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Crisp-Set Qualitative Comparative Analysis (csQCA), Contradictions and Consistency Benchmarks for Model Specification

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Abstract

The purpose of this paper is to address and test two assumptions on which csQCA is based, namely that csQCA will generate contradictions and low consistency scores if models are ill-specified. The first part of the paper introduces csQCA in general and as a stepwise approach. In a second part a real-life example is introduced with the purpose of illustrating how csQCA operates and as an input for a simulation in the subsequent part. The third part introduces contradictions, consistency, their interrelatedness and the assumptions which are made with regard to contradictions and consistency. Subsequently the assumptions are tested via a simulation on the basis of a csQCA analysis of over 5 million random datasets. The paper argues that researchers cannot always assume that csQCA will generate contradictions or low consistency scores when models are ill-specified. Such an assumption is only justified when csQCA applications take limitations with regard to model specification (the number of conditions and the number of cases) into account. Benchmark tables for model specification purposes are developed. Since these tables are based on a probability value of 0.5 the paper also tests the results for contradictions and consistency for the probabilities which were present in a real-life example. This test shows that the 0.5 probability generates an appropriate measure for the occurrence of contradictions and consistency indicating that the benchmark tables can be used for different applications with different distributions of 0's and 1's in the conditions and outcomes. The paper ends with a conclusion.

Keywords: Qualitative Comparative Analysis (csQCA), comparative research, Configurational Analysis, contradictions, consistency

Introduction

Some authors observe a bifurcation in the nature of studies with regard to the research population or sample size in the social sciences. On the one hand many qualitative single case studies or a limited number of case studies (N < 5) are conducted. On the other hand many variable-oriented large N studies (N > 100) are performed. There are only a limited number of medium sized studies (5 < N < 100). However, a medium sized research design can contribute both to theory development as well as theory testing (Koppell, 2010; Ragin, 2000; Dul & Hak, 2008). Crisp Set Qualitative Comparative Analysis (hereafter csQCA) was developed by Charles C. Ragin for the analysis of a medium number of cases (Berg-Schlosser et al. 2009; Ragin 1987, 1994, 2000, 2008; Rihoux 2003, 2008; Varone et al. 2006).

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csQCA is a comparative case-oriented research technique based on set theory and Boolean algebra. Ragin's aim was to develop a new research approach which combined some strengths of qualitative and quantitative research methods. csQCA aims to develop explanatory models on the basis of a systematic comparison of a limited number of cases (N < 100). csQCA has been applied in numerous studies in sociology, political science, policy analysis, organisational studies and other fields[1]. As noted by Gerring (2001) csQCA is one of the few genuine methodological innovations of the last few decades.

The result of a csQCA analysis, an explanatory model which contains one or more causal paths to the explained outcomes, is based on a constant dialogue between theory and evidence (Ragin & Rihoux, 2004; De Meur & Rihoux, 2002; Rihoux, 2003). QCA forces researchers to 'craft' a model on the basis of theoretical information and selected variables on the one hand and empirical information on these variables in the context of specific cases on the other hand. The key mechanism by which csQCA applications generate an explanatory model is by solving contradictions (Seawright 2005; Ragin 1987, 1994, 2005; Kogut & Ragin, 2006; Rihoux & Ragin, 2008). csQCA is built on the assumption that contradictions will always occur if the explanatory model is not correctly specified (omitted variables, measurement error, heterogeneity of the research population, etc.) or when it does not make theoretical sense. This assumption was analysed by Marx (2010). Marx (2010) performed a csQCA analysis on randomly created datasets and found that in certain circumstances QCA produced an explanatory model on the basis of random data. It was argued that the ratio of conditions to cases determines whether csQCA will generate an explanatory model on random data. As a result, model specification in csQCA needs to take model specification parameters into account.

Marx (2010) was only able to explore the relationship between model specification and the occurrence of contradictions. Recent advances in mathematical and computing approaches in csQCA (Dusa, 2010) allow for precise estimates with regard to model specification. In addition, new features gradually have been introduced in QCA which allow researchers to assess their results. This includes an assessment of the consistency of set theoretic relations, i.e. the degree to which a configuration of explanatory conditions is a subset of the outcome. It is assumed that (1) consistency will be very low when the explanatory model is ill-specified or does not make theoretical sense and that (2) high consistency indicates the validity of the set-theoretic relation and hence of the analysed model. This paper tests both assumptions, namely the occurrence of contradictions and low scores of consistency when QCA is applied to random data. The assumptions are tested via a simulation on the basis of random datasets. In order to generate very precise estimates on the occurrence of contradictions and test the assumption with regard to consistency 1,500 random datasets for *each* combination of conditions (range 2-13) and cases (range 2-300) were created[2]. Hence in total 5,832,000 random datasets were created (3,588 cells*1,500 random datasets for each cell) and analysed, using csQCA, in the methodological simulation. The random datasets were created on the basis of 0.5 probability distribution between 0's and 1's. In order to assess the validity of this probability distribution a replication using a real-life study was conducted which takes the probability distribution of the variables from this study as an input for the creation of the random datasets. The real life study is introduced in the first part of the paper.

The paper argues that the assumptions of the occurrence of contradictions and low level of consistency only hold when one takes the number of conditions into account for a given number of cases. The paper provides two tables which can be used to benchmark models with regard to the occurrence of contradictions and consistency. In the annex two benchmark tables are provided which presents results for up to 300 cases and 13 conditions. The paper also argues that the use of 0.5 distribution benchmark tables provide a stringent assessment of the assumptions. The paper first introduces csQCA and a real-life application. The second part focuses on the issues of contradictions and consistency. The third part discusses the results of the random simulations. The paper ends with a conclusion.

Introducing QCA

A general introduction

csQCA provides a set of tools for analysing the necessary and sufficient conditions that explain outcomes, mapping out similarities and differences between various configurations of conditions and cases. csQCA

enables researchers to systematically compare a limited number of cases. The aim of csQCA is to develop a research strategy which develops a middle road between the case-oriented (qualitative) and the variable-oriented (quantitative) approaches (Ragin, 1987, p.12ff; 2000; 2008). The goal of this systematic comparative case strategy is to "*integrate the best features of the case-oriented approach with the best features of the variable-oriented approach*" (Ragin 1987, p.84).

This approach consists of three central features, namely that it is a case approach which is comparative and systematic which allow researchers to develop an explanatory model. It is a ***case*** approach which implies that each individual case is considered as a complex entity (a whole – a configuration of conditions) which needs to be comprehended and which should not be forgotten in the course of the analysis. Different parts of each case are understood in relation to one another and in terms of the total picture that they form together. The organising idea is that the parts of a case do constitute a coherent whole (Ragin 1987, 2000, 2008). One aspect of a case cannot be understood in isolation from other aspects of the same case. What matters most is that the researcher makes sense of multiple aspects of each case in an encompassing manner, using substantive and theoretical knowledge to guide the research (Ragin, 1987, 2000, 2008). Cases in this context are regarded as configurations of conditions. The essence of case analysis is to understand the configuration of conditions and how that configuration is linked to a certain outcome. As such, this approach resembles more qualitative-oriented case research than quantitative-oriented variable research and hence can easily complement a qualitative description of cases.

Second, it is ***comparative*** in the sense that it explores and finds similarities and differences in outcome across comparable cases by comparing configurations of conditions (Ragin, 1987, 1994; 2000; 2003; Rihoux & Ragin, 2008; Rihoux, 2008). Hence, it clusters cases and describes diversity across cases. Diversity is here understood in terms of types of cases. The goal is to unravel the different configurations of causal conditions connected to the presence or absence of an outcome – causal patterns that separate cases into different subgroups. Consequently, in comparative research the examination of diversity – patterns of similarities and differences – goes hand in hand with the study of causes. Generally, researchers expect different causal conditions to be linked to divergent outcomes in interpretable ways. Thus, the goal of the researcher's examination of patterns of similarities and differences is to identify how different **configurations** of causal conditions produce different outcomes across the range of cases included in a study.

As a result, a systematic comparative case analysis allows for ***equifinality* or *multiple conjunctural causation*** (Ragin, 1987, 2000; Rihoux 2003; Maggetti 2007). This implies that: 1) most often, it is a combination of *conditions* that produces a phenomenon, the *outcome*; 2) several different combinations of conditions may produce the same outcome; and 3) depending on the context, on the "conjuncture," a given condition may very well have a different impact on the outcome. This implies that different causal paths – each path being relevant in a distinct way – may lead to the same outcome (De Meur & Rihoux, 2002, pp. 28-30). Thus one rejects any form of context-free causality (Ragin, 1987, p. 55) since causality is context sensitive. csQCA recognises that a condition can have opposite effects depending on the context (relationship with other conditions) in which it operates. Hence, csQCA can address complex and seemingly contradictory patterns of causation - a condition can be important in both its presence and absence – and it eliminates logically irrelevant causes via logical minimisation (*infra*). This approach hence differs significantly, on the one hand, from a variable-oriented research strategy which often starts from the assumption that variables (conditions) act 'on their own', *i.e.* that they affect the outcome independently. On the other hand, the approach also differs from a single case approach where one often assumes that cases are unique, and a causal explanation is so complex, so case-bound, that it defies generalisation. csQCA actually starts from this assumption, but then mounts an assault on it by comparing different 'unique' cases and analyzing which similar factors combine within these cases to generate a certain outcome. The existence and importance of multiple causation has been recognised and empirically validated by many researchers who have used QCA (Bakker, 2010; De Meur & Rihoux, 2002; Marx, 2008; Marx & Van Hootegem, 2007; Kogut &Ragin, 2006; Rihoux, 2001; Stokke, 2003, 2007; Wickham-Crowley, 1992).

Thirdly, csQCA is ***systematic*** in the sense that it uses a formal logic to compare cases, explore causal diversity and reduce the wealth of case information. The analytical procedure which facilitates this analysis of diversity

is Boolean logic. Boolean analysis allows one to identify causal regularities that are parsimonious, i.e. which combine the fewest possible conditions within a set of conditions that are considered in an analysis. The key procedure in csQCA is Boolean minimisation – that is, reducing a full case description to the shortest possible expression (the minimal equation) that shows the putatively causal regularities in the data. It is then up to the researcher to interpret theoretically this minimal equation. In other words, Boolean algebra is used to reduce the complexity of data sets and make comparison between cases possible.

Performing a csQCA analysis in general requires 9 distinct steps.

1. Decide what outcome needs to be investigated.
2. Define the research population and select the cases for analysis with sufficient variation on the outcome. Several case selection strategies are available (see Gerring, 2007).
3. List the most significant conditions, other than the scoping conditions used to define the research population, which might contribute to an explanation of the outcome. Several condition selection strategies can be used (Amenta & Poulsen 1994; Berg-Schlosser, & De Meur, 2009).
4. Define each condition and outcome as a binary condition. In a csQCA-analysis both the presence and absence of a condition or outcome are meaningful. As a result, each explanatory factor is discussed and operationalised as a crisp-set condition which will be used in a csQCA analysis (binary code 1 or 0). This implies that for each case an explanatory condition is coded 1 if the condition is present for that case and 0 if the condition is absent in that case. Provide transparent measurement procedures for coding condition as either being absent or present.
5. Code each condition for each case and bring this information together in a data matrix.
6. Analyze the data matrix by specifying an explanatory model and resolving contradictions (*infra).*
7. Transform the data matrix to produce a truth table.
8. Analyze the model and generate the most parsimonious explanation on the basis of the minimisation procedure which is available in csQCA. The minimisation procedure is based on the following procedure: if two Boolean expressions differ in only one causal condition, yet produce the same outcome, then the causal condition that distinguishes the two expressions can be considered irrelevant and can be removed to create a simpler, combined expression.
9. Interpret the resulting explanatory models, both models which explain the presence of an outcome and models that explain the absence of an outcome. This often requires a return to the cases in order to find out how the configuration of the explanatory conditions leads to the outcome, i.e. to unpack the dynamics of cases. The last step may allow researchers to identify mechanisms which link explanatory conditions to an outcome.

An application of csQCA: the case of non-state market regulation in the International Sport Footwear Industry and the Fair Labor Association (FLA)[3]

Production is increasingly outsourced to countries where labour rights and human rights violations frequently occur. Some observers have been sceptical about the ability of states or international organisations to tackle the problem of labour rights violations. Other observers argue that the management of labour conditions is increasingly taken up by private actors and non-state market governance mechanisms. One of the most prominent non-state market mechanisms is certification. Certification is a process through which transnational networks of diverse actors set and enforce standards for the management of labour conditions and human rights around the world. The study aimed to provide an assessment of the conditions under which multinational branded firms join certification initiatives. The case of the Fair Labor Association, a certification initiative, and 17 international sport footwear companies is selected for this purpose. This selection was based on three criteria: (i) the variability of the conditions under consideration including the outcome; (ii) the significance of the companies (international and branded firms) and the multi-stakeholder initiative (FLA); and (iii) data availability. The study used the csQCA technique to analyze the 17 cases. It aimed to identify structural preconditions for joining a certification initiative and further seeks to identify the different configurations of conditions which are linked to joining a certification initiative. The study identified 4 conditions which were hypothesised to contribute to explaining joining a certification initiative. First, it was hypothesised that firms which were under sustained pressure from NGO's via different campaigns will join a

certification initiative. Secondly, building on several arguments, it was suggested that firms with a headquarters in countries with strong unions (corporatist countries) will join a certification initiative. A third factor related joining a certification initiative to the public ownership of firms. Firms traded on the stock exchange were expected to join a certification initiative. A final explanatory condition focused on the track record of firms with regard to implementing organisational change with regard to managing labour conditions throughout the supply chain. Each of these conditions was operationalised as a dichotomous condition. The presence of the condition is given a score of 1, the absence a score of 0. All information was then brought together in a data matrix (Table 1).

