making criterion calls for a sharper assessment of conditions’ sorting power, which can be conceived of as a matter of numerosity rather than of overall fit. Even the most skewed condition must be recognized as having some power if it can unravel the last instance and prevent a contradiction in the truth table.

.1. Import

The first measure of explanatory power, *import*, rests on the number of instances with same outcome that a condition singles out of an unspecified population. The operation is almost banal.

Let $\mathcal{M}$ be a model explaining **Y** with $\mathcal{k}$ specifying conditions, tested on a population $\mathcal{P}$ of $\mathcal{N}$ instances. Let **X** be the $\mathcal{k}$-th explanatory condition in $\mathcal{M}$; $\mathcal{m}_X$ be a sub-model of $\mathcal{M}$ such that $\mathcal{m}_X = \{\mathbf{X}\}$; $\mathcal{p}_X$ be the subpopulation of instances observed in non-contradictory primitives generated by $\mathcal{m}_X$; and $\mathcal{n}_X$ the numerosity of $\mathcal{p}_X$. The import of **X** in $\mathcal{P}$ is then given by the following ratio:

$$\text{import}_X = \mathcal{n}_X / \mathcal{N}$$

The index can take values between 0 and 1. The highest score proves a condition to be necessary and sufficient to the outcome, as it can order the population in two non-contradictory clusters. Just the opposite, its lowest score proves the condition has no sorting power in $\mathcal{P}$.

Applied to our fictional example of trivialness, we see from Table 3.a and Table 3.b that both condition **A** and condition **B** generate a non-contradictory cluster of 4 instances out of 8, as $\mathcal{p}_A$={i3, i4, i5, i6} while $\mathcal{p}_B$={ i1, i2, i5, i6}. Therefore, $\text{import}_A = \text{import}_B = 4/8 = 0.5$. Table

3.c makes it clear that condition **C** actually has no sorting power, as it clusters all instances in a contradictory configuration. Thus, $\text{import}_C = 0/8 = 0$.

-- TABLE 3 --

.2. Essentiality

Import can improve our knowledge of the explanatory power of single conditions but does not capture the whole of it. The other side of such a power is decided by the conjunction of each condition with the remaining explanatory factors – that is, by observed primitives. In each primitive there may be non-contradictory instances to which **X** is not decisive, as they would nevertheless be singled out; and instances that are non-contradictory due only to **X** – alone or in conjunction with another factor. Those instances that would fall into a contradictory primitive were the condition dropped, thus, provide the key test of its *essentiality* in the model. Essentiality can therefore be gauged as the difference in terms of contradictory instances between the full model and the same model without that condition.

More precisely: let $\mathcal{M}$ be the model explaining **Y** with k specifying conditions, tested on population $\mathcal{P}$ of $\mathcal{N}$ instances. Let **X** be the k-th explanatory condition in $\mathcal{M}$, and m'_X be a sub-model of $\mathcal{M}$, such that $\mathcal{M} \backslash m'_X = \{X\}$. Let $\mathcal{Q}$ be the subpopulation of contradictory instances from $\mathcal{M}$; q'_X be the subpopulation of contradictory instances from m'_X; and q''_X be the difference $q'_X \setminus \mathcal{Q}$. When $\mathcal{M}$ is truly overspecified, $\mathcal{Q} = \{\emptyset\}$. If **X** is non-essential, then $q'_X = \mathcal{Q}$ and $q''_X = \{\emptyset\}$; if **X** is essential, then $q'_X > \mathcal{Q}$ and $q''_X \neq \{\emptyset\}$. Thus, if we indicate with n''_X the numerosity of q''_X, the essentiality of **X** reads:

$$\text{essentiality}_X = n''_X / \mathcal{N}$$

Again, the index spans from 1 to 0. Dropping a non-essential condition generates no new contradictions; if a condition is non-essential, its n'' takes the 0-value, and the ratio is null.

Dropping the only necessary and sufficient condition instead turns the entire population into a single contradiction, thus making its $\boldsymbol{n}'' = \boldsymbol{\mathcal{N}}$ and giving the index the value of 1.

When applied to our fictional model, we find again that **C** is non-essential, as its exclusion does not generate contradictions. We know that $\boldsymbol{\mathcal{N}}$=8. From Table 1.b, we learn that $\boldsymbol{Q}$ = {Ø} and, from Table 4.c, that $\boldsymbol{q}'_{\mathbf{C}}$ = {Ø}. Hence, $\boldsymbol{n}''_{\mathbf{C}}$=0, and $\text{essentiality}_{\mathbf{C}}$ =0/8=0. When we consider the model without **A**, Table 4.a tells us that $\boldsymbol{q}'_{\mathbf{A}} = \boldsymbol{q}''_{\mathbf{A}}$ ={i3, i4, i7, i8}, so that $\boldsymbol{n}''_{\mathbf{A}}$=4 and $\text{essentiality}_{\mathbf{A}}$ = 4/8 = 0.5. From Table 4.b we learn that **B** gets the same essentiality score, although it is based on partially different elements, as $\boldsymbol{q}'_{\mathbf{B}}$ = {i1, i2, i7, i8}.

