# A Coincidence Analysis of a Causal Chain: The Swiss Minaret Vote

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## Abstract

This article applies *coincidence analysis* (*CNA*), a Boolean method of causal analysis presented in Baumgartner (2009a), to configurational data on the Swiss minaret vote of 2009. CNA is related to *qualitative comparative analysis* (QCA) (Ragin 2008), but contrary to the latter does not minimize sufficient and necessary conditions by means of Quine–McCluskey optimization, but based on its own custom built optimization algorithm. The latter greatly facilitates the analysis of data featuring chain-like causal dependencies among the conditions of an ultimate outcome—as can be found in the data on the Swiss minaret vote. Apart from providing a model of the causal structure behind the Swiss minaret vote, we show that a CNA of that data is preferable over a QCA.

## Keywords

causal modeling, Swiss minaret vote, coincidence analysis (CNA), qualitative comparative analysis (QCA), causal chains

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## Introduction

Baumgartner (2009a) introduced *coincidence analysis* (*CNA*)—a Boolean methodology of causal data analysis—as an alternative to *qualitative comparative analysis* (*QCA*), which was first presented in Ragin (1987) and further developed in Ragin (2000, 2008). CNA shares all of QCA's basic goals and intentions: It focuses on configurational complexity rather than on net effects (which are scrutinized by standard quantitative methods), it processes the same kind of data as QCA, that is, small- to intermediate-$N$ configurational data, it searches for rigorously minimized sufficient and necessary conditions of causally modeled outcomes, and it implements the same regularity theoretic notion of causation as QCA, that is, the notion, for example, developed by Mackie (1974).

There are two main differences between CNA and QCA. First, while QCA is designed to treat exactly one factor $Z_i$ as outcome and all other factors in an analyzed factor set as (mutually independent) potential direct causes of $Z_i$, CNA can treat any number of factors in an analyzed set $\{Z_1, \ldots, Z_i\}$ as outcomes. That is, CNA does not only search for direct causal dependencies among $Z_1, \ldots, Z_{i-1}$, on one hand, and $Z_i$, on the other, but also for dependencies among the conditions $Z_1, \ldots, Z_{i-1}$ themselves. Second, whereas all currently available variants of QCA (crisp-set QCA [*csQCA*], fuzzy-set QCA [*fsQCA*], multivalue [*mvQCA*], temporal QCA [*TQCA*], two-step QCA, enhanced standard analysis [ESA]–QCA[1]) minimize sufficient and necessary conditions of an outcome on the basis of Quine–McCluskey optimization (Q-M), which is a Boolean minimization procedure standardly used in electrical engineering or digital logic design, CNA minimizes sufficient and necessary conditions by means of its own optimization algorithm that is custom built for the discovery of complex causal structures.

In Baumgartner (2013), it has been demonstrated that these differences are particularly advantageous for CNA when it comes to causally modeling data that stem from causal chains, that is, from structures that feature at least one factor that is both an effect and a cause in the structure. Causal chains or mechanisms leading up to an ultimate outcome, as for example, Goertz (2006, esp. chap. 9) shows, are of great importance in many social scientific research contexts. Moreover, in the field of quantitative methods, considerable interest has recently arisen in developing methods that are designed to uncover causal chains (cf. esp. Imai, Keele, and Tingley 2010; Imai et al. 2011). Yet, QCA does not search for chain-like structures to begin with. Accordingly, numerous well-known QCA studies miss chain-like dependencies that can easily be recovered on the basis of a method as CNA that

searches for causal chains. At a glance (and for readers familiar with the original studies), here are some examples:

- In the Wickham-Crowley (1991:88) data on Latin American revolutions, CNA, in addition to the ordinary conditions that lead to the *Absence of Revolutions* (Wickham-Crowley 1991:101), finds paths that lead from *Guerilla Strength* OR *Weak Patrimonial Regime* AND *Loss of U.S. Support* to *Peasant Support*, which in one particular configuration, in turn, contributes to *Absence of Revolutions*. This is a path Wickham-Crowley does not find with QCA.
- In the data Rihoux and De Meur (2009:41) assembled—following Lipset's (1960) indicators—in order to investigate the causes of the survival of democracies in the interwar period, which is a frequently discussed data set in QCA studies (e.g., also Skaaning 2011), CNA finds a very strong path from INDLAB to GNPCAP that is missed in all QCA studies. The overall Boolean model CNA outputs for that data is this:

$$(\text{INDLB} \rightarrow \text{GNPCAP}) * (\text{GNPCAP} * \text{GOVSTAB} \rightarrow \text{SURVIVAL}).$$

  QCA only finds the lower part of this causal chain.

- Similarly, in data on the improvement of irrigation systems in Nepal which Lam and Ostrom (2010) recently analyzed by means of QCA, CNA uncovers a chain that Lam and Ostrom miss. More concretely, there are several paths from the *Existence of Consistent Leadership* OR the *Absence of Provisions of Fines* AND the *Existence of Rules for Irrigation Operation* via the *Existence of Collective Action Among Farmers* to the *Improvement in Water Adequacy*.

Moreover, as we shall see in detail in the fourth section, that QCA does not find causal chains is not merely due to the accidental unavailability of a QCA search strategy focusing on chain-like dependencies. Rather, QCA's reliance on Q-M creates a severe problem for QCA when it comes to uncovering causal chains. More specifically, it entails that QCA could only uncover a chain-like structure at the price of assuming at least one straight-out logical contradiction.

To anticipate this problem at this point already, note that in every application of QCA exactly one factor in the data is treated as outcome and all other factors as conditions. To eliminate redundancies from relationships of sufficiency and necessity involving $n$ conditions, Q-M requires $2^n$ possible configurations among those conditions. If some of these configurations are

missing from the data, QCA prompts the researcher to introduce them counterfactually by assumption. Now, suppose we apply QCA to analyze data generated by a causal structure that features the chain $A \longrightarrow B \longrightarrow C$. In a first QCA performed on that data, $C$ is treated as outcome and $A$ and $B$ as conditions. $A$ and $B$ are thus assumed to be configurable in $2^2$ combinations. This, in turn, is tantamount to assuming that $A$ and $B$ are mutually independent, and in particular, that the configuration $A*b$ is possible.[2] However, if we then perform a second QCA—this time treating $B$ as outcome—$A$ and $B$ will no longer be assumed to be independent. $A$ can only be identified as sufficient condition of $B$, as induced by the structure $A \longrightarrow B \longrightarrow C$, if QCA assumes that the configuration $A*b$ is impossible. Overall, thus, to find the chain $A \longrightarrow B \longrightarrow C$, QCA—due to its reliance on Q-M—must assume that the configuration $A*b$ is both possible and impossible, that is, that $A$ and $B$ are both dependent and independent. But of course, as everything follows from a logical contradiction, the QCA search for chains is thereby completely trivialized.

By contrast, as we shall see in the third section, the optimization algorithm implemented by CNA does not require $2^n$ configurations of $n$ conditions and, accordingly, succeeds in recovering chains without ever assuming that the conditions of an ultimate outcome are independent. In particular, to find the chain $A \longrightarrow B \longrightarrow C$ CNA does not need the configuration $A*b$. CNA can properly process data tables featuring any number of combinations smaller than $2^n$ without being compelled to resort to counterfactual reasoning.

So far, CNA and QCA have only been compared relative to artificial data that were purposefully tailored to bring out the differences between these two methods as transparently as possible. For the first time, this article provides a detailed CNA of real-life data and contrasts it with a corresponding QCA. The data analyzed to this end stem from the minaret controversy in Switzerland which, in November 2009, culminated in 57.5 percent of participating voters and 22 of the 26 cantons (Swiss states) approving a popular initiative demanding a constitutional amendment that bans the construction of new minarets (and which subsequently made the headlines around the world). We investigate the causal dependencies among the following six factors: high rate of old xenophobia ($A$), strong left parties ($L$), high share of Serbian or Croatian or Albanian speaking population ($S$), traditional economic structure ($T$), high rate of new xenophobia ($X$), and acceptance of the minaret initiative ($M$). These factors constitute an ideal test case for a comparison of CNA and QCAs of real-life data because theoretical expectations have it not only that the first five factors contributed in one way or another to the sixth, that is, to the outcome of the vote, but also that the conditions that led to the

acceptance of the initiative are not themselves causally independent, that is, that the causal structure underlying the minaret data is of chain-like form.

We shall find that the advantages of CNA in regard to analyzing data originating from causal chains carry over from idealized to real-life contexts. CNA models our exemplary data in terms of a causal chain which model is only found by QCA at the price of assuming at least one logical contradiction. Plainly though, on pain of trivialization, no methodology of causal analysis must be allowed to base its inferences on contradictory assumptions.

The second section presents the subsequently scrutinized factors, theoretical expectations about the causal interplay among them, and the pre-processed data underlying our study. In the third and fourth sections, we then analyze that data on the basis of CNA and QCA, respectively. The article ends with a discussion of the obtained results.

## The Data

We selected the factors for our study of the rather surprising acceptance of the Swiss minaret ban (*M*) based on explanation attempts published in the press shortly after the ballot of November 29, 2009. The historian Urs Altermatt, for example, surmised that the outcome of the vote was due to age-old reflexes induced by a phobia against nonnatives that is deeply rooted in the Swiss society and has repeatedly led to discriminations of minorities (cf. Furger 2009). We do justice to this *explanation from old reflexes* by incorporating the factor *high rate of old xenophobia* (*A*), which reproduces the voting behavior of the Swiss cantons in regard to the xenophobic initiatives brought before voters in the 1970s.