Table 1: Data Matrix – Non-state market regulation of sport footwear industry

CASE	**EXPLANATORY CONDITIONS**				**OUTCOME**
Firm	**Unions**	**NGO Pressure**	**Public**	**Prior Change**	**Member FLA**
Nike	0	1	1	1	1
Adidas	1	1	1	1	1
Puma	1	1	1	1	1
Reebok	0	1	1	1	1
New Balance	0	1	0	1	0
Diadora	1	0	0	0	0
Fila	1	1	1	0	0
Karhu	1	0	0	0	0
Kelme	-	0	0	0	0
Mizuno	1	0	1	0	0
Saucony	0	0	1	0	0
Asics	1	1	1	1	1
Brooks	0	0	0	0	0
Decathlon	1	0	0	1	0
Lotto	1	0	0	0	0
Kappa	1	0	1	1	0
Umbro	0	1	1	0	1

This data matrix can be re-arranged in a truth table which brings together cases with the same configuration of conditions. The 17 cases reappear as 11 configurations together with information on the outcome (Table 2 (truth table) and 2a (truth table summary))[4].

Table 2: Truth Table

A: UNION
B: NGO PRESSURE
C: PUBLIC
D: PRIOR CHANGE
OUT: MEMBER FLA
freq0: frequency of outcome equal to 0
freq1: frequency of outcome equal to 1

	A	B	C	D	OUT	freq0	freq1	Cases
1	0	0	0	0	0	1	-	Brooks, Kelme
2	0	0	0	1	?	-	-	-
3	0	0	1	0	0	1	-	Saucony
4	0	0	1	1	?	-	-	-
5	0	1	0	0	?	-	-	-
6	0	1	0	1	0	1	-	New Balance
7	0	1	1	0	1	-	1	Umbro
8	0	1	1	1	1	-	2	Nike, Reebok
9	1	0	0	0	0	3	-	Diadora, Karhu, Lotto
10	1	0	0	1	0	1	-	Decathlon
11	1	0	1	0	0	1	-	Mizuno
12	1	0	1	1	0	1	-	Kappa
13	1	1	0	0	?	-	-	-
14	1	1	0	1	?	-	-	-
15	1	1	1	0	0	1	-	Fila
16	1	1	1	1	1	-	3	Adidas, Puma, Asics

Table 2a: Truth Table Summary

Row	**Outcome = 1 (Member FLA)**	**N**
1	UNION*NGO*PUBLIC*CHANGE	3
2	union*NGO*PUBLIC*CHANGE	2
3	union*NGO*PUBLIC*change	1
	Outcome = 0 (No Member FLA)	
4	UNION*ngo*public*change	3
5	union*ngo*public*change	2
6	union*ngo*PUBLIC*change	1
7	UNION*ngo*PUBLIC*change	1
8	UNION*ngo*public*CHANGE	1
9	union*NGO*public*CHANGE	1
10	UNION*ngo*PUBLIC*CHANGE	1
11	UNION*NGO*PUBLIC*change	1

On the basis of the truth table the researcher can identify the most parsimonious model and identify necessary conditions. The identification of the most parsimonious model is done via the minimisation procedure (*supra*). In this example, a comparison of rows 1 and 2 shows that the condition union/UNION is irrelevant in the context where the other 3 conditions and the outcome are present. The minimisation rules suggest that this condition can be removed from the explanation in order to achieve parsimony. The csQCA-software allows researchers to systematically compare all rows and achieve minimisation. Applying the minimisation procedure to all paired comparisons generates the following results:

FLA = NGO*PUBLIC*CHANGE +union*NGO*PUBLIC
fla = ngo*change + UNION*ngo + UNION*PUBLIC*change + union*NGO*public*CHANGE

In addition an analysis of necessary conditions was performed. Based on the minimisation procedure different combinations of the three crucial conditions (NGO, PUBLIC and CHANGE) were tested through the necessary conditions analysis in csQCA. Table 2 shows that the condition of being publicly owned (PUBLIC) and being under sustained pressure by NGOs (NGO) are necessary conditions for joining the FLA. As a result, the combination of the two conditions is a necessary condition for FLA. Based on this analysis a return to the cases and case knowledge was undertaken in order to identify the underlying mechanisms which link the explanatory configurations to the outcome. The underlying mechanism which was identified was uncertainty reduction and information control in order to manage reputation. Joining a certification initiative signals a proactive approach toward the management of labour standards on a global scale and generates third-party controlled information on this issue. This is an important tool to manage information and communicate it externally. The working of this mechanism was best illustrated by the case of Umbro, a UK based firm. Initially Umbro had not joined the FLA. It was not until its initial public offering on the London Stock Exchange in mid-2005 that it joined FLA, following pressure from NGOs in light of London's bid for the Olympics (Fair Olympics campaign).

From Contradictions to Consistency

In *The Comparative Method* Charles Ragin (1987) introduced csQCA as an analytic technique to develop explanatory models for medium-sized N research designs. The development or specification of models, as we have just illustrated, occurs on the basis of theoretical information and selected variables on the one hand and empirical information on these variables in specific cases on the other hand. One mechanism of building models in csQCA is by solving contradictions (see Ragin, 1987, pp. 113-118). csQCA is built on the assumption that contradictions will always occur if the explanatory model is not correctly specified (omitted variables, measurement error, heterogeneity of the research population, etc.) or when it does not make theoretical sense. Contradictions occur in the transformation of a data matrix to a truth-table. The occurrence of contradictions is signalled in the output (truth table) of a csQCA analysis. The output presents the number of configurations which lead to the presence of the outcome (1-terms), the number of configurations of conditions which lead to the absence of the outcome (0-terms) and the number of configurations which lead both to the presence and absence of the outcome (i.e. contradictory configurations: C-terms). As Ragin (1987, p. 118) notes the "*lesson here is that an existing data set should not be considered an irrevocable starting point. In qualitative comparative work, the representation of the empirical world in terms of a truth table is a crucially important part of the investigation"*. This transformation reveals contradictions which should be resolved, primarily by identifying omitted causal conditions. (Ragin, 1987, p. 118; see also Rihoux & De Meur, 2009, p. 48)

The importance of the issue of contradictions in model construction via csQCA is repeatedly stressed by csQCA-users. Ragin (2005, p. 34) argued that a csQCA-analysis forces "*researchers to deepen their knowledge of cases, as they confront sets of cases that are similar with respect to specified causal conditions but different in their outcomes (such cases are called 'contradictions' in CSQCA). It is incumbent upon the researcher to resolve as many of such contradictions as possible, through case-oriented analysis, before synthesising cross-case patterns […] The resolution of contradictions […] deepens knowledge and understanding of cases and also may expand and elaborate theory.*" In a more recent article, together with Bruce Kogut, the importance of contradictions was again stressed: "*contradictions flag potential problems with the theoretical specification, especially regarding potential contamination by neglecting other causal factors*." (Kogut & Ragin, 2006, p. 48). In a recently published handbook on csQCA Rihoux and De Meur (2009, pp. 48-56) discuss extensively several strategies to resolve contradictions.

If, for example, crucial conditions are omitted from an explanatory model – it is assumed – a QCA analysis will not generate a full account of the cases and will result in contradictions. Since QCA aims to explain every case with a given model it is not straightforward to come up with a model which explains all cases but at the same time omits a key variable. The presence of the contradictions points to the fact that some cases cannot be

explained by the model (contradictory cases – infra). In other words, it is argued that QCA only produces explanatory models when they exist in the data and in all other circumstances produces models that include unresolved contradictions.

Contradictions occur in QCA when an identical configuration of conditions is associated with both the presence and absence of an outcome. In QCA-terms[5] a contradiction occurs when:

A.b.C is associated with the outcome D

A.b.C is associated with the outcome d

In more recent publications (Ragin, 2000, 2006, 2008) the focus on assessing the validity of a model has shifted from contradictions to the introduction of new measures in QCA which aim to capture the validity of a model, namely consistency. Consistency "*assesses the degree to which the cases sharing a given condition or combination of conditions […] agree in displaying the outcome in question*" (Ragin, 2006, p. 292).

In other words, consistency in crisp-set relations is the proportion of cases with a given cause or combination of causes that also display the outcome (Ragin, 2006; Ragin, 2008a, p. 77). Charles Ragin (2006, p. 293) advises researchers to craft models which generate high consistency measures. "*In general, consistency scores should be as close to 1.0 (perfect consistency) as possible. With observed consistency scores below 0.75, it becomes increasingly difficult on substantive grounds to maintain that a subset relation exists*". Low consistency measures flag problems with the explanatory model such as omitted conditions or measurement error.

As a result, in new versions of csQCA contradictions are less prominent. The users are now advised (Ragin, 2008a, pp. 44-47) to perform two main tasks when performing a csQCA analysis. First, the researcher needs to make an assessment of the distribution of cases across different logically possible combinations of causal conditions. This assessment allows researchers to classify, on the basis of a frequency threshold, some causal paths as relevant and others as irrelevant based on the number of cases covered by the causal paths. *"When the total number of cases in an analysis is relatively small, the frequency threshold should be 1 or 2. When the total N is large, however, a more substantial threshold should be used. It is very important to examine the distribution of cases across causal combinations.* (Ragin, 2008a, p. 46)". The second task is to assess the consistency of the causal combinations and the outcome.

However, contradictions and consistency are interrelated. Consistency in csQCA is measured on the level of a row of a truth table and, as indicated, is the proportion of cases with a given cause or combination of causes that also display the outcome. If for example 17 out of the 20 cases displaying a cause or causal combination also display the outcome, then consistency is 0.85. (Ragin 2006, p. 293). This indicates that three cases do not display the outcome (either the outcome is absent or no information is available). In previous versions of csQCA, the result would be a C-term, indicating a contradiction. As a result, where previously csQCA was built on the assumption that contradictions will occur if the model is not correctly specified (Marx, 2010; Seawright, 2005) the current version is build on the assumption that ill-specified models will generate very low consistency results. Consequently a csQCA analysis on random data should result in low consistency results. Marx (2010) explored the assumption with regard to contradictions on the basis of some selected simulations and found that under certain conditions this assumption did not hold. In a next section we again test this assumption of contradictions, but now on the basis of extensive computer generated simulations resulting in robust estimates. Furthermore we extend the simulations to test the assumption with regard to consistency measures. While testing the assumptions we develop benchmark tables which can be used by researchers in order to assess whether it is safe to make the consistency assumption for the model they aim to test. Finally, we confront the results of simulation on the basis of our 0.5 probability value with those that use the probability function on 0's and 1's of our real-life example. In order to test the assumptions the paper worked within the csQCA framework (both technically (Boolean Algebra) and philosophically) in order to generate a deeper understanding of how it functions and malfunctions within the context of the Boolean mathematics on which it is founded.

The simulation procedure was performed using the R software, where a special QCA package is available (and suitable) for simulation purposes (Dusa, 2010). It is a computationally intensive process which begins with the definition of the empty matrices with 300 rows and 13 columns, and iterates over each of the individual cells corresponding to the unique pair of the number of cases and the number of causal conditions. For each iteration[6] , the algorithm draws 1,500 random samples of data, using a probability of 0.5 for both 0 and 1. For replication purposes, a special seed (see also Annex 1) was inserted in the code before each individual sample, using the following (arbitrary) formula:

i*j + k

where "i" is the number of cases, "j" is the number of causal conditions and "k" is a counter for the number of samples[7].

Annex 1 provides the R code used for the generation of the random samples. For each of the random samples drawn, the procedure uses the function truthTable() in order to construct the truth table, and finally inserts in each of the matrices measures for the occurrence of contradictions, and two measures concerning consistency and complexity.

Measuring Contradictions and Consistency

Contradictions

The assumption of the presence of contradictions in ill-specified models was tested in a previous study (Marx 2010). A csQCA analysis was performed on randomly created datasets expecting that this would always result in contradictions. The analysis showed that in certain circumstances csQCA produced an explanatory model without contradictions on the basis of random data. The results indicate that, given a particular sample size, there is an upper-limit to the number of conditions which can be included in a csQCA dataset. In addition, the ratio of conditions to cases determines whether csQCA will generate an explanatory model on random data. As a result, model specification in csQCA is crucial and needs to take these limiting factors into account. Marx (2010) was able to explore and explain the relationship between model specification and the occurrence of contradictions. He however was only able to provide approximate estimations for the specification of models in csQCA. Recent advances in mathematical and computing approaches in csQCA (Dusa, 2007), as described above, allow for precise estimates with regard to when contradictions occur. csQCA researchers should specify their model (the ratio of conditions to cases) in such a way that contradictions would normally (always) occur when this model specification is used to analyse a random dataset. Hence, the occurrence of contradictions on random data can be used as a criterion for model specification.

In order to benchmark whether contradictions occur on random data a benchmark measure is constructed which measures the occurrence of contradictions (OCCON). The first measure focuses on the presence of at least one configuration which is contradictory (C Term). The measure is calculated by summing all analysed random datasets which contain at least one contradiction and dividing it by N (the number of random datasets for a given combination of conditions and cases, in the present study a 1500 random datasets).

$$OCCON = \frac{\sum_{i=1}^{N} C_i}{N}$$

where $C_i = 1$ in cases where a contradiction exists and 0 otherwise, for N random datasets

If the indicator is 1 this means that each random dataset of the N random datasets which was analysed in csQCA generated at least one configuration which was contradictory. The estimated probability of finding an explanatory model (a model which results in no contradictions) on a random dataset is non-existing. Researchers can assume that the identified model, which will be used in subsequent analytic steps in csQCA, can make a distinction between random data and real data. If it is 0 this implies that no random dataset out of N datasets generated a contradiction when analysed with csQCA. In this case, researchers are not able to distinguish real from random data and cannot distinguish whether the specified model identifies a meaningful pattern in the data.

