Improving the Marriage of Modeling and Theory for Accurate Forecasts of Outcomes

Building Generalizable Case-Based Theory in Human Resources Management

Huat Bin (Andy) Ang, Arch G. Woodside,

BUILDING GENERALIZABLE CASE-BASED THEORY IN HUMAN RESOURCES MANAGEMENT

Huat Bin (Andy) Ang and Arch G. Woodside

ABSTRACT

*This study applies asymmetric rather than conventional symmetric analysis to advance theory in occupational psychology. The study applies systematic case-based analyses to model complex relations among conditions (i.e., configurations of high and low scores for variables) in terms of set memberships of managers. The study uses Boolean algebra to identify configurations (i.e., recipes) reflecting complex conditions sufficient for the occurrence of outcomes of interest (e.g., high versus low financial job stress, job strain, and job satisfaction). The study applies complexity theory tenets to offer a nuanced perspective concerning the occurrence of contrarian cases – for example, in identifying different cases (e.g., managers) with high membership scores in a variable (e.g., core self-evaluation) who have low job satisfaction scores and when different cases with low membership scores in the same variable have high job satisfaction. In a large-scale empirical study of managers (*n = 928*) in four (contextual) segments of the farm industry in New Zealand, this study tests the fit and predictive validities of set membership configurations for simple and complex antecedent conditions that indicate high/low core self-evaluations, job stress, and high/low job satisfaction. The findings support the conclusion that complexity theory in combination with configural analysis offers useful insights for explaining nuances in the causes and outcomes to high stress as well as low stress among farm*

Improving the Marriage of Modeling and Theory for Accurate Forecasts of Outcomes
Advances in Business Marketing & Purchasing, Volume 25, 85–154

ISSN: 1069-0964/doi:10.1108/S1069-096420180000025007

managers. Some findings support and some are contrary to symmetric relationship findings (i.e., highly significant correlations that support main effect hypotheses).

Keywords: Asymmetric test; case research; core self-evaluation; job satisfaction; job strain; job stress

INTRODUCTION

The present study attempts to see both the forest and the trees – that is, describe, explain, and model alternative, configurational, asymmetric, case-based configurations of how individual and industry sub-categories, job stressors, core self-evaluation theory, and job strain identify high as well as low job satisfaction (JS). The study's use of asymmetric case-based modeling also includes separate models indicating either high or low JS. The study provides case-level model profiles that are high in accuracy consistently in predicting managers high (and separate models for managers low) in JS. Thus, the study focuses on case-based modeling using somewhat precise outcome testing (SPOT, Woodside, 2016) and avoids the fatal flaws in using null hypothesis statistical testing (NHST) (Armstrong, 2012; Gigerenzer & Brighton, 2009; Hubbard, 2016; Trafimow, 2014; Trafimow & Marks, 2015) and the flaws in examining the relative sizes of betas in regression models (Armstrong, 2012; Hubbard, 2016). The study contributes to the literature by describing how complexity theory and configurational analysis applies in constructing asymmetric models in case-based research on JS. The study advances McClelland's (1998) algorithm asymmetric analysis, with predictive validation using additional samples, to solve the pervasive current mismatch between theory and analysis (Fiss, 2011) in human resource management (HRM) research.

This asymmetric research perspective rests on a foundation of complexity theory. Adopting asymmetric perspective goes beyond the dominant logic in the literature of symmetric, variable-based, theory construction/testing. The asymmetric approach to theory construction and data analysis recognizes and models cases supporting main effects hypothesis (e.g., generalized self-efficacy associates positively with JS) as well as cases exhibiting relationships contrarian to such symmetric hypothesis (e.g., high-generalized self-efficacy contributes to low JS in some contexts). Complexity theory and asymmetric analysis go beyond the empirically support of small, medium, and large main effects of relationships of independent on dependent variables. For example, a complexity theory tenet suggests the need for modeling the configuration of causes that include contrarian associations in JS research, such as for cases (employees or managers) where high job stress associates with high job performance; such cases occur in possibly all studies with moderate-to-large sample sizes but are typically ignored in studies focusing on the general finding of a modest effect size, negative, main effect for job stress and JS. Rather than adopting a symmetric stance, complexity theory supports the perspective that a configurational asymmetric perspective is necessary for examining complex antecedent conditions to achieve deep understanding and for reporting complex wholes of causes – because different cases occur whereby job stressors and job satisfaction relationships support and run counter to intuitive associations as well as cases where the same job stressors do not associate with job satisfaction.

Heretofore, nearly all reports (e.g., Hiller & Hambrick, 2005; Judge & Bono, 2001; Nguyen & Borteyrou, 2016) of research on decision-making and JS rely on symmetric variable-based theory and empirical tests of variable relationships (exceptions include Alegre, Mas-Machuca, & Berbegal-Mirabent, 2014; Gigerenzer & Brighton, 2009; Hsiao, Jaw, Huan, & Woodside, 2015; McClelland, 1998). A few studies recognize that symmetric theory and tests (e.g., correlations, multiple regression analyses (MRAs), and structural equation models, SEMs) do not provide high levels of accuracy in predicting individual outcomes of cases (e.g., predicting implemented firm strategies or highly competent versus typical managers, see Fiss, 2007, 2011, Fiss, Marx, & Cambré, 2013, McClelland, 1998; Ordanini, Parasuraman, & Rubera, 2014). McClelland's (1998) solution for identifying highly competent managers is to create complex asymmetric algorithms (e.g., screening by identifying highly competent executives to be managers in the top quintiles across five of seven antecedent conditions). Unlike symmetric models attempting to predict low and high scores, asymmetric models are one-directional in their explanations and predictions; these models predict only the high-scoring cases – positive or negative outcomes separately. Consequently, theory and testing to understand high versus low JS benefit from identifying separate sets of antecedent conditions relevant for each outcome. The asymmetric approach in HRM research constructs and tests theory from a complexity theory perspective. Complexity theory holds that a simple condition (say X) relates both positively and negatively to an outcome condition (Y) in the same data set – this relationship depends on the presence of specific combinations of additional simple conditions appearing with X (e.g., conditions, T, R, and S versus T, L, and not S). Complexity theory also proposes the tenet of causal asymmetry, that is, the causal configuration indicating cases with a high outcome (Y) are not the mirror opposite of the causal conditions indicating cases with a low outcome (Y). Thus, for high accuracy and understanding, the study of low JS requires constructing separate models versus the models that accurately predict high JS (Hsiao et al., 2015). The present study proposes and tests this tenet and other core tenets of complexity theory for describing, explaining, and predicting JS. As such, the present study suggests adopting a radical stance for understanding dispositional and contextual sources of JS.

McClelland (1998) emphasizes that examining and reporting antecedents for high versus typical employee performance in terms of symmetrical tests (e.g., ANOVA, correlation, MRA) understates and misrepresents the significance of the focal relationship (i.e., managers who are highly competent), while configural statements based on tipping-points provide highly useful "competency algorithms." For a classification of "outstanding" versus "typical" performer, the competency algorithm screen that McClelland (1998, p. 334) describes requires a case (i.e., individual executive) to achieve "for at least 1 of the 3 individual-initiative competencies, 1 of the organizational competencies, and 6 of the 12 valid competencies overall." Ragin (2008) advances theory and provides useful software (fsQCA.com) for model-building and empirical-testing alternative algorithm screens that identify cases with high (or low) focal outcomes with high consistency. An algorithm is a conjunctive statement that requires the presence of two-or-more conditions in a given case for a favorable (unfavorable) outcome to occur. For example, the following algorithm predicts a high performer and is a complex antecedent condition (a recipe) that combines four simple antecedent conditions: a frontline employee who is happy-at-work (H), works well with other employees (O), never causes peer conflicts (~C), and always arrives to work on-time (T) is a high performer (P):

$$H \bullet O \bullet \sim C \bullet T \leq P \quad (1)$$

where the tilde ("~") represents negation; the mid-level dot ("·") represents the logical "AND" condition, meaning that a case must have a high score in each simple condition in the complex statement. Model 1 states that cases high conjunctively across all four simple conditions in the configuration have high scores in work performance. Unlike symmetric tests, researchers use Boolean algebra rather than matrix algebra to test such models; thus, since the model states that high scores in all four conditions indicates a high outcome condition (P), a case (e.g., employee) low in any one of the four simple conditions causes the complex condition to have the same low score. The model applies a conjunctive rule and not a compensatory rule. This configurational statement does not tell us that exhibiting this recipe is the only recipe that results in the identification of a high performer; the statement states that only an employee high in all four ingredients is a high performer. The statement indicates sufficiency but not necessity. "Equifinality" (i.e., different configurations of causes indicate the same outcome) is another core tenet of complexity theory.

Thus, the focus of the present study differs radically from most prior studies in describing, explaining, and predicting JS. The focus here is on "statistical sameness" (Hubbard, 2016) rather than on statistical difference from zero; that is, do high scores in a model identify high scores in model's outcome condition consistently? Rather than examining effect sizes of relationships between each X (an independent variable) affecting the level of Y (JS) via a symmetric test, the present study proposes simple and complex antecedent conditional statements (i.e., algorithms) which indicate cases with high scores consistently in the outcome of interest (i.e., high JS) via asymmetric tests. Thus, the focus here is on "somewhat" precise outcome testing (SPOT) that provides moderately complex statements useful for consistently (almost always) identifying cases exhibiting specific outcomes (cf. Hubbard's, 2016 advocacy of "precise outcome models" in behavioral research). While symmetric variable low-high relationships are testable by symmetric matrix-algebra-based statistical tools (e.g., MRA), SPOT consists of algorithmic screening statements testable by asymmetric Boolean-based statistical tools (e.g., fuzzy-set, qualitative comparative analysis) for achieving consistent accuracy in predicting an outcome of interest. Woodside (2016) observes that several independent sources of evidence (Anscombe, 1973; Armstrong, 2012; Soyer & Hogarth, 2012) support the conclusion that symmetric statistical test outputs are misleading even among the world's leading experts in econometrics (Soyer & Hogarth, 2012). Such indexes as t, p, F, r, and r^2 fail to answer the most pressing theoretical and practical question: does a high (or low) score by the model predict accurately and consistently the outcomes in additional samples? The reliance on reporting correlation sizes with respect to zero and relative sizes of correlations among independent variables can be highly misleading. "Anscombe's quartet" of different observable data displays for identical symmetric test findings is highly instructive in reaching this conclusion. Anscombe (1973) created four XY plots of four different data sets having the identical averages, standard deviations, and correlations to illustrate the great usefulness of showing relationships visually – such visual displays should be done before and/or after symmetric as well as asymmetrical testing. The study that follows does present XY plots of the models' performances in being able to consistently predict the outcome scores of cases.

Consequently, asymmetric case-based modeling/testing avoids the severe problems inherent in NHST that Gigerenzer (2004, 2010), Hubbard (2016), Armstrong (2012), Fiss (2011), Meehl (1978a), Zellner (2001), and Trafimow and Marks (2015) describe. Hubbard (2016) provides useful reviews on these widely known but equally widely ignored severe problems in using NHST. The present study expands on Hubbard's (2016) call for using "precise outcome models" by showing how to do "somewhat precise outcome testing" (SPOT) for indicating managers high in job satisfaction and the use of indexes for indicating the usefulness of SPOT-based models. The study's findings support the value and need for adopting an asymmetric causality stance: SPOT-based models are useful for creating and testing the predictive validity of unique antecedent configurations indicating low JS cases as well as additional models for indicating high JS.

The four core self-evaluations (CSEs) that Judge, Locke, and Durham (1997) propose occupy central roles in constructing the following case-based general theory of individual and contextual influences on JS. Judge et al. (1997) propose the following four CSEs as indicators of a higher order construct, the positive self-concept: self-esteem, generalized self-efficacy, locus of control, and emotional stability (low neuroticism). Unlike prior work focusing on establishing that each of the CSEs has a positive significant correlation with JS and that combining the four traits to form a single latent construct (i.e., positive self-concept) associates positively with JS, the study proposes, tests, and confirms that cases occur where low scores on some of the traits occur for cases (individuals) having high JS, and high scores on some of the traits occur among cases having low JS. Such cases are more than unexplainable blips. Such cases are likely due to contextual influences that are accountable by using asymmetric rather than symmetric modeling. The study that follows confirms that using all four in one algorithm screening model (i.e., identifying cases with high scores in all four traits) works well in identifying cases with high JS, but this screening algorithm identifies fewer high job-satisfaction cases than building a few (i.e., 3) unique configurations of two of the four traits. The study contributes by proposing a paradigm shift from variable-based theory construction and symmetric testing to case-based theory construction and asymmetric testing.