-- TABLE 4 --

The information about conditions' essentiality can be further validated by a backward specification procedure. The protocol is almost intuitive, and consists of testing whether the dismissal of the non-essential conditions from the full model yields contradictions. Otherwise, the surviving model is less complex yet still capable of sound solutions.

When applied to the fictional example, the backward specification of the model confirms the inessentiality of the constant based on the conditions' unraveling power in $\boldsymbol{\mathcal{P}}_1$. When condition **A** is dropped from the model (Table 4.a), the primitive *BC* is still consistent, while *bC* clusters together two positive instances, i3 and i4, and two negatives, i7 and i8. Similarly, when condition **B** is dropped (Table 4.b), *AC* is explanatory but *aC* becomes contradictory. The procedure confirms the only distribution without contradictions is from the model without condition **C** (Table 4.c), which qualifies as the "correct" model to $\boldsymbol{\mathcal{P}}_1$.

3. Road-testing import and essentiality

When applied to actual data, these two simple ratios prove capable of detecting dependencies and offering interesting insights into the reasons for disappearing necessary conditions.

.1. Shame and compliance to international regimes

An illuminating example comes from Stokke's analysis on the role of shaming in governments' compliance with international fishery regimes (Stokke 2007). The original model maintains that shaming can improve compliance "by exposing certain practices to third parties whose opinion matters to the intended target of shaming" (Stokke 2007:503). The analysis then narrows on the conditions under which non-complying governments change their behavior in response to shaming pressures.

The model pinpoints two factors related to regime design: **A** for advice, gauging "whether the shamers can substantiate their criticisms by referencing explicit advice by the regime's scientific body"; and **C** for commitment, capturing "whether the target behavior violates commitments assumed under the regime." Three additional conditions are related to the direct institutional environment of the government under analysis: **I** for inconvenience, meaning the costs of compliance; **S** for the shadow of the future, indicating the risk that shame will bring the government into international disrepute as a partner; and **R** for reverberation, referring to the shame echoed by strong domestic constituencies that can undermine consensus by the government. The model is tested on a population of 9 regimes implemented in three regions since the 1970s: Barents Sea, Northwest Atlantic, and Antarctic.

-- TABLE 5 --

The data, displayed in Table 5.a, generate a truth table of 32 primitives, 8 of which are observed. The analysis of individual consistency (Table 5.b) pinpoints two necessary conditions: **A**, for which it is true that $A \leftarrow Y$ and that $a \rightarrow y$, and **I**, for which it holds that $i \rightarrow Y$ and $I \leftarrow y$. Parsimonious minimizations rule out **A** from the solution to the positive outcome, in spite of the theoretical import that Stokke gives it; and the solution reads $i + SR \rightarrow Y$. Plausible minimizations bring **A** back into positive results, turning the solution into $A(i + SR) \rightarrow Y$ and thus making it truer to observations.

While the puzzle of **A**'s disappearance has been widely scrutinized (Ragin 2008, Schneider and Wagemann 2012), it has seldom been considered in light of the treatment given to condition **I**. Indeed, **I** does not disappear from solutions despite its consistency scores being close to **A**'s. Its different stability is not justified by a different import, however: as displayed in Table 6, **A** and **I** both have a sorting power: the former, of negative instances; the latter, of positive ones. Instead, the difference rests on essentiality scores. The explanatory capacity of the model is independent on **A**, and highly dependent on **I**, without which contradictory configurations arise to cover 4 out of 9 instances.

– TABLE 6 & TABLE 7 –

From Table 7, we learn that **C** is also an inessential element in the model. Its lack of import accounts for its being dropped from Standard solutions. The population's diversity, therefore, can be explained by the sole non-regime conditions **S**, **I**, and **R**. The "correct" truth table lists eight alternative configurations, and the distribution leaves two logical remainders for which directional expectations are still required. Parsimonious and intermediate minimizations find the same solution to the positive outcome, again reading $i + SR \rightarrow Y$.

.2. Democracy in interwar Europe

The textbook example of disappearing necessary conditions remains Lipset's hypothesis, as applied to the breakdown of democracy in the interwar Europe (Rihoux and De Meur 2009, Berg-Schlosser and De Meur 1994). With five conditions to gauge wealthy (*W*), industrialized

(*I*), urbanized (*U*), literate (*L*) social systems with stable (*S*) governments, the model generates 32 primitives, of which the selected cases leave 23 unobserved, as displayed in Table 8.a.

– TABLE 8 –

As Table 8.b shows, individual consistency scores prove *L* is as necessary a condition to *Y* as are *W* and *S*. Nonetheless, parsimonious minimizations drop it from solutions, reading *WS* → *Y*. When conditioned to directional expectations, minimizations restore *L* and the plausible solution reads *WLS* → *Y*.