For each combination of conditions (a maximum of 13) and cases (a maximum of a 300) an OCCON-Measure was calculated by analyzing 1500 random datasets via csQCA. The distribution of 1's and 0's in the data matrix was based on a randomness value of 0.5 (equal chances for 1's and 0's to occur). The result of the simulation is a benchmark table which allows researchers to assess the probability of finding a model on random data for a combination of conditions and cases (model specification). The measure ranges between 0 and 1.

Consistency

As indicated above, consistency is measured on the level of a row in a truth table. For the purpose of this paper we need a consistency-related measure on the level of the truth table as a whole. A truth table summary in csQCA provides an overview of the number of configurations and cases for all 0 outcomes, 1 outcomes, -outcomes (missing scores for the outcome) and C-outcomes. Table 3 provides a hypothetical truth table (and table 3a a truth table summary) for an analysis of 30 cases. It shows that there are in total 12 configurations explaining the 30 cases. It also shows that there are in total 19 cases in the 5 contradictory configurations. On the basis of this truth table summary one can calculate two consistency-related measures, one that focuses on the configurations and the other one on the cases. In order to distinguish our consistency measure calculated in the statistical software R from the one calculated in the fsQCA software (Ragin, 2008a) we will refer to consistency-R in the rest of the paper.

Table 3: Hypothetical Truth Table Summary

	A	B	C	D	OUT	freq0	freq1
1	0	0	0	0	?	-	-
2	0	0	0	1	0	2	-
3	0	0	1	0	0	2	-
4	0	0	1	1	0	2	-
5	0	1	0	0	?	-	-
6	0	1	0	1	0	2	-
7	0	1	1	0	1	-	1
8	0	1	1	1	1	-	1
9	1	0	0	0	?	-	-
10	1	0	0	1	1	-	1
11	1	0	1	0	C	2	3
12	1	0	1	1	C	1	1
13	1	1	0	0	?	-	-
14	1	1	0	1	C	2	2
15	1	1	1	0	C	3	3
16	1	1	1	1	C	1	1

Table 3a: Hypothetical Truth Table Summary

	Configurations	Cases
0-terms	4	8
1-terms	3	3
--terms	4	0
C-terms	5	19
Cases in the contradictory rows without the outcome		9
Cases in the contradictory rows with the outcome		10
Total	12	30

Our first consistency-R measure is the proportion of configurations that have no contradictions, out of the total number of observed configurations. If it reaches 1 all configurations are consistent (non-contradictory), and if it reaches 0 than all configurations are contradictory. In the hypothetical truth table this corresponds to:

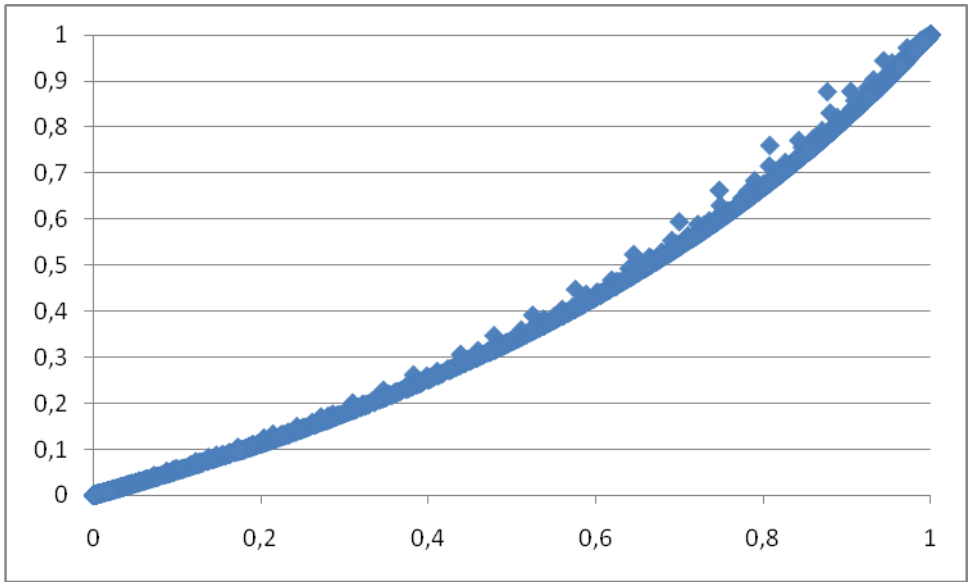
CONSIST.1 = 7/12 = 0.583

Our second consistency-R measure takes the number of cases into account and calculates the proportion of cases associated with non-contradictory configurations, out of the total number of observed cases. If it reaches 1, all cases are maximally consistent given that none of them are associated with a contradictory configuration. The second measure of consistency on the basis of the hypothetical truth table is:

CONSIST.2 = 11/30 = 0.367

These two measures are, as could be expected, highly correlated as is illustrated in Figure 1. Each measure was calculated for all possible combinations of conditions and cases on the basis of the random datasets. Figure 1 plots the results for the two measures. Each dot represents the result arising from the csQCA analysis of 1500 random datasets.

Figure1: Relationship between Consistency 1 (horizontal axis) and Consistency 2 (vertical axis)



Given the strong correlation between the two measures the benchmark table will be based on consistency-R measure 2 since it is more stringent than consistency-R measure 1 (consistency 1 > consistency 2).

Development of Benchmark tables and Benchmarking the Empirical Study

Development of Benchmark tables

Table 4 and 5 provide the results of the simulation for 10 conditions and 50 cases (the full tables for 13 conditions and 300 cases are included in annexes). Table 4 focuses on the occurrence of contradictions and table 5 provides the results for our chosen consistency-related measure. Table 4 shows that in some cells the proportion of random samples which result in contradictions is low or non-existing. The latter is a function of the number of conditions and number of cases. Researchers are advised to specify their model (the ratio of conditions to cases) in such a way that on the basis of random data contradictions should be omnipresent or at least 90% of the random samples should generate contradictions. Models with a specification in the dark area should not be analysed since the probability of generating results on random data are too high (>10%).

Table 4: Benchmark Contradictions Measure

		# Conditions (excluding outcome)								
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
# Cases	**2**	0.12	0.06	0.03	0.01	0.01	0.00	0.01	0.00	0.00
	3	0.34	0.18	0.09	0.04	0.03	0.01	0.00	0.00	0.00
	4	0.56	0.31	0.19	0.09	0.05	0.03	0.01	0.00	0.00
	5	0.70	0.47	0.26	0.15	0.09	0.04	0.02	0.01	0.01
	6	0.83	0.62	0.37	0.22	0.11	0.05	0.03	0.01	0.01
	7	0.92	0.72	0.50	0.30	0.16	0.07	0.04	0.02	0.01
	8	0.96	0.84	0.60	0.35	0.19	0.10	0.05	0.03	0.01
	9	0.97	0.89	0.68	0.43	0.24	0.12	0.07	0.05	0.02
	10	0.98	0.94	0.76	0.51	0.30	0.17	0.08	0.03	0.02
	11	0.99	0.97	0.83	0.58	0.36	0.17	0.09	0.05	0.02
	12	1.00	0.98	0.87	0.65	0.41	0.23	0.13	0.06	0.04
	13	1.00	0.98	0.92	0.70	0.48	0.28	0.14	0.08	0.04
	14	1.00	0.99	0.94	0.76	0.49	0.29	0.17	0.10	0.04
	15	1.00	1.00	0.96	0.81	0.58	0.35	0.19	0.10	0.05
	16	1.00	1.00	0.96	0.84	0.61	0.39	0.20	0.12	0.06
	17	1.00	1.00	0.99	0.88	0.65	0.40	0.23	0.13	0.06
	18	1.00	1.00	0.99	0.92	0.71	0.47	0.26	0.14	0.07
	19	1.00	1.00	0.99	0.93	0.72	0.51	0.28	0.18	0.07
	20	1.00	1.00	1.00	0.95	0.78	0.52	0.30	0.17	0.08
	21	1.00	1.00	1.00	0.95	0.82	0.57	0.35	0.18	0.09

22	1.00	1.00	1.00	0.97	0.84	0.58	0.38	0.20	0.11
23	1.00	1.00	1.00	0.98	0.87	0.64	0.40	0.20	0.12
24	1.00	1.00	1.00	0.98	0.89	0.67	0.43	0.23	0.14
25	1.00	1.00	1.00	0.99	0.91	0.69	0.43	0.26	0.14
26	1.00	1.00	1.00	1.00	0.92	0.73	0.47	0.26	0.16
27	1.00	1.00	1.00	1.00	0.94	0.73	0.50	0.30	0.17
28	1.00	1.00	1.00	1.00	0.94	0.78	0.53	0.30	0.18
29	1.00	1.00	1.00	1.00	0.97	0.79	0.55	0.32	0.18
30	1.00	1.00	1.00	1.00	0.97	0.80	0.58	0.36	0.20
31	1.00	1.00	1.00	1.00	0.97	0.83	0.59	0.35	0.22
32	1.00	1.00	1.00	1.00	0.98	0.87	0.64	0.36	0.20
33	1.00	1.00	1.00	1.00	0.98	0.87	0.65	0.40	0.24
34	1.00	1.00	1.00	1.00	0.99	0.90	0.67	0.42	0.24
35	1.00	1.00	1.00	1.00	0.99	0.90	0.68	0.45	0.26
36	1.00	1.00	1.00	1.00	1.00	0.90	0.70	0.46	0.26
37	1.00	1.00	1.00	1.00	0.99	0.93	0.72	0.50	0.29
38	1.00	1.00	1.00	1.00	1.00	0.92	0.75	0.48	0.31
39	1.00	1.00	1.00	1.00	1.00	0.95	0.76	0.51	0.29
40	1.00	1.00	1.00	1.00	1.00	0.95	0.78	0.54	0.33
41	1.00	1.00	1.00	1.00	1.00	0.95	0.79	0.59	0.32
42	1.00	1.00	1.00	1.00	1.00	0.97	0.83	0.54	0.35
43	1.00	1.00	1.00	1.00	1.00	0.97	0.83	0.58	0.35
44	1.00	1.00	1.00	1.00	1.00	0.97	0.84	0.59	0.39
45	1.00	1.00	1.00	1.00	1.00	0.98	0.86	0.63	0.37
46	1.00	1.00	1.00	1.00	1.00	0.98	0.87	0.63	0.39
47	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.66	0.41
48	1.00	1.00	1.00	1.00	1.00	0.98	0.89	0.66	0.42
49	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.71	0.44
50	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.70	0.43

Table 5 provides the results for the consistency measure. A similar result appears. csQCA seems able, on the basis of our chosen measure, to generate highly consistent results on random data. If one takes the 0.75 score (*supra*) as a point of departure the models which are specified according to the dark area would considered to be highly consistent, even on random data.

Table 5: Benchmark Consistency-R Measure

		# Conditions (excluding outcome)								
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
#	**2**	0.88	0.94	0.97	0.99	0.99	1.00	0.99	1.00	1.00
C	**3**	0.76	0.88	0.94	0.97	0.98	0.99	1.00	1.00	1.00
a	**4**	0.66	0.83	0.90	0.95	0.98	0.99	1.00	1.00	1.00
s	**5**	0.59	0.77	0.88	0.94	0.96	0.98	0.99	1.00	1.00
e	**6**	0.52	0.71	0.86	0.92	0.96	0.98	0.99	1.00	1.00
s	**7**	0.45	0.68	0.82	0.90	0.95	0.98	0.99	0.99	1.00
	8	0.39	0.63	0.79	0.90	0.95	0.97	0.99	0.99	1.00
	9	0.35	0.59	0.77	0.88	0.94	0.97	0.98	0.99	1.00
	10	0.31	0.55	0.76	0.87	0.93	0.96	0.98	0.99	1.00
	11	0.26	0.52	0.72	0.86	0.92	0.97	0.98	0.99	1.00
	12	0.23	0.49	0.70	0.84	0.92	0.96	0.98	0.99	0.99
	13	0.20	0.47	0.67	0.83	0.91	0.95	0.98	0.99	0.99
	14	0.17	0.44	0.66	0.81	0.90	0.95	0.97	0.99	0.99
	15	0.15	0.40	0.65	0.80	0.89	0.95	0.97	0.99	0.99
	16	0.13	0.38	0.62	0.79	0.89	0.94	0.97	0.98	0.99
	17	0.12	0.36	0.60	0.77	0.88	0.94	0.97	0.98	0.99
	18	0.10	0.33	0.59	0.77	0.87	0.93	0.97	0.98	0.99
	19	0.09	0.31	0.56	0.76	0.87	0.93	0.97	0.98	0.99
	20	0.08	0.29	0.55	0.74	0.86	0.93	0.97	0.98	0.99
	21	0.07	0.27	0.53	0.73	0.86	0.93	0.96	0.98	0.99
	22	0.06	0.26	0.51	0.72	0.85	0.92	0.96	0.98	0.99
	23	0.06	0.24	0.50	0.71	0.84	0.92	0.96	0.98	0.99
	24	0.05	0.22	0.48	0.69	0.83	0.91	0.95	0.98	0.99
	25	0.04	0.21	0.46	0.68	0.83	0.91	0.96	0.98	0.99