The present study also advances the theory of how to model contextual configurations that influence psychological conditions such as core self-evaluations that in turn influence occupational outcomes such as job stress, job strain, and job satisfaction. Heretofore, while most empirical studies present statistical summary demographic descriptions of cases in their samples of frontline employees or managers, these studies do not consider forming and exclude how different demographic configurations may influence the main psychological conditions (e.g., core self-evaluations); or, these studies examine demographic and psychological conditions as rivals in explaining work outcomes (e.g., Judge & Hurst, 2008). Using symmetric tests, Judge and Hurst (2008) present multiple regression models to demonstrate the individual relationship influences of age, gender, race, and core self-evaluations on job satisfaction, pay, and occupational status. The present study takes an asymmetric perspective to explain and predict how configurations of antecedent conditions affect specific outcomes rather than variable relationships. This study examines when a single demographic condition (e.g., older aged manager) is an ingredient in configurations indicating a high core self-evaluation and when the same condition is an ingredient in configurations indicating a low core self-evaluation score.

Case-level demographic configurations represent the contextual grounding in occupational psychology. The idea here extends Simon's (1990, p. 7) scissors metaphor into occupation psychology, "Human rational behavior is shaped by a scissors whose blades are the structure of task environments and the computational capabilities of the actor." Likewise, human demographic and specific industry characteristics and procedures may shape the psychological states of the actors and their occupational behavior and outcomes. A mid-level male manager working in the same industry for 25 years, married with no children living at home, working on a dairy farm with 1,000 cows, is likely to differ on core self-evaluations sub-traits from a farm manager with 5-years work experience, unmarried female working on a 500 hectare horticultural farm. The present study proposes and shows how to advance theory and how empirical research on different case-level contextual configurations affects psychological conditions of employees and their behavioral outcomes.

Following this introduction, second section provides a brief introduction to complexity theory tenets relevant to the research in HRM. Third section presents propositions and rationales constituting a case-based general theory of individual and contextual influences on JS. Fourth section presents the method for a large-scale empirical study testing the propositions in the theory. Fifth section presents the findings. Sixth section is the discussion section. Seventh section describes limitations in the study. Eighth section concludes with implications for HRM theory and practice, and suggestions for future research.

COMPLEXITY THEORY RELEVANCE IN HUMAN RESOURCES MANAGEMENT RESEARCH

Rather than seeking to identify variable relationships that are statistically significantly different from zero and the relative sizes of relationships, case-based theory construction and data analysis focuses on building models that indicate the same, or almost always the same, outcome – that is, cases having high scores in the outcome condition. The case-focused researcher seeks to construct models having consistent high accuracy in identifying cases having a specific outcome. "Outcome condition" is a more apt expression than dependent variable because case-based research focuses on computing expressions indicating case outcomes and not variable relationships.

Case-based model construction rests on a foundation of complexity theory tenets. Complexity theory tenets include the following propositions. First, no single antecedent condition is a sufficient or necessary indicator of a high score in an outcome condition. Thus, while the symmetric measure of association (correlation) of CSE individual traits as variables and JS as a variable may be positive, no one of the traits or one global summary measure of the four sub-traits will indicate cases with high scores in JS consistently. (Note the shift here from a focus on estimating a symmetric association among variables to estimating an asymmetric case-outcome condition.) Second, a few of many available complex configurations of antecedent conditions are sufficient indicators of high scores in an outcome condition. A "complex condition" is a configuration of two-or-more simple conditions. For example, the following word model is a complex condition, "Cases having high scores (e.g., top 20 percentile) across all four CSE sub-traits consistently will have high scores in JS."

Third, contrarian cases occur, that is, low scores in a single antecedent condition associates with both high and low scores for an outcome condition for different cases. Even if an association indicates a large effect size (i.e., $r \geq 0.50$;

Cohen, 1977), about 10% or more of the cases in the data set will indicate a reverse association to the main effect. Often, such contrarian cases do not occur as unaccountable blips but occur due to the alternative contexts that differ from the contexts associated with the principal main effect relationship. The pervasive practice dominating the reporting of main and moderating variable effects is to ignore such contrarian cases. Case-based models seek to explain and predict outcomes accurately for such contrarian cases.

Fourth, causal asymmetry occurs, that is, accurate causal models for high scores for an outcome condition are not the mirror opposites of causal models for low scores for the same outcome condition. Similar to Weick and Sutcliffe's (2007) focus on describing and explaining highly reliable organizations unique with respect to profit-focus behavioral theory of the firm, the study of cases exhibiting high JS is more unique than complementary to the study of cases exhibiting low JS. Different sets of complex configurations of antecedent conditions are necessary for the study of high JS versus low JS. Studies by Fiss (2011), Ordanini et al. (2014), and Wu, Yeh, Huan, and Woodside (2014) illustrate the causal asymmetry tenet in several contexts, including how different contexts with high happiness as an ingredient in different recipes indicate high as well as low job performance (e.g., Hsiao et al., 2015).

Fifth, creating a complex screening algorithm to identify cases with scores above a cutoff (e.g., above the 80 percentile) for each of few (e.g., 4) simple conditions appearing in the algorithm serves to increase consistency in identifying cases with high scores in an outcome condition than the use of a simpler algorithm of computing the sum of the simple conditions and establishing a cutoff of cases above the 80 percentile. In studies of firms or individuals, with the use of three or more simple conditions, less than half of the cases with scores above the 80 percentile on any one simple antecedent condition can be expected to have scores above the 80 percentile for all other simple conditions. A complex asymmetric model proposing that cases in the top quintile for each of the four CSE sub-traits are high in JS in the Judge, Erez, and Bono (1998) dispositional JS paradigm is a much tougher rule than proposing that cases in the top quintile of the sum of the four sub-traits are high in JS. In general, for models working well in identifying cases with high scores in an outcome condition, adding simple conditions to complex antecedent conditions serves to increase the accuracy while reducing the coverage of the models. In case-based modeling, achieving high consistency in correctly identifying cases with high scores in the outcome is the primary objective. Researchers accomplish models of high coverage of most cases with high scores in the outcome condition by constructing a few relevant models whereby each model provides high consistency but low coverage.

Table 1 is a summary of five tenets of complexity theory. Each of these tenets is applicable in constructing alternative models relevant for predicting, explaining, and describing either high JS or low JS cases. Such a case-based approach includes building contextual firm and individual case conditions (e.g.,

Table 1. Core Tenets of Complexity Theory.

Tenet	Concept	Description	Boolean Expression
T1	Insufficiency	High X may be necessary, but this condition is insufficient for identifying high Y	$X // \rightarrow Y$
T2	Equifinality	A few, not one, distinctly unique complex configurations of antecedents indicate the same outcome	$(X \bullet R) \leq Y + (\sim X \bullet T) \leq Y$
T3	Contrarian	Both high X and low X associate with high Y	$(X \bullet R) \leq Y + (\sim X \bullet T) \leq Y$
		Both high X and low X associate with low Y	$(X \bullet W) \leq \sim Y + (\sim X \bullet F) \leq \sim Y$
T4	Causal asymmetry	Complex antecedent conditions for low Y are not the mirror opposite of complex antecedent conditions for high Y	$(X \bullet R) \leq Y \neq (\sim X \bullet \sim R) \leq \sim Y$
T5	Emergence	System effects occurring in creating configurations of simple conditions are greater than the sum of the simple conditions (where SE = self-esteem, GSE = generalized self-efficacy, LC = locus of control, ES = emotional stability, and CSE = core self-evaluations)	$(SE \bullet GSE \bullet LC \bullet ES > CSE_{total})$

Key: Boolean algebra operational meanings: mid-level dot "•" indicates the logical "and"; sideways tilde "~" indicates negation; the plus size "+" indicates "or"; the less than or equal sign "≤" indicates that the scores for the model input statement are all or nearly all lower than scores for the outcome, Y or (Y • Z); the not equal sign "//→" indicates that the input model (simple or complex) does not indicate an asymmetric pattern that screens for Y or ~Y where "Y" refers to cases with high Y scores and "~Y" refers to cases with low Y scores, the negation of a Y score; "X" refers to high X scores and "~X" refers to low X scores. X, R, F, and W refer to simple antecedent conditions; Y and Z refer to simple outcome conditions; "≠" refers to causal asymmetry.
Note: A useful heuristic is to discretize scores for calibrating values of a variable into fuzzy-set scores so that all cases in the lowest quintile have fuzzy-scores ≤ 0.10 and cases in the highest quintile have fuzzy-scores ≥ 0.90. Configural analysis and setting consistency requirements are "fuzzy" in deciding what constitutes low (e.g., ~Y) and high (Y) scores and in deciding on the limit necessary for models of complex antecedent conditions to surpass to indicate high accuracy in predicting Y or ~Y.

age, nationality) along with more focal antecedent conditions (e.g., CSE subtraits) into the same models rather than the widespread practice of reporting summary tables of contextual conditions and then ignoring these conditions in modeling main and moderating effect hypotheses for variables of central interests. The following general model of individual and contextual configurations indicating high versus low JS cases illustrates this case-based approach.

Data Analytics Relevant to Complexity Theory

Because "scientists' tools are not neutral" (Gigerenzer, 1991, p. 264), a brief introduction to the use of set analysis appears here as a bridge connecting complexity theory to "statistical sameness testing" (Hubbard, 2016) via SPOT. The use of the statistical sameness versus statistical difference perspective occurs in adopting the paradigm shift to asymmetric SPOT from symmetric NHST. Fuzzy-set qualitative comparative analysis (fsQCA) is a Boolean theory and Venn set-based data analysis tool and conceptual basis for analyzing data on the basis of complexity theory. Because fsQCA applies the concept of set membership, a researcher needs to transform (i.e., calibrate) original measures to reflect the extent to which each condition for a case indicates membership in the condition. For fsQCA all variable measures are calibrated into fuzzy-set scores ranging from 0.00 to 1.00. These values indicate the degree of membership of the case in each condition. The set membership scores that result from calibrating original scores into fuzzy-set scores are not probabilities, but instead are transformations of ordinal or interval scales into degree of membership in the target set. "In essence, a fuzzy membership score attaches a truth value, not a probability, to a statement (for example, the statement that a country is in the set of development countries)" (Ragin, 2008, p. 183). Ragin (2008) emphasizes that fuzzy sets, unlike conventional variables, must be calibrated. "Because they must be calibrated, they are superior in many respects to conventional measures, as they are used in both quantitative and qualitative social sciences. In essence, I argue that fuzzy sets offer a middle path between quantitative and qualitative measurement. However, this middle path is not a compromise between the two; rather, it transcends many of the limitations of both" (Ragin, 2008, p. 174). Much of variation captured by ratio-scale indicators such as age and income is simply irrelevant to the distinction by low and high values. The original values must be adjusted on the basis of accumulated substantive knowledge in order to be able to interpret low versus high scores in a way that resonates appropriately with existing theory (cf. Ragin, 2008, p. 18). Ragin (2008) points out that there is a world of difference between living in a country with a gross national product (GNP) per capita of $2,000 and living in one with a GNP per capita of $1,000; however, there is virtually no difference between living in one with a GNP per capita of $22,000 and living in one with a GNP per capita of $21,000. Calibration of fuzzy-set measures addresses such issues directly. Fuzzy-set calibration makes use of external information on the degree to which cases satisfy membership criteria and not inductively derived determination (e.g., using sample means). Criteria need to be set for three breakpoints in fuzzy-set calibration with endpoints of 0.00 for full non-membership to 1.00 for full membership. The breakpoints include 0.05 for threshold for full non-membership, 0.50 for the crossover point of maximum membership ambiguity; and 0.95 for the threshold of full membership. Determination of the three breakpoints permits calibration of all original values into membership values using a direct method and an indirect method (see Ragin, 2008). Similar to the mathematics involved in calculating partial standardized regression coefficients for variables in MRA using the Statistical Packages for the Social Sciences (SPSS), performance of the mathematical calculations to calibrate all membership scores for a simple condition can be done by using a software routine in the program, www.fs/QCA. See Ragin (2008, pp. 104–105) for an example of using this procedure.