– TABLE 9 & TABLE 10 –

Table 9 shows that, indeed, **W**, **L**, and **S** are the only conditions in the model with import. From Table 10, we learn that **W** and **S** are essential conditions that alone account for the entirety of the diversity. Moreover, they generate a fully specified truth table with a single solution, overlapping with parsimonious minimizations of the original model.

.3. Independent regulators in policymaking

An intentionally layered explanatory model is developed by Maggetti (2009) to account for the centrality of independent regulatory agencies in policymaking. He considers regulators' centrality (**Y**) to depend on two remote factors: first, the duality (**D**) of political and the administrative decision-making, which should prevent regulators' centrality; second, the professionalization (**P**) of the legislature, which again is expected to result in the marginalization of regulators. Three further proximate factors are added that concur with regulators' centrality and complement or correct the remote factors: namely, the regulators' technical expertise (**E**); their *de facto* independence from politicians in daily operations (**O**); and their *de facto* dependence on the regulated interests (**I**).

The model is tested on 6 agencies from two sectors – competition and financial services – in three small corporatist countries – Sweden, Switzerland and the Netherlands. The overall truth table, as from Table 11.a, again has 32 primitives and a severe problem of limited diversity, given that only 8 of them are observed. The analysis of individual consistency in Table 11.b reveals that – except for **E** – all of the conditions are necessary to the outcome with the expected sign. Moreover, **P** is proven a truly necessary and sufficient condition.

– TABLE 11 –

Following the two-step protocols, in the first round the sub-model with remote factors **P**, **D** is minimized for higher parsimony, finding that $p \rightarrow Y$. In the second round, the solution term p is added to the proximate factors **E**, **O**, **I**. The new sub-model is run for conservative minimizations, and the solution reads $pOi \rightarrow Y$.

– TABLE 12 & TABLE 13 –

When we apply the two gauges of import and essentiality, however, we see that not all theoretical diversity is empirically required. Indeed, the import scores from Table 12 show all explanatory conditions have import except for **E**. However, when essentiality is assessed, Table 13 indicates **P** is the only condition required for accounting for all diversity.

4. Discussion, and a final consideration

The article has revolved around a twofold tenet: that QCA is for correct causal ascription and that Standard minimizations cannot correctly specify models while ascribing causation, and thus yield possibly flawed results.

However, the many strategies developed to tackle this issue have not fully restored the technique's credibility. A reliance on sound counterfactuals (*Strategy #1*) makes solutions truer to observations, yet cast doubts of confirmation bias. A change in the algorithm (*Strategy #2*) ensures that the findings are correct yet not that they are meaningful or causal. Layered models (*Strategy #3*) seem equally unconvincing, as they either treat dependencies as unproven assumptions engrained in design or as data-driven sets of conjunctions again in need of a theory. Questioning the complexity of the model (*Strategy #4*) provides the most promising route but has, so far, resulted in protocols for compressing conditions and avoiding trivialness in explanations.

The article adds two further concepts to this fourth strategy – import and essentiality – based on instances with same outcome that a condition can set apart from an unspecified population, and instances that are in contradictory configurations when the same condition is dropped from the original model, respectively. Far from substituting the Standard parameters of fit, these two gauges rather complement them. They share the same rationale – that a condition is empirically necessary when the instances without it agree in not displaying the outcome and is empirically sufficient when the instances with it agree in displaying the outcome – but neither assesses subset relationships nor ascribes causation. Import and essentiality are simple tests for model specification and are applied before minimizations to ascertain conditions' difference-making power to the population. After the tests, we know which conditions have both import and essentiality, which have neither, and which have only one. The protocol is intuitive for conditions showing both or neither: we may definitely want the former included in the model and the latter excluded. The two remaining types require a decision, instead. If we stick to the requisites of set-theoretic causation and aim for a fully non-contradictory truth table, we only need to include the essential conditions, so causal ascription is the only task left to the Quine-McCluskey.

First applications to renowned studies show that essential models only include the conditions listed in the Standard parsimonious solution and retrieve the same results. However, the two gauges also show that additional conditions included in intermediate solutions from overspecified models are non-essential with proven import. These clues only follow from three studies and thus require far more testing before being held as true. If they were confirmed, however, they would be quite consequential to the current methodological debate about the merits of Standard Analysis in treating limited diversity.

The clues suggest that the Quine-McCluskey *can* retrieve the essential conditions from an overspecified model and unveil the structure of causation, which goes against this work's starting tenet. Standard minimizations drop inessential conditions without import as irrelevant; keep the essential ones; and, after considering plausibility, can add inessential conditions with import to solutions. Import without essentiality entails a causal ordering of factors; therefore, the relationship between parsimonious and plausible intermediate solutions from the Standard Analysis of inessential models may mirror plausible chained causation. Should these clues be confirmed, essentiality and import would also give new meaning to the distinction between "core" and "peripheral" conditions in solutions (Fiss 2011): the former would overlap the essential factors, and the latter would converge with the non-essential yet "important" completers.