26	0.04	0.20	0.45	0.68	0.82	0.90	0.95	0.98	0.99
27	0.03	0.19	0.44	0.66	0.81	0.91	0.95	0.97	0.99
28	0.03	0.18	0.43	0.66	0.81	0.90	0.95	0.97	0.99
29	0.02	0.17	0.41	0.64	0.80	0.90	0.95	0.97	0.99
30	0.02	0.16	0.40	0.64	0.79	0.89	0.94	0.97	0.99
31	0.02	0.15	0.39	0.62	0.79	0.89	0.94	0.97	0.98
32	0.01	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.99
33	0.01	0.13	0.36	0.60	0.78	0.88	0.94	0.97	0.98
34	0.01	0.12	0.35	0.60	0.77	0.88	0.94	0.97	0.98
35	0.01	0.11	0.34	0.59	0.76	0.88	0.94	0.97	0.98
36	0.01	0.11	0.33	0.57	0.76	0.87	0.94	0.97	0.98
37	0.01	0.10	0.31	0.57	0.76	0.87	0.93	0.97	0.98
38	0.01	0.09	0.30	0.56	0.75	0.87	0.93	0.97	0.98
39	0.01	0.09	0.29	0.55	0.75	0.86	0.93	0.96	0.98
40	0.00	0.08	0.29	0.54	0.74	0.86	0.93	0.96	0.98
41	0.00	0.07	0.28	0.53	0.73	0.86	0.93	0.96	0.98
42	0.00	0.07	0.27	0.53	0.72	0.85	0.92	0.96	0.98
43	0.00	0.07	0.26	0.52	0.72	0.85	0.92	0.96	0.98
44	0.00	0.06	0.26	0.51	0.72	0.84	0.92	0.96	0.98
45	0.00	0.06	0.25	0.50	0.71	0.84	0.92	0.96	0.98
46	0.00	0.05	0.24	0.49	0.70	0.84	0.92	0.96	0.98
47	0.00	0.05	0.24	0.48	0.70	0.83	0.91	0.96	0.98
48	0.00	0.05	0.22	0.47	0.69	0.83	0.91	0.96	0.98
49	0.00	0.05	0.22	0.47	0.68	0.83	0.91	0.95	0.98
50	0.00	0.04	0.21	0.46	0.69	0.83	0.91	0.95	0.98

As with the occurrence of contradictions the presence of high consistency-R scores is a function of the specification of the model (number of conditions/number of cases). As Marx (2010) argued the ratio of conditions to cases also influences the degree to which QCA can reduce case complexity. At one extreme there is full complexity and each case is covered by a unique configuration. In case of full complexity no contradictions can occur generating both low scores on the occurrence of contradictions and high scores on consistency-R. This relationship, between complexity and consistency-R, is presented in figure 2. Complexity is calculated as the ratio of the number of configurations, which are the result of an analysis of

real or random data, to the number of cases. A score of 1 indicates that there are as many configurations as cases. A score close to 0 indicates that all cases are captured in one configuration. A complexity score for each of the 3,600 cells (cases and conditions) for which 1,500 random datasets were created is calculated and plotted against the consistency-R score. The figure shows an extreme linear relationship between consistency and complexity indicating that consistency-R goes up when complexity goes up. As a result consistency-R is a function of the degree to which a model is 'forced' to reduce complexity. This in turn is a function of the number of conditions which are included in a model given the number of cases. Figure 3 shows the relationship between complexity and the design of a model. Design is calculated as the number of conditions/number of cases. The figure shows that complexity reduction only occurs when design is < 0.9 and gradually decreases as the design parameter decreases. This brings us back to the benchmark tables 4 and 5 which provide precise estimates for model specification in csQCA.

Figure 2: Relationship between consistency-R (vertical axis) & complexity (horizontal axis)

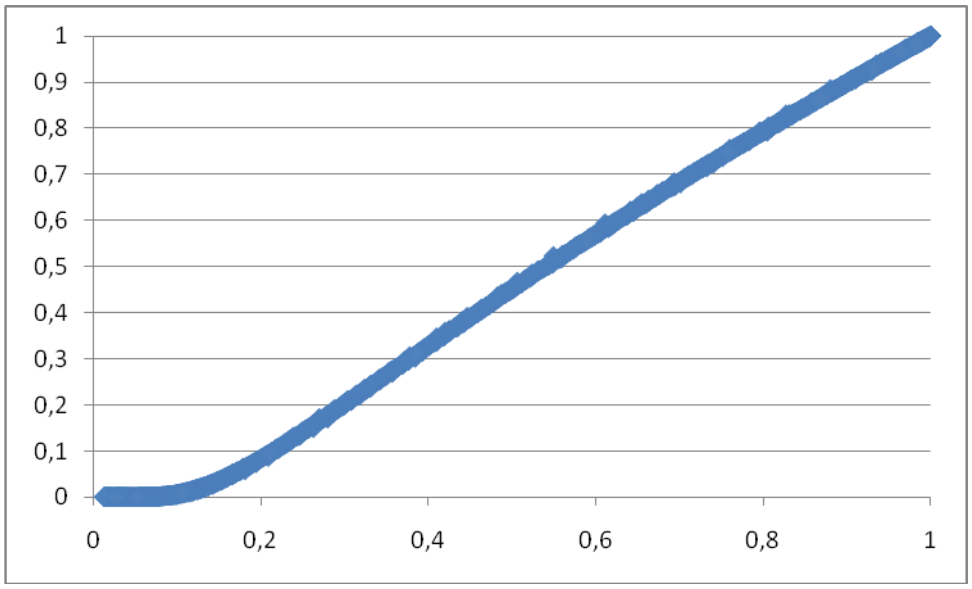
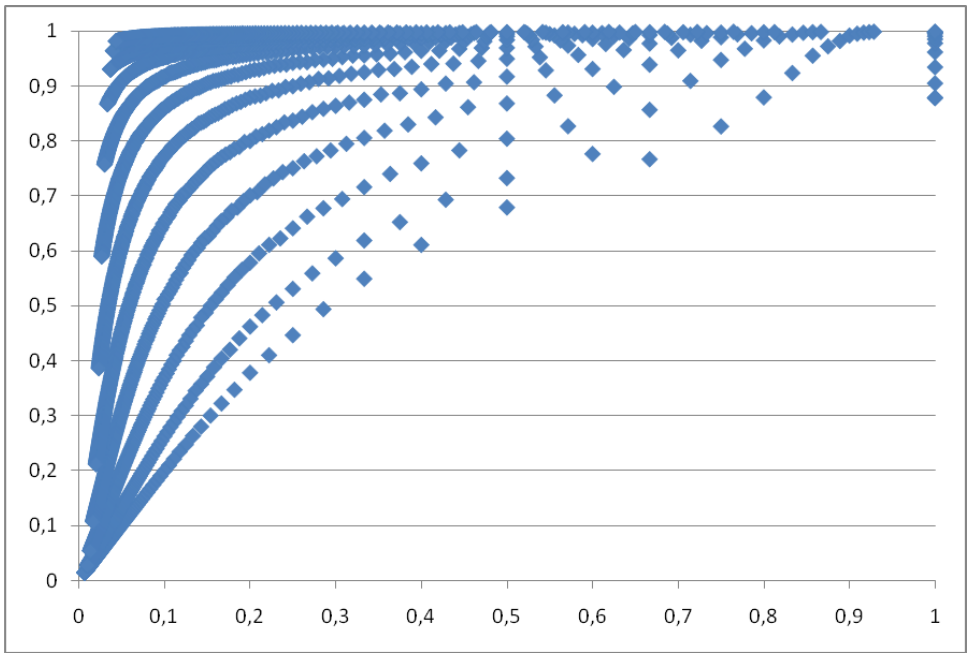


Figure 3: Relationship between Complexity (vertical axis) and Design (horizontal axis)



Benchmarking the empirical study

The empirical study presented before contained 5 variables (4 conditions and 1 outcome) and 17 cases. Benchmarked on both tables (4 conditions and 17 cases) the study falls within the white area, indicating that on the basis of random data the occurrence of contradictions on random data is omnipresent and low levels of consistency-R appear. Hence, the empirical example passes the test on the basis of the random datasets.

However, it could be argued that the use of 0.5 distribution probability of 0's and 1's is far removed from the real life application of csQCA since distributions differ between variables in a csQCA application. In order to explore this further we used the distribution of 0's and 1's of the 4 conditions and 1 outcome of the empirical example as probability values to generate 1,500 random datasets. In other words, we generated random datasets on the basis of a real-life example and then analysed the results. Table 6 compares the results of random simulation for 5 variables (4 conditions + 1 outcome) and 17 cases for the random trials with 0.5 probability and with variable probabilities taken from our real life example for the three measures of occurrence of contradictions, consistency-R and complexity. For the real life example, there are three columns depending on the decision with regard to the missing condition for Spain (the Kelme case) on union. In column 1 the variable is treated as missing, in column 2 the condition is assumed to be present and in column three the condition is assumed to be absent. The results only differ marginally.

Table 6: Complexity, Contradictions and Consistency Measure for a simulation based on the probability distribution of 0's and 1's of our real life example in comparison with the 0.5 probability distribution

	Real Life Example			**0.5**
Treatment of Kelme:	- = -	- = 1	- = 0	
Complexity	0.62	0.60	0.61	0.62
Occurrence of Contradictions	0.96	0.97	0.97	0.99
Consistency-R	0.62	0.60	0.61	0.60

Table 6 shows that in the case of a simulation on the basis of the probability distribution of the conditions of our particular real-life example the scores for the occurrence of contradictions are very similar to those in the simulation based on 0.5 probability indicating that the 0.5 probability constitutes at least for this particular case an appropriate measure for benchmarking purposes. Remember that high scores on the occurrence of contradictions indicate that contradictions occur systematically on the basis of random data confirming the assumption that contradictions will occur when a model is ill-specified. Lower scores on the occurrence of contradictions signal to researchers that either the number of cases should be increased or the numbers of conditions lowered in order to test a model which is subsequently used for analysis. A similar observation holds for the consistency-R measure. The measure for consistency-R on the basis of the probabilities of the real-life example is almost identical to the one for the 0.5 probability. On the basis of this particular real life example, it seems that 0.5 probability benchmark tables can also be used for benchmarking purposes for consistency-R. These results add support to the finding of Marx (2010, pp. 151-153) who conducted a similar simulation for an uneven distribution of 0's and 1's on the outcome variable only. Those results showed that the occurrence of contradictions is not influenced by the distribution of 0's and 1's on the outcome variable. Several probability distributions were tested. The present real life simulation confirms this result, not only for varying probabilities for the outcome but also for the conditions.

A key implication of the results is that researchers using csQCA need, in relation to the size of their dataset, to take the number of conditions they include into a model into account. Just adding conditions to a model in csQCA is seldom a valid strategy. Given the limitations with regard to model specification researchers are

forced to limit the number of conditions in an analysis. The most important strategy in this respect is defining the research population and the selection of cases. csQCA researchers are advised to use a Most Similar Systems Different Outcome research design for the selection of cases (i.e. MSDO-design) since it allows researchers to hold other (scoping) conditions under control. (Gerring 2007, for applications see Marx, 2008; Marx & Van Hootegem, 2007). In an MSDO research design the selection of cases is guided by two principles (Przeworski and Teune, 1970).

Principle 1. Maximise the variation on the outcome and explanatory conditions under investigation.

Principle 2. Homogenise (hold constant) other explanatory conditions which are not under investigation.

The application of the combination of these two principles resembles an experimental design, aims to strengthen the homogeneity of the research-population and allows researchers to limit the number of conditions in an analysis. The requirement of homogeneity is important for making inferences and states that the cases in an analysis should be identical in all relevant aspects except for the outcome and conditions of interest (King et al., 1994; Ragin, 2000, pp. 61–63). Clearly, the strong version of this requirement is only achievable via experimental research. As Ragin (1987, pp. 31-32) argues, the systematic comparative case approach attempts to approximate experimental rigour by identifying comparable instance of a phenomenon of interest and then analysing the theoretically important similarities and differences among them. Hence, a careful assessment of the comparability of cases, given a certain theoretical framework, is also important in observational research. In other words, homogeneity of the research population requires that cases should be comparable given a certain research question and the theoretical/explanatory model. As a result cases are selected which on the one hand are very similar, but on the other hand display variation on the conditions under investigation. The limitation of the number of conditions is, as is argued in the paper, important if one aims to stay, given the size of one's dataset, within the parameters set by the benchmark tables. Other case-selection strategies will most often result in an increase of conditions which is not always defensible from the perspective outlined in the current paper.

In our empirical example above, a MSDO case selection strategy was chosen. For this reason a specific market niche was selected. By focusing on a specific market niche and internationally operating branded companies, several relevant explanatory conditions which influence firm behaviour are held constant (Carroll & Hannan 1999)[8]. In other words, instead of looking for maximal variation, the design aimed to have variation on a number of conditions under consideration while holding other conditions constant (i.e. industry sector [sport footwear], markets on which they operate [all operate internationally] and type of products [all companies are branded companies instead of off-branded companies or private label companies]). The conditions that are held constant are also referred to as scoping conditions (Ragin 2000).

Conclusion

The purpose of this paper was to address and test two assumptions on which csQCA is based, namely that csQCA will generate contradictions and low consistency scores if models are ill-specified. In an era of doubts concerning macro-quantitative approaches (Kittel, 2006; Ebbinghaus, 2005) and increased attention to case studies in many social sciences (Brady & Collier, 2004; George & Bennett, 2005, Bates et. al., 1998; Box-Steffensmeier, Brady and Collier, 2008; Rihoux & Ragin, 2009, Poteete et al. 2010) csQCA holds the potential to provide a valuable set of tools to compare similarities and differences within a limited set of comparable cases and identify conditions which precede a relevant outcome. The first part of the paper introduced csQCA in general and as a stepwise approach. In a second part a real-life example was introduced with the purpose of illustrating how csQCA operates and as an input for a simulation in the subsequent part.