The original values in a 7-point Likert scale can be calibrated so that $1.5 = 0.05$; $4 = 0.50$; $6.5 = 0.95$, but the calibration selected depends upon the distribution of responses among the cases. This procedure was done in the study here. However, if respondent scores ignore an extreme score such as 1 or 7 on a Likert scale, the calibration scores would have been adjusted accordingly; for example, if only one respondent among 200+ respondents provided a strongly disagree response (score of "1") among several Likert items, then the calibration would need to shift upward. Typically, the median score is selected to represent the 0.50 membership score in calibrating a variable into a condition.

Index Metrics for Measuring Consistency and Coverage of a Complex Configuration

The consistency index gauges the degree to which the cases share a simple or complex condition in displaying the outcome in question – consistency is analogous to a correlation in statistical analysis. The coverage index in fsQCA assesses the degree to which a simple and complex causal condition (recipe) "accounts for" instances of an outcome condition – coverage is analogous to an r^2 in a statistical difference analysis. In QCA a consistency index above 0.85 with a coverage index of 0.45 indicates high membership scores in the outcome condition for nearly all high scores in the antecedent statement and a substantial share of the cases fitting an asymmetric sufficiency distribution. Consistency $\mathbf{(Xi \leq Yi) = \Sigma\{min\ (Xi, Yi)\}\ /\Sigma(Xi)}$ where Xi is case i's membership score in set X; Yi is case i's membership score in the outcome condition, Y; $(Xi \leq Yi)$ is the subset relation in question; and "min" dictates selecting the lower of the two scores. Coverage $\mathbf{(Xi \leq Yi) = \Sigma\{min\ (Xi, Yi)\}\ /\Sigma(Yi)}$. The formula for coverage of Y by X substitutes $\Sigma(Yi)$ for $\Sigma(Xi)$ in the denominator of the formula for consistency. See Ragin (2008) and Woodside (2013a, 2013b) for elaborations and numerical examples. Due to substantial space requirements necessary to fully describe the method, this section only provides an introduction to the theory and use of QCA. Ragin (2008) provides an extensive description of theory and method of QCA; a user's manual and software for QCA is available at www.fsQCA.com. QCA studies cases as configurations of causes and conditions rather treating each independent variable in a given analysis as analytically distinct and separate as done in conventional quantitative methods. "The key difference between the two is captured in the idea of a causal 'recipe' – a specific combination of causally relevant ingredients linked to an outcome. In set-theoretic work, the idea of a causal recipe is straightforward, for the notion of combined causes is directly captured by the principle of set intersection" (Ragin, 2008, p. 9).

Both symmetric (e.g., correlation) and asymmetric (e.g., consistency) measures of relationships can be misleading. A correlation can be high and yet an XY plot of the relationship may indicate X does not have a symmetric relationship with Y. Anscombe (1973) illustrates this point with his presentation of four substantially different XY plots having the identical correlation ($r = 0.76$). Anscombe (1973) stresses the need to show the XY plot of findings to verify the usefulness of the relationship of X and Y. Anscombe's (1973) recommendation is relevant when X is a complex antecedent condition and Y is a simple or complex outcome condition and a researcher is testing whether or not the findings support an asymmetric association. Consistency can be very high (≥ 0.90) but the plot reveals low and high Y outcomes to have about the same X scores. Consequently, the findings for the present study include showing several XY plots.

Fig. 1 includes four basic XY plots. Panel A in Fig. 1 illustrates the finding that X and Y do not vary in any systematic manner – the XY relationship is rectangular. Panel B illustrates the finding that X and Y have a symmetric

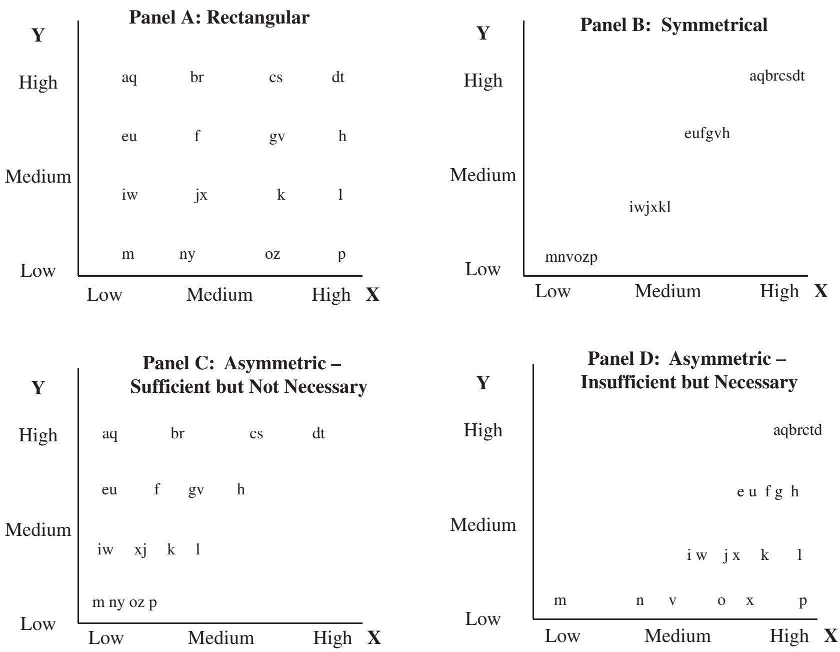


Fig. 1. Hypothetical Relationships where X is a Complex Configural Condition (e.g., CSE•~S•~T•D) and Y is Job Satisfaction. *Dictionary*: CSE = high core self-evaluation; S = stress; T = strain; D = dairy farm manager; "~" = negation.

relationship ($r \geq 0.80$); consistency is also high for the association in panel B (C1 = consistency ≥ 0.80). Panel C illustrates the finding that X and Y have a symmetric relationship: high X indicates high Y; low X associates with both low and high Y. For panel C data, the correlation is about 0.40 but the consistency is above 0.80 because the consistency index is a measure of an asymmetric relationship and not a symmetric relationship. For significant findings, almost all findings in management journals report correlation findings below 0.50 (except for reliability estimates) because the actual relationships observed are asymmetric but symmetric tests only are being applied. The asymmetric relationship in panel C indicates that high X is sufficient but not necessary for high Y to occur. SPOT is appropriate for testing asymmetric relationships. Asymmetric-based theory construction embraces the restriction of attempting to create useful models whereby high X indicates high Y − a screening model. The construction of asymmetric models to predict the negation of Y is possible; based on the causal asymmetry tenet in complexity theory, the prediction of the negation of Y involves additional theory construction and testing of additional causal, complex, antecedent conditions.

Panel D in Fig. 1 indicates a necessary but not sufficient condition − a second category of asymmetric association. High X is necessary for high Y to occur but low Y also occurs with high X. The correlation for the association X and Y in Panel D is the same value as the correlation for the XY data in Panel C. The consistency index is close to zero for the XY plot in Panel D. Many necessary but insufficient simple conditions are easy to identify but frequently do not contribute to advancing theory, for example, tractors are necessary but insufficient for effective horticulture farming.

A CASE-BASED GENERAL THEORY OF INDIVIDUAL AND CONTEXTUAL INFLUENCES ON JOB SATISFACTION

Fig. 2 is a visual summary of the general model demographics, core self-evaluations, job stressors and strains, and job satisfaction. Construction and empirical testing of the model rests on the foundation of complexity theory tenets and SPOT. Given that several studies examine, compare, and confirm asymmetric models' greater theoretical, analytical, and practical usefulness versus symmetric theory construction and testing (e.g., Frösén, Luoma, Jaakkola, Tikkanen, & Aspara, 2016; Gigerenzer & Brighton, 2009; McClelland, 1998; Ordanini et al., 2014), the present study focuses the space available on reporting the asymmetric-based theory and empirical findings. (Upon request, the complete data are available from either author for additional model construction and testing using NHST.)

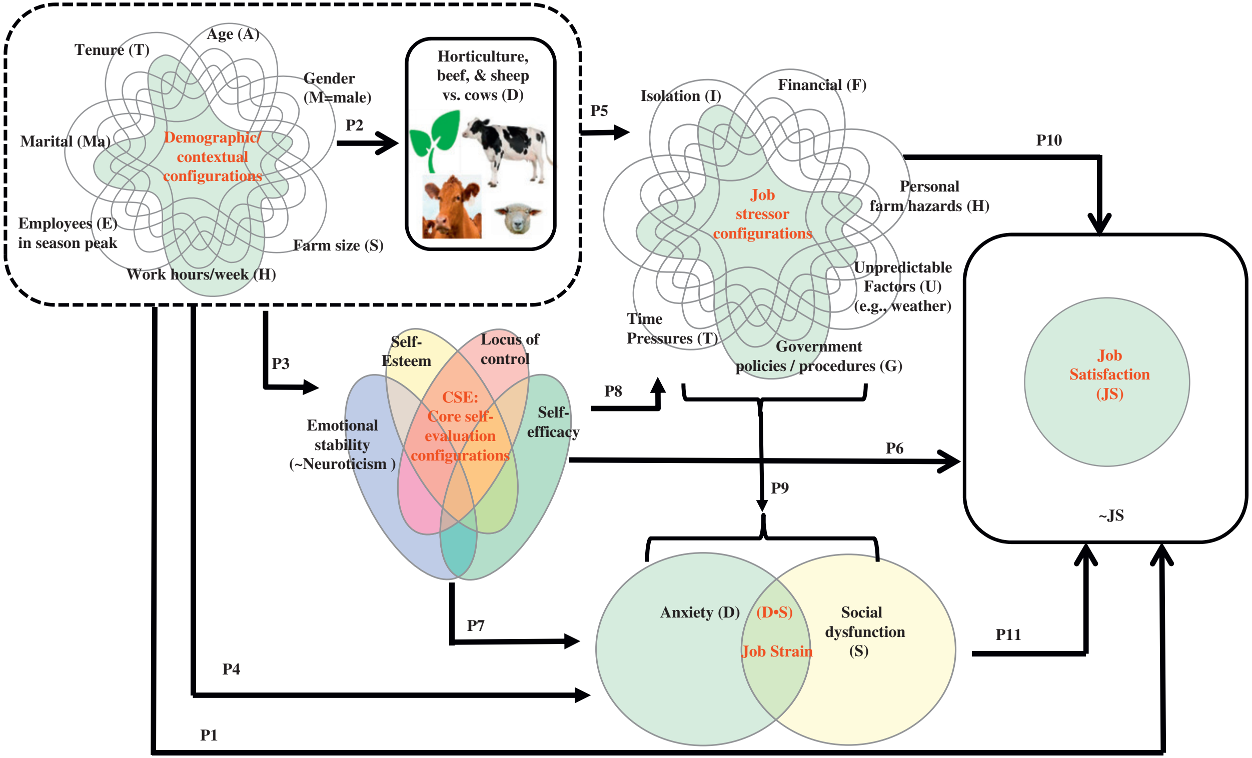


Fig. 2. General Configurational Model of Farmographics, Core Self-Evaluations, Job Stressors and Strains, and Job Satisfaction.

Fig. 2 includes 11 complex configurational antecedent-outcome propositions. To limit the appearance of complexity, the theory includes additional propositions beyond these 11 propositions that do not appear in Fig. 2. The additional propositions refer to improving the identification of outcomes conditions consistently by increasing the conditions in antecedent statements. For example, P12: a few complex configurations of demographic and CSE simple conditions increase accurate identification of high job satisfaction versus the limited complex configurations in propositions 1 versus 7 by themselves. P12 implies that while a screen for CSE is a useful model in identifying high JS cases, accuracy in identifying such cases substantially increases by increasing the complexity of the CSE screen using demographic information. The findings below do not support P13; the CSE screen alone proves to be an excellent rubric in identifying farm managers high in JS. However, a parallel version of P13 does receive support – when testing for the impact of a negative CSE screen on identifying farm managers who are low in CSE, including demographic conditions improves the accuracy of the negative CSE screening rubric. The present section focuses on describing the 11 principal propositions in the case-based general theory.