These considerations compel a final note. Neither the Standard parameters of fit nor import and essentiality seem fully capable of addressing the vexing "garbage in-garbage out" issue of empirical research. Indeed, a model with only essential conditions can strengthen a claim that causal ascription is correct and its findings are credible. Adding inessential conditions with import may provide further evidence about a generative hypothesis when they are deemed as the "catalysts" of the essential chemical causation. However, their explanatory status can only be credibly claimed in a deductive design when the first condition selection is performed after a meaningful guess. When employed for explanatory purposes, as many other techniques QCA can only falsify a hypothesis about generating an outcome that must be credible in itself. A data-driven analysis of a seriously overspecified model can hardly yield sound results because the causal story, as formally correct as it may be, could eventually make fairly little sense.

References

Baumgartner, Michael, and Alrik Thiem. 2015a. "Identifying complex causal dependencies in configurational data with Coincidence Analysis." *The R Journal* 7.1: 176-184.

Baumgartner, Michael, and Alrik Thiem. 2015b. "Model ambiguities in configurational comparative research." *Sociological Methods & Research* OnlineFirst: 1-34.

Baumgartner, Michael. 2008. "Regularity theories reassessed." *Philosophia* 36.3: 327-354.

Baumgartner, Michael. 2009. "Inferring causal complexity." *Sociological Methods & Research* 38.1: 71-101.

Baumgartner, Michael. 2012. "Detecting causal chains in small-N data." *Field Methods* 25.1:3-24.

Berg-Schlosser, Dirk, and Gisèle De Meur. 1994. "Conditions of democracy in interwar Europe: A Boolean test of major hypotheses." *Comparative Politics* 26. 3: 253-279.

Berg-Schlosser, Dirk, and Gisèle De Meur. 2009. "Comparative research. Case and variable selection". Pp. 19-32 in *Configurational Comparative Methods*, edited by Charles C. Ragin and Benoît Rihoux. London: Sage.

Fiss, Peer C. 2011. "Building better causal theories: a fuzzy set approach to typologies in organization research." *Academy of Management Journal* 54.2: 393–420.

Goertz, Gary. 2006. "Assessing the trivialness, relevance, and relative importance of necessary or sufficient conditions in social science." *Studies in Comparative International Development* 41.2: 88-109.

Lewis, David. 2001. "Truthmaking and Difference-Making." *Noûs* 35.4: 602-615.

Lipset, Seymour M. 1959. “Some social requisites of democracy: Economic development and political legitimacy.” *American Political Science Review* 53.01: 69-105.

Mackie, John L. 1965. “Causes and conditions.” *American Philosophical Quarterly* 2.4: 245-264.

Maggetti, Martino. 2009. “The role of independent regulatory agencies in policy-making: a comparative analysis.” *Journal of European Public Policy* 16.3:450-70.

Marx, Axel. 2010. “Crisp-set Qualitative Comparative Analysis and model specification”. *International Journal of Multiple Research Approaches* 4.2:138-58.

Ragin, Charles C. 1987. *The Comparative Method. Moving Beyond Qualitative and Quantitative Strategies*. Berkeley: University of California Press.

Ragin, Charles C. 2000. *Fuzzy-Set Social Science*. Chicago: University of Chicago Press.

Ragin, Charles C. 2006. “Set relations in social research: evaluating their consistency and coverage.” *Political Analysis*, 14.3: 291-310.

Ragin, Charles C. 2008. *Redesigning Social Inquiry: Fuzzy Sets and Beyond.* Chicago: University of Chicago Press.

Ragin, Charles C., and John Sonnett. 2004. “Between complexity and parsimony: limited diversity, counterfactual cases, and comparative analysis.” Pp. 180-197 in *Vergleichen in der Politikwissenschaft*, edited by Sabine Kropp and Michael Minkenberg. Wiesbaden: VS Verlag für Sozialwissenschaften.

Rihoux, Benoît, and Gisèle De Meur. 2009. “Crisp-set Qualitative Comparative Analysis (csQCA).” Pp. 33-68 in *Configurational Comparative Methods*, edited by Charles C. Ragin and Benoît Rihoux. London: Sage.

Schneider, Carsten Q., and Claudius Wagemann. 2006. “Reducing complexity in Qualitative Comparative Analysis (QCA): Remote and proximate factors and the consolidation of democracy.” *European Journal of Political Research* 45.5: 751–786.

Schneider, Carsten Q., and Claudius Wagemann. 2012. *Configurational Comparative Methods.* Cambridge, UK: Cambridge University Press.

Schneider, Carsten Q., and Claudius Wagemann. 2013. "Doing justice to logical remainders in QCA: moving beyond the Standard Analysis." *Political Research Quarterly* 66.1: 211–220.