The psychiatrist Berthold Rothschild took the minaret vote to be the result of a collective feeling of powerlessness, which stems from Switzerland's dependency on the European integration and on international markets (cf. Rothschild 2009). The stronger the feeling of powerlessness, the more the Swiss population is inclined to protect its home against all allegedly dangerous exterior influences. According to this *explanation from powerlessness*, the minaret ban should have gained highest acceptance in predominantly agricultural cantons where the impact of the market opening is felt most intensely. We test this hypothesis by including the factor *T* representing *traditional economic structure*.

The publicist and historian Rudolf Walther conjectured that the minaret ban was essentially caused by the supporting campaign mounted by right-wing political parties. That campaign played on resentments against Muslims and the Islam and, in light of the economic crisis and growing unemployment,

triggered a sort of "alpine chauvinism" against the unknown (cf. Walther 2010a, 2010b). According to this *explanation from political campaigning*, xenophobia and collective powerlessness are latent factors that only politically manifest themselves in contexts that systematically activate them. We measured political campaigning via the strength of political parties in corresponding cantons. As the absence of the factor *strong left parties* ($L$) turned out to cover[3] $M$ to a higher degree than the seemingly more directly relevant factor *strong right parties*, we included the former rather than the latter into our study.

According to the writer and filmmaker Leon de Winter, the outcome of the minaret vote was brought about by widespread resentment over the fact that Muslims tend to disregard the local customs in their host countries and over the development of "Muslim ghettos" with high crime and unemployment rates (cf. de Winter 2009). De Winter claimed that, as political elites and the media ignored these problems for too long, this resentment gave way to a feeling of impotence in large parts of the population, which, in turn, was expressed by voters at the polls in an act of defiance. We account for this *explanation from culture clash* by integrating the factor $S$ representing *high share of people natively speaking Serbian, Croatian, or Albanian* among the foreign population. We gave preference to measuring the degree of culture clash via language rather than via religion or legal status because the Muslim population can be most accurately identified linguistically and because difficulties in communication most directly lead to animosities against foreigners.

Finally, to test whether in addition to old reflexes there might have been *new reflexes* responsible for the acceptance of the minaret ban, we added the factor $X$ representing *high rate of new xenophobia* which reproduces the voting behavior of Swiss cantons with respect to xenophobic initiatives between 1996 and 2008. We suspect that, if $X$ in fact turns out to be causally relevant for $M$, it is an intermediate factor on a causal chain from $A$, $T$, $L$, or $S$ to $M$.

For a popular initiative to pass in Switzerland, both the majority of participating voters and the majority of cantons need to approve. Accordingly, as indicated above, we chose cantons as our measuring units for assigning values to the factors in the set $\{A, L, S, T, X, M\}$. In the raw data of our study, which can be consulted in the online appendix which can be found at http://smr.sagepub.com/supplemental/ (cf. appendix Table 2), all factors, except for $M$, are given as continuous variables. As CNA, so far, has only been fully worked out in a crisp-set version (a fuzzy-set version is currently being developed), we subsequently contrast a CNA of the minaret data with a csQCA thereof.[4] In order to render continuous variables processable by

**Table 1.** Truth Table $\mathcal{T}_M$ Which Resulted From a Suitable Preprocessing of the Raw Data in Table 2 in the Online Appendix Which Can Be Found at http://smr.sagepub.com/supplemental/.

| $\mathcal{T}_M$ | A | L | S | T | X | M | Cantons |
|---|---|---|---|---|---|---|---|
| $c_1$ | 1 | 0 | 1 | 1 | 1 | 1 | LU, UR, SZ, OW, NW, AR, AI |
| $c_2$ | 1 | 0 | 1 | 0 | 1 | 1 | GL, ZG, SO, SG, AG |
| $c_3$ | 0 | 1 | 0 | 0 | 0 | 0 | VD, NE, GE |
| $c_4$ | 0 | 0 | 1 | 1 | 1 | 1 | GR,TG |
| $c_5$ | 1 | 1 | 1 | 0 | 1 | 1 | ZH |
| $c_6$ | 1 | 1 | 1 | 1 | 1 | 1 | BE |
| $c_7$ | 1 | 0 | 0 | 1 | 0 | 1 | FR |
| $c_8$ | 1 | 1 | 0 | 0 | 0 | 0 | BS |
| $c_9$ | 1 | 1 | 0 | 0 | 1 | 1 | BL |
| $c_{10}$ | 0 | 1 | 1 | 0 | 1 | 1 | SH |
| $c_{11}$ | 0 | 0 | 0 | 0 | 1 | 1 | TI |
| $c_{12}$ | 0 | 0 | 0 | 1 | 0 | 1 | VS |
| $c_{13}$ | 0 | 1 | 0 | 1 | 0 | 1 | JU |

*Note*: This truth table is the basis for the subsequent coincidence analysis (CNA) and qualitative comparative analysis (QCA).

CNA, their values, in a first step, must be dichotomized. To this end, we used the standards of "good practice" commonly implemented in csQCA studies (cf. Rihoux and De Meur 2009:42). Details concerning the chosen thresholds are provided in the online appendix which can be found at http://smr.sagepub.com/supplemental/. Overall, the preprocessing of our raw data resulted in the truth table $\mathcal{T}_M$ given in Table 1. While the leftmost column of Table 1 numbers the different configurations of our factors, the rightmost column indicates which cantons (named by their International Organization for Standardization [ISO] 3166-2 abbreviations) exemplify which configuration. In the third section, we analyze $\mathcal{T}_M$ by means of CNA and, in the fourth section, we provide a corresponding QCA.

## The CNA

The procedural details of CNA have been presented in Baumgartner (2009a, 2009b) and are not going to be repeated here. For brevity, we subsequently confine ourselves to introducing the core notions implemented by CNA as well as to indicating the basic methodological ideas behind the procedure.

Just as QCA, CNA searches for dependencies of minimal sufficiency and minimal necessity among the factors in a truth table over a set of factors

$\{Z_1, \ldots, Z_i\}$. While in the QCA context, the relevant sufficiency and necessity relations are commonly defined in a set-theoretic terminology, CNA is developed against the background of a truth-functional or logical terminology, but, in the end, these two terminologies are completely equivalent.[5]

In the context of CNA, a conjunction of factors $Z_1*Z_2* \ldots *Z_h, h \geq 1$, is called a *sufficient condition* of a factor $Z_i$ in a truth table $\mathcal{T}$ if, and only if, $\mathcal{T}$ contains at least one row featuring $Z_1*Z_2* \ldots *Z_h$ in combination with $Z_i$ and no row featuring $Z_1*Z_2* \ldots *Z_h$ in combination with the absence of $Z_i$, namely with $z_i$. Moreover, $Z_1*Z_2* \ldots *Z_h$ is a *minimally* sufficient condition of $Z_i$ in $\mathcal{T}$ if, and only if, no proper part of $Z_1*Z_2* \ldots *Z_h$ is itself sufficient for $Z_i$, where a proper part of a conjunction is that conjunction reduced by at least one conjunct.

Analogously, a disjunction $\Phi_1 + \Phi_2 + \ldots + \Phi_h, h \geq 1$, where $\Phi_1, \Phi_2$, and so on, are placeholders for conjunctions (or configurations) of factors, is called a *necessary condition* of a factor $Z_i$ in a truth table $\mathcal{T}$ if, and only if, every row in $\mathcal{T}$ featuring $Z_i$ also features at least one disjunct of $\Phi_1 + \Phi_2 + \ldots + \Phi_h$. Furthermore, $\Phi_1 + \Phi_2 + \ldots + \Phi_h$ is a *minimally* necessary condition of $Z_i$ if, and only if, no proper part of $\Phi_1 + \Phi_2 + \ldots + \Phi_h$ is itself necessary for $Z_i$, where a proper part of a disjunction is that disjunction reduced by at least one disjunct.

Note that, usually, in the prose around solution formulas in QCA studies only necessary conditions that consist of single factors are explicitly labeled "necessary conditions."[6] In fact, however, every QCA solution formula that identifies complex sufficient conditions for the absence of an outcome is tantamount to a solution formula that identifies a complex necessary condition for the presence of the outcome (by contraposition), and vice versa. For instance, a formula that identifies $A*C$ and $d$ as two alternative sufficient conditions for $b$ is logically equivalent to a formula that identifies $a*D + c*D$ as necessary condition for $B$. Disjunctive necessary conditions can be interpreted as imposing restrictions on the space of alternative causes of an outcome. For example, that $a*D + c*D$ is necessary for $B$ means that there are exactly two causal paths leading to $B$, one involving $a*D$ and another one involving $c*D$. More concretely, suppose we analyze the causes of a law being passed ($B$) in a particular country $\omega$. It might turn out that there are exactly two alternative paths leading to $B$: Either the corresponding law does not conflict with human rights ($a$) and is passed by the parliament of $\omega$ ($D$) or the law does not conflict with $\omega$'s constitution ($c$) and is passed by the parliament. Constellations of this sort are absolutely commonplace.

Thus, necessary conditions normally are just as complex as sufficient conditions, and CNA simply makes all necessary conditions transparent,

independently of their complexity. Subject to the regularity theoretic notion of causation underlying both CNA and QCA, a Boolean solution formula φ for an outcome $Z_i$ can be causally interpreted if, and only if, φ amounts to a minimally necessary disjunction of minimally sufficient conditions of $Z_i$ (cf. Baumgartner 2008; Mackie 1974).

