Entrepreneurial climate and self-perceptions about entrepreneurship: A country comparison using fsQCA with dual outcomes

Abstract

This study investigated the relationship between entrepreneurial climate (EC) and self-perceptions about entrepreneurship (SPaE). The variables and data were derived from the Global Entrepreneurship Monitor (GEM) dataset and framework. Specifically, the study examined variables closely related to the GEM concepts of entrepreneurial capacity and preferences across 54 countries. Fuzzy-set qualitative comparative analysis (fsQCA) was conducted to investigate associations between EC and SPaE. Three condition variables described EC: economic stage of development, entrepreneurial framework conditions, and entrepreneurial status. Four items described SPaE: perceived start-up opportunities, perceived capabilities, fear of failure, and entrepreneurial intention. Two forms of single outcome measures were constructed from the four items that described SPaE. A standard factor analysis-based score yielded the outcome $SPaE^F$. Fuzzy cluster analysis produced a two-cluster-based outcome $SPaE^C$. Having two outcomes referring to the same concept (SPaE) leads to discussion on what should be done to facilitate "same concept" based analyses using fsQCA. The findings open up discussion on the efficacy of fsQCA as regards its sensitivity to slight changes in the outcome. Practical applied issues surrounding entrepreneurship (EC and SPaE) are also discussed.

Keywords: fsQCA; Entrepreneurial Climate; Self Perception; Entrepreneurship; GEM

Introduction

Small and medium-sized enterprises (SMEs) that create innovation, employment, and economic growth are a focus for policymakers globally, particularly in developed economies (Acs, Brooksbank, O'Gorman, & Terjesen, 2012). The general entrepreneurial climate (EC) and individual's self-perceptions about entrepreneurship (SPaE) are therefore of great importance. Evidence of this importance is that the Global Entrepreneurship Monitor (GEM) survey, which is used to research entrepreneurial activity, attitudes, and perceptions in various countries, gathers data on EC and SPaE (Acs et al., 2012; Anwar ul Haq, Usman, Hussain, & Anjum, 2014). In this study, fuzzy-set qualitative comparative analysis (fsQCA) was used to study the relationship between EC and SPaE (Ragin, 2000). FsQCA is suitable for small-*n* data analysis (Woodside, 2013). Accordingly, it was suited to the country-level study presented here.

Scholars have previously analyzed GEM data using fsQCA-related techniques. For example, Coduras, Clemente, and Ruiz (2016) noted that fsQCA can extend the analysis and understanding of the role of GEM indicators, in their case Total Economic Activity (TEA), and provide further research insights involving other groups of countries, different combinations of GEM indicators, and geographical configurations. Kuckertz, Berger, and Mpeqa (2016) also used fsQCA with international GEM data to examine how specific components of economic freedom (EF) encourage high levels of entrepreneurial activity (EA) in countries at different levels of economic development. Beynon, Jones, and Pickernell (2016a) undertook country-based comparison of TEA, using fsQCA with GEM data to investigate the effect of entrepreneurial attitudes.

In the present study, the same four items from the GEM survey (i.e., perceived opportunities, perceived capabilities, fear of failure, and entrepreneurial intentions) were used to model SPaE, although here SPaE was taken as the outcome. This study therefore makes an applied contribution to knowledge, not only by building on the studies cited previously, but also by further evaluating the GEM conceptual framework (discussed later) in terms of the drivers of SPaE.

The condition variables that described each country's economic climate, and subsequently the relationship between EC and SPaE, were derived from the GEM framework. These variables were economic stage of development (ESD), entrepreneurial framework conditions (EFC), and entrepreneurial status (ES). The approach of using variables derived from the GEM framework was consistent with the data-gathering instrument, namely the GEM survey itself. The condition variables together represented each country's EC, which was analyzed with respect to the outcome SPaE. Only three condition variables were considered because the study was multidimensional in nature, with two versions of the outcome measure SPaE considered, and because the problem fit within the GEM analysis framework.

This paper also makes a technical contribution by considering and comparing two separate approaches to combining the SPaE constituent items into a single outcome measure. The first approach was based on the factor analysis single factor score ($SPaE^F$) (Hair, Black, Babin, & Anderson, 2010), whereas the second approach was based on the fuzzy cluster analysis two-cluster solution ($SPaE^C$) (Bezdek, 1980). Although both $SPaE^F$ and $SPaE^C$ interpret the concept of SPaE, the country specific values vary across the two measures. We therefore developed two separate models using the two SPaE outcome measures ($SPaE^F$ and $SPaE^C$) but the same condition variables. Comparisons were made between the fsQCA model taking $SPaE^F$ as the outcome and the fsQCA model taking $SPaE^C$ as the outcome. With the same condition variables in both models, the same configurations were considered (with the same country groupings). The variation between the models stemmed from the inherent variation in the outcome values associated with $SPaE^F$ and $SPaE^C$ (both representing SPaE).

Considering different outcomes (i.e., $SPaE^F$ and $SPaE^C$), but the same constituent data, contributes to the debate on the use of fsQCA. Specifically, our approach explores fsQCA's sensitivity to "the same" outcome derived in two different ways. Indeed, this is a special case of separately considering the same condition variables for multiple outcomes in fsQCA (e.g., Boudet, Jayasundera, & Davis, 2011; David, Shin, Pérez, Anderies, & Janssen, 2016; Lam & Ostrom, 2010, where there is no discussion at the fsQCA level regarding technical assumptions to facilitate this multiple outcome consideration). This raises the following technical question (see Ragin, 2008): When comparing across different fsQCA models, what thought must be given to the consistency thresholds in the sufficiency analyses, across the different models, to be pertinent in the comparisons? To aid comparison between models in this study, we presented the results graphically.

We sought to enable comparison between low-SPaE countries (i.e., $\sim SPaE^F$ and $\sim SPaE^C$) and high-SPaE countries (i.e., $SPaE^F$ and $SPaE^C$) in terms of EC-based recipes. We also sought to identify the most relevant individual conditions that appear consistently in different recipes. This approach enables identification of more robust policies to improve SPaE because of the links between SPaE-type variables and new business creation across countries and genders (Arenius & Minniti, 2005) and because policymakers focus on EC conditions (particularly EFC) when trying to influence entrepreneurship (Freytag & Thurik, 2007). By revealing countries with similar configurations of conditions, the results of this analysis also enable policymakers to identify countries that can potentially serve as a benchmark.

Data and method

This section discusses the variables used in the analysis of EC and SPaE and then provides a brief description of fsQCA, including the required pre-processing of the continuous condition and outcome measures.

Outcome evaluation

In this study, four items (constituent variables) were considered. These same items were used as condition variables for country-based comparison analysis using fsQCA to investigate the effect of entrepreneurial attitudes on TEA (Beynon et al., 2016a). In the present study, these four items were combined to yield a single outcome describing SPaE. The way these variables were combined was one of the technical issues considered in this study to explore how fsQCA handles variations in outcome measurement. Table 1 presents a description of these variables and descriptive statistics for the data from the 2015 GEM survey for 54 countries.

Insert Table 1 here.

Perceived start-up opportunities (Prcvd_Opps) are increasingly considered the most distinctive, fundamental characteristic of entrepreneurship (Arenius & Minniti, 2005). Inadequate entrepreneurial activity levels result in deficient opportunities within existing businesses (Krueger, 2000). Perceived opportunity can drive opportunity entrepreneurship, which generates higher economic growth than necessity-driven enterprises (Acs, 2006). *Perceived capabilities* (Prcvd_Caps) also differentiate independent entrepreneurs from entrepreneurial employees (Nyström, 2012). Acs, Desai, and Hessels (2008) posited that the perceptions people have of their environment and themselves drive them toward or away from entrepreneurship. *Fear of failure* (Fr_of_Flr) prevents individuals from starting businesses (Vaillant & Lafuente, 2007) because many individuals are risk adverse (Arenius & Minniti, 2005), though this differs across countries (Anwar ul Haq et al., 2014; Vaillant & Lafuente, 2007). *Entrepreneurial intention* (Entrp_Intnt) is important because individuals' expectations to start a business (Bosma, Wennekers, & Amorós, 2012; Mazzarol, Volery, Doss &Thein,

1999) are based on several entrepreneurial intent drivers from planned behavior theory (Autio, Keeley, Klofsten, Parker, & Hay, 2001), including personal, social, and cultural drivers.