Yamasaki, Sakura, and Benoît Rihoux. 2009. "A commented review of applications." Pp. 123-146 in *Configurational Comparative Methods*, edited by Charles C. Ragin, and Benoît Rihoux. London: Sage.

Tables

Table 1. Dataset *(a)* from a constant *C* and fictional conditions **A**, **B** with single known solution *A*+*B* → *Y* and *ab* → *y*; and the related truth table*(b)*.

(a)

instances	**A**	**B**	**C**	**Y**
i1	0.2	0.8	1.0	0.9
i2	0.1	0.7	1.0	0.8
i3	0.7	0.1	1.0	0.8
i4	0.8	0.2	1.0	0.9
i5	0.7	0.8	1.0	0.8
i6	0.8	0.7	1.0	0.9
i7	0.1	0.1	1.0	0.1
i8	0.1	0.1	1.0	0.2

(b)

A	**B**	**C**	*instances*	**Y**	S-cons	**y**	S-cons
0	1	1	***i1***, ***i2***	1	1.00	0	0.40
1	0	1	***i3***, ***i4***	1	1.00	0	0.40
1	1	1	***i5***, ***i6***	1	1.00	0	0.41
0	0	1	*i7*, *i8*	0	0.53	1	0.81
0	1	0					
1	0	0					
1	1	0					
0	0	0					

Table 2. Consistency of necessity and of sufficiency: individual scores of conditions **A**, **B**, **C** against **Y** as in Table 1.a.

Conditions tested	Outcome: *Y*		Outcome: *y*	
	N-consistency S-coverage	S-consistency N-coverage	N-consistency S-coverage	S-consistency N-coverage
A	0.65	1.00	0.38	0.29
a	0.54	0.64	1.00	0.58
B	0.65	1.00	0.38	0.29
b	0.54	0.64	1.00	0.58
C	1.00	0.67	1.00	0.32
c	0.00	1.#IND00	0.00	-1.#IND00

Table 3. Sorting power of (a) condition **A**, (b) condition **B**, and (c) condition **C** on the instances from Table 1.

(a)

A	*instances*	*nr*	**Y**
1	*i3, i4, i5, i6*	4	1
0	*i1, i2, i7, i8*	4	Cd

$\mathscr{p}_{A}$ = {i3, i4, i5, i6}
$\mathscr{n}_{A} = 4$; $\mathcal{N} = 8$
import$_{\mathbf{A}} = \mathscr{n}_{A} / \mathcal{N} = 4/8 = 0.5$

(b)

B	*instances*	*nr*	**Y**
1	*i1, i2, i5, i6*		1
0	*i3, i4, i7, i8*		Cd

$\mathscr{p}_{B}$ = {i1, i2, i5, i6}
$\mathscr{n}_{B} = 4$; $\mathcal{N} = 8$
import$_{\mathbf{B}} = \mathscr{n}_{B} / \mathcal{N} = 4/8 = 0.5$

(c)

C	*instances*	*nr*	**Y**
1	*i1, i2, i3, i4, i5, i6, i7, i8*	8	Cd
0	-		1

$\mathscr{p}_{C}$ = {Ø}
$\mathscr{n}_{C} = 0$; $\mathcal{N} = 8$
import$_{\mathbf{C}} = \mathscr{n}_{C} / \mathcal{N} = 0/8 = 0$

Table 4. Truth tables obtained by dropping (a) **A**, (b) **B**, (c) **C** from the model in Table 1.

(a)

B	**C**	*instances*	**Y**
1	1	***i1, i2, i5, i6***	1
0	1	***i3, i4,*** *i7, i8*	Cd
1	0		
0	0		

$\mathcal{Q}$ ={ Ø }, $\mathscr{q}'_{A}$ ={ ***i3, i4,*** *i7, i8* }
$\mathcal{N}$=8; $\mathscr{n}''_{A} = 4$
essentality$_{A} = \mathscr{n}''_{A} / \mathcal{N} = 0.5$

(b)

A	**C**	*instances*	**Y**
1	1	***i3, i4, i5, i6***	1
0	1	***i1, i2,*** *i7, i8*	Cd
1	0		
0	0		

$\mathcal{Q}$ ={ Ø }, $\mathscr{q}'_{B}$ ={ ***i1, i2,*** *i7, i8* }
$\mathcal{N}$=8; $\mathscr{n}''_{B} = 4$
essentality$_{B} = \mathscr{n}''_{B} / \mathcal{N} = 0.5$

(c)

A	**B**	*instances*	**Y**
1	1	***i5, i6***	1
1	0	***i3, i4***	1
0	1	***i1, i2***	1
0	0	*i7, i8*	0

$\mathcal{Q} = \mathscr{q}'_{C}$ ={ Ø }
$\mathcal{N}$=8; $\mathscr{n}''_{C} = 0$
essentality$_{C} = \mathscr{n}''_{C} / \mathcal{N} = 0$