As anticipated in the introduction, CNA does not presuppose that one particular factor in an analyzed truth table $\mathcal{T}$ can be identified as the outcome of the underlying causal structure prior to applying CNA. In principle, CNA is designed to recover all relationships of sufficiency and necessity among the factors in $\mathcal{T}$ and to rigorously minimize these relationships. In sociological practice, however, it is commonly known from the outset which factors are exogenous and which endogenous. What is more, often enough theoretical knowledge is available to order the factors in $\mathcal{T}$ causally, where a *causal ordering* is a relation $Z_i <_{\mathcal{T}} Z_j$ entailing that, in light of prior theoretical knowledge, $Z_j$ cannot be a cause of $Z_i$ (e.g., because $Z_i$ is instantiated temporally before $Z_j$). That is, an ordering excludes certain causal dependencies but does not stipulate any. Accordingly, in addition to a truth table $\mathcal{T}$, CNA may be given a subset W of endogenous factors (i.e., possible effects) in $\mathcal{T}$ and an ordering $<_{\mathcal{T}}$ over the factors in $\mathcal{T}$ as input. Minimally sufficient and necessary conditions are then calculated for the members of W in accordance with $<_{\mathcal{T}}$ only.

The algorithmic core of CNA consists of two parts. In the first part, sufficient conditions of all $Z_i \in$ W are identified in an input table $\mathcal{T}$. Moreover, all sufficient conditions $Z_1 * Z_2 * \ldots * Z_h$ of $Z_i$ are minimized by systematically eliminating conjuncts from $Z_1 * Z_2 * \ldots * Z_h$ and testing whether the resulting conjunctions (e.g., $Z_2 * Z_3 * \ldots * Z_h$ or $Z_1 * Z_3 * \ldots * Z_h$, etc.) are still sufficient for $Z_i$ in $\mathcal{T}$. In the second part, necessary conditions of all $Z_i \in$ W are built by disjunctively concatenating the minimally sufficient conditions of $Z_i$ identified in the first part: $Z_i \rightarrow \Phi_1 + \Phi_2 + \ldots + \Phi_h$. Likewise, the necessary conditions $\Phi_1 + \Phi_2 + \ldots + \Phi_h$ of $Z_i$ are minimized by systematically eliminating disjuncts from $\Phi_1 + \Phi_2 + \ldots + \Phi_h$ and testing whether the resulting disjunctions (e.g., $\Phi_2 + \Phi_3 + \ldots + \Phi_h$ or $\Phi_1 + \Phi_3 + \ldots + \Phi_h$, etc.) are still necessary for $Z_i$ in $\mathcal{T}$.[7]

In the optimal case, the two core algorithmic phases of CNA yield exactly one minimally necessary disjunction of minimally sufficient conditions for each $Z_i \in$ W, which—if W has more than one element—are then conjunctively concatenated to CNA solution formulas. As in case of QCA, however, minimizations may give rise to ambiguities, to the effect that CNA outputs multiple solutions formulas for one truth table $\mathcal{T}$. Multiple solutions formulas represent multiple causal structures that are compatible with the data recorded in $\mathcal{T}$, that is, that account for (or fit) the data equally well.

Furthermore, as the data processed by CNA and QCA tend to be noisy, that is, confounded by uncontrolled (unmeasured) causes of analyzed outcomes, it may happen that no configuration of factors is strictly sufficient or necessary for a given $Z_i \in W$. To still extract some causal information from such data, Ragin (2006) has introduced so-called *consistency* and *coverage* measures (cf. also Braumoeller and Goertz 2000; Goertz 2003). *Consistency* reproduces the degree to which the behavior of a given outcome obeys a corresponding sufficiency or necessity relationship (or a whole solution formula), whereas *coverage* reproduces the degree to which a sufficiency or necessity relationship (or a whole solution formula) accounts for the behavior of the corresponding outcome. More explicitly, the consistency of a sufficiency relation $Y \rightarrow Z$ is defined as the ratio of the number of $Y * Z$-cases to the number of $Y$-cases in the analyzed data.[8] The coverage of $Y \rightarrow Z$ is defined as the ratio of the number of $Y * Z$-cases to the number of $Z$-cases. Often, this notion of coverage is more specifically called *raw coverage*, in order to distinguish it from so-called *unique coverage* that measures the degree to which one particular conjunction of factors uniquely covers a corresponding outcome (cf. Ragin 2008:63-68). That is, the unique coverage of $Y \rightarrow Z$ is the ratio of the number of $Y * Z$-cases that, apart from $Y$, do not feature any other sufficient conditions of $Z$ to the number of $Z$-cases. (For convenience, by *coverage* we subsequently always refer to raw coverage.) Moreover, as $Y$ is sufficient for $Z$ if, and only if, $Z$ is necessary for $Y$, consistency and coverage are defined reciprocally for necessity relationships: The consistency of a necessity relation is equal to the coverage of the corresponding sufficiency relation, and vice versa for coverage. Where needed, we shall subsequently speak of *suf-consistency/coverage* and *nec-consistency/coverage* to keep these notions apart. Against this conceptual background, Ragin (2006) shows that by lowering the thresholds for consistency and coverage below maximum values, solution formulas are rendered amenable to a causal interpretation even if they do not exhibit strictly sufficient or necessary conditions for a corresponding outcome (cf. also Ragin 2008:chap. 3).

These techniques for handling noise in configurational data, which are meanwhile well established in the framework of QCA, are directly transferrable to CNA. By lowering the suf-consistency threshold to a nonmaximal value $k$, CNA is authorized to treat a configuration $\Phi$ as sufficient for a factor $Z$, even if only a ratio of $k$ among all $\Phi$-cases also feature $Z$. Similarly, by lowering the suf-coverage threshold (which is tantamount to lowering the nec-consistency threshold), CNA can treat $\Phi$ as necessary for $Z$, even if only a ratio of $k$ among all $Z$-cases also feature $\Phi$. To illustrate, suppose the disjunction $\Phi_1 + \Phi_2$ is present in 80 percent of all $Z_1$-cases in a given set of

configurational data. Hence, $\Phi_1 + \Phi_2$ is not strictly necessary for $Z_1$, that is, there are $Z_1$-cases not accounted for by $\Phi_1 + \Phi_2$. If the suf-coverage threshold for $\Phi_1 + \Phi_2 \rightarrow Z_1$ (or equivalently, the nec-consistency threshold for $Z_1 \rightarrow \Phi_1 + \Phi_2$) is now lowered to 0.8, CNA nonetheless treats $\Phi_1 + \Phi_2$ as necessary for $Z_1$. To test whether $\Phi_1 + \Phi_2$ is moreover minimally necessary for $Z_1$, CNA then proceeds to eliminating disjuncts from $\Phi_1 + \Phi_2$ and checking whether the remaining disjunct still accounts for 80 percent of the $Z_1$-cases. $\Phi_1 + \Phi_2$ is minimally necessary for $Z_1$ if, and only if, neither $\Phi_1$ nor $\Phi_2$ alone have the same suf-coverage as $\Phi_1 + \Phi_2$.

Lowering consistency and coverage thresholds in light of noisy data must be done with great caution. In the QCA literature, usually, only lowest bounds are provided for suf-consistency thresholds. For instance, Schneider and Wagemann (2010) recommend a lowest bound of 0.75 for suf-consistency. We contend, however, that there are good reasons to impose lowest bounds at least for suf-coverage of whole solution formulas as well. The suf-coverage of a solution formula being low means that it only accounts for few instances of an outcome. Or differently, in many cases where the outcome is given, there are causes at work that are not contained in the set of measured factors. However, unmeasured causes are likely to confound the data. The existence of potential confounders casts doubts on the causal interpretability of all other dependencies subsisting in the data, even on dependencies of perfectly consistent sufficiency. For uncontrolled causes might be covertly responsible for some of the dependencies manifest in the data. That is, the more likely it is that our data are confounded by uncontrolled causes, the less reliable a causal interpretation of resulting solution formulas becomes. In our view, suf-coverage of solution formulas should be used as a measure for the likelihood of confounding. The higher the coverage, the less likely it becomes that we are facing data confounding, the more reliable a causal interpretation of resulting solution formulas. We hence submit the same lowest bound for suf-coverage of solution formulas as usually imposed on suf-consistency: 0.75.

Now we are in a position to apply CNA to the truth table $\mathcal{T}_M$ (cf. Table 1). As $A$ (high rate of old xenophobia) reproduces voting behavior from the 1970s while the other factors in $\mathcal{T}_M$ are anchored in later periods of time, none of the latter can be causes of $A$. Moreover, prior theoretical knowledge determines that the causes of a strong traditional economic sector ($T$) are not among the factors assembled in $\mathcal{T}_M$. That is, $A$ and $T$ are exogenous in $\mathcal{T}_M$. The set of endogenous factors in $\mathcal{T}_M$ hence is this: $W_{\mathcal{T}_M} = \{L, S, X, M\}$. In addition, based on considerations of temporal ordering it can be excluded that $M$ (acceptance of minaret initiative) is a cause of $L$ (strong left parties), $S$ (high share of people natively speaking Serbian, Croatian, or Albanian), and $X$ (high

rate of new xenophobia); similarly, $X$ can be excluded as cause of $L$ and $S$. In sum, we can impose the following causal ordering on the factors in $\mathcal{T}_M$:

$$A, T <_{\mathcal{T}_M} L, S <_{\mathcal{T}_M} X <_{\mathcal{T}_M} M.$$

Thus, we only employ CNA to search for minimally sufficient and necessary conditions of the factors in $W_{\mathcal{T}_M}$ in accordance with $<_{\mathcal{T}_M}$. For brevity, we subsequently confine ourselves to analyzing the causal structures behind the positive factors in $\mathcal{T}_M$. Also, we are going to illustrate the operation of CNA by means of a few exemplary calculation steps only (for more detailed illustrations of CNA cf. Baumgartner 2009a; 2013). First, let us implement CNA to find sufficient conditions of $L$ among its candidate causes in $\mathcal{T}_M$. A sufficient condition of $L$ is a condition that is co-instantiated (or combined) with $L$ but not with $l$ in $\mathcal{T}_M$. In virtue of $<_{\mathcal{T}_M}$, the candidate causes of $L$ in $\mathcal{T}_M$ are $A$, $S$, and $T$. The first row of $\mathcal{T}_M$ that contains an instance of $L$ is row $c_3$. In that row, $L$'s candidate causes are configured as follows: $a*s*t$. Is that configuration a sufficient condition of $L$? That is not the case because $\mathcal{T}_M$ also contains a row in which $a*s*t$ is combined with $l$, namely row $c_{11}$.[9] The first row of $\mathcal{T}_M$ that actually features a sufficient condition of $L$ is $c_8$. Here, $L$ is combined with $A*s*t$ and no other row of $\mathcal{T}_M$ contains $A*s*t$ in combination with $l$. Row $c_{10}$ comprises another sufficient condition of $L$: $a*S*t$. These are the only two sufficient conditions of $L$ in $\mathcal{T}_M$.