The question now is if and how these four variables can be grouped into a single measure that describes country SPaE. Two approaches, namely factor analysis and fuzzy cluster analysis, offer alternate ways of grouping these variables. In general, the two approaches differ in the following ways (see Krebs, Berger, & Ferligoj, 2000; Dogruparmak, Keskin, Yaman, & Alkan, 2014, who compare factor analysis and fuzzy clustering for the same problem):

i) Factor analysis focuses on the homogeneity of variables, which results from the similarity of values assigned to variables by respondents. In the case of one factor, this results in a single value measure for that factor. Therefore, factor analysis implies the aspiration of establishing a latent variable (the factor or dimension).

ii) Traditional cluster analysis is characterized not only by homogeneity of objects but also by between heterogeneity of variables. The goal of cluster analysis is to find an empirical classification or an *a priori* theoretically defined cluster structure.

Point *ii)* regarding clustering needs to be reconsidered for two reasons. First, fuzzy clustering softens the associated heterogeneity issue by allowing for grades of membership to more than one cluster. Second, when considering only two clusters (as in this study), the grades of membership in fuzzy clustering enable a form of latent variable to be considered in terms of the grade of membership to either of the two clusters. As long as variables used in the clustering have consistent relationships with each cluster, the two clusters are at the limits of a future variable scale domain (discussed later).

Thus, while both factor and fuzzy cluster analysis approaches can be used to create a single measure, we would expect them not to generate identical results. The use of these two approaches here allows us to explore the impact upon fsQCA when such a situation arises (as would be the case when having multiple outcomes).

Factor analysis

The first approach is based on principal component factor analysis of the four variables making up SPaE, which are described in Table 1. Table 2 shows the results of this analysis.

Insert Table 2 here.

The results in Table 2 show that the four items load onto one factor (one eigenvalue above 1, see Hair et al., 2010), and they describe 62.777% of the total variance in the four items. After identifying this factor, we evaluated the associated loadings of each variable onto this single factor. We note one issue from pre-analysis, namely the need to reverse-code Fear of Failure as 100 minus the original value because the scale is a percentage.

We next considered how the individual variables load onto the single factor. Based on varimax rotation (Hair et al., 2010), the associated loadings for the four items (ordered by size) and the associated Cronbach's alpha score are presented in Table 3.

Insert Table 3 here.

The results in Table 3 show that the loadings range from 0.666 to 0.900 (variation in loading values acknowledges variations in contributions across item variables). The associated Cronbach's alpha value of 0.800 enables the construction of the associated factor describing $SPaE^F$, with superscript F denoting that it is factor based. Using the regression approach to evaluate scores, we evaluated the associated $SPaE^F$ values (Hair et al., 2010). For the 54 countries under study, the associated $SPaE^F$ values are reported over a probability density function (pdf) graph in Figure 1 (Andrews, Beynon, & McDermott, 2016).

Insert Figure 1 here.

In Figure 1, the points in the top row indicate each country's $SPaE^F$ value position over the created SPaE domain. With a mind to employing this variable in fsQCA, the pdf enables evaluation of the necessary lower-threshold ($x^{\perp}$), upper-threshold (x^{T}), and crossover-point ($x^{\times}$) qualitative anchors with respect to the direct method (Ragin, 2008), which enables calibration of fuzzy membership scores through the log-odds transform (e.g., Beynon et al., 2016a; Beynon, Jones, & Pickernell, 2016b). We retain the $SPaE^F$ term here to refer now to the membership score values. Following the direct method, the set of membership score values describes the level of membership of each case to the set of high $SPaE^F$—membership to low $SPaE^F$ ($\sim SPaE^F$) is 1 minus membership to high $SPaE^F$.

<u>Cluster analysis</u>

The cluster analysis approach starts with the first part of the two-step approach (Zhang, Ramakrishnon, & Livny, 1996) to find the optimal number of clusters for the four items Prcvd_Opps, Prcvd_Caps, Fr_of_Flr, and Entrp_Intnt. The next step is to apply the fuzzy *c*-means (FCM) clustering technique (Bezdek, 1980) to identify the centroids of the clusters (across the four items).

The two-step approach revealed that the optimal number of clusters is two. Under FCM, the two clusters (C1 and C2), based on their centroids (values over each item [Prcvd_Opps, Prcvd_Caps, reverse-coded Fr_of_Flr, Entrp_Intnt]), are as follows: C1 [36.624, 43.189, 59.840, 14.513] and C2 [51.456, 65.200, 71.506, 37.638]. The two sets of centroids imply that

C1 and C2 are consistently associated with low and high SPaE, respectively, across all four items. C1 centroid values are consistently lower than C2 centroid values. The result of the FCM is fuzzy membership score values μ_{C1} and μ_{C2}, which denote each country's membership to each cluster C1 and C2. With only two clusters, the membership scores for a single country sum to one ($\mu_{C1} + \mu_{C2} = 1$). Hence, the two membership score values, μ_{C1} and μ_{C2}, are each in the correct scale (on 0–1 domains), for the outcome membership score values required by fsQCA for $SPaE^C$ (μ_{C2}: high $SPaE^C$) and not-$SPaE^C$ (μ_{C1}: low $SPaE^C$, also denoted ~$SPaE^C$), based on $SPaE^C$ (Figure 2).

Insert Figure 2 here.

In Figure 2, each point represents the membership scores for clusters C1 (μ_{C1}: low $SPaE^C$) and C2 (μ_{C2}: high $SPaE^C$) for each of the 54 countries in the sample. Because $\mu_{C1} + \mu_{C2} = 1$, the points may only lie on the line $y = -x + 1$ from [0, 1] to [1, 0], as shown. The μ_{C2} fuzzy membership score is referred to in the later use of the $SPaE^C$ measure.

<u>Comparison of $SPaE^F$ and $SPaE^C$ evaluated SPaE values</u>

This subsection briefly investigates the level of similarity between the two sets of SPaE (i.e., $SPaE^F$ and $SPaE^C$) values employed as outcomes in the fsQCA (see Figure 3).

Insert Figure 3 here.

In Figure 3, the $SPaE^F$ and $SPaE^C$ values for each country are plotted on a scatter plot over the domain 0 to 1 (membership score domain). If a perfect same-value relationship existed across the two SPaE models, a set of points would lie on the line $y = x$ (dashed line in Figure

3). This is not the case here, so the values for many countries vary across the two $SPaE^F$ and $SPaE^C$ sets of values. A correlation analysis of these two sets of values yields a Pearson coefficient value of 0.892, which is significant at the 1% level, suggesting there is limited difference between the two sets of values. This finding has two implications.

i) Both SPaE models, $SPaE^F$ and $SPaE^C$, provide similar information on each country's SPaE.

ii) How the slight variation in pairs of $SPaE^F$ and $SPaE^C$ values for each country affects the subsequent fsQCA is a pertinent question considered in this study.

Condition variable description (and pre-coding)

To compare SPaE across countries, and observe the variation in SPaE using two separate $SPaE^F$ and $SPaE^C$ outcome measures, three condition variables[1] were considered. These variables offer insights into the countries, considered antecedents of SPaE in terms of the EC of each country. Motivation for considering these variables is derived from the pre-existing GEM framework (Kelley, Singer, & Herrington, 2015). Figure 4 illustrates the basic version of the framework.

Insert Figure 4 here.

The GEM framework in Figure 4 highlights the broad interdependencies conceptualized in the GEM approach among the factors that drive entrepreneurial activity. Kelley et al. (2015), however, explicitly reported that national framework conditions (through phases of economic development) and EFC (which aid the creation of new businesses) are conceptualized as influencing entrepreneurial activity both directly and through influencing

[1] The use of three variables here is without loss of generality to the use of more variables.

norms (social values regarding entrepreneurship). Such social norms or values assist in determining the value society places on entrepreneurship. Three broad EC condition variables were derived from this GEM framework. These variables are reported in Table 4 and are subsequently discussed. These variables potentially affect the SPaE (individual attributes) considered previously in Beynon et al. (2016a) to drive TEA.