P1 to P5: Impacts of Complex Configurations of Demographic Conditions

P1 to P5 are propositions indicating that a few complex configurations of demographic conditions indicate high scores in specific outcome conditions. These propositions are fundamental building-block word computations that test such beliefs that certain persons having certain demographic profiles have high (or low) JS, CSE, stress configurations, job strain. "A few complex configurations" refers to the equifinality tenet that a few algorithms lead to the same outcome. For the present study, less than ten demographic configurations are likely to occur to accurately indicate high JS as well as the other outcome propositions involving demographic conditions. Applying the causal asymmetry tenet, the "less than ten" algorithm rule should apply to the negation of JS as well. Before the data analysis, a consistency requirement equal to 0.85 was set as a standard for identifying complex antecedent conditions that are highly accurate and consistent in identifying cases with high scores in the outcome condition. Consider for a moment that using only three levels (i.e., low, medium, and high) for five of the seven demographic conditions and two levels for marital status and gender, a total of 972 complex configurations are possible. Thus, the use of SPOT for identifying a few complex configurations that perform with high consistency in identifying certain outcomes represents a step forward for both theory and practice.

A total coverage requirement of 0.20 was set before examining the findings, that is, across the models that are found to be high in consistency; these models should include coverage of 20% or more of the cases with high scores in the outcome condition. For example, if the output of the analysis only indicates a single model with high consistency (≥0.85) but low coverage (≤ 0.20), then a claim of support is unjustifiable for the proposition that complex configurations of the antecedent conditions associate with the outcome.

P1a: A few demographic contextual configurations indicate high JS. P1b: A few demographic configurations indicate low JS. P1a and P1b build from the causal asymmetry tenet in complexity theory that the causes for a high versus low scores for an outcome condition differ in content also, not just valences of antecedent conditions. Findings from prior research in a consumer service context (Hsiao et al., 2015) support P1a and P1b. The belief that certain demographic configurations associate consistently with employees having high family-work conflicts who are disgruntled about their jobs have led to some national regulations preventing the collection of certain demographic information in hiring interviews (e.g., in Australia, firms are precluded from collecting marital status and children at home data to stop the use of "young, single, parent, less than high school" as a job-applicant rejection rubric). Consequently, more specific complex configurations indicating high JS may be identifiable than simply stating that a few configurations associate with high JS and others with low JS.

P2a: A few farmographic contextual configurations associate with dairy farm managers, others with the sheep farm managers, while other configurations associate with horticultural farm managers. Obviously, hiring and working hours vary during the seasons more so for horticultural farm managers than dairy farmers. But do demographic configurations provide highly accurate models of farmers by industry categories? Brief answer is that the findings do support P2a but only for dairy farmers.

P2b: A few farmographic models indicate not being a member of specific farming sub-industries. Given the asymmetric theory and analysis, the study should be able to identify who is not a dairy farmer by specific farmographic configurations. While P2b receives support for dairy farmers, the same cannot be stated for the other farming sub-industries.

P3a: A few demographic contextual recipes indicate high positive self-concept (i.e., high scores in a screen for overall CSE sub-traits). While Judge and Kammeyer-Mueller (2011) focus on the implications of stability in core self-evaluations for management, they mention that "much of management is about trying to mold the attitudes and motivation of individuals who are already in a job." As an example, Judge and Kammeyer-Mueller (2011) describe a laboratory study by Schinkel, van Dierendonck, and Anderson (2004) that included giving feedback to Dutch undergraduate participants on a bogus job performance test. After the test, all participants received a notice on non-membership among the top 20% performers on the test. Members in one group received extensive feedback with a rejection notice on their performances, whereas the members in another group received limited feedback (i.e., rejection notice only). The undergraduates who received feedback had a decrease in overall CSEs, but those who did not receive feedback had an increase in overall CSEs. Such one-setting laboratory findings for undergraduate students may have limited relevancy on the issue of stability of CSE.

P3b: A few demographic contextual recipes indicate the negation of positive self-concept (i.e., low scores in a screen for overall CSE sub-traits). The present study examines whether or not certain demographic recipes associate with not-high overall CSE, where overall CSE is measured as a screen. While the screen identifies the managers with high scores across each of the four sub-traits of CSE, if a manager scores low in any one of the four traits, the manager has a low final score for CSE. The findings below provide only limited support that demographic recipes indicate managers high in the CSE screen. However, the findings provide substantial evidence that some demographic recipes indicate membership in the negation of the CSE screen. Only one configuration of complex demographic conditions indicates high scores for the CSE screen; however, several configurations of complex demographic conditions indicate the negation of the CSE screen. Details appear below.

P4a: A few demographic recipes indicate job strain. P4b: Additional demographic recipes indicate the negation of job strain. Fig. 2 shows job strain as a recipe of two sub-traits: work-related anxiety and social dysfunction. Persons high on both work-related anxiety and social dysfunction are high on job strain. Wall, Jackson, Mullarkey, and Parker (1996) provide an extensive review of studies on the causes of job strain – all studies in the review use symmetric tests and Wall et al. provide additional findings from their own symmetric tests. All these tests do not actually identify cases (i.e., individuals) high in job strain. Wall et al. (1996) propose that high job demands and low ability to control contexts indicate high job strain. Associating with this perspective, the present study proposes that specific demographic recipes represent individuals perceiving high job demands. For example, a young farm manager, with high peak employment, working a large farm, not married, with low tenure no matter his/her farming industry (dairy, sheep, horticulture, or beef) is likely to have high job strain.

P4b: The negation of job strain is an outcome of additional demographic recipes. P4b indicates managers with low job strain should be identifiable by demographic recipes that include agricultural industry. Based on Wall et al.'s (1996) perspectives, the combination of demographic characteristics with membership in the high CSE screen should identify low job strain individuals. Thus, the analysis should confirm the following computation word model or similar models:

$$\text{cows}\bullet\text{tenure}\bullet\text{marital}\bullet\sim\text{peak\_employ}\bullet\text{size}\bullet\text{CSE\_screen} \leq \sim\text{job strain}$$

This model states that a dairy farm manager of a small farm with no high peak employment requirements and with a high score in the CSE screen has low job strain. The study is able to construct useful models of demographic plus CSE screen recipes for indicating the negation of job strain.

P5a: Demographic recipes indicate managers with high job stress. P5b: Additional demographic recipes indicate managers with low job stress. Prior research supports some value in the study of both the antecedent and consequences of job stressors. However, all prior research is based on asymmetric variable-focused theory and analytics with findings of small-to-medium effect sizes – mostly small-to-non-significant effect sizes (e.g., Kokkinos, 2007; Spector, Dwyer, & Jex, 1988).

The literature on stress in farming identifies several sub-traits of stressors (Deary, Willock, & McGregor, 1997; Walker & Walker, 1987). The present study includes examination of complex antecedent conditions and outcomes associated with six stressors. The six stressors include felt time pressure, government policies and procedures, unpredictable factors (e.g., weather), personal farm hazards, financial difficulties, and social isolation. The present study appears to be the first to show whether or not certain demographic configurations indicate cases (i.e., managers) with high JS in a screen of job stressors. The same observation holds for identifying managers identifiable by the negation of the job stressors' screen. The findings appearing below include strong support for P5a and P5b.

This study permits examination of whether or not Bart Simpson offers sage advice, "Don't have a cow, man!" The findings below do not indicate that the cows alone associate with high stress. The findings support the opposite advice – have cows indicate the negation of stress. Details appear in the findings section.

P6 to P8: Impacts of Complex Configurations of Core Self-Evaluations (CSEs), Job Strain, and Job Stressors

The summary of the general model in Fig. 2 includes three propositions of the impact of the four sub-traits of CSEs as well as a total score for CSE. Each proposition includes (a) identifying cases with high and (b) low outcome scores. In NHST research of whether or not a relationship exists, Chang et al. (2012) refers to measuring the impact of CSE individual sub-traits as the indirect approach and measuring a composite measure of CSE as the direct approach. These authors observe, "In terms of relative prediction of indirect and direct measures of CSE, results are mixed. While Judge, Erez, Bono, and Thoresen (2003) found that the CSES [indirect] out predicts a composite of the four traits, Gardner and Pierce (2009) found the opposite. Findings from out meta-analysis are also mixed" (Chang et al., 2012, p. 87). The present study offers a method to solve this inconsistency and, rather than focusing on the relative effect sizes of the individual sub-traits, the present study shows which configurations of sub-traits indicate similar high consistencies in predicting high JS as well as low JS.

P6a: More than one complex configuration of the four sub-traits of CSE, as well as an overall CSE screen, indicate high scores in JS. Thus, model 2 here states that managers with high scores across all four CSE sub-traits consistently have high job satisfaction:

$$\mathrm{SE}\bullet\mathrm{GSE}\bullet\mathrm{ES}\bullet\mathrm{LOC} \leq \mathrm{JS} \tag{2}$$

where SE = self-esteem; GSE = generalized self-efficacy; ES = emotional stability; LOC = local of control; JS = high job satisfaction. Model 2 represents an algorithm only a few managers are capable of achieving, that is, having high scores for each of the four CSE sub-traits. A manager with a low or moderate score for any one of the four traits would not be relevant to this screen and thus eliminated for the test. The prediction is that all of managers with high scores for all four sub-traits have high scores consistently in JS. Typically, a study creates and tests such asymmetric algorithms built in some wiggle room; that is, the study recognizes that a limited number of false positives are likely to occur even when the algorithm includes several hurdles to accomplish. For example, a priori to data analysis a researcher may set a consistency index greater than or equal to 0.90 to conclude that a model's findings be highly consistent.

P6b: More than one complex configuration of the four sub-traits of CSE indicate the negation of high scores in JS with high consistency. Model 3 is the negative overall screen for the negation of JS:

$$\sim\mathrm{SE}\bullet\sim\mathrm{GSE}\bullet\sim\mathrm{ES}\bullet\sim\mathrm{LOC} \leq \sim\mathrm{JS} \tag{3}$$

Model 3 states that managers having low scores for all four sub-traits consistently have low scores for job satisfaction.

The present study focuses on the usefulness of CSE as an indicator for high as well as low JS cases – not in testing the existence of positive or negative CSE and JS relationships but whether or not the construction of CSE indirect or direct screens is useful consistently as indicators of individuals (cases) high in JS – as well as estimating whether or not CSE screens can identify individuals (cases) who are low in JS. Because cases occur almost always that exhibit opposite associations to significant directional relationships with large effect sizes ($r^2 \geq 0.25$; Cohen, 1977), more than one model of complex antecedent conditions are necessary to capture a substantial share of total cases for an outcome condition.