Next, CNA minimizes the sufficient conditions diagnosed in the previous step by systematically eliminating conjuncts and testing whether the remaining conjunctions are still sufficient for corresponding outcomes. If $A*s*t$ is reduced by $A$, we are left with $s*t$. That $s*t$ is not sufficient for $L$ is exhibited in row $c_{11}$ which features $s*t$ in combination with $l$. Therefore, $A$ cannot be eliminated from $A*s*t$ without loss of sufficiency. Eliminating $s$ leaves us with $A*t$, which again is no longer sufficient for $L$, for in $c_2$ $A*t$ is combined with $l$. Finally, eliminating $t$ from $A*s*t$ yields $A*s$ which is no longer sufficient for $L$ either, for $A*s$ is combined with $l$ in row $c_7$. Overall, as no element of $A*s*t$ can be eliminated without loss of sufficiency, $A*s*t$ is diagnosed to be minimally sufficient for $L$ by CNA. The same holds for $a*S*t$: Every elimination of an element from that sufficient condition of $L$ induces a loss of sufficiency; hence, $a*S*t$ is minimally sufficient for $L$. By contrast, compare this to the sufficient condition $A*l*S*t$ of $X$ given in row $c_2$. If we eliminate $A$ from this condition, we are left with $l*S*t$, which is not combined with $x$ in any row of $\mathcal{T}_M$. That means $l*S*t$ is itself sufficient for $X$, that is, $A$ is redundant. Moreover, removing $S$ from $l*S*t$ leaves us with $l*t$, which also is not

combined with $x$ in $\mathcal{T}_M$. Thus, $l*t$ is itself sufficient and, in fact, minimally sufficient for $X$.

In the same vein, CNA identifies minimally sufficient conditions for the other factors in $W_{\mathcal{T}_M}$ according to $<_{\mathcal{T}_M}$. Overall, the first part of a CNA of $\mathcal{T}_M$ yields the following minimally sufficient conditions of the members of $W_{\mathcal{T}_M}$:

|     | Minimally sufficient conditions: |
| --- | --- |
| L:  | $A*s*t$ , $a*S*t$ |
| S:  | $A*l*t$ , $A*L*T$ |
| X:  | $A*L*T$ , $l*t$ , $S$ |
| M:  | $l$ , $S$ , $T$ , $X$ |

CNA now proceeds to building necessary conditions for the elements of $W_{\mathcal{T}_M}$ by disjunctively concatenating their minimally sufficient conditions. In case of our truth table $\mathcal{T}_M$, it turns out that $l + S + T + X$ is in fact a perfectly consistent necessary condition for $M$, for it holds that whenever $M$ is given, so is at least one of the disjuncts in $l + S + T + X$. By contrast, neither $A*s*t + a*S*t$ is consistently necessary for $L$, nor $A*l*t + A*L*T$ for $S$, nor $A*L*T + l*t + S$ for $X$. That means there exist factors that are causally relevant for the elements of $W_{\mathcal{T}_M}$ which we do not control (measure) in our study. Put differently, our data do not allow for (suf-)covering all the instances of $L$, $S$, and $X$. The following list exhibits the degrees to which the minimally sufficient conditions identified above cover the elements of $W_{\mathcal{T}_M}$ in $\mathcal{T}_M$.

$$A*s*t + a*S*t \rightarrow L \quad (\text{Cov} : {}^3/_9 = 0.333) \tag{1}$$

$$A*l*t + A*L*T \rightarrow S \quad (\text{Cov} : {}^6/_{17} = 0.353) \tag{2}$$

$$A*L*T + l*t + S \rightarrow X \quad (\text{Cov} : {}^{18}/_{19} = 0.947) \tag{3}$$

$$l + S + T + X \rightarrow M \quad (\text{Cov} : {}^{22}/_{22} = 1) \tag{4}$$

It is evident from this list that our data provide no basis whatsoever for covering $L$ and $S$ to an informative degree. There are simply too many causes of both $L$ and $S$ that we do not control in our study, which means that the likelihood that the data in table $\mathcal{T}_M$ are confounded with respect to $L$ and $S$ is very high. Plainly, this finding is not surprising, for, after all, we did not

select our factors with either $L$ or $S$ as ultimate outcomes in mind. As a consequence, we abstain from causally interpreting both equations (1) and (2) and, henceforth, treat $L$ and $S$ as exogenous relative to $\mathcal{T}_M$.[10] The case of $X$ is different. The minimally sufficient conditions of $X$ we identified above account for 18 of the 19 cases featuring $X$. By all standards of Boolean causal modeling, the resulting suf-coverage of 0.947 is perfectly acceptable.

This leaves us with $X$ and $M$ as endogenous factors. Correspondingly, equations (3) and (4) are the two disjunctions of minimally sufficient conditions we pass on to the second phase of our CNA. As we have seen above, $l + S + T + X$ is a perfectly consistent necessary condition for $M$. By lowering the suf-coverage (or equivalently, the nec-consistency) for $X$ to 0.947, we allow CNA to also treat $A*L*T + l*t + S$ as necessary condition for $X$. Next, CNA systematically eliminates disjuncts from these two conditions and tests whether the suf-coverage (or nec-consistency) of the remaining disjunctions is thereby affected. If, and only if, such eliminations of disjuncts do not lower the suf-coverage (nec-consistency) of the remaining disjunctions, the eliminated disjuncts are redundant and, hence, not part of a minimally necessary condition of the corresponding outcome. The following list comprises all possible ways of reducing equation (3) by one disjunct and indicates resulting suf-coverages.

$$l*t + S \rightarrow X \quad (\text{Cov} : {}^{18}/_{19} = 0.947) \tag{5}$$

$$A*L*T + S \rightarrow X \quad (\text{Cov} : {}^{17}/_{19} = 0.895) \tag{6}$$

$$A*L*T + l*t \rightarrow X \quad (\text{Cov} : {}^{7}/_{19} = 0.368) \tag{7}$$

As can easily be seen from expression (5), eliminating $A*L*T$ from equation (3) does not negatively affect the resulting suf-coverage. That is, $l*t + S$ covers the instances of $X$ just as well as $A*L*T + l*t + S$. In other words, $A*L*T$ makes no difference to $X$ over and above $l*t + S$ and is thus redundant. As causes are defined as difference-makers for their effects (cf. Mackie 1974), $A*L*T$ is thereby shown not to be a cause of $X$. By contrast, eliminating any of the other disjuncts from equation (3) results in suf-coverage drops. That shows that both $l*t$ and $S$ are needed to account for a maximal amount of the cases featuring $X$ in $\mathcal{T}_M$, or differently, that neither $l*t$ nor $S$ is redundant in equation (3). Both $l*t$ and $S$ are difference-makers for $X$. While eliminating $l*t$ only mildly lowers the suf-coverage, eliminating $S$ results in a total suf-coverage collapse. The reason for this is that $S$ has by far the highest unique coverage of all disjuncts of equation (3): the unique coverage of $S$ is 0.579, while the unique coverage of $l*t$ is 0.053 and the unique coverage of $A*L*T$ is 0. That is, $S$ is by far the most important condition for $X$, whereas $A*L*T$,

which never uniquely covers $X$, makes no difference to $X$. Since every further elimination of disjuncts from equation (5) negatively affects suf-coverage values, CNA concludes that equation (5) features a minimally necessary disjunction of minimally sufficient conditions of $X$.

Next, the same redundancy testing is repeated for equation (4). Here is a corresponding list with possible reductions of equation (4):

$$T + X \rightarrow M \quad (\text{Cov} : {}^{22}/_{22} = 1) \tag{8}$$

$$l + S + X \rightarrow M \quad (\text{Cov} : {}^{21}/_{22} = 0.955) \tag{9}$$

$$l + S + T \rightarrow M \quad (\text{Cov} : {}^{21}/_{22} = 0.955) \tag{10}$$

$$T \rightarrow M \quad (\text{Cov} : {}^{13}/_{22} = 0.591) \tag{11}$$

$$X \rightarrow M \quad (\text{Cov} : {}^{19}/_{22} = 0.864) \tag{12}$$

Equation (8) reveals that removing $l$ and $S$ from equation (4) does not lower the suf-coverage for $M$ at all. Hence, both $l$ and $S$ make no difference to $M$ over and above $T + X$. As we shall see below, $l$ and $S$ only have an indirect influence on $M$, one that is mediated via $X$. Expressions (9) and (10) exhibit that eliminating either $T$ or $X$ from equation (4) yields suf-coverage drops. Finally, equations (11) and (12) show that eliminating further factors from equation (8) comes with decreased suf-coverage values as well. Overall, it follows that of all the disjuncts of equation (4) only $T$ and $X$ are difference-makers for $M$. CNA hence eliminates both $l$ and $S$ from equation (4) and issues $T + X$ as minimally necessary disjunction of minimally sufficient conditions of $M$, as expressed in equation (8).