Insert Table 4 here.

Economic stage of development (ESD)

Both WEF (2011) and GEM broadly divide countries into factor, efficiency, and innovation-driven economies (Xavier, Kelley, Kew, Herrington, & Vorderwülbecke, 2012). GEM also defines intermediate stages between factor-driven and efficiency economies and between efficiency and innovation economies. In data terms, ESD is therefore a five-point scale ranging from 1 to 5, associated with the terms (1) factor driven, (2) transition to efficiency driven, (3) efficiency driven, (4) transition to innovation driven, and (5) innovation driven.

To convert the phases of ESD into values in fsQCA, we had to pre-process them into fuzzy membership scores (over the 0–1 domain). Experts on the applied problem and the use of fsQCA (i.e., university professors with extensive research experience in overlapping entrepreneurship and economic development issues) discussed how the five stages should be scaled over the 0–1 domain. Following discussion among the experts, it was decided that, going from factor-driven up to innovation-driven economies, the membership values 0.00, 0.30, 0.55, 0.80, and 1.00 should be employed. This effectively closer grouping of efficiency-driven with innovation-driven economies is also based on the implications of discussions concerning entrepreneurship and economic development in studies such as those by Wennekers, Van Wennekers, Thurik, and Reynolds (2005) and Acs et al. (2008).

Entrepreneurial framework conditions (EFC)

The variables, derived from the GEM dataset (expert opinion survey for such conditions), were identified through factor analysis as suitable to be combined into a single factor termed Entrepreneurial Framework Conditions. The variables themselves are a smaller subset of those identified within the full set of GEM entrepreneurial framework conditions (Kelley et al., 2015) that are said to enhance (or hinder) new business creation. These conditions encompass incentives, markets, resources, and supporting institutions (Bosma, Jones, Autio, & Levie, 2008, p. 40).

Entrepreneurial status (ES)

The same process of factor analysis also identified three variables combined into a single factor termed Entrepreneurial Status. GEM frameworks and processes focus on how society values entrepreneurship in terms of career choice, social status, and media profile in promoting the development of a national entrepreneurial culture.

The results of the factor analysis to construct EFC and ES appear in Appendix A. The regression-based factor scores, like that of ESD (and $SPaE^F$ previously), must be converted into fuzzy membership scores. We again followed Ragin's (2008) direct method (Figure 5), as we did to configure the necessary qualitative anchors for $SPaE^F$ (Andrews et al., 2016).

Insert Figure 5 here.

The pdfs in Figure 5 show the sets of required qualitative anchors for the lower threshold ($x^{\perp}$), upper threshold (x^{T}), and crossover point ($x^{\times}$), from which the necessary membership scores are evaluated.

Results and analysis

This section presents the results of a series of analyses using fsQCA to study the EC condition variables and SPaE outcomes (i.e., $SPaE^{F}$ and $SPaE^{C}$). Throughout the analysis, fsQCA v2.5 software was used. This program is freely available on the COMPASS website (http://www.compasss.org/software.htm). Having processed the condition and outcome measures into membership scores, the fsQCA results were broken down into three parts: necessity analyses, explanation of configurations, and sufficiency analyses.

Necessity analyses

This section presents the results of the necessity analyses (Ragin & Davey, 2014) for the conditions ESD, EFC, and ES and the outcomes $SPaE^{F}$ and $SPaE^{C}$. The necessity analyses evaluated whether a condition must be present for an outcome to occur. For the necessity analyses of individual condition variables for $SPaE^{F}$ ($SPaE^{F}$ and $\sim SPaE^{F}$) and $SPaE^{C}$ ($SPaE^{C}$ and $\sim SPaE^{C}$), see Table 5.

Insert Table 5 here.

Table 5 shows one condition with a consistency value above the standard threshold of 0.90 (Ragin, 2008). Thus, ESD is a necessary condition, but only for the outcome $\sim SPaE^{F}$ (low SPaE) (for a discussion on relationships between SPaE and TEA, see Beynon et al., 2016a). This result implies that ESD is necessary for low SPaE, but only for the version of this outcome derived from factor analysis. Hence, while the majority of conditions are not individually necessary for $SPaE^{F}$ (or $\sim SPaE^{F}$) and $SPaE^{C}$ (or $\sim SPaE^{C}$), the analysis suggests that ESD is necessary for $\sim SPaE^{F}$ because the results are not consistent across $\sim SPaE^{F}$ and $\sim SPaE^{C}$. ESD was retained, however, to enable full comparison of results across $SPaE^{F}$ and $SPaE^{C}$.

Explanation of configurations

This subsection outlines the causal configurations of the three conditions (ESD, EFC, and ES) for the two outcome measures of SPaE ($SPaE^F$ and $SPaE^C$). The configurations appear in Table 6.

Insert Table 6 here.

With three condition variables, Table 6 shows the 8 (= 2^3) possible configurations. Seven of these configurations (all except configuration 1) have at least one country associated with them in strong membership terms.[2] Table 6 shows the consistency[3] associated with each configuration as regards the separate outcomes: $SPaE^F$, $\sim SPaE^F$, $SPaE^C$, and $\sim SPaE^C$. The Venn diagram in Figure 6 illustrates the strong membership association of countries to the configurations in Table 6.

Insert Figure 6 here.

Each region of the Venn diagram in Figure 6 represents a configuration, which is indexed by a three-digit combination of 0s and 1s in the corner of the corresponding cell. Although the use of three condition variables is limiting, inspection of the groupings of countries shows that less developed economies tend to group together, and more developed economies tend to group together. These groupings may be geographically disparate, however.

---

[2] Strong membership relates to the assignment of 0 or 1 for a fuzzy membership score when its value is < 0.5 and ≥ 0.5, respectively.

[3] Consistency scores are a measure of the theoretical importance of a given configuration. The values are computed by dividing the sum of consistent membership in the configuration by the sum of membership in the outcome (see Ragin et al., 2008).

This finding is potentially important because it suggests that countries that wish to develop policies to encourage entrepreneurship may need to examine activities of countries that are neither physically nor culturally close, widening the scope for benchmarking.

Sufficiency analyses

This section presents the results of the sufficiency analyses (Ragin & Davey, 2014) based on the configurations in Table 6 (truth table) and Figure 6. The analysis of sufficiency determines whether a given condition or combination of conditions can produce the outcome. For the sufficiency analyses in this study, we had to consider the implication of examining two different measures for the same outcome.

Table 6 shows the number of countries associated in strong membership terms to each configuration. These data help inform the choice of frequency threshold, which is a cut-off value used to decide the number of cases that must be associated with a configuration for it to be further considered. For $SPaE^F$ and $SPaE^C$, configurations with at least one country associated with them were further considered. Hence, configuration 1 is termed a remainder throughout this study (Ragin, 2008).

For the consistency threshold, a previously employed criterion (Beynon et al., 2016b), was to choose the largest-least consistency threshold value that did not allow a configuration to be associated with both $SPaE^F$ and $\sim SPaE^F$ or both $SPaE^C$ and $\sim SPaE^C$ in the outcome and not-outcome analyses. Here, the two outcome measures describe the same outcome, so sameness is extended in terms of choice of consistency thresholds, described later.

For $SPaE^F$ and $SPaE^C$, using the previously stated criterion, the consistency thresholds are 0.82 and 0.76, respectively (Table 6). Likewise, the associated numbers of configurations are three for $SPaE^F$, four for $\sim SPaE^F$, two for $SPaE^C$, and five for $\sim SPaE^C$ (Table 6). The notion of sameness now comes to the fore through the following dilemma. Should the separate fsQCA sufficiency analyses be undertaken with the consistency thresholds of 0.82 for $SPaE^F$ and 0.76 for $SPaE^C$, or should 0.76 be raised to 0.82 for $SPaE^C$? Note that it is impossible to lower 0.82 for $SPaE^F$ to 0.76 for $SPaE^F$ because to do so would break the criterion of not having the same considered configurations for both $SPaE^F$ and $\sim SPaE^F$.