The third part introduced contradictions, a consistency-related measure (consistency-R), their interrelatedness and the assumptions which are made with regard to contradictions and consistency-R. The first assumption is that csQCA will generate contradictions when a model is not correctly specified (omitted conditions), when non-relevant cases are included or when measurement error occurs. As a consequence, previous studies using QCA assumed that a lack of contradictions implies one had generated a valid model which explained the

outcome under investigation. This assumption was tested by creating 1,500 random datasets (for which probability of 0's and 1's was set at 0.5) for each combination of conditions and cases and analysing these datasets via csQCA-software. The random simulations presented in this paper clearly show that the assumption does not always hold. Under certain circumstances csQCA does not generate contradictions for a model even on random data. Whether this problem arises or not is a function of the number of conditions and cases which are included in the analysis. Given any particular number of cases, there is a ceiling to the number of conditions which can be included safely in an analysis. The paper also tested, with an identical set of random datasets, a second assumption, which builds on the first assumption, namely that a csQCA analysis will result in low consistency-R scores when a model is not correctly specified (omitted variables), when non-relevant cases are included or when measurement error occurs. It is assumed that a high consistency-R score implies one has a valid model. Again it was shown on the basis of simulations using randomly generated datasets that this assumption is not always supported. Under certain circumstances csQCA does generate high consistency-R scores for a model, even on random data. This situation arises as a function of the number of conditions and cases which are included in the analysis. Also in this case there is a ceiling to the number of conditions which can be included in an analysis depending on the number of cases.

The paper provides two tables which provide estimates for these ceilings and which can be used to benchmark models with regard to the occurrence of contradictions and consistency. The tables provide information on the occurrence of contradictions and consistency scores on the basis of random, meaningless, data. If random data results in the absence of contradictions and high levels of consistency it indicates that csQCA is not able to distinguish real from random data and researchers cannot make any assumptions on the basis of the Boolean analysis alone. Benchmarking the real-life example to the scores in the benchmark table shows that the real-life example specified the model in such a way that an identical model tested on random data would result in the occurrence of contradictions (99% of the random datasets generated contradictions) and low consistency-R scores. The model specification parameters (4 conditions – 17 cases) of the real-life example pass the benchmark tests. It should be noted that the white and grey areas identified in this paper (tables 4 and 5) are to a certain degree arbitrary. One can set the thresholds differently. A lowering of the thresholds might result in the acceptance of a model for further analysis. This might be defensible on theoretical grounds.

However, it could be objected that the probability value used to construct the benchmark table (for each condition and outcome the probability is 0.5) is far removed from the various probabilities of achieving values of 0's and 1's of a real-life application. This was tested by using the probabilities of the real-life example described in the paper. This test shows that for this particular example the 0.5 probability generates an appropriate measure for the occurrence of contradictions and consistency-R suggesting that the benchmark tables can be used for different applications with different distributions of 0's and 1's in the conditions and outcomes, and hence constitute appropriate guides for model specification in csQCA. This particular claim is supported in a more general way by earlier work (Marx 2010).

Notes

[1] For an overview of csQCA applications see http://www.compasss.org

[2] In order to consolidate the results we also calculated the different measures for several combinations of variables and cases with 10000 random data matrices. Only minor differences occur, most of the times after the third decimal which is not included in the benchmark table. Hence, the results are robust.

[3] The application draws on an earlier paper by one of the current authors (Marx, 2008).

[4] In the case of Kelme there is a missing score for the condition UNION. This condition was measured on the level of the country in which the headquarters of the firm is based. In the case of KELME this is Spain. The strength of the presence of unions was measured on the basis of several country-level indicators, none of which contained sufficient information on Spain. Full details on the operationalisation of the UNION condition are presented in Marx (2008, pp.258-260). Since UNION, for the purpose of the paper (Marx, 2008), was only considered to be present when the scores for the different indicators which capture different dimensions of the condition where high the missing condition (UNION) is assumed to be absent in the case of KELME since no additional information supported the argument to code it as present.

[5] Uppercase letters indicate the presence of an explanatory condition or outcome. Lowercase letters indicate the absence of the condition or outcome. (see also Ragin, 1987; 1994).

[6] For each unique combination (cell) of rows (cases) and columns (conditions) a simulation was conducted. For each cell presented in Tables 4 and 5 1,500 random datasets were created and analyzed in csQCA (using the QCA package in R).

[7] In computer simulations where random numbers are extracted, it is impossible for other researchers to replicate identically the results, because they would always get other random numbers, simply because they are random. In order to allow for replication, random number generators have the possibility to start from a so-called "seed" (which can be any arbitrary number), which ensures the random numbers are always the same. Those numbers are still random, in the sense that the researcher does not know what numbers are going to be drawn, but starting from the same seed ensures the same random numbers will be generated. The formula "i*j + k" provides a number that is used as a seed for all random numbers generated by the algorithm, and the datasets generated are always unique given the fact that the number of rows and columns is always different.

[8] A key feature of organisations is that they vary on many different parameters both with regard to their internal structure and processes as well as with regard to the external environment. These parameters are often of crucial importance to the research question under consideration. This diversity has led many organisational researchers to argue that 'organisation scholars' should pay special attention to the construction of the research population on which they are focusing. As Carroll & Hannan (1999) comment, in biological and ecological sciences, ants, starfish, amoeba, elephants and cats are not involved in the same research project. Organisational scholars should follow the same example and pay special attention to the construction of research populations from which cases or observations are sampled. Following this argument researchers are often confronted with a limited number of observations (small-N) for an analysis which in turn limits the use of traditional methods and sometimes requires specific methodological approaches.

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Biographies

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Appendices

Appendix 1: The R code used for the generation of the random samples
Appendix 2: Full Benchmark Table 1 – Contradictions
Appendix 3: Full Benchmark Table 2 - Consistency

Appendix 1: The R code used for the generation of the random samples

```
nrows <- 300
ncols <- 13
nsamples <- 1500

NofCsamples <- Complexity <- AvgCs <- Consistency1 <- Consistency2 <- matrix(0, nrow=nrows, ncol=ncols)

library(QCA)

for (i in seq(2, nrows)) {           # number of cases
    for (j in seq(2, ncols)) {       # number of causal conditions
        Contra <- TotConf <- ContraConfig <- NofCs <- consist1 <- consist2 <- 0
        for (k in seq(nsamples)) {   # number of random samples
            set.seed(i*j + k)        # arbitrary formula
            mydata <- matrix(sample(0:1, i*(j+1), replace=TRUE), ncol=j+1)
            colnames(mydata) <- c(LETTERS[1:j], "OUT")
            mydata <- as.data.frame(mydata)
            tt <- truthTable(mydata, outcome="OUT", quiet=TRUE)$tt
            consist1 <- consist1 + sum(tt$OUT %in% c("1", "0")) / nrow(tt)
            consist2 <- consist2 + sum(c(as.numeric(tt$freq1[tt$OUT == "1"]),
                                         as.numeric(tt$freq0[tt$OUT == "0"])))/i
            NofConfig <- nrow(tt)
            if ("C" %in% tt$OUT) {
                Contra <- Contra + 1
                NofCs <- NofCs + sum(tt$OUT == "C")
                ContraConfig <- ContraConfig + sum(tt$OUT == "C")/NofConfig
            }
            TotConf <- TotConf + NofConfig
        }
        NofCsamples[i, j]  <- Contra/nsamples
        Complexity[i, j]   <- TotConf/(nsamples*i)
        AvgCs[i, j]        <- ContraConfig/nsamples
        Consistency1[i, j] <- consist1/nsamples
        Consistency2[i, j] <- consist2/nsamples
```

Appendix 2: Contradictions Benchmark Table (rows = cases / columns = conditions (excluding outcome))

	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
2	0.12	0.06	0.03	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
3	0.34	0.18	0.09	0.04	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00
4	0.56	0.31	0.19	0.09	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.00
5	0.70	0.47	0.26	0.15	0.09	0.04	0.02	0.01	0.01	0.00	0.00	0.00
6	0.83	0.62	0.37	0.22	0.11	0.05	0.03	0.01	0.01	0.00	0.00	0.00
7	0.92	0.72	0.50	0.30	0.16	0.07	0.04	0.02	0.01	0.01	0.00	0.00
8	0.96	0.84	0.60	0.35	0.19	0.10	0.05	0.03	0.01	0.01	0.00	0.00
9	0.97	0.89	0.68	0.43	0.24	0.12	0.07	0.05	0.02	0.01	0.01	0.00
10	0.98	0.94	0.76	0.51	0.30	0.17	0.08	0.03	0.02	0.01	0.00	0.00
11	0.99	0.97	0.83	0.58	0.36	0.17	0.09	0.05	0.02	0.01	0.01	0.00
12	1.00	0.98	0.87	0.65	0.41	0.23	0.13	0.06	0.04	0.02	0.01	0.00
13	1.00	0.98	0.92	0.70	0.48	0.28	0.14	0.08	0.04	0.02	0.01	0.01
14	1.00	0.99	0.94	0.76	0.49	0.29	0.17	0.10	0.04	0.03	0.01	0.00
15	1.00	1.00	0.96	0.81	0.58	0.35	0.19	0.10	0.05	0.02	0.01	0.00
16	1.00	1.00	0.96	0.84	0.61	0.39	0.20	0.12	0.06	0.03	0.02	0.01
17	1.00	1.00	0.99	0.88	0.65	0.40	0.23	0.13	0.06	0.03	0.02	0.00
18	1.00	1.00	0.99	0.92	0.71	0.47	0.26	0.14	0.07	0.03	0.01	0.01
19	1.00	1.00	0.99	0.93	0.72	0.51	0.28	0.18	0.07	0.04	0.02	0.01
20	1.00	1.00	1.00	0.95	0.78	0.52	0.30	0.17	0.08	0.05	0.02	0.02
21	1.00	1.00	1.00	0.95	0.82	0.57	0.35	0.18	0.09	0.04	0.02	0.01
22	1.00	1.00	1.00	0.97	0.84	0.58	0.38	0.20	0.11	0.05	0.03	0.01
23	1.00	1.00	1.00	0.98	0.87	0.64	0.40	0.20	0.12	0.07	0.02	0.02
24	1.00	1.00	1.00	0.98	0.89	0.67	0.43	0.23	0.14	0.06	0.03	0.01
25	1.00	1.00	1.00	0.99	0.91	0.69	0.43	0.26	0.14	0.07	0.04	0.02
26	1.00	1.00	1.00	1.00	0.92	0.73	0.47	0.26	0.16	0.08	0.04	0.02
27	1.00	1.00	1.00	1.00	0.94	0.73	0.50	0.30	0.17	0.08	0.04	0.02

28	1.00	1.00	1.00	1.00	0.94	0.78	0.53	0.30	0.18	0.09	0.04	0.02
29	1.00	1.00	1.00	1.00	0.97	0.79	0.55	0.32	0.18	0.09	0.05	0.03
30	1.00	1.00	1.00	1.00	0.97	0.80	0.58	0.36	0.20	0.10	0.05	0.02
31	1.00	1.00	1.00	1.00	0.97	0.83	0.59	0.35	0.22	0.11	0.06	0.03
32	1.00	1.00	1.00	1.00	0.98	0.87	0.64	0.36	0.20	0.11	0.06	0.03
33	1.00	1.00	1.00	1.00	0.98	0.87	0.65	0.40	0.24	0.12	0.06	0.03
34	1.00	1.00	1.00	1.00	0.99	0.90	0.67	0.42	0.24	0.13	0.06	0.03
35	1.00	1.00	1.00	1.00	0.99	0.90	0.68	0.45	0.26	0.12	0.07	0.04
36	1.00	1.00	1.00	1.00	1.00	0.90	0.70	0.46	0.26	0.14	0.06	0.04
37	1.00	1.00	1.00	1.00	0.99	0.93	0.72	0.50	0.29	0.14	0.08	0.04
38	1.00	1.00	1.00	1.00	1.00	0.92	0.75	0.48	0.31	0.17	0.08	0.04
39	1.00	1.00	1.00	1.00	1.00	0.95	0.76	0.51	0.29	0.18	0.09	0.04
40	1.00	1.00	1.00	1.00	1.00	0.95	0.78	0.54	0.33	0.18	0.09	0.04
41	1.00	1.00	1.00	1.00	1.00	0.95	0.79	0.59	0.32	0.17	0.10	0.05
42	1.00	1.00	1.00	1.00	1.00	0.97	0.83	0.54	0.35	0.17	0.10	0.06
43	1.00	1.00	1.00	1.00	1.00	0.97	0.83	0.58	0.35	0.18	0.11	0.06
44	1.00	1.00	1.00	1.00	1.00	0.97	0.84	0.59	0.39	0.20	0.12	0.05
45	1.00	1.00	1.00	1.00	1.00	0.98	0.86	0.63	0.37	0.22	0.11	0.06
46	1.00	1.00	1.00	1.00	1.00	0.98	0.87	0.63	0.39	0.22	0.13	0.06
47	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.66	0.41	0.25	0.12	0.06
48	1.00	1.00	1.00	1.00	1.00	0.98	0.89	0.66	0.42	0.24	0.13	0.06
49	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.71	0.44	0.25	0.13	0.08
50	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.70	0.43	0.27	0.13	0.07
51	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.68	0.45	0.27	0.14	0.07
52	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.72	0.48	0.28	0.16	0.08
53	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.74	0.49	0.29	0.13	0.07
54	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.75	0.52	0.27	0.17	0.08
55	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.76	0.50	0.29	0.17	0.09