Finally, CNA conjunctively concatenates the minimally necessary disjunctions of minimally sufficient conditions of the endogenous factors and issues the resulting conjunction/conjunctions as solution formula/formulas. In the case of our study of the Swiss minaret vote, CNA outputs exactly one solution formula, namely the conjunction of equations (5) and (8):

$$(l*t + S \rightarrow X) * (T + X \rightarrow M). \tag{13}$$

The overall suf-coverage of equation (13) amounts to the lowest suf-coverage value of its conjuncts, which is 0.947 of equation (5). Furthermore, equation (13) has maximal suf-consistency, that is, 1, for all of its disjuncts amount to minimally sufficient conditions in the strict (logical) sense.[11]

Hence, relative to the configurational data in truth table $\mathcal{T}_M$, CNA infers that the minaret ban was accepted in cantons that had already endorsed other recent xenophobic initiatives ($X \rightarrow M$) or that feature a traditional economic structure ($T \rightarrow M$). In addition, $l*t$ and $S$ have an indirect influence on $M$ that is mediated via $X$. High rates of new xenophobia tend to be given in contexts

that feature weak left parties without a traditional economic structure ($l*t \rightarrow X$) or a high share of people natively speaking Serbian, Croatian, or Albanian ($S \rightarrow X$).

This result supports the initial hypothesis that, if $X$ has an influence on $M$, it figures as an intermediate link on a causal chain from the exogenous factors to $M$. Likewise, a number of the explanatory conjectures sketched in the second section receive confirmation. For instance, the causal relevance of $S$ for $X$ and, via $X$, for $M$ exhibited in equation (13) confirms the explanation from culture clash. Similarly, as left-wing parties tend to be weak in those cantons whose political discourse is dominated by right-wing parties, the relevance of $l$ for $X$ and by mediation of $X$ for $M$ confirms the explanation from political campaigning. Equation (13) also validates the explanation from powerlessness: $T$ has a direct effect on $M$. By contrast, the explanation from old reflexes is not confirmed by our study: The factor $A$ makes no difference to either $X$ or $M$ and, therefore, drops out as redundant. This result is surprising, as it conflicts with the presumption that the current xenophobic movement carries on the heritage of its predecessors from the 1960s and 1970s. Yet according to our analysis, new xenophobia is not directly tied to old xenophobia.

A possible explanation for the absence of a causal path from old to new xenophobia might be that Switzerland has undergone at least two different phases of immigration each of which affected different contexts. In a first phase after the Second World War, the expanding industrial sector was in dire need of workforce which then immigrated mainly from southern European countries such as Italy, Spain, and Portugal. The opposition against this immigration principally came from two xenophobic movements: the *Nationale Aktion für Volk und Heimat* and the *Republicans*, both of which had their roots in urban and industrialized cantons. By the mid-1990s, the native population in these regions might have adapted to the presence of foreigners from southern Europe, who were fairly well integrated into the Swiss society. In consequence, these social and economic contexts were less susceptible to the xenophobic mobilization against the second phase of immigration that began in the aftermath of the economic crisis in the 1970s (cf. Skenderovic and D'Amato 2008). In the 1980s and 1990s, people immigrated mainly from the successor states of Yugoslavia and from Turkey. For the most part, they were employed in the agricultural, the tourism, and in the service sector. Furthermore, the refugees that came to Switzerland in the 1990s fleeing from the civil wars in Ex-Yugoslavia were proportionally distributed over the Swiss cantons (cf. Gross 2006a, 2006b). In consequence, geographic regions were affected by this second phase of immigration that

had been unaffected by the first. The xenophobic mobilization of the 1980s and 1990s primarily came from the *Swiss People's Party* that originated from agricultural cantons (cf. Skenderovic 2009). Thus, it could be that there is no causal connection between old and new xenophobia because the corresponding movements had their roots in different geographic, social, and economic contexts and opposed different sorts of immigration.

Since the main focus of this article is on methodological issues, we abstain from further pursuing the question as to the proper explanation for the unexpected finding that $A$ is no difference-maker for $X$. What is important for our purposes is that equation (13) provides a causal model that, overall, squares nicely with theoretical expectations, which have it that the factors in the set $\{A, L, S, T, X\}$ not only directly contributed, in one way or another, to the outcome of the Swiss minaret vote ($M$) but also that there are causal dependencies among those factors themselves. Equation (13) specifies minimally sufficient conditions that moreover cover the two endogenous factors $X$ and $M$ to a very high degree. Thus, by all standards of configurational methods equation (13) is a good candidate for an adequate model of the causal structure behind the Swiss minaret vote. A configurational method of causal analysis should find that model.

## The QCA

In this section, we analyze $\mathcal{T}_M$ by means of QCA. In particular, we are going to investigate whether QCA finds the chain model (equation 13). As indicated in the second section, we confine our analysis to csQCA. We assume that the reader is familiar with the procedural details of csQCA (cf. Ragin 1987, 2008; Rihoux and Ragin 2009). In what follows, we only discuss those computational parts of QCA that are relevant for our purposes.

First of all, it must be noted that all currently available search strategies of (all variants of) QCA—that range from conservative to liberal (cf. Ragin and Sonnett 2005)—treat exactly one factor in an analyzed truth table as outcome and all remaining factors as potential causes (conditions). In light of this, it is clear from the outset that QCA will never assign a causal chain, that is, a structure with multiple outcomes, to a truth table. In its current state, QCA is designed to uncover causal structures featuring *exactly one* effect and, hence, does not search for chain models with multiple outcomes to begin with (cf. Baumgartner 2013).

That however does not mean that QCA could not be amended by a further search strategy that might indeed find causal chains. In particular, it may be argued that a subdivision of causal chains into their separate layers yields

causal substructures that are amenable to a *stepwise* QCA. Indeed, Schneider and Wagemann (2006) suggest a stepwise application of QCA to remote and proximate conditions of an outcome in order to distinguish among relevant background contexts in which proximate conditions are causally efficacious. Even though this so-called two-step approach is not designed to uncover causal chains, a suitable adaption of two-step QCA for multiple outcomes might be proposed as a new QCA search strategy to process chain-generated data.[12] More concretely, a conceivable strategy to find equation (13) by means of QCA might be to run two iterative QCAs of $\mathcal{T}_M$, the first with $M$ as outcome and the second with $X$ as outcome.

In order to determine whether such an iterative search might indeed model $\mathcal{T}_M$ in terms of a causal chain some preliminaries are required. Most of all, the computational core of QCA, which is constituted by Quine-McCluskey optimization (Q-M), must be clearly understood. Q-M is a standard Boolean procedure to minimize truth-functional expressions (cf. Quine 1959). QCA makes use of Q-M to eliminate redundancies from sufficient and necessary conditions, that is, to identify minimally sufficient and necessary conditions. The operational details of Q-M are best presented by means of concrete examples.

Let us hence minimize an exemplary sufficient condition of $M$ in $\mathcal{T}_M$ by virtue of Q-M. The configuration $A*l*S*T*X$, which is combined with $M$ in row $c_1$, is sufficient for $M$, because $\mathcal{T}_M$ does not contain a row where $A*l*S*T*X$ is combined with $m$. To determine whether $A*l*S*T*X$ is not only sufficient but also *minimally* sufficient for $M$, Q-M parses the input table $\mathcal{T}_M$ to find other rows that accord with $c_1$ in regard to the outcome and all other factors except for one. Such a row with exactly one difference is easily found. In $c_2$, $M$ is combined with the configuration $A*l*S*t*X$, which accords with $A*l*S*T*X$ in all factors except for $T$. The pair of rows $\langle c_1, c_2 \rangle$ reveals that, in the context of $A*l*S*X$, $M$ occurs both if $T$ is given and if it is not. In that context, $T$ makes no difference to $M$. It is redundant to account for $M$. Therefore, Q-M eliminates $T$ from $A*l*S*T*X$ and $t$ from $A*l*S*t*X$ to yield $A*l*S*X$. Similarly, the configuration in row $c_5$ coincides with the one in row $c_6$ in all factors except for $T$ which is present in $c_6$ and absent in $c_5$. Consequently, Q-M removes $T$ and $t$ from the corresponding sufficient conditions of $M$ to yield: $A*L*S*X$. Next, since a comparison of the two sufficient conditions, $A*l*S*X$ and $A*L*S*X$, that result from the two previous minimization steps reveals that $L$ makes no difference to $M$ in contexts that feature $A*S*X$, Q-M continues to eliminate $l$ and $L$, respectively.

The feature of this minimization procedure that will be of crucial importance for the sequel of this article is that Q-M only eliminates conjuncts of a

sufficient condition if the corresponding truth table actually contains a pair of rows that accord with respect to the outcome as well all factors *except for one*. If such a pair of rows does not exist for a particular sufficient condition, the latter cannot be further minimized. To facilitate later reference to this restriction, we label it the *one-difference restriction*.

In light of the one-difference restriction, reducing the complexity of sufficient conditions by means of Q-M to a substantial degree, obviously, presupposes that the analyzed truth table exhibits high diversity with respect to the logically possible configurations of potential causes (conditions). Consider, for example, row $c_{11}$ which features $M$ in combination with the configuration $a*l*s*t*X$. As there is no row in $\mathcal{T}_M$ where $a*l*s*t*X$ is combined with $m$, $a*l*s*t*X$ is sufficient for $M$. However, $\mathcal{T}_M$ does not contain a row that accords with $c_{11}$ with respect to the outcome and all conditions except for one. Thus, it is not possible to eliminate redundancies from $a*l*s*t*X$ based on the configurations contained in $\mathcal{T}_M$. The data diversity counts as *limited* in the QCA framework if not all $2^n$ logically possible configurations of $n$ conditions of an investigated outcome are contained in these data (cf. Ragin 2000:139). Logically possible configurations that are missing from analyzed truth tables are termed *logical remainders*.