In light of this consistency threshold discussion, three fsQCA sufficiency analyses were conducted: *i*) analysis of $SPaE^F$ with consistency threshold 0.82, *ii*) analysis of $SPaE^C$ with consistency threshold 0.76, and *iii*) analysis of $SPaE^C$ with consistency threshold 0.82. These latter two analyses of $SPaE^C$ could both be considered comparable to the analysis of $SPaE^F$, albeit for different reasons. The following tables and figures summarize the sufficiency analyses in two forms: *i*) an amended version of Ragin and Fiss's (2008) notation in tabular form, where each column represents an alternative causal configuration of conditions linked to the outcome (Ragin 2008), and *ii*) a scatterplot of subset relations for each causal configuration.

$SPaE^F$ (consistency threshold 0.82)

Insert Table 7 here.

Insert Figure 7 here.

$SPaE^C$ (consistency threshold 0.76)

Insert Table 8 here.

Insert Figure 8 here.

$SPaE^C$ (consistency threshold 0.82)

Insert Table 9 here.

Insert Figure 9 here.

The results are broadly consistent across the two measures, particularly when the same consistency threshold is used. Evidence is displayed in Tables 6 to 9 and Figures 6 to 9. The analysis yields the following conclusions.

- Configurations associated with SPaE (high SPaE) typically represent countries at the lower end of economic development. Conversely, configurations associated with ~SPaE (low SPaE) typically represent countries at the higher end of economic development. These findings are consistent with earlier studies by Beynon et al. (2016a) related to TEA.
- Perhaps linked to the economic development levels of countries identified in the SPaE and ~SPaE configurations, a greater number of recipes relate to ~SPaE than to SPaE. This finding suggests greater complexity in the explanation of ~SPaE.
- Those (principally developing) countries with SPaE are represented by a causal recipe where economic development is absent and ES is present.
- Those (though by no means exclusively) countries associated with ~SPaE are represented by causal recipes where EFC or ESD are present and ES is absent. Where ES is absent, either the presence of EFC or ESD acts as a substitute in the causal recipes. The presence of EFC and ESD appear together only in the causal recipe where ES is neither present nor absent. The results illustrate that for the 11-country Configuration 7 (Belgium, Estonia, Germany, Latvia, Luxembourg, Malaysia, Mexico, South Korea, Spain, Sweden, and

Switzerland), all three of these causal recipes apply. Conversely, for the 14-country Configuration 8 (Australia, Chile, China, Ecuador, Finland, Indonesia, Ireland, Kazakhstan, Macedonia, Netherlands, Portugal, Taiwan, Thailand, and UK), only one causal recipe applies (presence of EFC and ESD and neither presence nor absence of ES).

In high-SPaE countries (SPaE), ES is seemingly of most benefit and is therefore of most relevance in policymaking. The results also suggest that in many low-SPaE countries (~SPaE), a policy focus on EFC may be counterproductive for raising SPaE. Instead, greater focus on ES may be of more direct benefit for raising SPaE. For countries in Configuration 8, however, more direct focus on the SPaE conditions (perceived start-up opportunities, capabilities, fear of failure, and entrepreneurial intention) may be more relevant.

The findings differ across the two outcome measure evaluation approaches. For the same consistency thresholds, with the factor analysis approach, there are two causal recipes for $SPaE^F$, including the nine-country Configuration 6 (Barbados, Brazil, Columbia, Egypt, Guatemala, Israel, Peru, Romania, and South Africa). In contrast, with the cluster analysis approach ($SPaE^C$), only one causal recipe is identified, which excludes Configuration 6 from the analysis and reduces the number of causal recipes applicable to Configuration 2 (Burkina Faso, Cameroon, Iran, and Vietnam). Otherwise, the causal recipes and associated configurations are identical for the two outcome measure evaluation approaches.

To further illustrate the variations in analyses using fsQCA, Figure 10 presents Venn diagrams for the three models. These diagrams show the associations of configurations with the outcome and not-outcome (across the three sufficiency analyses undertaken).

Insert Figure 10 here.

In Figure 10a, the eight possible configurations are shown with the associated number of countries in strong membership terms. Configuration 000 is shaded white, since it is not considered further because no country is associated with it (same for all analyses). For $SPaE^F$ (using consistency threshold 0.82), configurations 001, 011, and 101 are darkly shaded, and configurations 010, 100, 110, and 111 are lightly shaded, indicating that these two sets of configurations are described by causal recipes associated with $SPaE^F$ and $\sim SpaE^F$, respectively.

The shading of the configurations in Figures 10b and 10c, compared with Figure 10a, is therefore of technical interest. In Figure 10b, for $SpaE^C$ (using consistency threshold 0.76), the same number of configurations as in Figure 10a is associated with causal recipes, but configuration 101 is described by causal recipes associated with $\sim SpaE^C$ (as opposed to $SpaE^F$, as in Figure 10a). Figure 10c, for $SPaE^C$ (using consistency threshold 0.76), also varies. Configuration 6 (101) is shaded white in the Venn diagram, not because it was not considered (like 000), but because of the increase in the consistency threshold from 0.76 to 0.82. Table 6 shows that Configuration 6 (101) has maximum consistency of 0.764 for the outcome $\sim SPaE^C$.

The reason for these comparisons is to evaluate sameness across the fsQCA models. Accordingly, Figure 10 suggests the closest resemblance of $SPaE^C$ to $SPaE^F$ is reflected in Figure 10c, where Configuration 6 (101) is not included among the causal recipes, rather than being oppositely assigned as in Figure 10b.

This finding suggests that if only the cluster-analysis-based outcome measure is used, the analysis potentially exhibits less sensitivity, with fewer recipes identified by clustering than by factor analysis. This highlights the sensitivity inherent to fsQCA regarding the methods that generate the data. Using both methods together adds robustness and verifies the results by identifying the causal recipes and configurations that emerge for both methods.

Conclusions, limitations, and further research

This study is of practical interest because of its use of fsQCA to derive technical and theoretical contributions regarding the way entrepreneurial climate drives SPaE. This non-traditional fsQCA approach challenges established practice, enriching the theory by identifying multi-factor causal recipes (rather than individual factors) that affect SPaE. It also identifies groups of countries that are affected by the same causal recipe and equivalent SPaE level, thereby aiding policymaking.

Specifically, the results of the analysis suggest that in highly economically developed, low-SPaE countries (~SPaE) (e.g., Germany, Mexico, and South Korea), greater focus on improving ES may be more beneficial to raising SPaE than a broader policy focus on EFC, which may in fact be counterproductive. These findings are supported by, for example, Kalden, Cunningham, and Anderson (2017) in the context of Germany. In other developed economies (e.g., Australia, China, Taiwan, Thailand, and the UK), more direct focus on SPaE conditions themselves may be more appropriate. In countries where SPaE is present, ES seems to be of most benefit and therefore of most relevance in policymaking. Because we detect groups of countries facing similar conditions, this study also enables policymakers to identify benchmark countries for measures designed to raise ES or alternative policymaking measures.

The study also makes a significant technical contribution by comparing dependent variables (outcome measures) generated by factor and cluster analysis. We identify the degree of sensitivity of the fsQCA results if both methods are available and show how both may be used in conjunction to strengthen the robustness of the results. Another practical implication of this study is the description of variation between two fsQCA models with different measures for the same outcome. These measures were derived from different technical approaches, but both represented SPaE.

In terms of limitations and the need for further research, this contrived scenario highlights a number of pertinent questions regarding the use of fsQCA. Crucially, the substance of this investigation can also be transferred to the more realistic case when the same set of condition variables is considered for multiple outcomes that do not reflect the same phenomenon. The results here are also limited in terms of being from only one study. Additional studies are therefore required. Our results nonetheless suggest that, given a choice of consistency threshold to employ across fsQCA models with different outcomes, choosing the same consistency threshold value across the models may be wise. According to our findings, employing different consistency thresholds across different models can have knock-on effects regarding comparison across different outcomes.

References

Acs, Z. (2006). How is entrepreneurship good for economic growth? *Innovations*, *1*(1), 97–107.

Acs, Z., Brooksbank, D., O'Gorman, P. D., & Terjesen, S. (2012). The knowledge spillover theory of entrepreneurship: an application to foreign direct investment. *International Journal of Entrepreneurship and Small Business*, *15*(2), 237–261.