Table 5. Stokke (2007): original model *(a)*, and consistency of single conditions *(b).*

(a)

A	**C**	**S**	**I**	**R**	*instances*	**Y**
1	0	1	1	1	of	1
1	0	0	1	0	m1	0
1	0	0	1	1	m2	0
0	0	0	1	0	lh,k1	0
1	1	1	1	1	c	1
1	1	1	1	0	EC1	0
1	1	1	0	0	EC2	1
1	0	0	0	0	kR	1

$\mathcal{Q}$ ={ Ø }

(b)

	Out: Y		Out:y	
	N-cons	*S-cons*	*N-cons*	*S-cons*
A	**1.00**	0.57	0.60	0.43
a	0.00	0.00	0.40	**1.00**
C	0.50	0.67	0.20	0.33
c	0.50	0.33	0.80	0.67
S	0.75	0.75	0.20	0.25
s	0.25	0.20	0.80	0.80
I	0.50	0.29	**1.00**	0.71
i	0.50	**1.00**	0.00	0.00
R	0.50	0.67	0.20	0.33
r	0.50	0.33	0.80	0.67

Table 6. Import of explanatory conditions in Stokke (2007).

($\mathcal{N}$ =9)

(a)

A	*instances*	**Y**
1	of, **m1**, **m2**, cp, **EC1**, EC2, kR	Cd
0	**lh**, **k1**	0

$\wp_A$ ={ lh, k1 }
$import_A$ = 0.22

(b)

C	*instances*	**Y**
1	cp, **EC1**, EC2	Cd
0	of, **m1**, **m2**, **lh**, **k1**, kR	Cd

$\wp_C$ ={ Ø}
$import_C$ = 0

(c)

S	*instances*	**Y**
1	of, cp, **EC1**, EC2	Cd
0	**m1**, **m2**, **lh**, **k1**, kR	Cd

$\wp_S$ ={ Ø}
$import_S$ = 0

(d)

I	*instances*	**Y**
1	of, **m1**, **m2** ,**lh**, cp, **EC1**, **k1**	Cd
0	EC2, kR	1

$\wp_I$ ={ EC2, kR }
$import_C$ = 0,22

(e)

R	*instances*	**Y**
1	of, **m2**, cp	Cd
0	**m1**, **lh**, **EC1**, EC2, **k1**, kR	Cd

$\wp_R$ ={ Ø }
$import_R$ = 0

Table 7. Essentiality of Stokke's conditions.

($\mathcal{N}$ =9, $\mathcal{Q}$=Ø)

(a)

condition tested: A

C	**S**	**I**	**R**	*inst*	**Y**
0	1	1	1	of	1
0	0	1	0	**m1,lh,k1**	0
0	0	1	1	**m2**	0
1	1	1	1	cp	1
1	1	1	0	**EC1**	0
1	1	0	0	EC2	1
0	0	0	1	kR	1

q'_A ={ Ø }

essentality$_A$ = 0

(b)

condition tested: C

A	**S**	**I**	**R**	*inst*	**Y**
1	1	1	1	of,cp	1
1	0	1	0	**m1**	0
1	0	1	1	**m2**	0
0	0	1	0	**lh,k1**	0
1	1	1	0	**EC1**	0
1	1	0	0	EC2	1
1	0	0	0	kR	1

q'_C ={ Ø }

essentality$_C$ = 0

(c)

condition tested: S

A	**C**	**I**	**R**	*inst*	**Y**
1	0	1	1	of,**m2**	Cd
1	0	1	0	**m1**	0
0	0	1	0	**lh,k1**	0
1	1	1	1	cp	1
1	1	1	0	**EC1**	0
1	1	0	0	EC2	1
1	0	0	0	kR	1

q'_S={ of, m2 }

essentality$_S$ = 0.22

(d)

condition tested: I

A	**C**	**S**	**R**	*inst*	**Y**
1	0	1	1	of	1
1	0	0	0	**m1**,kR	Cd
1	0	0	1	**m2**	0
0	0	0	0	**lh,k1**	0
1	1	1	1	cp	1
1	1	1	0	**EC1**,EC2	Cd

q'_I ={ m1, kR, EC1, EC2 }

essentality$_I$= 0.44

(e)

condition tested: R

A	**C**	**S**	**I**	*inst*	**Y**
1	0	1	1	of	1
1	0	0	1	m1,m2	0
0	0	0	1	lh,kl1	0
1	1	1	1	cp,**EC1**	Cd
1	1	1	0	EC2	1
1	0	0	0	kR	1

q'_R ={ cp, EC1 }

essentality$_R$= 0.22

Table 8. Rihoux and De Meur (2009): original model *(a)*, and consistency of single conditions *(b).*

(a)