An overall screening algorithm that requires cases to have high scores across each sub-trait represents a rigorous direct measure of CSE. Both the left and right side of the following statement represent this algorithm (model 4). Note that model 4 is simply a way of computing an overall score for CSE using Boolean algebra that represents a tough set of hurdles to accomplish.

$$\mathrm{SE}\bullet\mathrm{GSE}\bullet\mathrm{ES}\bullet\mathrm{LOC} = \mathrm{CSE}_{\mathrm{screen}} \quad (4)$$

$\mathrm{CSE}_{\mathrm{screen}}$ differs from $\mathrm{CSE}_{\mathrm{total}}$, in that $\mathrm{CSE}_{\mathrm{total}}$ is simply the summed scores across the average scores for the four sub-traits. For identifying cases with high scores for an outcome condition, $\mathrm{CSE}_{\mathrm{screen}}$ represents a tough screening rule and $\mathrm{CSE}_{\mathrm{total}}$ represents an easy screening rule. Thus, using matrix algebra (here, the plus sign, "+" is addition while in Boolean algebra, the plus sign represents the logical "or"):

$$\mathrm{SE} + \mathrm{GSE} + \mathrm{ES} + \mathrm{LOC} = \mathrm{CSE}_{\mathrm{total}} \quad (5)$$

P7: Core self-evaluations and job strain. Based on symmetric tests, a meta-analysis of 28 effect size estimates (Chang et al., 2012) indicates a negative moderate effect size impact of $\mathrm{CSE}_{\mathrm{total}}$ and job strain (corrected correlation, $\rho = -41$). Job strains are maladaptive responses that include psychological (e.g., negative emotions, exhaustion), physical (e.g., psychosomatic complaints), and behavioral components (e.g., substance abuse) (Chang et al., 2012; Spector & Jex, 1998). Rather than testing the direction of relationships among CSE sub-traits and overall CSE and job strain, the present study proposes and tests the proposition that managers with high scores across all four CSE sub-traits are low in job strain consistently. Also, the present study proposes and tests the proposition that managers with low scores across all four CSE sub-traits are high in job strain consistently:

$$\mathrm{P7a}: \mathrm{SE}\bullet\mathrm{GSE}\bullet\mathrm{ES}\bullet\mathrm{LOC} \leq {\sim}\mathrm{S}\bullet{\sim}\mathrm{D} \quad (6)$$

where S•D is job strain, that is the conjunction of S = social dysfunction and D = anxiety. Model 6 is the prediction that managers consistently high in CSE across all four CSE sub-traits are low in job strain.

$$\mathrm{P7b}: {\sim}\mathrm{SE}\bullet{\sim}\mathrm{GSE}\bullet{\sim}\mathrm{ES}\bullet{\sim}\mathrm{LOC} \leq \mathrm{S}\bullet\mathrm{D} \quad (7)$$

The general configurational model includes additional propositions regarding CSE sub-traits and job strain that do not appear in Fig. 2. For example, consider the following testable case-based propositions. High scores in two or three CSE sub-traits are sufficient for identifying a manager low in job strain. No one CSE sub-trait is sufficient for identifying managers consistently with low scores in job strain. Low scores in two or three CSE sub-traits are sufficient for identifying managers with high scores in job strain. No one CSE sub-trait is sufficient for identifying managers consistently with high scores in job strain.

Thus, the general configuration model proposes that high (low) scores for two-to-four of the CSE sub-traits need to be present to identify managers consistently having low (high) scores in job strain.

P8: Configurations of CSE sub-traits are useful in consistently identifying managers with scores low (high) in job stress for specific job stressors as well as for configurations of job stressors. Because of the complexity theory tenet indicating causal asymmetry, separate propositions are necessary for testing P8 for managers with high versus low scores for the job stressors. *P8a: Configurations of CSE sub-traits with high scores are useful in consistently identifying managers with scores low in job stress for specific job stressors as well as for configurations of job stressors. P8b: Configurations of CSE sub-traits are useful in consistently identifying managers with scores high in job stress for specific job stressors as well as for configurations of job stressors.*

$$\mathrm{SE}\bullet\mathrm{GSE}\bullet\mathrm{ES}\bullet\mathrm{LOC} \leq \sim \text{Job Stressor} \tag{8}$$

$$\sim\mathrm{SE}\bullet\sim\mathrm{GSE}\bullet\sim\mathrm{ES}\bullet\sim\mathrm{LOC} \leq \text{Job Stressor} \tag{9}$$

Because meta-analyses of symmetric tests indicate moderate overall effect sizes for $\mathrm{CSE}_{\mathrm{total}}$ and overall job stress ($\rho = -.43$, see Table 6 in Chang et al., 2012, p. 98), P8 includes the sub-proposition that reversals occur. *P8c: High scores in configurations of two or more CSE sub-traits indicate high scores for some managers in individual conditions and configurations of job stress*. "My high coping skills permits me to manage the high stress – even enjoy the high stress" is a trope summarizing such a positive-positive case for high CSE and high job stress. Given that the substantial majority of cross-tabulations of cases by their quintiles for any two measured variables indicate the presence of such reversals for some cases (8% to 15% of the total cases) whereby the variables have moderate and even high correlations, both theory and analytics need to account for such reversals. *P8d: Cases that are negative-negative for CSE and job stress also occur for one or more CSE sub-traits*. Additional factors including a delusional belief that the job is not stressful when, in fact, the job is highly stressful may be salient for specific managers reporting low scores for CSE sub-traits and low scores for job stress. The construction of cross-tabs brings to light such reversals to researchers. Theory and additional analyses need to be performed to account for positive-positive and negative-negative case reversals when the overall symmetric tests indicate a moderate-to-large negative relationship between the two variables.

P9 and P10: Job Stressors as Complex Antecedent Conditions

Symmetric tests indicate job stress to be a significant predictor of job strain. Correlation and structural equation modeling findings by Fogarty et al. (1999)

include an overall measure for stress to be the most influential independent variable indicating job strain (e.g., standardized partial regression coefficient equal to 0.48 in their study of 153 participants working full-time across a number of occupations). In a meta-analysis of four to nine studies, Spector and Jex (1998) report positive correlations that are moderate in effect sizes for three job stressors (interpersonal conflict at work scale, organizational constraints scale, and quantitative workload scale) and one job strain scale (physical symptoms inventory). Moving beyond a variable approach to data analysis and job satisfaction theory, the present study examines an asymmetric theory and tests of job stressors and job strain. The present study proposes that a few configurations of job stressors are able to identify farm managers with high job strain. The study also proposes and tests configurations of job stressors that are unique in identifying farm managers having low job strain.

P9a: Farm managers with configurations of high scores in four or more job stressors have high scores in job strain. P9b: Farm managers with configurations of low scores in four or more job stressors have low scores in job strain. P9c: Configurations of job stressors indicating high job strain different in their ingredients – not just valence – from the configurations of job stressors indicating low job strain. P9c reflects the causal asymmetry tenet in complexity theory that the complex causal conditions indicating high scores for an outcome differ in content from the causal conditions indicating low scores for the same outcome.

Referring to the six job stressors in Fig. 2, the occurrence of the following three example configurations would support P9a: I•F•H•T + F•H•G•T + I•H•U•G ≤ S•D, with "+" indicating the logical "OR." The following three example configurations would support P9b: ~I•~U•~G•~T + ~H•~U•~G•~T + ~I•~F•~G•~T ≤ ~S•D. Note that none of these example negation configurations for P9b are the mirror opposite of the example configurations for P9a; such a set of empirical findings would support P9c.

The present study includes selecting high scores in each of four or more job stressors as indicating high job strain because the configurational presence of four plus stressors is likely to be a tipping point (Gladwell, 2000) in causing high job strain. The ability to cope effectively breaks down and symptoms of job strain become self-apparent to these managers. The present study tests whether or not case-based asymmetric tests support or reject this theory.

P10a: Configurations of high scores in four plus job stressors are sufficient in consistently predicting farm managers with low job satisfaction. P10a reflects the view that high stress across several stressors is sufficient to cause low job satisfaction. Farm managers are likely to view the presence of multiple job stressors not only to cause high strain but as support for concluding that the job dissatisfies. Prior symmetric tests include findings that job stress relates negatively to job satisfaction across for separate studies (Fogarty et al., 1999; Sprietzer, Kizilos, & Nason, 1997). However, the present study contributes by proposing and testing the proposition that configurations of job stressors alone are sufficient for identifying farm managers with high job dissatisfaction.

P10b: Configurations of low scores in four plus job stressors are insufficient for consistently predicting farm managers with high job satisfaction. Rationale: High job satisfaction has to include additional psychological conditions than stress-free work-days. While high scores in several job stressors can cause farmers to conclude that they are unhappy, low scores in several job stressors alone may cause death by boredom; thus, configurations of low job stressors is insufficient for predicting high JS. The presence of high job stressors can hurt but their absence does little to help job satisfaction.

P11: Job Strains and Job Satisfaction

P11: High job strain alone is sufficient for identifying cases of low job satisfaction consistently: $D{\bullet}S \leq JS$. As appearing in Fig. 2, job strain is the configuration of high anxiety and high social dysfunction. Prior symmetric research focuses on examining the impact of global metric of job strain on JS; for example, Fogarty et al. (1999) report a standardized partial regression coefficient equal to $-.39$ ($p < .001$) for the impact of strain on JS – an impact significantly larger than three additional effects significantly influence JS. However, a single metric of job strain is likely to be an insufficient screen for identifying only high scores in JS because the relationship between job strain and JS is not symmetrical – cases occur where managers report high job strain and high JS. This proclamation is verified easily by constructing quintiles for both job strain and JS and cross-tabbing the two sets of quintiles. High strain identifying high JS consistently is likely to occur only by creating tough screening requirements of two or more subscales of strain. The empirical test following this presentation of the case-based theory examines the veracity of this line of reasoning.

METHOD

For the present study, a national (New Zealand) online and mail survey of farm managers ($n = 1{,}041$ usable responses) was completed in 2010 to examine the case-based model of JS empirically. Agriculture in New Zealand is the largest sector of the tradable economy, contributing about two-thirds of exported goods in 2006–2007 (Brazil, 2008). The New Zealand agricultural sector is unique in being the only developed country to be totally exposed to the international markets since subsidies, tax concessions, and price supports were removed in the 1980s (Hutching, 2006). Pastoral farming is the largest land use but there are increases in land area devoted to horticulture.

Agriculture is the top ranked industry in New Zealand by income. The following summary is a short briefing on the agriculture industry (Products, 2016). About 50% of total export income comes from meat, dairy products, and wool; the land supports some 68 million sheep and 4.8 million beef cattle. New Zealand is one of the world's largest exporters of lamb and mutton, has a growing beef industry (about 75% of which is produced in the North Island), and supplies about 90 countries with meat (the major markets are the United Kingdom, Iran, Russia, Japan, United States, and Canada). New Zealand is also one of the largest and most efficient exporters of dairy products. The combination of a good growing climate, stable rainfall, and lush grass year-round has produced an average herd of about 120 cows; most of the 3.3 million dairy cows in the country are Jerseys or Friesians (that's one cow per New Zealand resident). Butter (mostly to the United Kingdom) and cheddar cheese (mostly to Japan and the United Kingdom) are the major dairy exports, but casein (mainly to the United States) and skim-milk powder (to a number of countries, mainly in Asia) are also in demand. New Zealand's rich and creamy dairy products are among the best in the world. Sheep are a predominant part of the landscape throughout the whole of New Zealand. New Zealand is the second-largest producer of sheep (after Australia) and largest supplier of medium-to-coarse crossbred wool (for carpets, upholstery, and clothing) in the world, with an average flock of about 1,800 sheep. Most of the crops – wheat, barley, maize, oats, vegetables, berry fruit, and tobacco – are grown for the local market. However, malting barley, herbage seeds, some herbs, and oilseed rape have become export crops. Grass and clover seed markets have developed in the United States, the United Kingdom, and Australia. The citrus export industry has grown dramatically, as kiwifruit, tamarillos, feijoas, and passionfruit have increased in popularity worldwide; apples and pears are also important exports. Orchards in the North produce apples, apricots, peaches, plums, nectarines, berry fruit, cherries, lemons, and oranges, mostly for local consumption, but increasingly for export.

Measures

Psychometric analysis of all measures used in the present research supported the conclusion that all have adequate internal consistency. This section provides details for each of the scales in the study.

Stressors

Stressors were measured using the Edinburgh Farming Stress Inventory (EFSI). The EFSI was created by Deary et al. (1997). A standard question in the EFSI references "Changes in Common Agricultural Policy," which was considered relevant only to the European farmers, was omitted. A total of six domains, consisting of 34 items, to assess farm-related stress were identified in the inventory original pool: government bureaucracy; financial debts; unpredictable factors in farming (such as weather and machinery breakdown at busy times; time pressures; personal farm hazards; and geographical isolation; Deary et al., 1997). The questionnaire was prefaced by the statement, "Each of the items and situations below represents a potential source of farming-related stress. The respondents were instructed to rate the severity and frequency of the occurrence of the stressors, using a scale from 1 to 5, "none" to "very severe," respectively.