56	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.78	0.53	0.31	0.17	0.09
57	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.79	0.53	0.33	0.20	0.10
58	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.79	0.55	0.34	0.17	0.11
59	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.79	0.56	0.35	0.20	0.09
60	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.82	0.57	0.34	0.19	0.09
61	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.83	0.57	0.38	0.20	0.09
62	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.84	0.61	0.36	0.20	0.11
63	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.86	0.62	0.38	0.21	0.10
64	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.87	0.61	0.38	0.22	0.11
65	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.86	0.63	0.41	0.23	0.13
66	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88	0.64	0.41	0.23	0.11
67	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.65	0.40	0.21	0.13
68	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.68	0.42	0.25	0.11
69	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.68	0.42	0.25	0.14
70	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.72	0.45	0.24	0.14
71	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.71	0.44	0.28	0.12
72	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.71	0.46	0.27	0.14
73	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.94	0.74	0.45	0.30	0.14
74	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.75	0.47	0.27	0.15
75	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.74	0.50	0.27	0.16
76	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.77	0.49	0.29	0.16
77	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.76	0.49	0.30	0.17
78	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.76	0.53	0.32	0.15
79	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.78	0.51	0.31	0.17
80	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.78	0.54	0.33	0.17
81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.78	0.56	0.33	0.17
82	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.83	0.56	0.34	0.19
83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.80	0.56	0.33	0.18

84	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.80	0.56	0.35	0.19
85	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.82	0.56	0.35	0.19
86	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.82	0.58	0.36	0.20
87	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.84	0.60	0.38	0.20
88	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.83	0.62	0.39	0.21
89	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.86	0.64	0.37	0.21
90	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.85	0.63	0.41	0.22
91	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.86	0.62	0.41	0.21
92	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.86	0.65	0.39	0.22
93	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.88	0.65	0.40	0.23
94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88	0.66	0.40	0.23
95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.89	0.67	0.42	0.23
96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.68	0.42	0.24
97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.67	0.43	0.24
98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.68	0.44	0.25
99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.70	0.46	0.24
100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	0.68	0.45	0.28
101	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.71	0.48	0.29
102	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.90	0.74	0.48	0.26
103	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.71	0.47	0.25
104	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.93	0.71	0.50	0.27
105	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.74	0.48	0.27
106	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.73	0.48	0.29
107	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.77	0.50	0.28
108	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	0.75	0.50	0.31
109	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.77	0.50	0.31
110	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.78	0.49	0.32
111	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.94	0.78	0.53	0.30

112	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.78	0.54	0.31
113	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.77	0.54	0.33
114	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.80	0.54	0.34
115	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.78	0.55	0.32
116	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.81	0.57	0.33
117	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.81	0.56	0.33
118	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.83	0.54	0.34
119	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.82	0.56	0.36
120	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.85	0.58	0.34
121	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.84	0.60	0.34
122	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85	0.58	0.36
123	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.83	0.59	0.36
124	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.84	0.57	0.37
125	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.84	0.63	0.38
126	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85	0.63	0.37
127	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.86	0.63	0.39
128	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.87	0.61	0.40
129	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.86	0.62	0.40
130	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.87	0.63	0.40
131	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.88	0.66	0.41
132	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88	0.66	0.43
133	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.64	0.42
134	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.88	0.65	0.41
135	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88	0.66	0.41
136	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.68	0.45
137	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.69	0.44
138	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.89	0.69	0.43
139	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.69	0.43

140	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.69	0.45
141	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.71	0.44
142	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.70	0.47
143	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.69	0.45
144	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.72	0.48
145	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.93	0.72	0.46
146	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	0.74	0.47
147	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.72	0.47
148	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.76	0.47
149	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	0.74	0.49
150	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.95	0.73	0.49
151	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.75	0.50
152	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.72	0.49
153	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.76	0.51
154	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.76	0.50
155	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.78	0.52
156	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.77	0.53
157	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.77	0.54
158	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.78	0.53
159	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.96	0.78	0.54
160	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.79	0.53
161	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.79	0.53
162	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.80	0.55
163	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.81	0.53
164	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.81	0.54
165	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.81	0.55
166	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.81	0.56
167	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.82	0.59

168	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.84	0.58
169	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.83	0.56
170	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.83	0.58
171	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.84	0.61
172	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.83	0.60
173	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.84	0.57
174	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.84	0.61
175	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.83	0.60
176	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85	0.59
177	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.86	0.63
178	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.87	0.61
179	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.86	0.63
180	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.87	0.63
181	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.87	0.61
182	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.86	0.63
183	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.88	0.63
184	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.86	0.63
185	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.88	0.66
186	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88	0.63
187	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88	0.65
188	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88	0.66
189	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88	0.64
190	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.65
191	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.68
192	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.67
193	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.69
194	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89	0.67
195	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.66

196	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90	0.69
197	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.70
198	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.71
199	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.70
200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.72
201	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91	0.72
202	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.71
203	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.70
204	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92	0.72
205	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.73
206	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.93	0.74
207	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	0.71
208	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.74
209	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.93	0.73
210	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.75
211	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.93	0.74
212	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.75
213	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.73
214	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.76
215	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.76
216	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.94	0.76
217	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.94	0.76
218	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.76
219	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.76
220	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.74
221	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.77
222	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.96	0.76
223	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.95	0.78

224	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.80
225	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.78
226	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.78
227	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.80
228	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.80
229	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.81
230	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.81
231	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.81
232	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.80
233	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.80
234	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.82
235	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.80
236	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.81
237	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.82
238	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.82
239	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.83
240	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.83
241	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.83
242	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.82
243	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.83
244	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.83
245	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85
246	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.86
247	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.83
248	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85
249	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.84
250	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85
251	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.85

252	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85
253	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.87
254	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85
255	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.86
256	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.85
257	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.88
258	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.87
259	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.87
260	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88
261	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.87
262	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88
263	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.87
264	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.89
265	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.88
266	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.88
267	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.87
268	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.88
269	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89
270	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90
271	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89
272	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90
273	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89
274	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89
275	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91
276	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89
277	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89
278	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89
279	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91

280	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.89
281	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91
282	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92
283	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90
284	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91
285	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.90
286	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92
287	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92
288	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.91
289	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92
290	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92
291	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.93
292	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.92
293	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.93
294	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.93
295	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93
296	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93
297	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93
298	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.94
299	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94
300	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93

Appendix 3: Consistency-R Benchmark Table (rows = cases / columns = conditions (excluding outcome))

	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
2	0.88	0.94	0.97	0.99	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00
3	0.76	0.88	0.94	0.97	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00
4	0.66	0.83	0.90	0.95	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00
5	0.59	0.77	0.88	0.94	0.96	0.98	0.99	1.00	1.00	1.00	1.00	1.00

6	0.52	0.71	0.86	0.92	0.96	0.98	0.99	1.00	1.00	1.00	1.00	1.00
7	0.45	0.68	0.82	0.90	0.95	0.98	0.99	0.99	1.00	1.00	1.00	1.00
8	0.39	0.63	0.79	0.90	0.95	0.97	0.99	0.99	1.00	1.00	1.00	1.00
9	0.35	0.59	0.77	0.88	0.94	0.97	0.98	0.99	1.00	1.00	1.00	1.00
10	0.31	0.55	0.76	0.87	0.93	0.96	0.98	0.99	1.00	1.00	1.00	1.00
11	0.26	0.52	0.72	0.86	0.92	0.97	0.98	0.99	1.00	1.00	1.00	1.00
12	0.23	0.49	0.70	0.84	0.92	0.96	0.98	0.99	0.99	1.00	1.00	1.00
13	0.20	0.47	0.67	0.83	0.91	0.95	0.98	0.99	0.99	1.00	1.00	1.00
14	0.17	0.44	0.66	0.81	0.90	0.95	0.97	0.99	0.99	1.00	1.00	1.00
15	0.15	0.40	0.65	0.80	0.89	0.95	0.97	0.99	0.99	1.00	1.00	1.00
16	0.13	0.38	0.62	0.79	0.89	0.94	0.97	0.98	0.99	1.00	1.00	1.00
17	0.12	0.36	0.60	0.77	0.88	0.94	0.97	0.98	0.99	1.00	1.00	1.00
18	0.10	0.33	0.59	0.77	0.87	0.93	0.97	0.98	0.99	1.00	1.00	1.00
19	0.09	0.31	0.56	0.76	0.87	0.93	0.97	0.98	0.99	1.00	1.00	1.00
20	0.08	0.29	0.55	0.74	0.86	0.93	0.97	0.98	0.99	1.00	1.00	1.00
21	0.07	0.27	0.53	0.73	0.86	0.93	0.96	0.98	0.99	1.00	1.00	1.00
22	0.06	0.26	0.51	0.72	0.85	0.92	0.96	0.98	0.99	1.00	1.00	1.00
23	0.06	0.24	0.50	0.71	0.84	0.92	0.96	0.98	0.99	0.99	1.00	1.00
24	0.05	0.22	0.48	0.69	0.83	0.91	0.95	0.98	0.99	1.00	1.00	1.00
25	0.04	0.21	0.46	0.68	0.83	0.91	0.96	0.98	0.99	0.99	1.00	1.00
26	0.04	0.20	0.45	0.68	0.82	0.90	0.95	0.98	0.99	0.99	1.00	1.00
27	0.03	0.19	0.44	0.66	0.81	0.91	0.95	0.97	0.99	0.99	1.00	1.00
28	0.03	0.18	0.43	0.66	0.81	0.90	0.95	0.97	0.99	0.99	1.00	1.00
29	0.02	0.17	0.41	0.64	0.80	0.90	0.95	0.97	0.99	0.99	1.00	1.00
30	0.02	0.16	0.40	0.64	0.79	0.89	0.94	0.97	0.99	0.99	1.00	1.00
31	0.02	0.15	0.39	0.62	0.79	0.89	0.94	0.97	0.98	0.99	1.00	1.00
32	0.01	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.99	0.99	1.00	1.00
33	0.01	0.13	0.36	0.60	0.78	0.88	0.94	0.97	0.98	0.99	1.00	1.00

34	0.01	0.12	0.35	0.60	0.77	0.88	0.94	0.97	0.98	0.99	1.00	1.00
35	0.01	0.11	0.34	0.59	0.76	0.88	0.94	0.97	0.98	0.99	1.00	1.00
36	0.01	0.11	0.33	0.57	0.76	0.87	0.94	0.97	0.98	0.99	1.00	1.00
37	0.01	0.10	0.31	0.57	0.76	0.87	0.93	0.97	0.98	0.99	1.00	1.00
38	0.01	0.09	0.30	0.56	0.75	0.87	0.93	0.97	0.98	0.99	1.00	1.00
39	0.01	0.09	0.29	0.55	0.75	0.86	0.93	0.96	0.98	0.99	1.00	1.00
40	0.00	0.08	0.29	0.54	0.74	0.86	0.93	0.96	0.98	0.99	1.00	1.00
41	0.00	0.07	0.28	0.53	0.73	0.86	0.93	0.96	0.98	0.99	0.99	1.00
42	0.00	0.07	0.27	0.53	0.72	0.85	0.92	0.96	0.98	0.99	0.99	1.00
43	0.00	0.07	0.26	0.52	0.72	0.85	0.92	0.96	0.98	0.99	0.99	1.00
44	0.00	0.06	0.26	0.51	0.72	0.84	0.92	0.96	0.98	0.99	0.99	1.00
45	0.00	0.06	0.25	0.50	0.71	0.84	0.92	0.96	0.98	0.99	0.99	1.00
46	0.00	0.05	0.24	0.49	0.70	0.84	0.92	0.96	0.98	0.99	0.99	1.00
47	0.00	0.05	0.24	0.48	0.70	0.83	0.91	0.96	0.98	0.99	0.99	1.00
48	0.00	0.05	0.22	0.47	0.69	0.83	0.91	0.96	0.98	0.99	0.99	1.00
49	0.00	0.05	0.22	0.47	0.68	0.83	0.91	0.95	0.98	0.99	0.99	1.00
50	0.00	0.04	0.21	0.46	0.69	0.83	0.91	0.95	0.98	0.99	0.99	1.00
51	0.00	0.04	0.21	0.46	0.67	0.82	0.91	0.96	0.98	0.99	0.99	1.00
52	0.00	0.04	0.20	0.45	0.67	0.82	0.91	0.95	0.97	0.99	0.99	1.00
53	0.00	0.03	0.19	0.44	0.67	0.81	0.90	0.95	0.98	0.99	0.99	1.00
54	0.00	0.03	0.18	0.43	0.66	0.81	0.90	0.95	0.97	0.99	0.99	1.00
55	0.00	0.03	0.18	0.43	0.65	0.81	0.90	0.95	0.97	0.99	0.99	1.00
56	0.00	0.03	0.17	0.42	0.65	0.80	0.90	0.95	0.97	0.99	0.99	1.00
57	0.00	0.03	0.17	0.41	0.64	0.80	0.89	0.95	0.97	0.99	0.99	1.00
58	0.00	0.02	0.17	0.41	0.64	0.80	0.90	0.95	0.97	0.99	0.99	1.00
59	0.00	0.02	0.16	0.40	0.63	0.80	0.89	0.95	0.97	0.99	0.99	1.00
60	0.00	0.02	0.15	0.40	0.63	0.79	0.89	0.94	0.97	0.99	0.99	1.00
61	0.00	0.02	0.15	0.39	0.63	0.79	0.89	0.94	0.97	0.98	0.99	1.00