Social scientists are inevitably confined to the variety of cases social reality and history happen to provide for them. Accordingly, the data diversity may be limited for a host of different reasons. A particular configuration may be missing due to mere historical contingencies or because it is in fact empirically impossible or excluded. Of course, the reason why a configuration is missing from the data cannot be read off that data itself. A complete QCA of limitedly diverse data, hence, calls for recourse to other sources of evidence, in the first instance, to prior theoretical knowledge about the causal dependencies among investigated conditions and outcomes. Such theoretical background knowledge may have different implications for whether or not logical remainders could possibly have been instantiated in analyzed cases and for the values the outcomes would have taken, had remainders in fact been observed. That means background theories may have different ramifications for *counterfactual cases*. To do justice to these differences in background knowledge, Ragin and Sonnett (2005) distinguish three different strategies researchers may adopt when analyzing limitedly diverse data. According to the first and most conservative strategy—call it $\mathcal{S}_1$—, logical remainders are taken to be excluded (or false), that is, relevant background knowledge tells the researcher that corresponding remainders could under no circumstances have been observed. As to the second, intermediate strategy—$\mathcal{S}_2$—remainders are determined to

be empirically possible by background knowledge, which moreover supplies enough information to decide which values an investigated outcome would have taken, had a pertaining remainder in fact been observed. Finally, the third and most liberal strategy—$\mathcal{S}_3$—treats remainders as so-called *don't care* cases, that is, as empirically possible cases for which outcomes may be set to whichever value yields the most parsimonious solution formulas. In the terminology of QCA, *don't care* cases are said to be available as *simplifying assumptions*.

An iterative QCA search strategy $i\mathcal{S}$ for causal structures with multiple outcomes can be construed from either of the existing search strategies $\mathcal{S}_1$ to $\mathcal{S}_3$. Correspondingly, we shall label iterative applications of $\mathcal{S}_1$, $\mathcal{S}_2$, and $\mathcal{S}_3$ with the aim to analyze a truth table in regard to multiple outcomes $i\mathcal{S}_1$, $i\mathcal{S}_2$, and $i\mathcal{S}_3$, respectively. In order to compare the solution formulas assigned to table $\mathcal{T}_M$ by those iterative QCA search strategies with the solution formula of CNA, we presuppose the same causal ordering ($<_{\mathcal{T}_M}$) as we did for the CNA. Moreover, we impose the same consistency and coverage thresholds. Apart from enhancing the comparability, this allows us to abbreviate the QCA of $\mathcal{T}_M$. We have already found in the previous section that the data recorded in $\mathcal{T}_M$ does not cover $L$ and $S$ to a sufficient degree. Hence, we can confine the QCA to the outcomes $X$ and $M$. According to $<_{\mathcal{T}_M}$, $M$ is the ultimate outcome which, in turn, can be excluded as possible cause of $X$. Hence, in a first QCA iteration, $M$ is treated as outcome and the factors in $\{A, L, S, T, X\}$ as conditions, whereas in a second iteration $X$ is treated as outcome and the factors in $\{A, L, S, T\}$ as conditions.

Let us first implement that idea based on the conservative search strategy $\mathcal{S}_1$, that is, we first apply $i\mathcal{S}_1$ to $\mathcal{T}_M$. If QCA treats all logical remainders as excluded and, consequently, does not use any of them for minimizations, the sufficient conditions of $M$ contained in $\mathcal{T}_M$ cannot be substantially optimized. Moreover, to reach a perfect suf-coverage—as we did for our CNA model of $M$—a complex array of alternatives must be admitted. $i\mathcal{S}_1$ produces the following solution formula for $M$:

$$A*S*X + A*L*t*X + a*s*T*x + L*S*t*X \\ + l*s*T*x + l*S*T*X + a*l*s*t*X \rightarrow M. \tag{14}$$

Just as the CNA solution formula we found in the previous section, equation (14) respects $<_{\mathcal{T}_M}$ and has a suf-consistency and suf-coverage of 1. The corresponding $i\mathcal{S}_1$ solution formula for $X$ as outcome is this:

$$A*S + L*S*t + l*S*T + a*l*s*t \rightarrow X. \tag{15}$$

Equation (15) is maximally suf-consistent and covers $X$ to the same degree as equation (5), namely 0.947.

Overall, the conjunction "(15) $*$ (14)" is the complex solution formula that $i\mathcal{S}_1$ assigns to $\mathcal{T}_M$. Against the background of our considerations in the previous section it is clear that both equation (14) and equation (15) feature a host of redundancies. For instance, table $\mathcal{T}_M$ does not contain rows in which $S$, $T$, and $X$ are combined with $m$. Thus, $S$, $T$, and $X$ are themselves sufficient for $M$. Nevertheless, QCA cannot further optimize the causal model for $M$ by virtue of $i\mathcal{S}_1$ because Q-M imposes the one-difference restriction which prohibits further optimizations without supplementing $\mathcal{T}_M$ by a significant amount of counterfactual cases as simplifying assumptions.

Indeed, it turns out that QCA only succeeds in eliminating all redundancies from the solution formulas for $X$ and $M$ if it is allowed to treat all logical remainders in $\mathcal{T}_M$ as *don't care* cases. That is, the intermediate search strategy $i\mathcal{S}_2$ produces solution formulas for $X$ and $M$ whose complexity is somewhere between equations (5) and (8), on one hand, and equations (15) and (14), on the other. For brevity, we do not discuss the details of an $i\mathcal{S}_2$ analysis of $\mathcal{T}_M$ and directly turn to $i\mathcal{S}_3$.[13] As indicated above, this maximally liberal search strategy introduces all required logical remainders as simplifying assumptions and sets the corresponding outcome/outcomes to whichever value/values yield/yields the most parsimonious solution formula/formulas. If QCA is iteratively run on $\mathcal{T}_M$ by first treating $M$ and then $X$ as outcomes, it in fact produces the exact same models for $M$ and $X$ as CNA, namely equations (8) and (5). A conjunctive concatenation then yields the same overall solution formula as CNA (with a total consistency of 1 and coverage of 0.947):

$$(l*t + S \rightarrow X) * (T + X \rightarrow M). \tag{13}$$

An iterative application of QCA based on a search strategy that treats all logical remainders as *don't care* cases hence assigns the same causal chain model to table $\mathcal{T}_M$ as CNA. This finding raises the question whether QCA can be rendered applicable to chain-generated data by simply supplementing it with a further iterative strategy in the vein of $i\mathcal{S}_3$. In the remainder of this article, we are going to show that an $i\mathcal{S}_3$ analysis of chain-generated data has at least two decisive disadvantages compared to a corresponding CNA.

First, treating all logical remainders as *don't care* cases amounts to introducing numerous configurations of analyzed factors as simplifying assumptions for which there is no empirical evidence. It goes without saying that methodologies of causal discovery implemented in empirical disciplines should only be allowed to reason counterfactually as a last resort. And as we

have seen in the third section, it is not the case that the causal dependencies among the factors in $\mathcal{T}_M$ can only be completely minimized if counterfactual simplifying assumptions are made. In fact, CNA manages to eliminate all redundancies from those dependencies without counterfactually introducing configurations that are not contained in $\mathcal{T}_M$ at all. That is, recourse to counterfactual reasoning can be avoided, and accordingly, on methodological grounds, should be avoided.[14]

Second, what is even more disadvantageous for QCA is that $i\mathcal{S}_3$ manages to completely eliminate redundancies from the dependencies of sufficiency and necessity among the factors in $\mathcal{T}_M$ only at the price of assuming at least one *logical contradiction*. We explicitly speak of *logical* contradictions here in order to emphasize that the assumptions $i\mathcal{S}_3$ needs to eliminate redundancies from chain models are not to be confounded with what are called *contradictory simplifying assumptions* in the QCA literature. A "contradictory" simplifying assumption is an assumption to the effect that a configuration $\Phi$ (of remainders) is combined with both the presence and the absence of an outcome $Z_i$. However, assuming that $\Phi$ can be combined with both $Z_i$ and $z_i$ is not contradictory in the (original) logical sense of the term—that is, false/unsatisfiable on purely logical grounds—but merely entails that $\Phi$ is neither (consistently) sufficient for $Z_i$ nor for $z_i$.[15] Accordingly, "contradictory" simplifying assumptions only have mildly negative effects for corresponding QCA studies, for example, they tend to bring down suf-coverage values. By contrast, as we shall see below, the assumptions $i\mathcal{S}_3$ requires to find chain models are contradictory in the strict logical sense of the term; and correspondingly, they give rise to a very serious problem for QCA.

The detailed proof of this will involve some intricacies, but the basic proof idea is simple: In order to completely minimize the sufficient and necessary conditions of $M$ and to find the second conjunct of the chain model in equation (13), QCA must assume at least one configuration $\Phi$ of remainders to be (empirically) possible that is determined to be impossible (or excluded) by the first conjunct of equation (13); in consequence, in the second iteration of QCA induced by $i\mathcal{S}_3$, which minimizes the sufficient and necessary conditions of $X$ and finds the first conjunct of equation (13), $i\mathcal{S}_3$ must assume that $\Phi$ is not possible after all, that is, it must assume the negation of $\Phi$. Overall, QCA can only find equation (13) at the cost of assuming the logical contradiction $\Phi * \neg\Phi$ which assumption, of course, entails anything, that is, not only equation (13) but also the negation of equation (13) and, thus, trivializes the whole $i\mathcal{S}_3$ analysis of $\mathcal{T}_M$.