Strain

Strain was measured using the General Health Questionnaire-12 (GHQ-12) (Kalliath, O'Driscoll, & Brough, 2004). The General Health Questionnaire is in use widely to detect psychiatric disorders in a community (Goldberg & Williams, 1991), and psychological strain (Winefield, Goldney, Winefield, & Tiggermann, 1989). Low scores indicate low levels of psychological strain and high scores indicate high levels of psychological strain. The measurement of the GHQ-12 employed a similar scale to the prior research with a six-point response scale ranging from 1 = "never" to 6 = "all the time." The GHQ-12 consists of six positively worded items (such as "Felt capable of making decisions about things"; "Been able to concentrate on what you are doing") and six negatively worded items (such as "Been thinking of yourself as worthless person"; "Been feeling unhappy or depressed"). Full membership in the high job strain cases in the study are defined to be farmers who score in the 90th percentile for both anxiety and social dysfunction subscales in the study's metrics for job strain.

Core Self-Evaluations

Using the instrument developed by Judge and Bono (2001), the study measured the 12-items scale of "Core Self-Evaluations." Of the 12 items, 6 are positively worded and 6 are negatively worded. Respondents were asked to express the extent of their agreement to questions such as "I complete my tasks successfully"; "When I try, I generally succeed"; and "Sometimes when I fail I feel worthless", "Sometimes I feel depressed" (reverse scored). The CSE scales include items measuring four CSEs: self-esteem, self-efficacy, locus of control, and emotional stability (not neurotic).

Judge and Bono (2001) report that self-esteem is the basic appraisal people make of themselves. At its core, self-esteem is the most fundamental core evaluation of the self, because it is the overall value that one places on oneself as a person. The evidence is substantial that self-esteem relates to job satisfaction (Locke, McClear, & Knight, 1996). Although Bandura (1997) treats self-efficacy as task specific, Judge et al. (1997) extend the concept to a global level. Judge et al. defined generalized self-efficacy as one's estimates of one's capabilities to mobilize the motivation, cognitive resources, and courses of action necessary to exercise general control over events in one's life. Locus of control is the degree to which individuals believe that they control events in their lives (internal locus of control) or believe that the environment or fate controls events (external locus of control; Rotter, 1966). Individuals who score high on measures of neuroticism are likely to be insecure, guilty, and timid (Costa & McCrae, 1988). Neurotic individuals also are prone to anxiety, which manifests itself in tendencies to be fearful of novel situations and susceptibility to feelings of dependence and helplessness (Costa & McCrae, 1988).

While prior research measures the associations of individual sub-traits of CSE and a global measure of CSE with JS, the present study examines which configurations of the four sub-traits as well as whether or not a global screening condition across all four sub-traits identifies farm managers with high JS. The study also asks if the negation of specific CSE sub-traits with additional sub-traits accurately indicate the negation of JS. Prior symmetric testing examines the relative effect sizes of individual CSE sub-traits on JS. The present asymmetric testing examines if configurations of the sub-traits are sufficient for identifying specific outcomes, that is, farm managers with high JS. Separately, the present study considers whether additional sub-trait models are sufficient for identifying farm managers high in the negation of JS.

Job Satisfaction

Job satisfaction was measured with five items from the Brayfield-Rothe (1951) index of job satisfaction, using a 7-point Likert scale ranging from 1 = "strongly disagree" to 7 = "strongly agree," with the neutral response being "neither agree nor disagree" (such as "I feel fairly satisfied with my present job").

Correlations and Confirmatory Factor Analysis

Descriptive statistics and correlations among variables appear in Fig. 3. A measurement model, which involved four latent constructs, was estimated using maximum-likelihood method in the AMOS version17 program. The model is

	Demographics							Stress						Core Self-Evaluations				Job Strain		Job Satisfaction
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Gender		-07*	14	01	-03	14	19	03	01	-03	-12	-08*	-10	04	06	09	08	-03	-14	03
2 Cows (dairy)			- 15	07*	-06*	16	-32	-11	-07*	00	07*	07*	-08*	08*	-12	-03	-01	03	09*	09
3 Years				05	02	-00	50	05	17	-05	-03	05	01	02	03	03	07*	-03	-05	02
4 Farm size					-00	05	-03	-01	05	-01	04	-03	-02	06	-01*	-01	02	00	-02	07*
5 Employ peak						-09	08*	09*	06*	01	05	-02	07*	-01	-07*	-00	-05	03	-01	-04
6 Hours		Farmographics					-27	10	06	04	22	11	03	06	-05	-09*	-12	11	13	-01
7 Age								01	15	-06	-19	-05	-07*	-06*	-02	10*	11	-07*	-06	01
8 Financial									27	30	33	25	23	-14	-32	-16	-20	27	-16	-17
9 Gov. policy & proc										18	31	29	26	-03	-14	-08*	-14	10	06	-10
10 Isolation											43	42	19	-12	-16	-11	-15	07*	16	-14
11 Time pressure												39	42	-16	-42	-26	-27	23	28	-25
12 Farm hazards								Stressors					31	-11	-14	-15	-19	08*	19	-14
13 Unpredictable														-14	-18	-21	-20	14	15	-20
14 Self-esteem															46	32	42	-12	-25	47
15 Locus of control																33	41	-31	-34	50
16 Self-efficacy															CSE		52	-25	-26	33
17 Not neurotic (emotional stability)																		-27	-29	43
18 Anxiety																			46	-26
19 Social dysfunction																				-39
20 Job satisfaction																				
Mean	.80	.53	19.4	340.4	5.9	53.8	50	198	32	21.4	78.7	32.7	8.3	6	5.6	5.0	4.8	140.5	309.3	17.8
Standard Deviation	.40	.47	12.6	1261	12	18.4	11.4	433	30	61	96.6	41.9	4.7	.63	.97	1.3	1.3	448.7	846.6	2.5

Fig. 3. Correlations of All Independent Variables with Job Satisfaction. *Note*: Decimals omitted. Significance: *$p < .01$; underline $p < .001$.

an improved fit when the value of the measurement model chi-square is less than that of the baseline model chi-square value, as suggested by Anderson and Gerbing (1988). Generally, for a model to be acceptable, the RMSEA value has to be less than .08 (Joreskog, 1993). Similarly, SRMR values less than .08 are indicative of a good fit and the minimum acceptable value of CFI is .90 (Hu & Bentler, 1999). Missing values of the data matrix represent less than 5% and are considered random. Since all the variables have a high reliability (α >.70), the average value was used to impute missing values. To validate the maximum-likelihood estimation, the missing values were replaced with the mean of the respective indicators. The respondent's own observed items for each of his or her missing items reflect the substitution of the mean for the missing item.

The dotted boxes in Fig. 3 indicate key patterns among the symmetric associations. The one large effect size among the farmographics is unsurprising: age of the farm manager associates positively with years working in farming ($r = .50$). The farmographics include dairy farming with the variable scaled to include five levels from 1.00 for a large (300+ cows) to zero cows. Note that the correlations for dairy farming include an inconsistent pattern of associations with stress, a positive association with strain, and a positive association with JS. The pattern does not provide substantial support for adopting Bart Simpson's advice about not having a cow. However, examining the patterns of correlations is unsuitable for reporting if dairy farming associates with farm managers having high stress. The findings below include evidence that dairy farming along with additional farmographics indicates managers having low stress and dairy farming is not an ingredient in farmographic configurations indicating farmers with high stress or high strain.

The patterns of the correlations in Fig. 3 indicate high nomological validity for these symmetric findings. For example, each of the four CSE sub-traits associates positively among themselves and with JS; JS associates negatively with job stressors and job strain. Judge and Bono (2001, p. 84) mention that prior research includes criticisms that available research does not provide much clarity in terms of which of the CSE sub-traits are most "fruitful" in explaining JS. The framing of CSE sub-traits as rivals in explaining JS follows from using MRA/SEM for data analysis – the output of such analysis includes standardized partial regression weights of influence (beta coefficients) for the four CSE sub-traits. Such analyses mismatch theory and analytics (Fiss, 2007). Rather than viewing the four sub-traits as rivals in explaining JS, the present study asks which of the configurations of the four sub-traits are sufficient (if any) in accurately indicating high scores in JS. Rather than viewing asymmetric analysis as complementing symmetric analysis (i.e., the "let's make nice" stance, see Misangyi et al., 2016), the present study adopts Hubbard's (2016) perspective that symmetric testing of significance of positive and negative directionality of relationships and the relative sizes of beta coefficients are corrupt research (cf. Woodside, 2014). Consequently, the present study goes beyond symmetric tests in case-based, SPOT. Principally, the present study asks, which complex antecedent conditions consistently indicate farm managers high in JS? As well as asking, can farmographic configurations alone indicate high JS consistently? The case-based model also proposes additional complex configurations for identifying specific case-based outcomes.

Participants

Over 6,000 registered farm managers are members of New Zealand five major farming organizations. In 2011 these five farming organizations agreed to distribute the questionnaires to their members by mail and provided an online response option through email. Participation was voluntary and anonymous. There were 1,041 questionnaires returned, representing a 17.4% response rate. The total breakdown of responses includes 46% (479) online survey and 54% (562) mail survey. The sample respondents consists of 80% (819) men and 20% (207) women with a median age of 48 years (SD = 11.6), consistent with the New Zealand labor force participation rate for women in farming. Participants reported working an average of 54 hours (standard deviation = 19) per week. This sample worked longer hours than the standard paid working hours per week for New Zealand's working population (about 40 hours per week over the past 20 years) (Bascand, 2009).

FINDINGS

This section reports findings including asymmetric empirical models that support or refute the 11 propositions in Fig. 2. This section includes additional "computing with words" (Zadeh, 1996) asymmetric models to describe deep configurational models that include ingredients covering farmographic, CSE, job stressors, and job strain that should and do predict high JS. The section also reports additional deep configurational models that include farmographic, CSE, job stressors, and job strain ingredients that should and do predict low JS.

Findings for P1: Farmographic Configurations Indicating Job Satisfaction

The findings support P1a: A few demographic contextual configurations indicate high JS. P1b: A few demographic configurations indicate low JS. Table 2a describes six configurations of farmographics that indicate high JS. All six models have high consistencies, that is, nearly all cases scoring high on each of these six models have high scores on JS. Note that in Table 2a none of the simple antecedents are high or low consistently across all six models – though being

Table 2a. Farmographic Configurations and Job Satisfaction.

Model	hours	peak_employ	marital	size	gender	tenure	age	C1	C2
1	~	•	•	•	~	•		0.87	0.10
2	~		•	•	•	•	•	0.88	0.04
3		•	•	•	~	•	•	0.89	0.09
4	•	~	~	•	~	~	~	0.89	0.04
5	~	~	•	•	~	~	•	0.88	0.08
6	•	•	•	~	~	~	•	0.88	0.07

Overall: Solution consistency, C1 = 0.83; Solution coverage, C2 = 0.15.
Note: Mid-level dot "•" indicates presence of antecedent condition in the model; sideways tilde "~" indicates the negation of the antecedent condition in the model; empty space indicates absence of the antecedent condition in the model; absence indicates that the antecedent condition does not contribute or take-away from the consistency of a given model.
P1a: A few farmographic/contextual configurations indicating *high* job satisfaction (at high consistency levels (C1 ≥ 0.88)).
Model: job_sat_c ≥ f (hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure, age_c).

married appears in five of the six models. The combination of married and large farm appears in four of the six models. Being female (~G) appears in five of the six models. The first model in Table 2a has the highest coverage: a farm manager working a low number of hours per week, hiring workers for peak employment, married, managing large farms, female, and having lengthy tenure; age is not an ingredient in model 1.

Note in Table 2a that the minimum requirement for entry into the solutions was set at a consistency equal or greater than 0.88. This high requirement keeps the number of solutions to a minimum whereby the coverage for each model includes more than one case. The resulting models in Table 2a equals 0.15 − the six useful farmographics models fail to account for the majority of cases high in JS. However, the models are useful for identifying cases fitting each screen to be high in JS.

The findings do not support P1b. P1b is the statement that a few demographic contextual configurations associate with dairy farm managers, others with the sheep farm managers, while other configurations associate with managers in the horticultural farm managers. Details of findings appear in Table 2b. None of the configurational models in Table 2b have a sufficiently high consistency to be useful for identifying farm managers with low JS. Table 2b includes nine models that are marginally useful in identifying farm managers high in the negation of JS. Interestingly, all nine models include female farm managers. Marital status is not an ingredient in any of these nine models. These two characteristics in combination do not assure identifying farm managers low in JS. To find farm managers consistently having low JS, additional information about them is necessary beyond their farmographic profiles.