62	0.00	0.02	0.15	0.38	0.62	0.79	0.89	0.94	0.97	0.99	0.99	1.00
63	0.00	0.02	0.14	0.38	0.61	0.79	0.89	0.94	0.97	0.98	0.99	1.00
64	0.00	0.02	0.13	0.37	0.61	0.78	0.88	0.94	0.97	0.98	0.99	1.00
65	0.00	0.02	0.13	0.36	0.61	0.78	0.88	0.94	0.97	0.98	0.99	1.00
66	0.00	0.02	0.13	0.36	0.60	0.77	0.88	0.94	0.97	0.98	0.99	1.00
67	0.00	0.01	0.12	0.36	0.59	0.77	0.88	0.94	0.97	0.98	0.99	1.00
68	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98	0.99	1.00
69	0.00	0.01	0.12	0.34	0.58	0.77	0.87	0.93	0.97	0.98	0.99	1.00
70	0.00	0.01	0.11	0.34	0.58	0.76	0.88	0.94	0.97	0.98	0.99	1.00
71	0.00	0.01	0.11	0.33	0.58	0.76	0.87	0.94	0.97	0.98	0.99	1.00
72	0.00	0.01	0.10	0.33	0.57	0.76	0.87	0.93	0.97	0.98	0.99	1.00
73	0.00	0.01	0.10	0.32	0.57	0.75	0.87	0.93	0.97	0.98	0.99	1.00
74	0.00	0.01	0.10	0.32	0.56	0.75	0.87	0.93	0.96	0.98	0.99	1.00
75	0.00	0.01	0.10	0.31	0.56	0.75	0.86	0.93	0.96	0.98	0.99	1.00
76	0.00	0.01	0.09	0.31	0.56	0.74	0.86	0.93	0.96	0.98	0.99	1.00
77	0.00	0.01	0.09	0.30	0.55	0.74	0.86	0.93	0.96	0.98	0.99	1.00
78	0.00	0.01	0.09	0.30	0.55	0.74	0.86	0.93	0.96	0.98	0.99	1.00
79	0.00	0.01	0.08	0.30	0.54	0.74	0.86	0.93	0.96	0.98	0.99	1.00
80	0.00	0.01	0.08	0.29	0.54	0.74	0.86	0.92	0.96	0.98	0.99	1.00
81	0.00	0.01	0.08	0.28	0.54	0.73	0.85	0.92	0.96	0.98	0.99	1.00
82	0.00	0.00	0.08	0.28	0.53	0.73	0.85	0.92	0.96	0.98	0.99	0.99
83	0.00	0.00	0.07	0.27	0.53	0.73	0.85	0.92	0.96	0.98	0.99	1.00
84	0.00	0.00	0.07	0.27	0.52	0.72	0.85	0.92	0.96	0.98	0.99	0.99
85	0.00	0.00	0.07	0.26	0.52	0.72	0.85	0.92	0.96	0.98	0.99	1.00
86	0.00	0.00	0.07	0.26	0.51	0.72	0.84	0.92	0.96	0.98	0.99	0.99
87	0.00	0.00	0.06	0.26	0.51	0.71	0.84	0.92	0.96	0.98	0.99	0.99
88	0.00	0.00	0.06	0.26	0.50	0.71	0.84	0.92	0.96	0.98	0.99	0.99
89	0.00	0.00	0.06	0.25	0.50	0.71	0.84	0.92	0.96	0.98	0.99	0.99

90	0.00	0.00	0.06	0.25	0.50	0.71	0.84	0.92	0.96	0.98	0.99	0.99
91	0.00	0.00	0.06	0.24	0.49	0.71	0.84	0.92	0.96	0.98	0.99	0.99
92	0.00	0.00	0.06	0.24	0.49	0.70	0.84	0.91	0.96	0.98	0.99	0.99
93	0.00	0.00	0.06	0.23	0.49	0.70	0.84	0.92	0.96	0.98	0.99	0.99
94	0.00	0.00	0.05	0.23	0.48	0.69	0.83	0.91	0.96	0.98	0.99	0.99
95	0.00	0.00	0.05	0.23	0.48	0.69	0.83	0.91	0.95	0.98	0.99	0.99
96	0.00	0.00	0.05	0.22	0.48	0.69	0.83	0.91	0.95	0.98	0.99	0.99
97	0.00	0.00	0.05	0.22	0.47	0.69	0.83	0.91	0.95	0.98	0.99	0.99
98	0.00	0.00	0.05	0.22	0.47	0.68	0.83	0.91	0.95	0.98	0.99	0.99
99	0.00	0.00	0.05	0.21	0.46	0.68	0.82	0.91	0.95	0.98	0.99	0.99
100	0.00	0.00	0.04	0.21	0.46	0.68	0.82	0.91	0.95	0.98	0.99	0.99
101	0.00	0.00	0.04	0.21	0.46	0.68	0.82	0.91	0.95	0.98	0.99	0.99
102	0.00	0.00	0.04	0.21	0.45	0.67	0.82	0.91	0.95	0.97	0.99	0.99
103	0.00	0.00	0.04	0.20	0.45	0.67	0.82	0.90	0.95	0.98	0.99	0.99
104	0.00	0.00	0.04	0.20	0.45	0.67	0.82	0.91	0.95	0.98	0.99	0.99
105	0.00	0.00	0.04	0.20	0.44	0.67	0.82	0.90	0.95	0.97	0.99	0.99
106	0.00	0.00	0.04	0.19	0.44	0.66	0.81	0.90	0.95	0.98	0.99	0.99
107	0.00	0.00	0.03	0.19	0.44	0.66	0.81	0.90	0.95	0.97	0.99	0.99
108	0.00	0.00	0.03	0.18	0.43	0.66	0.81	0.90	0.95	0.97	0.99	0.99
109	0.00	0.00	0.03	0.18	0.43	0.66	0.81	0.90	0.95	0.97	0.99	0.99
110	0.00	0.00	0.03	0.18	0.42	0.65	0.81	0.90	0.95	0.97	0.99	0.99
111	0.00	0.00	0.03	0.17	0.42	0.65	0.81	0.90	0.95	0.97	0.99	0.99
112	0.00	0.00	0.03	0.18	0.42	0.65	0.80	0.89	0.95	0.97	0.99	0.99
113	0.00	0.00	0.03	0.17	0.41	0.65	0.80	0.90	0.95	0.97	0.99	0.99
114	0.00	0.00	0.03	0.17	0.41	0.64	0.80	0.90	0.95	0.97	0.99	0.99
115	0.00	0.00	0.03	0.16	0.41	0.64	0.80	0.90	0.95	0.97	0.99	0.99
116	0.00	0.00	0.03	0.16	0.41	0.63	0.80	0.89	0.95	0.97	0.99	0.99
117	0.00	0.00	0.02	0.16	0.40	0.64	0.80	0.89	0.94	0.97	0.99	0.99

118	0.00	0.00	0.02	0.16	0.40	0.63	0.79	0.89	0.95	0.97	0.99	0.99
119	0.00	0.00	0.02	0.16	0.40	0.63	0.79	0.89	0.94	0.97	0.99	0.99
120	0.00	0.00	0.02	0.15	0.39	0.63	0.79	0.89	0.94	0.97	0.99	0.99
121	0.00	0.00	0.02	0.15	0.39	0.62	0.79	0.89	0.94	0.97	0.99	0.99
122	0.00	0.00	0.02	0.15	0.39	0.62	0.79	0.89	0.94	0.97	0.99	0.99
123	0.00	0.00	0.02	0.15	0.38	0.62	0.79	0.89	0.94	0.97	0.99	0.99
124	0.00	0.00	0.02	0.15	0.38	0.62	0.79	0.89	0.94	0.97	0.99	0.99
125	0.00	0.00	0.02	0.14	0.38	0.62	0.78	0.89	0.94	0.97	0.98	0.99
126	0.00	0.00	0.02	0.14	0.38	0.61	0.78	0.88	0.94	0.97	0.98	0.99
127	0.00	0.00	0.02	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.98	0.99
128	0.00	0.00	0.02	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.99	0.99
129	0.00	0.00	0.02	0.13	0.37	0.60	0.78	0.88	0.94	0.97	0.98	0.99
130	0.00	0.00	0.02	0.13	0.36	0.60	0.78	0.88	0.94	0.97	0.98	0.99
131	0.00	0.00	0.02	0.13	0.36	0.60	0.77	0.88	0.94	0.97	0.98	0.99
132	0.00	0.00	0.02	0.13	0.36	0.60	0.78	0.88	0.94	0.97	0.98	0.99
133	0.00	0.00	0.02	0.12	0.35	0.60	0.77	0.88	0.94	0.97	0.98	0.99
134	0.00	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98	0.99
135	0.00	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98	0.99
136	0.00	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98	0.99
137	0.00	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.93	0.97	0.98	0.99
138	0.00	0.00	0.01	0.11	0.34	0.59	0.76	0.88	0.94	0.97	0.98	0.99
139	0.00	0.00	0.01	0.11	0.34	0.58	0.76	0.87	0.93	0.97	0.98	0.99
140	0.00	0.00	0.01	0.11	0.33	0.58	0.76	0.87	0.93	0.97	0.98	0.99
141	0.00	0.00	0.01	0.11	0.33	0.58	0.76	0.87	0.94	0.97	0.98	0.99
142	0.00	0.00	0.01	0.11	0.33	0.57	0.76	0.87	0.93	0.97	0.98	0.99
143	0.00	0.00	0.01	0.10	0.33	0.58	0.76	0.87	0.93	0.97	0.98	0.99
144	0.00	0.00	0.01	0.10	0.33	0.57	0.76	0.87	0.93	0.96	0.98	0.99
145	0.00	0.00	0.01	0.10	0.32	0.57	0.76	0.87	0.93	0.96	0.98	0.99

146	0.00	0.00	0.01	0.10	0.32	0.57	0.75	0.87	0.93	0.97	0.98	0.99
147	0.00	0.00	0.01	0.10	0.32	0.56	0.75	0.87	0.93	0.96	0.98	0.99
148	0.00	0.00	0.01	0.10	0.32	0.56	0.75	0.87	0.93	0.96	0.98	0.99
149	0.00	0.00	0.01	0.10	0.31	0.56	0.75	0.86	0.93	0.96	0.98	0.99
150	0.00	0.00	0.01	0.10	0.31	0.56	0.75	0.86	0.93	0.96	0.98	0.99
151	0.00	0.00	0.01	0.09	0.31	0.56	0.75	0.86	0.93	0.96	0.98	0.99
152	0.00	0.00	0.01	0.09	0.31	0.55	0.75	0.86	0.93	0.96	0.98	0.99
153	0.00	0.00	0.01	0.09	0.30	0.55	0.74	0.86	0.93	0.96	0.98	0.99
154	0.00	0.00	0.01	0.09	0.30	0.55	0.74	0.86	0.93	0.96	0.98	0.99
155	0.00	0.00	0.01	0.09	0.30	0.55	0.74	0.86	0.93	0.96	0.98	0.99
156	0.00	0.00	0.01	0.09	0.30	0.55	0.74	0.86	0.93	0.96	0.98	0.99
157	0.00	0.00	0.01	0.09	0.30	0.54	0.74	0.86	0.93	0.96	0.98	0.99
158	0.00	0.00	0.01	0.08	0.29	0.54	0.73	0.86	0.93	0.96	0.98	0.99
159	0.00	0.00	0.01	0.08	0.29	0.54	0.73	0.86	0.93	0.96	0.98	0.99
160	0.00	0.00	0.01	0.08	0.29	0.54	0.73	0.85	0.93	0.96	0.98	0.99
161	0.00	0.00	0.01	0.08	0.29	0.53	0.73	0.85	0.93	0.96	0.98	0.99
162	0.00	0.00	0.01	0.08	0.28	0.53	0.73	0.85	0.93	0.96	0.98	0.99
163	0.00	0.00	0.01	0.08	0.28	0.53	0.73	0.85	0.92	0.96	0.98	0.99
164	0.00	0.00	0.01	0.08	0.28	0.53	0.73	0.85	0.92	0.96	0.98	0.99
165	0.00	0.00	0.01	0.08	0.28	0.53	0.73	0.85	0.92	0.96	0.98	0.99
166	0.00	0.00	0.01	0.07	0.28	0.52	0.72	0.85	0.92	0.96	0.98	0.99
167	0.00	0.00	0.00	0.07	0.27	0.52	0.72	0.85	0.92	0.96	0.98	0.99
168	0.00	0.00	0.00	0.07	0.27	0.52	0.72	0.85	0.92	0.96	0.98	0.99
169	0.00	0.00	0.00	0.07	0.27	0.52	0.72	0.85	0.92	0.96	0.98	0.99
170	0.00	0.00	0.01	0.07	0.26	0.51	0.72	0.85	0.92	0.96	0.98	0.99
171	0.00	0.00	0.00	0.07	0.26	0.52	0.72	0.85	0.92	0.96	0.98	0.99
172	0.00	0.00	0.00	0.07	0.26	0.51	0.72	0.85	0.92	0.96	0.98	0.99
173	0.00	0.00	0.00	0.07	0.26	0.51	0.71	0.84	0.92	0.96	0.98	0.99