W	**I**	**U**	**L**	**S**	*instances*	**Y**
1	1	1	1	1	BEL, CZE, NLD, GBR	1
1	0	0	1	1	FIN, IRL	1
1	1	0	1	1	FRA, SWE	1
0	0	0	0	0	GRC, PRT, ESP	0
0	0	0	1	0	HUN, POL	0
0	0	0	0	1	ITA, ROU	0
1	1	0	1	0	AUT	0
1	1	1	1	0	DEU	0
0	0	0	1	1	EST	0
					$\mathcal{Q}$ ={ Ø }	

(b)

	Out: Y		Out:y	
	N-cons	*S-cons*	*N-cons*	*S-cons*
W	**1.00**	0.80	0.20	0.20
w	0.00	0.00	0.80	**1.00**
I	0.75	0.75	0.20	0.25
i	0.25	0.20	0.80	0.80
U	0.50	0.80	0.10	0.20
u	0.50	0.31	0.90	0.69
L	**1.00**	0.61	0.50	0.38
l	0.00	0.00	0.50	**1.00**
S	**1.00**	0.71	0.30	0.27
s	0.00	0.00	0.70	**1.00**

Table 9. Import of explanatory conditions in Rihoux and De Meur (2009).

($\mathcal{N}$ =18)

(a)

W	*instances*	Y
1	AUT, BEL, CZE, FIN, FRA, DEU, IRL, NLD, SWE, GBR	Cd
0	EST, GRC, HUN, ITA, POL, PRT, ROU, ESP	0
$\mathscr{P}_W$	={EST, GRC, HUN, ITA, POL, PRT, ROU, ESP }	
	$import_W = 0.44$	

(b)

I	*instances*	Y
1	AUT, BEL , CZE, FRA, DEU, NLD, SWE, GBR	Cd
0	EST, FIN, GRC, HUN, IRL, ITA, POL, PRT, ROU, ESP	Cd
$\mathscr{P}_I$	={Ø}	
	$import_I = 0$	

(c)

U	*instances*	Y
1	BEL , CZE, DEU, NLD, GBR	Cd
0	AUT, EST, FIN, FRA, GRC, HUN, IRL, ITA, POL, PRT, ROU, ESP, SWE	Cd
$\mathscr{P}_U$	={Ø}	
	$import_U = 0$	

(d)

L	*instances*	Y
1	AUT, BEL , CZE, EST, FIN, FRA, DEU, HUN, IRL, NLD, POL, SWE, GBR	Cd
0	GRC, ITA, PRT, ROU, ESP	0
$\mathscr{P}_L$	={GRC, ITA, PRT, ROU, ESP}	
	$import_L = 0.28$	

(e)

S	*instances*	Y
1	BEL , CZE, EST, FIN, FRA, IRL, ITA, NLD, ROU, SWE, GBR	Cd
0	AUT, DEU, GRC, HUN, POL, PRT, ESP	0
$\mathscr{P}_S$	={AUT, DEU, GRC, HUN, POL, PRT, ESP}	
	$import_S = 0.39$	

Table 10. Essentiality of explanatory conditions in Rihoux and De Meur (2009).

($\mathcal{N}$ =18, $\mathcal{Q}$=Ø)

(a)

condition tested: W

I	U	L	S	*inst*	Y
1	0	1	0	AUT	0
1	1	1	1	BEL , CZE, NLD, GBR	1
0	0	1	1	EST, FIN, IRL	Cd
1	0	1	1	FRA, SWE	1
1	1	1	0	DEU	0
0	0	0	0	GRC, PRT, ESP	0
0	0	1	0	HUN, POL	0
0	0	0	1	ITA, ROU	0

q'_A ={ EST, FIN, IRL }

essentality$_A$ = 0.17

(b)

condition tested: I

W	U	L	S	*inst*	Y
1	0	1	0	AUT	0
1	1	1	1	BEL, CZE, NLD, GBR	1
0	0	1	1	EST	0
1	0	1	1	FIN, IRL, FRA, SWE	1
1	1	1	0	DEU	0
0	0	0	0	GRC, PRT, ESP	0
0	0	1	0	HUN, POL	0
0	0	0	1	ITA, ROU	0

q'_C ={ Ø }

essentality$_C$ = 0

(c)

condition tested: U

W	I	L	S	*inst*	Y
1	1	1	0	AUT, DEU	0
1	1	1	1	BEL, CZE, FRA, SWE NLD, GBR	1
0	0	1	1	EST	0
1	0	1	1	FIN, IRL	1
0	0	0	0	GRC, PRT, ESP	0
0	0	1	0	HUN, POL	0
0	0	0	1	ITA, ROU	0

q'_S={ Ø }

essentiality$_S$ = 0

(d)

condition tested: L

W	I	U	S	*inst*	Y
1	1	0	0	AUT	0
1	1	1	1	BEL, CZE, NLD, GBR	1
0	0	0	1	EST, ITA, ROU	0
1	0	0	1	FIN, IRL	1
1	1	0	1	FRA, SWE	1
1	1	1	0	DEU	0
0	0	0	0	GRC, PRT, ESP, HUN, POL	**0**