Table 2b. Farmographics and the Negation of Job Satisfaction.

Model	hours	peak_employ	size	gender	tenure	age	C1	C2
1		•	~	~	~		0.78	0.13
2	~		•	~	•		0.78	0.11
3	•		~	~	~	•	0.80	0.09
4	~	•		~	~	•	0.78	0.09
5	~	•	~	~		•	0.77	0.09
6		•	•	~	•	~	0.79	0.11
7		~	•	~	•	•	0.79	0.10
8	•	•		~	~	~	0.80	0.11
9	•	•	•	~		~	0.80	0.10

Overall: Solution consistency, C1 = 0.72; Solution coverage, C2 = 0.19.
Note: Mid-level dot "•" indicates presence of antecedent condition in the model, sideways tilde "~" indicates the negation of the antecedent condition in the model; empty space indicates absence of the antecedent condition in the model. Absence of a condition indicates that the antecedent condition does not contribute or take-away from the consistency of a given model; marital status is not a contributory condition for indicating high scores in not JS.
P1b: A few farmographic configurations associate with the negation of job satisfaction (the consistency levels indicate informative models but the levels are lower than the consistency levels of the models predicting for high JS) (C1 requirement = 0.80).
Model: not_js_c ≥ f (hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, age_c).

P2: Farmographics for Specific Farm Industries

The respondents included 496 dairy farmers; 142 sheep farmers, 221 horticultural farmers, and 141 mixed sub-industry farmers. P2 receives partial support. P2: A few farmographic contextual configurations indicate dairy farm managers accurately, but no additional configurations indicate sheep farm managers or managers in the horticultural farm managers consistently.

Table 3a includes eight models that identify dairy farm managers consistently. Six of the eight models include young farmers with only a few years of farming. All eight models include young as an ingredient in identifying dairy farmers. Thus, young is a local necessary but not sufficient condition for identifying dairy farmers.

Table 3b includes eight different asymmetric models of farmographic configurations identifying the negation of farm managers. Note that older farm manager appears in five of the eight models in Table 3b. However, young farmer appears in three of the models. These findings illustrate the complexity theory tenet that reversals occur in how a simple antecedent condition may impact an outcome condition. Young farmer may indicate dairy farm manager; young farmer may indicate not a dairy farm manager. To understand which way young age indicates dairy farmer requires creating complex configurations that indicate specific outcomes consistently.

Table 3a. Farmographics Indicating Dairy Farmers.

Model	age	tenure	gender	size	peak_employ	hours	marital	C1	C2
1	~	~	•	•	~	•	~	0.84	0.07
2	~	~		~	~	•		0.84	0.03
3	~	~	~			•	•	0.81	0.11
4	~	~	~	~		~	~	0.87	0.03
5	~	~	•	~		~	~	0.82	0.04
6	~		•	~	~	•	~	0.84	0.05
7	~	~	~	•	•		•	0.84	0.11
8	~	•	•	•	•	•	~	0.83	0.04

Overall: Solution consistency, C1 = 0.82; Solution coverage, C2 = 0.34.
Note: Mid-level dot "•" indicates presence of antecedent condition in the model, sideways tilde "~" indicates the negation of the antecedent condition in the model; empty space indicates absence of the antecedent condition in the model. Absence indicates that the antecedent condition does not contribute or take-away from the consistency of a given model.
P2a: Demographic/contextual recipes influence job occupation specialty: working in dairy farming. P2 receives support.
Model: dairy_c ≥ f (age_c, tenure_c, gen_cc, size_c, peak_emp_c, hours_c, marital_c).

Table 3b. Farmographic Models for Not Being a Dairy Farmer.

Model	hours	peak_employ	marital	size	gender	tenure	age	C1	C2
1	~		~	~		~	~	0.90	0.06
2	~		•	~		~	•	0.90	0.28
3	•	~	~		~	~	~	0.86	0.04
4	~	~	~	~	•		~	0.88	0.05
5		•	•	~	~	~	•	0.87	0.08
6	~	•	•	~	•		•	0.89	0.25
7	•		~	~	•	•	•	0.89	0.05
8	~	~	~	~	•	~		0.89	0.05
9	~	~		~	•	~	•	0.89	0.18

Overall: Solution consistency, C1 = 0.88; Solution coverage, C2 = 0.40.
Note: Mid-level dot "•" indicates presence of antecedent condition in the model; sideways tilde "~" indicates the negation of the antecedent condition in the model; empty space indicates absence of the antecedent condition in the model. Absence indicates that the antecedent condition does not contribute or take-away from the consistency of a given model.
P2b: Farmographic configurations influence placement in job occupation specialty: Not working in dairy farming. Nine models with consistency cutoff at 0.88. Models here are less complex than models leading to placement in dairy industry.
Model: not_cows_c = f (hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, age_c).

Attempts made to predict beef and sheep, horticulture, and mixed animal and crops farm operations using the demographic conditions resulted in failure. The analyses support P2 only for the tests for dairy farming. However, the additional farming sectors are ingredients in the recipes that accurately predict high scores in the additional outcome conditions appearing in Fig. 2.

Findings Support P3: Farmographics Indicate Core Self-Evaluations

Tables 4 through 10 present findings that examine the associations of farmographics on core self-evaluations (CSEs). This section reports findings for each sub-trait as well as easy versus tough overall screens for a global measure of CSE. For each sub-trait, the analyses include constructing models for identifying farm managers with high membership scores on the sub-trait as well as constructing separate models identifying models of managers with low membership scores on the sub-trait. The study includes applying both sets of analyses for the easy and tough screens for global CSE.

Farmographic Configurations and Self-Esteem. As "the most fundamental manifestation of core self-evaluations as it represents the overall value that one places on oneself as a person" (Judge & Bono, 2001) the first set of findings focus on self-esteem. Table 4a includes five models of farmographic models indicating farm managers with high self-esteem. To limit the length of this report, this section of the findings focuses only on one sub-industry category among the farmographic conditions: dairy farming. (Additional findings that include details of farmographics and CSE sub-traits for horticulture, beef and sheep, and mixed farm managers are available from the authors.)

All five of these models include the presence (not absence) of dairy farm managers. However, note in Table 4 that as a condition, dairy farm manager is insufficient by itself to be a consistent indicator of high self-esteem. While dairy farm manager may appear to be a necessary condition even if insufficient, this conclusion is incorrect because Table 4a reports only the models at the highest levels of accuracy for identifying high self-esteem (and the findings are restricted to dairy farming or not dairy farming without direct examination of the additional farming sub-industries). The findings do support the conclusion that using farmographics for identifying dairy farm managers with high self-esteem is easier to do than identifying managers high in self-esteem who are not dairy farmers. Four of the five models include young age as an ingredient in the recipes; one model includes older farm managers as an ingredient. The most telling observation is the general point that farm managers with high self-esteem are identifiable by farmographic configurations (Table 4b).

Farmographic Configurations and Self-Efficacy. Self-efficacy is a self-estimate of one's fundamental ability to cope, perform, and be successful. Table 5a describes four farmographic models that indicate farm managers with high

Table 4a. Testing P3 by Farmographic Models for Identifying Farm Managers with High Self-Esteem.

	Model	raw coverage	unique coverage	consistency
1	hours_c*~peak_emp_c*~marital_c*~gen_cc*~tenure_c*cows_c*~age_c	0.03	0.01	0.93
2	peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*cows_c*age_c	0.09	0.04	0.94
3	~hours_c*~peak_emp_c*~marital_c*~size_c*gen_cc*~tenure_c*cows_c*~age_c	0.03	0.01	0.93
4	~hours_c*~peak_emp_c*marital_c*size_c*gen_cc*tenure_c*cows_c*~age_c	0.13	0.08	0.93
5	hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*~age_c	0.04	0.01	0.93
Solution coverage: 0.20; solution consistency: 0.92				

Note: Dairy farming is an ingredient in all five models. Dairy farming by itself is insufficient for indicating high self-esteem. Young age appears in four of the five models. Dairy farming and young age are initial indicators of possibly a farm manager high in self-esteem.
Model: self_esteem_c ≥ f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.93.

Table 4b. Testing P3 by Farmographic Models for Identifying Farm Managers with Low Self-Esteem.

	Model	raw coverage	unique coverage	consistency
1	~hours_c*peak_emp_c*marital_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.096	0.00	0.94
2	hours_c*~peak_emp_c*~marital_c*~gen_cc*~tenure_c*cows_c*~age_c	0.04	0.01	0.94
3	hours_c*marital_c*~size_c*~gen_cc*~tenure_c*~cows_c*age_c	0.085	0.00	0.95
4	~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*~cows_c*age_c	0.09	0.00	0.94
5	hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c	0.08	0.01	0.93
6	~hours_c*~peak_emp_c*~marital_c*~size_c*gen_cc*~tenure_c*~cows_c*age_c	0.04	0.01	0.95
7	~hours_c*~peak_emp_c*~marital_c*size_c*gen_cc*~tenure_c*cows_c*~age_c	0.04	0.01	0.95
8	~hours_c*~peak_emp_c*marital_c*~size_c*~gen_cc*~tenure_c*cows_c*age_c	0.07	0.01	0.94
9	~hours_c*peak_emp_c*marital_c*~size_c*~gen_cc*~tenure_c*~cows_c	0.10	0.00	0.94
10	peak_emp_c*marital_c*~size_c*~gen_cc*~tenure_c*~cows_c*age_c	0.09	0.00	0.95
Solution coverage: 0.19; solution consistency: 0.90				

Note: Not a dairy farmer appears in 7 of these 10 models indicating low self-esteem. Not a dairy farmer is insufficient alone is insufficient for indicating low self-esteem.

Model: not_self_esteem ≥ f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.94.

Table 5a. Testing P3 by Farmographic Models Indicating High Self-Efficacy.

	Model	raw coverage	unique coverage	consistency
1	~hours_c*peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*age_c	0.09	0.06	0.86
2	~hours_c*~peak_emp_c*~marital_c*size_c*gen_cc*~tenure_c*cows_c*~age_c	0.03	0.01	0.88
3	~hours_c*~peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*~cows_c*age_c	0.04	0.01	0.89
4	~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*age_c	0.04	0.00	0.92
Solution coverage: 0.11; solution consistency: 0.85				

Note: Not long hours is an ingredient in all four models indicating high self-efficacy. However, not long hours is insufficient by itself in indicating high self-efficacy. A key point: a few farmographic configurations are useful in identifying farm managers high in self-efficacy.
Model: self__eff_c ≥ f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.88.

Table 5b. Testing P3 by Farmographic Models Indicating the Negation of High Self-Efficacy.

	Model	raw coverage	unique coverage	consistency
1	hours_c*~peak_emp_c*~marital_c*~gen_cc*~tenure_c*cows_c*~age_c	0.03	0.01	0.93
2	~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*~cows_c*age_c	0.08	0.00	0.91
3	hours_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*~age_c	0.08	0.01	0.91
4	hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c	0.08	0.00	0.92
5	~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*age_c	0.08	0.00	0.92
Solution coverage: 0.11; solution consistency: 0.89				

Note: The negation of peak employment is an ingredient in four of five models and high peak employment appears in none of the models. A key point: Farmographic configurations are useful in identifying farm managers low in self-efficacy.
Model: not_self_c ≥ f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.91.

self-efficacy membership scores. Note that all four models include low scores in working hours. While high efficiency in working is insufficient by itself for indicating farm managers high in self-efficacy, negation in working many hours is an ingredient having "local necessity" in predicting these farmers. "Local necessity" is an ingredient that appears in all configurations indicating the same outcome consistently.