To carry out that proof idea, we show that to identify $T$ as minimally sufficient condition of $M$, as expressed in the second conjunct of equation

(13), QCA must assume that at least one configuration of remainders is possible—and, thus, can be counterfactually introduced—which is determined to be impossible by the first conjunct of equation (13). QCA isolates $T$ as minimally sufficient condition of $M$ by means of Q-M, which, as we have seen above, takes a complex sufficient condition of $M$ involving all of the other factors in $\mathcal{T}_M$ as input and successively optimizes that condition by contrasting it with other sufficient conditions of $M$ that differ in exactly one factor. Independently of which complex sufficient condition of $M$ Q-M starts from, in order to end up with $T$ as minimally sufficient condition, the last optimization step of the successive Q-M optimization must be based on one of the following four pairs of sufficient conditions of $M$ with exactly on difference:

$$\langle S*T,\ s*T \rangle \tag{16}$$

$$\langle T*X,\ T*x \rangle \tag{17}$$

$$\langle L*T,\ l*T \rangle \tag{18}$$

$$\langle A*T,\ a*T \rangle \tag{19}$$

If a truth table contains the two configurations contained in pair (16) in combination with $M$, Q-M infers that $S$ and $s$, respectively, make no difference to $M$ in contexts where $T$ is given. Therefore, Q-M eliminates $S$ from the first and $s$ from the second element of pair (16) and ends up with $T$ as minimally sufficient condition of $M$. Analogously, based on the configurations in pairs (17) to (19) Q-M eliminates $X$ and $x$, $L$ and $l$, and $A$ and $a$ from corresponding sufficient conditions—in each case ending up with $T$ as minimally sufficient condition for $M$. Q-M can only establish $T$ as minimally sufficient for $M$ via one of the pairs of configurations (16) to (19).

To arrive at the first configuration in the pair (16), that is, at $S*T$, $X$ (among other factors) must antecedently be shown to be redundant in the context of $S*T$. To this end, Q-M needs a pair $\langle S*T*X*\ldots,\ S*T*x*\ldots \rangle$, where the dots can be filled by any configuration of the remaining factors in $\mathcal{T}_M$. The second configuration in this latter pair, namely $S*T*x$, is not contained in $\mathcal{T}_M$. Accordingly, $i\mathcal{S}_3$ must counterfactually introduce that configuration (as simplifying assumption). However, the first conjunct of equation (13) determines that $S$ is sufficient for $X$ (i.e., whenever $S$ is given so is $X$). That is, the first conjunct of equation (13) entails that the configuration $S*T*x$ is impossible and, thus, cannot be counterfactually introduced. In other words, $S*T*x$ contradicts the first conjunct of equation (13). In close analogy, to arrive at the second configuration in the pair (17), that is, at $T*x$, $S$ must antecedently be shown to be redundant in the context of $T*x$. To this end, Q-M needs a pair $\langle S*T*x*\ldots, s*T*x*\ldots \rangle$. Again, it turns out that to

obtain the pair (17) $iS_3$ must counterfactually introduce the configuration $S*T*x$ which is determined to be impossible by the first conjunct of equation (13).

Furthermore, to arrive at the pairs (18) and (19), $S$ and $X$ must antecedently be shown to be redundant in the contexts of the configurations contained in those pairs. Yet, by the same token, this can only be accomplished if configurations are counterfactually introduced that are determined to be impossible by the first conjunct of equation (13). To see this, consider the first configuration in the pair (18), that is, $L*T$. Q-M can only arrive at $L*T$ via one of the following pairs:

$$\langle L*T*X, \ L*T*x \rangle \tag{20}$$

$$\langle L*S*T, \ L*s*T \rangle \tag{21}$$

$$\langle A*L*T, \ a*L*T \rangle \tag{22}$$

To arrive at pair (20), configurations must be introduced that allow for antecedently eliminating $S$. Accordingly, to obtain the second configuration in pair (20), namely $L*T*x$, the pair $\langle L*S*T*x*\ldots, \ L*s*T*x*\ldots \rangle$ is required. The configuration $L*S*T*x$, however, contradicts the first conjunct of equation (13) which determines $S$ to be sufficient for $X$. Likewise, to obtain the first configuration in pair (21), namely $L*S*T$, the pair $\langle L*S*T*X*\ldots, L*S*T*x*\ldots \rangle$ is required, which involves a configuration that is entailed to be impossible by the first conjunct of equation (13). Finally, to arrive at the first configuration in pair (22), Q-M needs to antecedently eliminate both $S$ and $X$ from $A*L*T$. To this end, Q-M requires one of the following pairs:

$$\langle A*L*T*X, \ A*L*T*x \rangle \tag{23}$$

$$\langle A*L*S*T, \ A*L*s*T \rangle \tag{24}$$

To obtain the second configuration in pair (23), namely $A*L*T*x$, the pair $\langle A*L*S*T*x, A*L*s*T*x \rangle$ is required. Yet, $A*L*S*T*x$ is impossible subject to the first conjunct of equation (13). And to arrive at the first configuration in pair (24), namely $A*L*S*T$, the pair $\langle A*L*S*T*X, A*L*S*T*x \rangle$ is called for, which again is incompatible with the first conjunct of equation (13).

Finally, it is plain that what we have now shown for the first configuration in the pair (18) can equivalently be shown for the first configuration in the pair (19), namely for $A*T$. To this end, simply substitute $A*T$ for $L*T$ in the previous paragraph. For the very same reason why $S$ and $X$ cannot be eliminated from configurations featuring $L*T$ without contradicting the first conjunct of equation (13), $S$ and $X$ cannot be eliminated from configurations featuring $A*T$ without contradicting the first conjunct of equation (13).

All of this demonstrates that QCA cannot obtain either of the pairs (16–19), and thus cannot establish $T$ as minimally sufficient condition of $M$, without assuming at least one configuration $\Phi$ (of remainders) to be possible which is determined to be impossible by the first conjunct of equation (13). Accordingly, when it comes to finding the first conjunct of equation (13) in a second iteration of QCA along the lines of $iS_3$, $\Phi$ must be assumed not to be possible after all, that is, the negation of $\Phi$ must be assumed—otherwise, $l*t$ and $S$ would not turn out to be sufficient for $X$. In sum, QCA can only find equation (13) by, in a first iteration, assuming that the configuration $\Phi$ is empirically possible, and in a second iteration, assuming that the configuration $\Phi$ is impossible, that is, by overall assuming the logical contradiction $\Phi * \neg\Phi$.

It is not surprising that QCA finds equation (13) by assuming a logical contradiction. *Everything* follows from a logical contradiction (ex falso quodlibet). Hence, from $\Phi * \neg\Phi$ any other solution formula can equally be inferred, which, of course, trivializes the above $iS_3$ analysis of $\mathcal{T}_M$. Or to put the problem in slightly different terms: After having found the solution formula $T + X \rightarrow M$ and, thus, after having counterfactually introduced the configuration $\Phi$ in a first iteration of $iS_3$, what reason could a researcher have to then, in a second iteration, stipulate that the configuration $\Phi$ is impossible after all? The only conceivable answer is that she wants to "find" a particular causal chain from the beginning. Using Q-M, this goal cannot be reached on the basis of a consistent set of empirical data. Hence, the QCA researcher is forced to introduce a logical contradiction to reach her predetermined goal. What is crucial here is that QCA does not infer the chain model from a consistent set of empirically possible data points, that is, from the data, but from the contradictory assumptive basis only.

Moreover, this problem is not due to some peculiarity of $\mathcal{T}_M$, but generalizes for all iterative QCAs of chain-generated data. In order to eliminate all redundancies from the sufficient and necessary conditions of the ultimate outcome $Z_i$ of a causal chain, the logical remainders in a corresponding truth table must be treated as *don't care* cases, which means that the conditions of $Z_i$ may be set to any logically possible configuration. This, in turn, means that QCA treats those conditions as *independent* in the course of identifying difference-makers for $Z_i$. However, when—in a further iteration—the dependencies of sufficiency and necessity among those conditions are then themselves minimized, they must no longer be treated as independent; otherwise, of course, all dependencies among them would vanish. That is, a first QCA iteration for the ultimate outcome of a causal chain assumes that the remaining factors in the data are independent, whereas subsequent iterations assume that they are *not* independent.

## Discussion

The main result of this article is methodological. We have seen that CNA has advantages over QCA when it comes to properly analyzing configurational data that stem from causal chains. QCA's reliance on Q-M as a tool to eliminate redundancies from sufficient and necessary conditions yields that QCA needs to impose the one-difference restriction. This, in turn, entails that QCA can only completely minimize relationships of sufficiency and necessity if analyzed truth tables feature $2^n$ combinations of $n$ potential cause factors (or *conditions* in the QCA terminology), that is, if those potential cause factors are mutually independent. However, causal chains inherently violate that independence requirement, for it is the characteristic feature of chains that there are not only dependencies among the ultimate outcome and its potential causes but also among the latter themselves. Therefore, any iterated QCA search strategy can only completely eliminate redundancies by assuming that the potential causes $Z_1, \ldots, Z_h$ of an ultimate outcome $Z_i$ are mutually independent, when minimizing the sufficient and necessary conditions of $Z_i$, and by assuming that $Z_1, \ldots, Z_h$ are not independent, when minimizing the relationships of sufficiency and necessity among $Z_1, \ldots, Z_h$ themselves.