Acs, Z. J., Desai, S., & Hessels, J. (2008). Entrepreneurship, economic development and institutions. *Small Business Economics*, *31*(3), 219–234.

Andrews, R., Beynon, M. J., & McDermott, A. M. (2016). Organizational capability in the public sector: a configurational approach. *Journal of Public Administration Research and Theory*, *26*(2), 239–258.

Anwar ul Haq, M., Usman, M., Hussain, N., & Anjum, Z. U. Z. (2014). Entrepreneurial activity in China and Pakistan: a GEM data evidence. *Journal of Entrepreneurship in Emerging Economies*, *6*(2), 179–193.

Arenius, P., & Minniti, M. (2005). Perceptual variables and nascent entrepreneurship. *Small Business Economics*, *24*(3), 233–247.

Autio, E., Keeley, R., Klofsten, M., Parker, G., & Hay, M. (2001). Entrepreneurial intent among students in Scandinavia and in the USA. *Enterprise and Innovation Management Studies*, *2*(2), 145–160.

Beynon, M. J., Jones, P., & Pickernell, D. (2016a). Country-based comparison analysis using fsQCA investigating entrepreneurial attitudes and activity. *Journal of Business Research*, *69*(4), 1271–1276.

Beynon, M., Jones, P., & Pickernell, D. (2016b). Country-level investigation of innovation investment in manufacturing: Paired fsQCA of two models. *Journal of Business Research*, *69*(11), 5401–5407.

Bezdek, J. C. (1980). A Convergence Theorem for the Fuzzy ISODATA Clustering Algorithms. *IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-2*(1), 1–8.

Bosma, N., Jones, K., Autio, E., & Levie, J. (2008). *Global Entrepreneurship Monitor, Executive Report 2007*. Babson Park, MA, London, UK: Babson College-London Business School.

Bosma, N., Wennekers, S., & Amorós, J. E. (2012). Global Entrepreneurship Monitor, 2011 Extended Report: Entrepreneurs and Entrepreneurial Employees across the Globe. Global Entrepreneurship Research Association (Retrieved from Global Entrepreneurship Monitor website: http://gemconsortium.org/report). Accessed on September 21, 2016.

Boudet, H. S., Jayasundera, D. C., & Davis, J. (2011). Drivers of conflict in developing country infrastructure projects: experience from the water and pipeline sectors. *Journal of Construction Engineering and Management*, *137*(7), 498–511.

Coduras, A., Clemente, J. A., & Ruiz, J., (2016). A novel application of fuzzy-set qualitative comparative analysis to GEM data. *Journal of Business Research*, *69*(4), 1265–1270.

David, J. Y., Shin, H. C., Pérez, I., Anderies, J. M., & Janssen, M. A. (2016). Learning for resilience-based management: Generating hypotheses from a behavioral study. *Global Environmental Change*, *37*, 69–78.

Dogruparmak, S. C., Keskin, G. A., Yaman, S., & Alkan, A. (2014). Using principal component analysis and fuzzy c–means clustering for the assessment of air quality monitoring. *Atmospheric Pollution Research*, *5*(4), 656–663.

Freytag, A., & Thurik, R. (2007). Entrepreneurship and its determinants in a cross-country setting. *Journal of Evolutionary Economics*, *17*(2), 117–131.

Hair Jr., J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th edition). NJ: Prentice Hall.

Kalden, J. N., Cunningham, J., & Anderson, A. R. (2017). The social status of entrepreneurs, *International Journal of Entrepreneurship and Innovation*, *18*(2), 91–104.

Kelley, D., Singer, S., & Herrington, M. (2015). Global Entrepreneurship Monitor 2015/16 Global Report, http://www.gemconsortium.org/report Accessed on September 21, 2016.

Krebs, D., Berger, M., & Ferligoj, A. (2000). Approaching achievement motivation-comparing factor analysis and cluster analysis. *New approaches in Applied Statistics, Metodoloski zvezki*, *16*, 147–171.

Kuckertz, A., Berger, E. S., & Mpeqa, A. (2016). The more the merrier? Economic freedom and entrepreneurial activity. *Journal of Business Research*, *69*(4), 1288–1293.

Krueger, N. F. (2000). The cognitive infrastructure of opportunity emergence. *Entrepreneurship: Theory and Practice*, *24*(3), 5–23.

Lam, W. F., & Ostrom, E. (2010). Analyzing the dynamic complexity of development interventions: lessons from an irrigation experiment in Nepal. *Policy Sciences*, *43*(1), 1–25.

Mas-Tur, A., Pinazo, P., Tur-Porcar, A. M., & Sánchez-Masferrer, M. (2015). What to avoid to succeed as an entrepreneur. *Journal of Business Research*, *68*(11), 2279–2284.

Mazzarol, T., Volery, T., Doss, N. & Thein, V. (1999). Factors influencing small business start-ups: A comparison with previous research. *International Journal of Entrepreneurial Behavior & Research*, 5(2), 48-63.

Nyström, K. (2012). Entrepreneurial employees: Are they different from independent entrepreneurs? CESIS Electronic Working Paper Series, No. 281.

Ragin, C. C. (2000). *Fuzzy set social science*. Chicago, IL: University of Chicago Press.

Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. Chicago, IL: University of Chicago Press.

Ragin, C. C., & Davey, S. (2014). *fs/QCA [Computer Program], version 2.5*. Irvine, CA: University of California.

Ragin, C. C., & Fiss, P. C. (2008). Net effects versus configurations: An empirical demonstration. In C. C. Ragin (Ed.), *Redesigning social inquiry: Fuzzy sets and beyond* (pp. 190–212). Chicago, IL: University of Chicago Press.

Vaillant, Y., & Lafuente, E. (2007). Do different institutional frameworks condition the influence of local fear of failure and entrepreneurial examples over entrepreneurial activity? *Entrepreneurship & Regional Development*, *19*(4), 313–337.

Wennekers, S., Van Wennekers, A., Thurik, R., & Reynolds, P. (2005). Nascent entrepreneurship and the level of economic development. *Small Business Economics, 24*(3), 293–309.

Woodside, A. G. (2013). Moving beyond multiple regression analysis to algorithms: calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory. *Journal of Business Research*, *66*(4), 463–472.

World Economic Forum (WEF) Global Competitiveness Report (2011). The Global Competitiveness Report 2011–2012. Geneva: World Economic Forum (Retrieved from http://www3.weforum.org/docs/WEF_GCR_Report_2011-12.pdf) Accessed on November 1, 2016.

Xavier, S. R., Kelley, D., Kew, J., Herrington, M., & Vorderwülbecke, A. (2012). Global Entrepreneurship Monitor 2012. *Global Entrepreneurship Report*. Global Entrepreneurship Research Association.

Zhang, T., Ramakrishnon, R., & Livny, M. (1996). BIRCH: An efficient data clustering method for very large databases. Proceedings of the *ACM SIGMOD* Conference on Management of Data. p. 103–114, Montreal, Canada.

Table 1:

Description of SPaE constituent items

Variable	Description	Min	Mean	Max
Perceived start-up opportunities (Prcvd_Opps)	Percentage of 18–64 age group who see good opportunities to start a firm in the area where they live	14.2	41.019	70.2
Perceived capabilities (Prcvd_Caps)	Percentage of 18–64 age group who believe they have the necessary skills and knowledge to start a business	25.4	49.711	78.0
Fear of failure (Fr_of_Flr)	Percentage of 18–64 age group with positive perceived opportunities who indicate that fear of failure would prevent them from setting up a business	24.6	63.296	85.3
Entrepreneurial intention (Entrp_Intnt)	Percentage of 18–64 age group (individuals involved in any stage of entrepreneurial activity excluded) who intend to start a business within three years	5.3	21.365	61.9

Table 2:

Total variance explained in factor analysis (of Prcvd_Opps, Prcvd_Caps, Fr_of_Flr, and Entrp_Intnt).