q'_I ={ Ø }

essentiality$_I$= 0

(e)

condition tested: S

W	I	U	L	*inst*	Y
1	1	0	1	AUT, FRA, SWE	Cd
1	1	1	1	BEL, CZE, DEU, NLD, GBR	Cd
0	0	0	1	EST, HUN, POL	0
1	0	0	1	FIN, IRL	1
0	0	0	0	GRC, PRT, ESP, ITA, ROU	0

q'_R ={ AUT, FRA, SWE, BEL, CZE, DEU, NLD, GBR }

essentiality$_R$= 0.44

Table 11. Maggetti (2009): full model *(a)*, and consistency of single conditions *(b)*.

(a)

D	**P**	**E**	**O**	**I**	*instances*	**Y**
1	1	0	1	1	sweco	0
0	0	0	1	0	swico	1
0	1	0	0	1	netco	0
0	0	1	1	0	swibk	1
0	1	1	1	0	netbk	0
1	1	1	0	1	swebk	0

$\boldsymbol{Q} = \{ \emptyset \}$

(b)

	Out: Y		Out:y	
	N-cons	*S-cons*	*N-cons*	*S-cons*
D	0.00	0.00	0.50	**1.00**
d	**1.00**	0.50	0.50	0.50
P	0.00	0.00	**1.00**	**1.00**
p	**1.00**	**1.00**	0.00	0.00
E	0.50	0.33	0.50	0.67
e	0.50	0.33	0.50	0.67
O	**1.00**	0.50	0.50	0.50
o	0.00	0.00	0.50	**1.00**
I	0.00	0.00	0.75	**1.00**
i	**1.00**	0.67	0.25	0.33

Table 12. Import of explanatory conditions in Maggetti (2009).

($\mathcal{N}$ =6)

(a)

D	*instances*	**Y**
1	sweco, swebk	0
0	swico, netco, swibk, netbk	Cd

$\mathcal{P}_D$ ={sweco, swebk}

import$_A$ = 0.33

(b)

P	*instances*	**Y**
1	sweco, netco, netbk, swebk	0
0	swico, swibk	1

$\mathcal{P}_P$ ={ sweco, netco, netbk, swebk, swico, swibk }

import$_C$ = 1

(c)

E	*instances*	**Y**
0	sweco, swico, netco	Cd
1	swibk, netbk, swebk	Cd

$\mathcal{P}_E$ ={ Ø}

import$_S$ = 0

(d)

O	*instances*	**Y**
1	sweco, swico, swibk, netbk	Cd
0	netco, swebk	0

$\mathcal{P}_O$ ={ netco, swebk }

import$_C$ = 0.33

(e)

I	*instances*	**Y**
1	sweco, netco, swebk	0
0	swico, swibk, netbk	Cd

$\mathcal{P}_I$ ={ swico, swibk, netbk }

import$_R$ = 0.5

Table 13. Essentiality of conditions in Maggetti (2009).

($\mathcal{N}$ = 6, $\mathcal{Q}$=∅)

(a)

condition tested: D

P	**E**	**O**	**I**	*inst*	**Y**
1	0	1	1	sweco	0
0	0	1	0	swico	1
1	0	0	1	netco	0
0	1	1	0	swibk	1
1	1	1	0	netbk	0
1	1	0	1	swebk	0

q'_D ={ ∅ }

essentality$_D$ = 0

(b)

condition tested: P

D	**E**	**O**	**I**	*inst*	**Y**
1	0	1	1	sweco	0
0	0	1	0	swico	1
0	0	0	1	netco	0
0	1	1	0	swibk, netbk	Cd
1	1	0	1	swebk	0

q'_P ={ swibk, netbk }

essentality$_P$ = 0.33

(c)

condition tested: E

D	**P**	**O**	**I**	*inst*	**Y**
1	1	1	1	sweco	0
0	0	1	0	swico, swibk	1
0	1	0	1	netco	0
0	1	1	0	netbk	0
1	1	0	1	swebk	0

q'_E={ ∅ }

essentality$_E$ = 0

(d)

condition tested: O

D	**P**	**E**	**O**	*inst*	**Y**
1	1	0	1	sweco	0
0	0	0	0	swico	1
0	1	0	1	netco	0
0	0	1	0	swibk	1
0	1	1	0	netbk	0
1	1	1	1	swebk	0

q'_O ={ ∅ }

essentality$_O$= 0

(e)

condition tested: I

A	**C**	**S**	**I**	*inst*	**Y**
1	1	0	1	sweco	0
0	0	0	1	swico	1
0	1	0	0	netco	0
0	0	1	1	swibk	1
0	1	1	1	netbk	0
1	1	1	0	swebk	0

q'_I ={ ∅ }

essentality$_I$= 0