By constrast, as CNA does not eliminate redundancies from sufficient and necessary conditions by means of Q-M, CNA is not forced to impose the one-difference restriction. CNA can completely minimize relationships of sufficiency and necessity without assuming that some factors are both independent and not independent. CNA eliminates redundancies from sufficient and necessary conditions based on a minimization procedure that successfully uncovers chain-like structures without recourse to counterfactual reasoning and, in particular, without counterfactually introducing logical remainders. In consequence, if CNA infers a chain model from a given data input, it does so based on the data and not based on contradictory assumptions. We take these to be decisive advantages of CNA over QCA.

Apart from this result on the methodological meta-level, the article, of course, also has corollaries on the social scientific object level. Our exemplary CNA of the structure behind the Swiss minaret vote yields a causal model, namely equation (13), which complements the existing literature on the causes of the Swiss minaret ban. While Hirter and Vatter (2010) investigate the factors that determined the outcome of the vote by means of a follow-up survey, a so-called VOX-analysis, of around 1,000 people who are entitled to vote, that is, on the level of individuals, our study focuses on the voting behavior on the level of cantons—whose majority, in combination with the majority of votes

cast, is decisive for the passing of initiatives in Switzerland. Still, our results agree in interesting respects with the results of the individual-level studies.

For instance, in light of the VOX-analysis, Christmann, Danaci, and Krömler (2011) emphasize the relevance of political campaigning of both the left-wing and the right-wing parties for the outcome of the vote. Vatter, Milic, and Hirter (2011) argue that the key to the acceptance of the minaret ban was that its supporters succeeded in transforming a legal issue regarding the construction of minarets into a fundamental ideological matter of protecting Switzerland against allegedly damaging exterior influences (Vatter et al. 2011:169). Moreover, in addition to level of eduction, gender, and attitude toward foreigners, Vatter et al. (2011) find that a voter's positioning on the left-right scale influenced her voting behavior. All of these diagnoses, obviously, concur with our findings.

By contrast, the study of Vatter et al. (2011) disagrees with our conclusion that the share of people natively speaking Serbian, Croatian, or Albanian was causally relevant for the minaret vote. Only 9 percent of people interviewed in the course of the VOX-analysis answered in the negative to the question whether Swiss and Islamic ways of living are compatible. Vatter et al. (2011:161) take this to show that the acceptance of the minaret initiative cannot be seen to be the result of a general hostility against Muslims and their religion in Switzerland. Plainly though, it may be suspected that the interviewees' answers to that question have been influenced by social expectancy or the so-called *spiral of silence* (cf. Noelle-Neumann 1993). In opposition to Vatter et al. (2011) and in accordance with our findings, Christmann et al. (2011:187-88) infer that xenophobic and islamophobic attitudes indeed influenced the outcome of the minaret vote. In addition, our results show that those attitudes are connected to the presence of the incriminated group. Still, while Christmann et al. (2011) embed the minaret initiative in the tradition of the xenophobic initiatives of the 1970s, our study does not reveal such a connection.

Overall, this article has substantiated that CNA is a Boolean method of configurational causal reasoning that can be effectively and fruitfully applied in actual social scientific contexts of causal discovery. Just as the well-known method of QCA, CNA is custom built for small- to intermediate-*N* data. But contrary to the former, the latter successfully uncovers chain-like causal structures.

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## Declaration of Conflicting Interests

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## Notes

1. *ESA* is the enhanced standard analysis for QCA introduced in Schneider and Wagemann (2012).
2. As is usual for Boolean algebra, we symbolize conjunction by "$*$", disjunction by "$+$", the presence of a factor by an uppercase $Z_i$, and its absence or negation by a lowercase $z_i$.
3. For the relevant notion of coverage cf. the third section.
4. We take this focus on the contrast between CNA and csQCA to have no bearing on the main argument of this article. As indicated in the introduction, our aim is to scrutinize the suitability of Q-M for the discovery of causal chains; and all currently available variants of QCA rely on a computational core that is constituted by Q-M.
5. That is, instead of *subset* and *superset* relations we speak of *sufficient* and *necessary* conditions. Explicit translations between these two terminologies can be found in Goertz (2003).
6. A commendable exception is Bol and Luppi (2013) who systematize the search for complex necessary conditions within the QCA framework.
7. In the QCA literature, it is often recommended to search for necessary conditions prior to searching for sufficient conditions (cf. e.g., Ragin 2000:106). On the face of it, however, every search for sufficiency is tantamount to a search for necessity. Correspondingly, if it is found that $a$ is sufficient for the absence of an outcome $O$, that is, $a \rightarrow o$, it is thereby found that $A$ is necessary for $O$, that is, $O \rightarrow A$, or vice versa ($a \rightarrow o$ and $O \rightarrow A$ state exactly the same, they are logically equivalent). As we have seen above, the same holds for more complex solution formulas. Searching for sufficient and necessary conditions are two sides of one coin; there is no question of what is done first. We take the idea behind the "necessity-first" practice in the QCA literature to be that the search for necessary conditions consisting of *single factors* should be conducted prior to the search for

necessary conditions consisting of more complex factor combinations. The search for necessary (or sufficient) conditions of different syntactic complexity can indeed be performed sequentially. In the CNA context, though, there is no need to focus on minimally complex necessary conditions first. CNA simply identifies all relations of necessity existing in scrutinized data—independently of the complexity of corresponding necessary conditions.

8. As we confine our discussion to crisp-set analyses, we confine ourselves to the crisp-set notions of consistency and coverage here. Note that the corresponding fuzzy-set notions are somewhat different (cf. Ragin 2008).

9. In the QCA literature, rows as $c_3$ and $c_{11}$ are labeled *contradictory* with respect to outcome $L$, because the same configuration of conditions is combined with both $L$ and $l$. In fact, however, there is nothing logically contradictory about two such rows. A pair of rows as $\langle c_3, c_{11} \rangle$ merely shows that a corresponding configuration of conditions (e.g., $a*s*t$) is neither sufficient for $L$ nor for $l$. Compare also the fourth section.

10. Note that abstaining from interpreting a dependency as, say, $A*s*t \rightarrow L$ causally does not amount to claiming that $A*s*t$ is causally *irrelevant* to $L$. Rather, it simply means that a potential relevance of $A*s*t$ to $L$ must be established on the basis of a different study—one that explicitly focuses on the strength of political parties and, accordingly, controls for factors that are relevant for $L$.

11. This illustration of the computational details of CNA clearly shows that the applicability of CNA in social scientific practice calls for a software implementation. CNA is currently being implemented in $R$. The CNA $R$-package will soon be available via the usual CRAN mirrors.

12. Another suggestion might be to develop a chain search strategy for QCA along the lines of Caren and Panofsky's (2005) temporal QCA (TQCA), which is designed to temporally order the causal conditions of an ultimate outcome. However, as is well acknowledged in the literature, by time-indexing analyzed factors, TQCA significantly increases the logical space of possible configurations. Thereby, the complexity of the analysis increases, along with the amount of logical remainders. As a result, TQCA is often not applicable in small-$N$ studies because the amount of observed cases is too small. Moreover, just like any other variant of QCA, TQCA also implements Q-M (cf. Caren and Panofsky 2005: 156), which, as we shall see below, is the source of all of QCA's problems with causal chains. For these reasons, we do not believe that TQCA is a promising starting point for developing a chain search strategy for QCA.

13. In recent years, it has become more and more common practice in the QCA literature to settle for intermediate solution formulas because completely eliminating all redundancies from solution formulas by means of QCA often requires the introduction of many so-called *difficult* counterfactual cases, which researchers want to avoid. Settling for intermediate solutions, however, generates

problems for their causal interpretation. Causes are difference-makers of their effects (cf. Mackie 1974). Yet, redundant factors do not make a difference to scrutinized outcomes. Therefore, solutions with redundant elements are not guaranteed to be amenable to a causal interpretation. As we are explicitly interested in *causally* modeling the Swiss minaret vote, we discard intermediate solutions here.

14. The worry might arise that, as $iS_3$ succeeds in inferring the same complex solution formula as CNA only on the basis of numerous simplifying assumptions, CNA is tacitly committed to the same simplifying assumptions as well. That, however, is not the case. The fact that two methods, for a particular data input, output the same causal models does not indicate that the underlying inferences are based on the same or even related assumptions. One and the same conclusion can be inferred from very different assumptions. For instance, "Socrates is mortal" can be inferred from the two assumptions "Socrates is a man" and "All men are mortal," or from "If Armstrong was the first man on the moon, then Socrates is mortal" and "Armstrong was the first man on the moon," or it can be inferred from any contradiction, for example, from "It rains and it does not rain." While QCA minimizes sufficient and necessary conditions—and, thus, infers causal dependencies—by counterfactually supplementing missing data points, CNA makes use of the negative existential claim that certain configurations are not contained in the data. More concretely, QCA makes assumptions as "Had $a*L*S*T$ occurred the outcome would have occurred as well" or "Had $A*l*s*t$ occurred the outcome would not have occurred," and so on. By contrast, CNA infers causation from negative existential claims as "$a*L*S*T$ is not contained in the data" or "$A*l*s*t$ is not contained in the data," and so on. Those are very different premises for causal inferences. For more details on the assumptions implemented by CNA, see Baumgartner (2009a).

15. That assuming $\Phi$ to be combinable with both $Z_i$ and $z_i$ is far from being contradictory can be easily seen if we let $\Phi$ stand for the set of people with blonde hair and $Z_i$ for the set of tall people. There are certain people with blonde hair who are tall and others who are not tall. Blonde hair is combinable both with tallness and nontallness, hence, assuming both of these combinations is not contradictory but sound. The combinability of blondness with tallness and nontallness merely shows that having blond hair is sufficient neither for being tall nor for being nontall.

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