174	0.00	0.00	0.00	0.07	0.26	0.51	0.71	0.84	0.92	0.96	0.98	0.99
175	0.00	0.00	0.00	0.06	0.25	0.51	0.71	0.84	0.92	0.96	0.98	0.99
176	0.00	0.00	0.00	0.06	0.25	0.50	0.71	0.84	0.92	0.96	0.98	0.99
177	0.00	0.00	0.00	0.06	0.25	0.50	0.71	0.84	0.92	0.96	0.98	0.99
178	0.00	0.00	0.00	0.06	0.25	0.50	0.71	0.84	0.92	0.96	0.98	0.99
179	0.00	0.00	0.00	0.06	0.25	0.50	0.71	0.84	0.92	0.96	0.98	0.99
180	0.00	0.00	0.00	0.06	0.25	0.50	0.70	0.84	0.92	0.96	0.98	0.99
181	0.00	0.00	0.00	0.06	0.24	0.50	0.70	0.84	0.92	0.96	0.98	0.99
182	0.00	0.00	0.00	0.06	0.24	0.49	0.70	0.84	0.92	0.96	0.98	0.99
183	0.00	0.00	0.00	0.06	0.24	0.49	0.70	0.84	0.92	0.96	0.98	0.99
184	0.00	0.00	0.00	0.06	0.24	0.49	0.70	0.84	0.92	0.96	0.98	0.99
185	0.00	0.00	0.00	0.06	0.24	0.49	0.70	0.84	0.91	0.96	0.98	0.99
186	0.00	0.00	0.00	0.05	0.24	0.48	0.70	0.83	0.91	0.96	0.98	0.99
187	0.00	0.00	0.00	0.05	0.23	0.48	0.69	0.83	0.91	0.96	0.98	0.99
188	0.00	0.00	0.00	0.05	0.23	0.48	0.69	0.83	0.91	0.96	0.98	0.99
189	0.00	0.00	0.00	0.05	0.23	0.48	0.69	0.83	0.91	0.95	0.98	0.99
190	0.00	0.00	0.00	0.05	0.23	0.48	0.69	0.83	0.91	0.95	0.98	0.99
191	0.00	0.00	0.00	0.05	0.23	0.48	0.69	0.83	0.91	0.96	0.98	0.99
192	0.00	0.00	0.00	0.05	0.22	0.47	0.69	0.83	0.91	0.95	0.98	0.99
193	0.00	0.00	0.00	0.05	0.22	0.47	0.69	0.83	0.91	0.95	0.98	0.99
194	0.00	0.00	0.00	0.05	0.22	0.47	0.69	0.83	0.91	0.95	0.98	0.99
195	0.00	0.00	0.00	0.05	0.22	0.47	0.68	0.83	0.91	0.95	0.98	0.99
196	0.00	0.00	0.00	0.05	0.22	0.47	0.68	0.83	0.91	0.95	0.98	0.99
197	0.00	0.00	0.00	0.05	0.21	0.46	0.68	0.83	0.91	0.95	0.98	0.99
198	0.00	0.00	0.00	0.05	0.21	0.46	0.68	0.82	0.91	0.95	0.98	0.99
199	0.00	0.00	0.00	0.05	0.21	0.46	0.68	0.82	0.91	0.95	0.98	0.99
200	0.00	0.00	0.00	0.04	0.21	0.46	0.68	0.82	0.91	0.95	0.98	0.99
201	0.00	0.00	0.00	0.04	0.21	0.45	0.67	0.82	0.91	0.95	0.98	0.99

202	0.00	0.00	0.00	0.04	0.21	0.46	0.68	0.82	0.91	0.95	0.98	0.99
203	0.00	0.00	0.00	0.04	0.20	0.45	0.68	0.82	0.90	0.95	0.98	0.99
204	0.00	0.00	0.00	0.04	0.20	0.45	0.67	0.82	0.91	0.95	0.98	0.99
205	0.00	0.00	0.00	0.04	0.20	0.45	0.67	0.82	0.90	0.95	0.97	0.99
206	0.00	0.00	0.00	0.04	0.20	0.45	0.67	0.82	0.90	0.95	0.98	0.99
207	0.00	0.00	0.00	0.04	0.20	0.45	0.67	0.82	0.91	0.95	0.98	0.99
208	0.00	0.00	0.00	0.04	0.20	0.44	0.67	0.82	0.90	0.95	0.97	0.99
209	0.00	0.00	0.00	0.04	0.20	0.44	0.67	0.82	0.90	0.95	0.97	0.99
210	0.00	0.00	0.00	0.04	0.19	0.44	0.66	0.81	0.90	0.95	0.97	0.99
211	0.00	0.00	0.00	0.04	0.19	0.44	0.66	0.81	0.90	0.95	0.97	0.99
212	0.00	0.00	0.00	0.04	0.19	0.44	0.66	0.81	0.90	0.95	0.97	0.99
213	0.00	0.00	0.00	0.04	0.19	0.44	0.66	0.81	0.90	0.95	0.97	0.99
214	0.00	0.00	0.00	0.04	0.19	0.43	0.66	0.81	0.90	0.95	0.97	0.99
215	0.00	0.00	0.00	0.03	0.19	0.43	0.66	0.81	0.90	0.95	0.97	0.99
216	0.00	0.00	0.00	0.03	0.19	0.43	0.66	0.81	0.90	0.95	0.97	0.99
217	0.00	0.00	0.00	0.03	0.18	0.43	0.66	0.81	0.90	0.95	0.97	0.99
218	0.00	0.00	0.00	0.03	0.18	0.43	0.65	0.81	0.90	0.95	0.97	0.99
219	0.00	0.00	0.00	0.03	0.18	0.43	0.65	0.81	0.90	0.95	0.97	0.99
220	0.00	0.00	0.00	0.03	0.18	0.43	0.65	0.81	0.90	0.95	0.97	0.99
221	0.00	0.00	0.00	0.03	0.18	0.42	0.65	0.81	0.90	0.95	0.97	0.99
222	0.00	0.00	0.00	0.03	0.17	0.42	0.65	0.81	0.90	0.95	0.97	0.99
223	0.00	0.00	0.00	0.03	0.18	0.42	0.65	0.81	0.90	0.95	0.97	0.99
224	0.00	0.00	0.00	0.03	0.17	0.42	0.65	0.81	0.90	0.95	0.97	0.99
225	0.00	0.00	0.00	0.03	0.17	0.41	0.65	0.80	0.90	0.95	0.97	0.99
226	0.00	0.00	0.00	0.03	0.17	0.41	0.64	0.80	0.90	0.95	0.97	0.99
227	0.00	0.00	0.00	0.03	0.17	0.41	0.64	0.80	0.90	0.95	0.97	0.99
228	0.00	0.00	0.00	0.03	0.17	0.41	0.64	0.80	0.89	0.95	0.97	0.99
229	0.00	0.00	0.00	0.03	0.17	0.41	0.64	0.80	0.90	0.95	0.97	0.99

230	0.00	0.00	0.00	0.03	0.17	0.41	0.64	0.80	0.89	0.95	0.97	0.99
231	0.00	0.00	0.00	0.03	0.16	0.41	0.64	0.80	0.89	0.95	0.97	0.99
232	0.00	0.00	0.00	0.03	0.16	0.40	0.64	0.80	0.89	0.95	0.97	0.99
233	0.00	0.00	0.00	0.03	0.16	0.40	0.64	0.80	0.89	0.95	0.97	0.99
234	0.00	0.00	0.00	0.02	0.16	0.40	0.63	0.80	0.89	0.94	0.97	0.99
235	0.00	0.00	0.00	0.03	0.16	0.40	0.63	0.80	0.89	0.94	0.97	0.99
236	0.00	0.00	0.00	0.02	0.16	0.40	0.63	0.79	0.89	0.94	0.97	0.99
237	0.00	0.00	0.00	0.02	0.16	0.40	0.63	0.79	0.89	0.94	0.97	0.99
238	0.00	0.00	0.00	0.02	0.16	0.40	0.63	0.79	0.89	0.94	0.97	0.99
239	0.00	0.00	0.00	0.02	0.15	0.40	0.63	0.79	0.89	0.94	0.97	0.99
240	0.00	0.00	0.00	0.02	0.15	0.39	0.63	0.79	0.89	0.94	0.97	0.99
241	0.00	0.00	0.00	0.02	0.15	0.39	0.63	0.79	0.89	0.94	0.97	0.99
242	0.00	0.00	0.00	0.02	0.15	0.39	0.62	0.79	0.89	0.94	0.97	0.99
243	0.00	0.00	0.00	0.02	0.15	0.39	0.62	0.79	0.89	0.94	0.97	0.99
244	0.00	0.00	0.00	0.02	0.15	0.39	0.62	0.79	0.89	0.94	0.97	0.99
245	0.00	0.00	0.00	0.02	0.15	0.39	0.62	0.79	0.89	0.94	0.97	0.99
246	0.00	0.00	0.00	0.02	0.15	0.38	0.62	0.79	0.89	0.94	0.97	0.98
247	0.00	0.00	0.00	0.02	0.14	0.38	0.62	0.79	0.89	0.94	0.97	0.99
248	0.00	0.00	0.00	0.02	0.14	0.38	0.62	0.79	0.89	0.94	0.97	0.99
249	0.00	0.00	0.00	0.02	0.14	0.38	0.62	0.78	0.89	0.94	0.97	0.98
250	0.00	0.00	0.00	0.02	0.14	0.38	0.62	0.78	0.89	0.94	0.97	0.98
251	0.00	0.00	0.00	0.02	0.14	0.38	0.61	0.78	0.88	0.94	0.97	0.98
252	0.00	0.00	0.00	0.02	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.99
253	0.00	0.00	0.00	0.02	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.98
254	0.00	0.00	0.00	0.02	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.98
255	0.00	0.00	0.00	0.02	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.98
256	0.00	0.00	0.00	0.02	0.14	0.37	0.61	0.78	0.88	0.94	0.97	0.98
257	0.00	0.00	0.00	0.02	0.13	0.37	0.61	0.78	0.88	0.94	0.97	0.98

258	0.00	0.00	0.00	0.02	0.13	0.37	0.61	0.78	0.88	0.94	0.97	0.98
259	0.00	0.00	0.00	0.02	0.13	0.36	0.60	0.77	0.88	0.94	0.97	0.98
260	0.00	0.00	0.00	0.02	0.13	0.36	0.60	0.78	0.88	0.94	0.97	0.98
261	0.00	0.00	0.00	0.02	0.13	0.36	0.60	0.78	0.88	0.94	0.97	0.98
262	0.00	0.00	0.00	0.02	0.13	0.36	0.60	0.77	0.88	0.94	0.97	0.98
263	0.00	0.00	0.00	0.02	0.13	0.36	0.60	0.78	0.88	0.94	0.97	0.98
264	0.00	0.00	0.00	0.02	0.13	0.36	0.60	0.77	0.88	0.94	0.97	0.98
265	0.00	0.00	0.00	0.02	0.13	0.36	0.60	0.77	0.88	0.94	0.97	0.98
266	0.00	0.00	0.00	0.02	0.13	0.35	0.59	0.77	0.88	0.94	0.97	0.98
267	0.00	0.00	0.00	0.02	0.12	0.35	0.60	0.77	0.88	0.94	0.97	0.98
268	0.00	0.00	0.00	0.02	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98
269	0.00	0.00	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98
270	0.00	0.00	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98
271	0.00	0.00	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98
272	0.00	0.00	0.00	0.01	0.12	0.35	0.59	0.77	0.88	0.94	0.97	0.98
273	0.00	0.00	0.00	0.01	0.12	0.34	0.59	0.76	0.88	0.94	0.97	0.98
274	0.00	0.00	0.00	0.01	0.12	0.34	0.59	0.77	0.87	0.94	0.97	0.98
275	0.00	0.00	0.00	0.01	0.12	0.34	0.59	0.76	0.88	0.94	0.97	0.98
276	0.00	0.00	0.00	0.01	0.11	0.34	0.58	0.76	0.87	0.93	0.97	0.98
277	0.00	0.00	0.00	0.01	0.11	0.34	0.58	0.76	0.87	0.93	0.97	0.98
278	0.00	0.00	0.00	0.01	0.11	0.34	0.58	0.76	0.87	0.93	0.97	0.98
279	0.00	0.00	0.00	0.01	0.11	0.34	0.58	0.76	0.87	0.93	0.97	0.98
280	0.00	0.00	0.00	0.01	0.11	0.34	0.58	0.76	0.87	0.93	0.97	0.98
281	0.00	0.00	0.00	0.01	0.11	0.33	0.58	0.76	0.87	0.93	0.97	0.98
282	0.00	0.00	0.00	0.01	0.11	0.33	0.58	0.76	0.87	0.93	0.97	0.98
283	0.00	0.00	0.00	0.01	0.11	0.33	0.58	0.76	0.87	0.93	0.97	0.98
284	0.00	0.00	0.00	0.01	0.11	0.33	0.58	0.76	0.87	0.93	0.97	0.98
285	0.00	0.00	0.00	0.01	0.11	0.33	0.57	0.76	0.87	0.93	0.97	0.98

286	0.00	0.00	0.00	0.01	0.11	0.33	0.57	0.76	0.87	0.93	0.97	0.98
287	0.00	0.00	0.00	0.01	0.11	0.33	0.57	0.76	0.87	0.93	0.97	0.98
288	0.00	0.00	0.00	0.01	0.10	0.33	0.57	0.75	0.87	0.93	0.97	0.98
289	0.00	0.00	0.00	0.01	0.11	0.32	0.57	0.75	0.87	0.93	0.97	0.98
290	0.00	0.00	0.00	0.01	0.11	0.32	0.57	0.75	0.87	0.93	0.97	0.98
291	0.00	0.00	0.00	0.01	0.10	0.32	0.57	0.75	0.87	0.93	0.97	0.98
292	0.00	0.00	0.00	0.01	0.10	0.32	0.57	0.75	0.87	0.93	0.96	0.98
293	0.00	0.00	0.00	0.01	0.10	0.32	0.56	0.75	0.87	0.93	0.96	0.98
294	0.00	0.00	0.00	0.01	0.10	0.32	0.57	0.75	0.87	0.93	0.96	0.98
295	0.00	0.00	0.00	0.01	0.10	0.32	0.56	0.75	0.87	0.93	0.96	0.98
296	0.00	0.00	0.00	0.01	0.10	0.32	0.56	0.75	0.87	0.93	0.97	0.98
297	0.00	0.00	0.00	0.01	0.10	0.31	0.56	0.75	0.86	0.93	0.96	0.98
298	0.00	0.00	0.00	0.01	0.10	0.31	0.56	0.75	0.86	0.93	0.96	0.98
299	0.00	0.00	0.00	0.01	0.10	0.31	0.56	0.75	0.86	0.93	0.96	0.98
300	0.00	0.00	0.00	0.01	0.10	0.31	0.56	0.75	0.86	0.93	0.96	0.98