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	2.511	62.777	62.777	2.511	62.777	62.777
2	.740	18.508	81.285			

Table 3:

Rotated component matrix

Variable	Component
Perceived capabilities	0.900
Entrepreneurial intentions	0.876
Perceived opportunities	0.700
Fear of failure	0.666
Cronbach's alpha (4 items)	0.800

Table 4:

Description of condition variables to consider against SPaE

Variable	Description
Economic stage of development (ESD)	A single variable with a five-point scale associated with stage of national economic development from (1) Factor Driven, (2) Transition to Efficiency Driven, (3) Efficiency Driven, (4) Transition to Innovation Driven, and (5) Innovation Driven.
Entrepreneurial framework conditions (EFC)	A single variable identified via factor analysis and consisting of the following: • R&D Transfer • Internal market burdens or entry regulation • Government entrepreneurship programs • Entrepreneurial education at school stage • Government policies, taxes, and bureaucracy • Government policies, support, and relevance • Entrepreneurial finance • Entrepreneurial education at post school stage
Entrepreneurial status (ES)	A single variable identified via factor analysis and consisting of the following: • Media attention for entrepreneurship • High status afforded to successful entrepreneurship • Entrepreneurship as a good career choice

Table 5:

Analysis of necessity results for $SPaE^F$ ($SPaE^F$ and ~$SPaE^F$) and $SPaE^C$ ($SPaE^C$ and ~$SPaE^C$)

Condition		$SPaE^F$				$SPaE^C$			
		$SPaE^F$		~$SPaE^F$		$SPaE^C$		~$SPaE^C$	
		Cons	Cov	Cons	Cov	Cons	Cov	Cons	Cov
ESD	Var	0.739	0.491	0.916	0.659	0.702	0.356	0.881	0.773
	not-var	0.487	0.842	0.293	0.549	0.552	0.729	0.266	0.606
EFC	Var	0.586	0.584	0.679	0.732	0.558	0.424	0.636	0.836
	not-var	0.731	0.678	0.614	0.616	0.784	0.555	0.562	0.687
ES	Var	0.778	0.724	0.563	0.567	0.842	0.598	0.525	0.644
	not-var	0.534	0.531	0.726	0.779	0.499	0.378	0.672	0.880

Note: Cons: Consistency; Cov: Coverage.

Table 6:

Truth table showing configurations of three condition variables, with raw consistency values for SPaE^F and ~SPaE^F and for SPaE^C and ~SPaE^C and frequency of countries in that configuration

Cnfg	ESD	EFC	ES	No.	Cons		Cons	
					SPaE^F	~SPaE^F	SPaE^C	~SPaE^C
~~1~~	~~0~~	~~0~~	~~0~~	~~0~~	~~0.924~~	~~0.807~~	~~0.817~~	~~0.851~~
2	0	0	1	4	**0.941**	0.584	**0.845**	0.649
3	0	1	0	1	0.813	**0.840**	0.757	**0.850**
4	0	1	1	2	**0.909**	0.625	**0.831**	0.671
5	1	0	0	13	0.660	**0.834**	0.543	**0.875**
6	1	0	1	9	**0.833**	0.713	0.725	**0.764**
7	1	1	0	11	0.657	**0.885**	0.438	**0.948**
8	1	1	1	14	0.737	**0.828**	0.568	**0.857**

Note: Cnfg: configuration; Cons: raw consistency; No.: frequency.

Table 7:

Sufficiency analyses results for SPaE^F and ~SPaE^F

Conditions	SPaE^F				
	SPaE^F		~SPaE^F		
ESD		⊖	•		●
EFC	⊖			•	●
ES	●	●	⊖	⊖	
Complex solution	**CO1**	**CO2**	**CN1**	**CN2**	**CN3**
Configurations	2, 6	2, 4	5, 7	3, 7	7, 8
Consistency	0.840	0.914	0.811	0.868	0.778
Raw coverage	0.593	0.436	0.679	0.509	0.624
Unique coverage	0.215	0.058	0.210	0.040	0.154
Solution consistency	0.834			0.750	
Solution coverage	0.651			0.873	
Parsimonious solution	**PO1**	**PO2**	**PN1**		**PN2**
Configurations	2, 6	2, 4	3, 5, 7		7, 8
Consistency	0.840	0.914	0.779		0.778
Raw coverage	0.593	0.436	0.726		0.624
Unique coverage	0.215	0.058	0.256		0.154
Solution consistency	0.834			0.732	
Solution coverage	0.651			0.880	

Note: Consistency threshold = 0.82.

Table 8:

Sufficiency analyses results for SPaE^C and ~SPaE^C

Conditions	SPaE^C		
	SPaE^C	~SPaE^C	
ESD	⊖		●
EFC		•	
ES	●	⊖	
Complex solution	**CO1**	**CN1**	**CN2**
Configurations	2, 4	3, 7	5, 6, 7, 8
Consistency	0.820	0.925	0.773
Raw coverage	0.513	0.445	0.881
Unique coverage	0.513	0.033	0.468
Solution consistency	0.820	0.770	
Solution coverage	0.513	0.914	
Parsimonious solution	**PO1**	**PN1**	**PN2**
Configurations	2, 4	3, 7	5, 6, 7, 8
Consistency	0.820	0.880	0.773
Raw coverage	0.513	0.672	0.881
Unique coverage	0.513	0.054	0.468
Solution consistency	0.820	0.768	
Solution coverage	0.513	0.935	

Note: Consistency threshold = 0.76.

Table 9:

Sufficiency analyses results for SPaE^C and ~SPaE^C

Conditions	SPaE^C			
	SPaE^C	~SPaE^C		
ESD	⊖	•		●
EFC			•	●
ES	●	⊖	⊖	
Complex solution	**CO1**	**CN1**	**CN2**	**CN3**
Configurations	2, 4	5, 7	3, 7	7, 8
Consistency	0.820	0.900	0.925	0.891
Raw coverage	0.513	0.619	0.445	0.586
Unique coverage	0.513	0.206	0.033	0.173
Solution consistency	0.820		0.863	
Solution coverage	0.513		0.825	
Parsimonious solution	**PO1**	**PN1**		**PN2**
Configurations	2, 4	3, 5, 7		7, 8
Consistency	0.820	0.880		0.891
Raw coverage	0.513	0.672		0.586
Unique coverage	0.513	0.260		0.173
Solution consistency	0.820		0.857	
Solution coverage	0.513		0.846	

Note: Consistency threshold = 0.82.

Figure 1:

Pdf of country FA-regression SPaE^F values

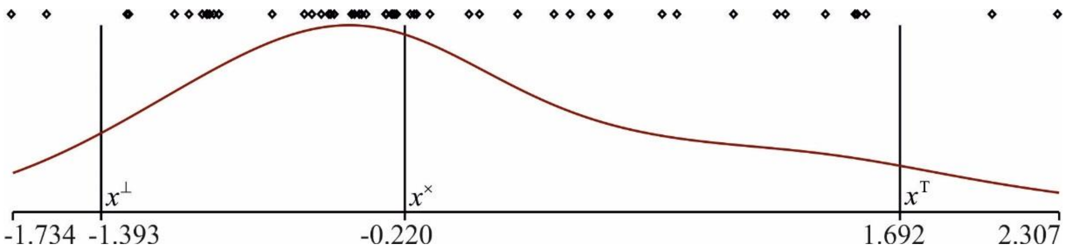


Figure 2:

Fuzzy membership scores of countries for two clusters: C1 (μ_{C1}) and C2 (μ_{C2})

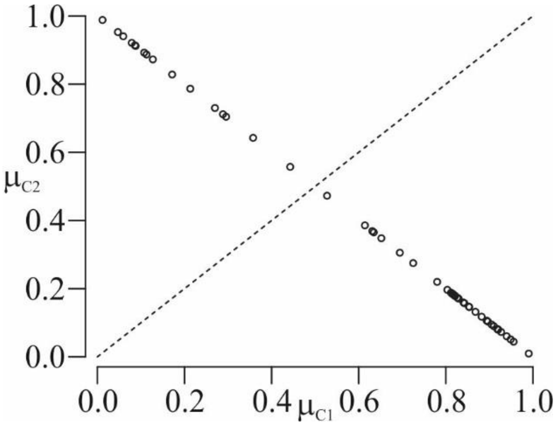


Figure 3:

Scatterplot of $SPaE^F$ and $SPaE^C$ pairs of values for 54 countries

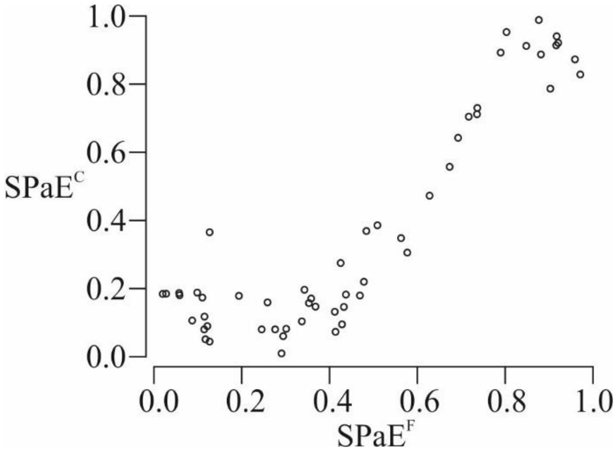


Figure 4:

GEM conceptual framework

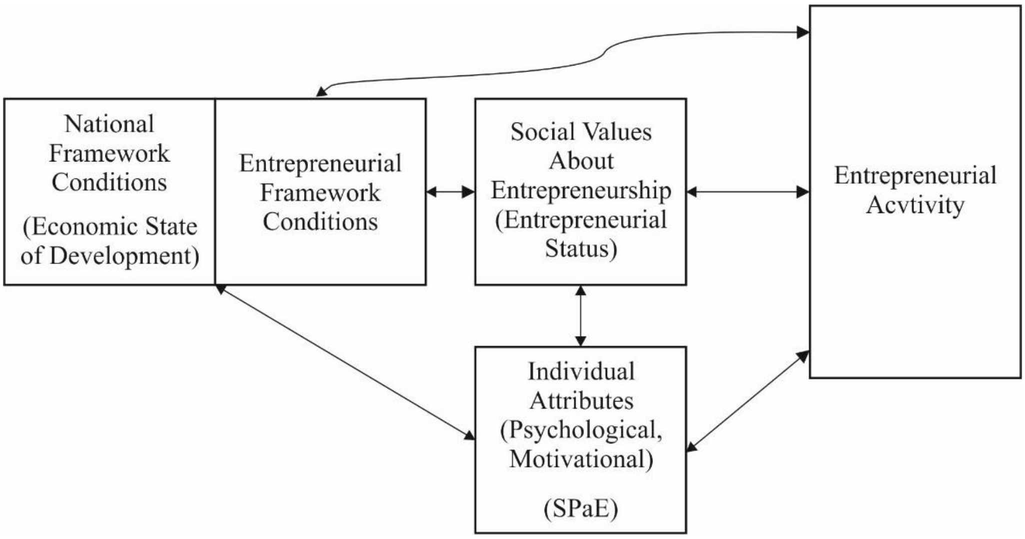


Figure 5:

Pdfs of entrepreneurial framework conditions and entrepreneurial status condition variables

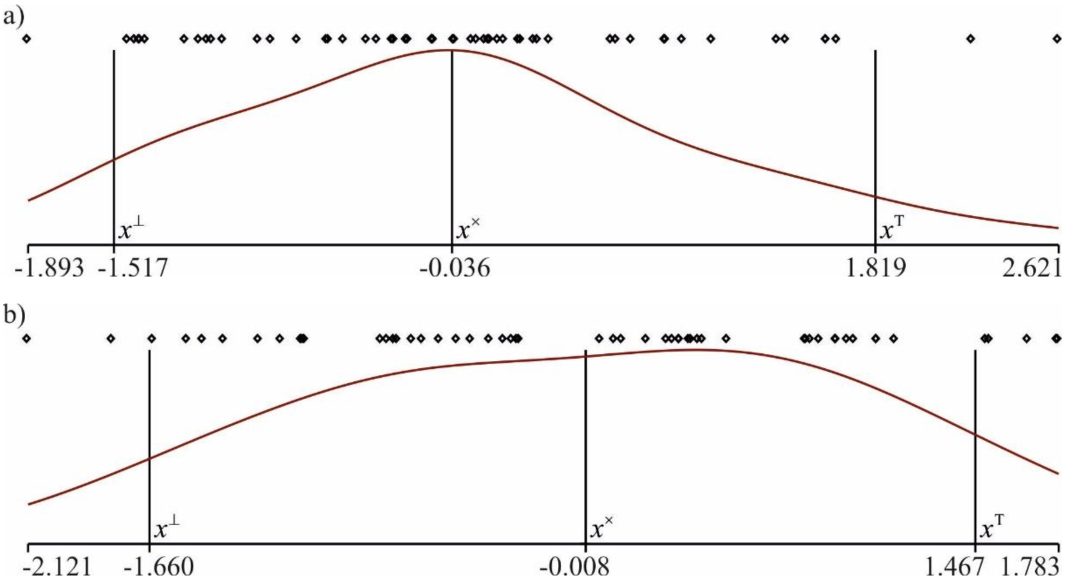


Figure 6:

Venn diagram of configurations with countries' positions based on association of strong membership

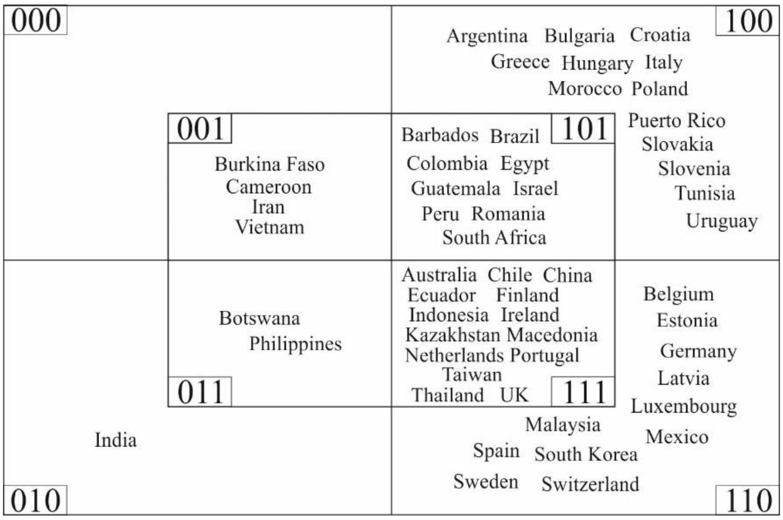


Figure 7:

Fuzzy causal pathway vs. fuzzy outcome perspective scatterplots associated with Table 7 results

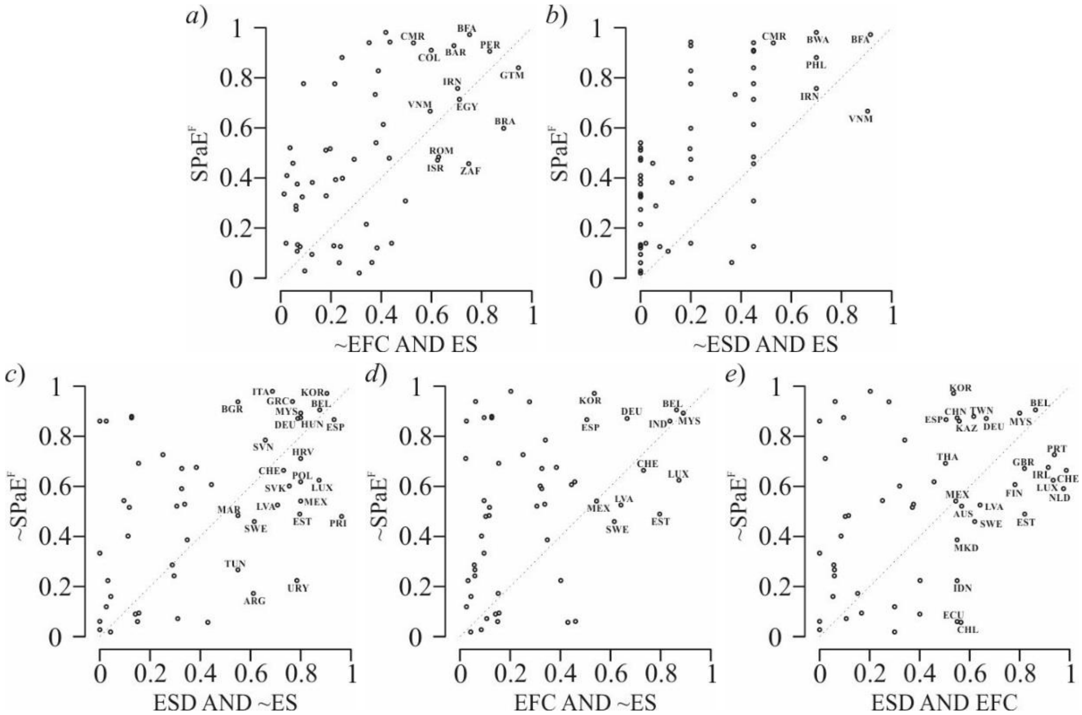


Figure 8:

Fuzzy causal pathway vs. fuzzy outcome perspective scatterplots associated with results in Table 8

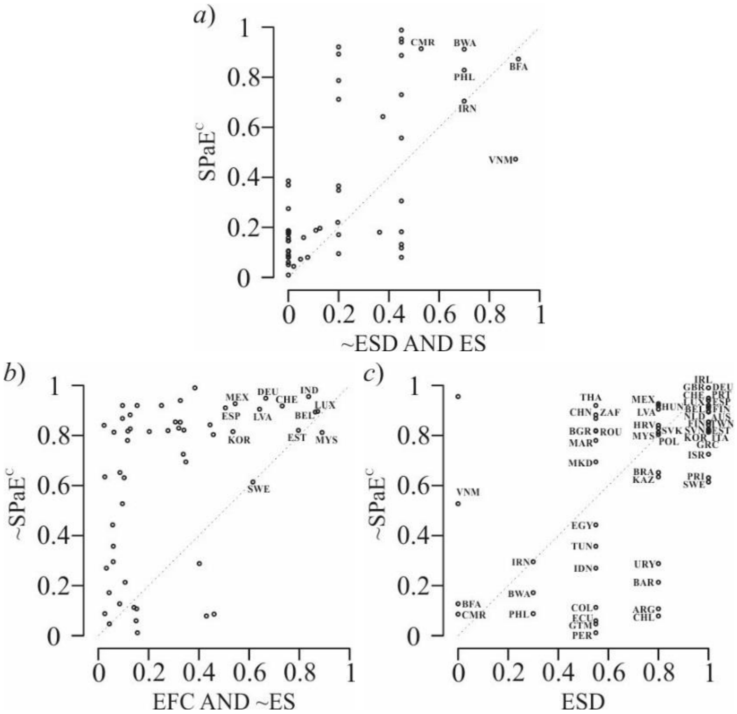


Figure 9:

Fuzzy causal pathway vs. fuzzy outcome perspective scatterplots associated with results in Table 9

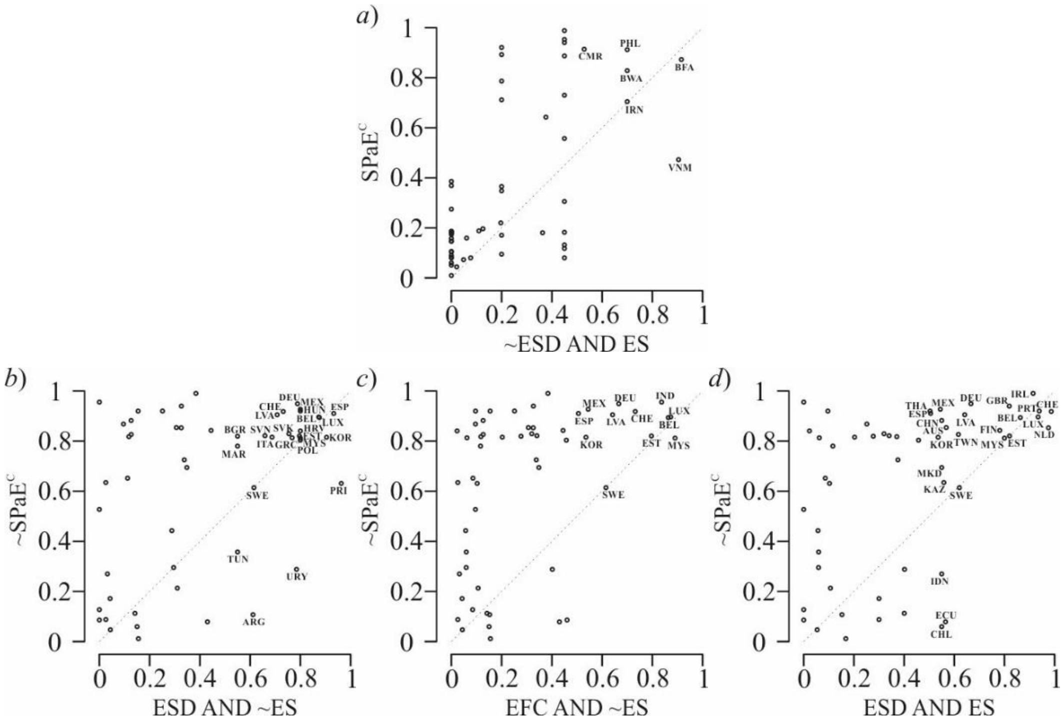
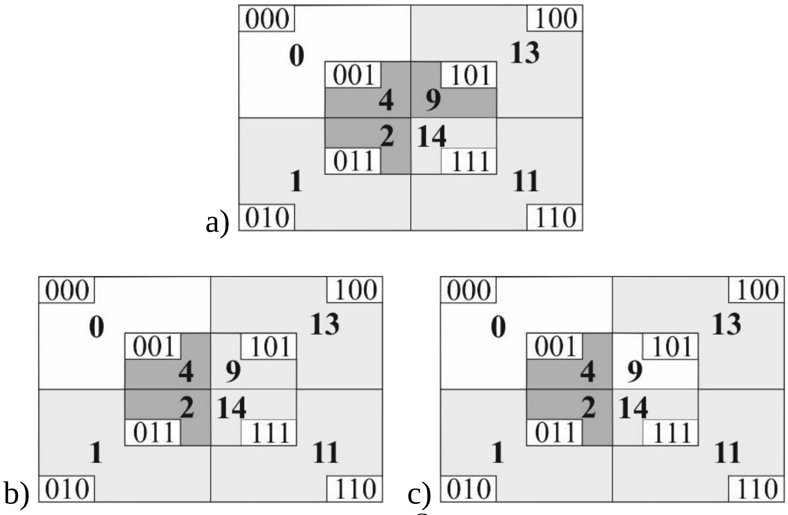


Figure 10:

Venn diagram of the sufficiency analysis association of configurations for a) $SPaE^{F}$, b) $SPaE^{C}$, and c) $SPaE^{C}$



Note: $SPaE^{F}$ consistency threshold = 0.82; $SPaE^{C}$ consistency threshold = 0.76; $SPaE^{C}$ consistency threshold = 0.82.

Appendix A

This appendix summarizes the factor analysis undertaken to create two of the three independent variables employed in the study, namely EFC and ES. The factor analysis was based on 12 items (questions) covering the issue of entrepreneurial framework conditions within the GEM framework and 3 items covering entrepreneurship status within the economy. Principal component factor analysis with varimax rotation was employed (results shown in Table A1).

Table A1:

Rotated component matrix, Total variance explained

Item	Component	
	1	2
R&D transfer	**0.885**	-0.133
Internal market burdens or entry regulation	**0.865**	-0.103
Government entrepreneurship programs	**0.822**	-0.233
Entrepreneurial education at school stage	**0.787**	0.181
Government policies, taxes and bureaucracy	**0.778**	0.102
Government policies, support and relevance	**0.764**	-0.072
Entrepreneurial finance	**0.751**	-0.169
Entrepreneurial education at post school stage	**0.675**	0.153
Media attention for entrepreneurship	0.166	**0.778**
High status to successful entrepreneurship	-0.028	**0.756**
Entrepreneurship as a good career choice	-0.262	**0.752**
Cronbach's alpha	0.899	0.656
Variance explained	46.725%	17.499%

Note: Extraction method: principal component analysis; rotation method: varimax with Kaiser normalization; rotation converged in 3 iterations.