Each model in Table 5 and other additional tables presenting configurations tells the gist of a story via "computing with words" (Zadeh, 1996). Consider the first story gist in model 1 in Table 5a: 1 ~hours_c*peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*age_c ≤ self-efficacy. This story gist informs that older women farm manager, working comparatively short hours, hiring seasonal employment, married, working a large farm for many years are high in self-efficacy consistently – the category of farming industry does not matter here. The additional three models in Table 4a include cases fitting two male dairy farm managers both unmarried but these descriptions here are incomplete. See Table 4a for the complete profiles.

Table 5b includes models for the negation of self-efficacy having high consistency. Not dairy farmer is an ingredient in four of the five models in Table 5b. Female farm manager appears in all five models; female farm manager is a local necessity condition for high membership score in the negation of self-efficacy. However, the majority of female farm managers are not low in self-efficacy; the findings inform only that female farm manager is one ingredient in recipes that do indicate low self-efficacy. See Table 5b for the complete story gist for all five models. The overall key finding is that farmographic configurations are useful in identifying farm managers who are low in self-efficacy.

Farmographic Configurations and Locus of Control. Persons having high locus of control believe they can control a broad array of factors in their lives. Table 6 provides models indicating that farmographic configurations are useful in identifying farm managers having high loci of control (Table 6a) and farm managers having low loci of control (Table 6b). In Table 6a, six of the seven models include unmarried farm managers as an ingredient in configurations indicating high locus of control. However, being unmarried is insufficient by itself in identifying farm managers high in locus of control. Large size farm occurs in all seven models; large size farm is a local necessity but insufficient condition for high locus of control. A key point: farmographic configurations do identify farm managers who are high in locus of control.

The findings in Table 6b cover five models indicating farm managers having low loci of control. The negation of cows (not a dairy farm manager) is an ingredient in all five farmographic configurations indicating low locus of control. However, while dairy farming is a local necessity condition, this ingredient is insufficient by itself for identifying farm managers having low locus of control. A key point: farmographic configurations do identify farm managers who have low locus of control.

Table 6a. Testing P3 by Farmographic Configurations Indicating High Locus of Control.

	Model	raw coverage	unique coverage	consistency
1	peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*cows_c*age_c	0.09	0.06	0.91
2	~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*~tenure_c*~cows_c*~age_c	0.04	0.00	0.91
3	hours_c*~peak_emp_c*~marital_c*size_c*~gen_cc*~tenure_c*cows_c*~age_c	0.03	0.00	0.92
4	~hours_c*~peak_emp_c*~marital_c*size_c*gen_cc*~tenure_c*cows_c*~age_c	0.03	0.00	0.91
5	~hours_c*~peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*~cows_c*age_c	0.04	0.00	0.91
6	hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*~cows_c*~age_c	0.04	0.00	0.91
7	~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*age_c	0.03	0.00	0.91
Solution coverage: 0.13; solution consistency: 0.89				

Note: Six of the seven models include unmarried farm managers as an ingredient in configurations indicating high locus of control. However, being unmarried is insufficient by itself in identifying farm managers high in locus of control. Large size farm occurs in all seven models; large size farm is a necessary but not sufficient condition for high locus of control. A key point: farmographic configurations do identify farm managers who are high in locus of control.
Model: loc_c ≥ f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.91.

Table 6b. Testing P3 by Farmographic Configurations Indicating High Negation of Locus of Control.

	Model	raw coverage	unique coverage	consistency
1	~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*~cows_c*age_c	0.09	0.00	0.95
2	hours_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*~age_c	0.08	0.01	0.95
3	hours_c*~peak_emp_c*~marital_c*size_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.04	0.01	0.95
4	hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c	0.08	0.00	0.96
5	~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*age_c	0.09	0.00	0.95
solution coverage: 0.11, solution consistency: 0.94				

Note: The negation of cows (not a dairy farm manager) is an ingredient in all five farmographic configurations indicating low locus of control. However, not having cows is insufficient by itself for identifying farm managers having low locus of control A key point: farmographic configurations do identify farm managers who have low locus of control.

Model: not_loc_c ≥ f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.95.

Farmographic Configurations and Emotional Stability. Emotional stability is reflecting confidence, security, and steadiness. Table 7a includes three models indicating high emotional stability. All three models include four simple conditions representing local necessity but insufficiency for alone or together for high emotional stability: high peak employment, large farm, high tenure, and dairy farming. These four ingredients taken together represent a core building block for indicating high emotional stability.

Table 7b includes 12 models indicating farm managers scoring high in the negation of emotional stability, that is, farmers scoring high in emotional instability. Not dairy farming is an ingredient in 11 of the 12 models (models 2−12) and dairy farming is absent in model 1. Thus, not dairy farming is a local necessity but insufficient condition in nearly all models in Table 7b. Large size is an ingredient in 12 of 12 models in Table 7b; large size is a local necessity but insufficient condition indicating high scores in emotional instability. An interesting finding: large size is a core building block for indicating both high emotional stability and instability – with the outcome depending upon what additional ingredients go into the more specific configurations. Such a finding indicates inconsistent findings in symmetric testing of variable relationships, but the complex nature of an ingredient's impact on both a consistent highly positive and negative outcome is identifiable via asymmetric testing.

Farmographics Indicating Easy versus Tough Overall CSE Screens. The study included creating an easy screen of total CSE sub-traits by calibrating the sum of the average original value for each sub-trait. Some farm managers could be in the 90th percentile or above, with a score below the 90th percentile in one to three traits for the easy CSE screen. The tough screen includes the requirement that to be in the 90th percentile or higher, a farm manager must be in the 90th percentile for each of the four sub-traits.

Table 8 summarizes the findings for the easy and tough CSE screen outcomes. Table 8a includes eight models indicating high score outcomes for the easy CSE screen. Seven of these eight models include dairy farm as an ingredient and one includes no farm industry ingredient. Thus, dairy farming is close to being a local necessity but insufficient condition for high scores in the easy CSE screen. No other simple condition is present in high or low valences consistently for high scores in the easy CSE screen. Table 8b includes one model. This model indicates an unmarried, older, male dairy farmer working a relatively low number of hours using peak seasons workers, having many years of job tenure to be high in CSE for the tough screen.

Table 9 presents the findings for farmographics indicating the negation of CSE using the tough screen. Using the tough CSE screen as an outcome, the configuration of young, not a dairy farmer, and low tenure for both males and females is an indicator of low CSE but this configuration is insufficient by itself to identify low CSE.

Table 7a. Testing P3 by Farmographic Configurations Indicating High Emotional Stability.

	Model	raw coverage	unique coverage	consistency
1	hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*~age_c	0.04	0.01	0.88
2	~hours_c*peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*cows_c*age_c	0.08	0.05	0.91
3	~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*age_c	0.04	0.00	0.94
Solution coverage: 0.10; solution consistency: 0.88				

Note: The conjoining of high peak employment, large farm size, long tenure, and dairy farming is an initial indicator of high emotional stability. However, these four simple conditions in combination do not assure high emotional stability.
Model: emot_stab_c ≥ f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.882.

Table 7b. Testing P3 by Farmographic Configurations Indicating High Emotional Instability.

	Model	raw coverage	unique coverage	consistency
1	hours_c*~peak_emp_c*~marital_c*size_c*~gen_cc*~tenure_c*~age_c	0.04	0.00	0.93
2	~hours_c*marital_c*size_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.09	0.00	0.93
3	~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*~cows_c*age_c	0.08	0.00	0.95
4	hours_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*~age_c	0.08	0.00	0.96
5	hours_c*~marital_c*size_c*gen_cc*tenure_c*~cows_c*~age_c	0.04	0.00	0.93
6	~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*age_c	0.08	0.00	0.95
7	~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*~tenure_c*~cows_c*~age_c	0.04	0.00	0.97
8	hours_c*~peak_emp_c*size_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.08	0.00	0.94
9	hours_c*~peak_emp_c*~marital_c*size_c*~tenure_c*~cows_c*~age_c	0.05	0.00	0.95
10	~peak_emp_c*marital_c*size_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.09	0.00	0.93
11	hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*~cows_c*~age_c	0.08	0.00	0.94
12	hours_c*~peak_emp_c*~marital_c*size_c*gen_cc*~cows_c*~age_c	0.04	0.00	0.94
Solution coverage: 0.14; solution consistency: 0.91				

Note: Large farm size appears in all 12 models; not a dairy farmer appears in 11 of the 12 models and dairy farming is not a condition in model 1. Not a dairy farmer is insufficient for indicating emotional instability by itself.
Model: neuro_c ≥f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.93.

Table 8a. Testing P3 by Farmographics Indicating Complex Outcome CSE Using an Easy CSE Screen.

	Model	raw coverage	unique coverage	consistency
1	~hours_c*~peak_emp_c*gen_cc*~tenure_c*cows_c*~age_c	0.17	0.02	0.93
2	~hours_c*~peak_emp_c*marital_c*~size_c*~tenure_c*cows_c*age_c	0.14	0.01	0.93
3	~hours_c*marital_c*size_c*gen_cc*~tenure_c*cows_c*~age_c	0.16	0.01	0.94
4	~hours_c*~peak_emp_c*marital_c*size_c*gen_cc*cows_c*~age_c	0.16	0.01	0.94
5	~hours_c*peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*age_c	0.09	0.01	0.94
6	peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*cows_c*age_c	0.09	0.01	0.95
7	~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*age_c	0.04	0.00	0.95
8	hours_c*peak_emp_c*marital_c*size_c*gen_cc*~tenure_c*cows_c*age_c	0.14	0.03	0.94
Solution coverage: 0.30; solution consistency: 0.90				

Note: Dairy farming is an ingredient in seven of the eight models and dairy farming is not an ingredient in model 5. Large farm size is an ingredient in six of the eight models. Dairy farming alone and farm size alone are insufficient for consistently indicating high CSE using the easy screen.
Model: cse_c_ave = f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.94.

Table 8b. Testing P3 by Farmographics Indicating Complex Outcome CSE Using a Tough CSE Screen.

Model	raw coverage	unique coverage	consistency
~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*age_c	0.06	0.06	0.85
Solution coverage: 0.06; solution consistency: 0.85			

Note: Using the tough screen for CSE, it can be found that old male farmer on a large dairy farm using high peak employment and working low hours indicates high CSE.
Model: cse_screen = f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.85.

Table 9. Testing P5: Farmographics Indicating Complex Outcome Negative CSE Using a Tough Negative CSE Screen.

	Model	raw coverage	unique consistency	
1	hours_c*~peak_emp_c*~marital_c*gen_cc*~cows_c*~age_c	0.04	0.00	0.98
2	hours_c*~peak_emp_c*~marital_c*~gen_cc*~tenure_c*cows_c*~age_c	0.02	0.00	1.00
3	~hours_c*~peak_emp_c*~marital_c*gen_cc*~tenure_c*cows_c*~age_c	0.03	0.00	0.99
4	~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*~cows_c*age_c	0.06	0.00	0.99
5	hours_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*~age_c	0.06	0.00	0.99
6	hours_c*~marital_c*size_c*gen_cc*tenure_c*~cows_c*~age_c	0.03	0.01	0.99
7	hours_c*peak_emp_c*marital_c*~gen_cc*~tenure_c*cows_c*~age_c	0.07	0.01	0.99
8	~hours_c*~peak_emp_c*marital_c*~size_c*~gen_cc*tenure_c*~cows_c*~age_c	0.05	0.00	0.98
9	~hours_c*~peak_emp_c*~marital_c*~size_c*gen_cc*~tenure_c*~cows_c*age_c	0.03	0.00	0.99
10	~hours_c*peak_emp_c*marital_c*size_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.06	0.00	0.98
11	~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*~tenure_c*~cows_c*~age_c	0.03	0.00	0.99
12	~hours_c*~peak_emp_c*marital_c*~size_c*~gen_cc*~tenure_c*cows_c*age_c	0.05	0.00	0.98
13	hours_c*peak_emp_c*marital_c*~size_c*~gen_cc*~tenure_c*~cows_c*age_c	0.05	0.00	0.99
14	~hours_c*peak_emp_c*marital_c*~size_c*~gen_cc*tenure_c*~cows_c*age_c	0.05	0.01	0.98
15	hours_c*peak_emp_c*~marital_c*~size_c*gen_cc*tenure_c*~cows_c*age_c	0.03	0.00	0.98
16	hours_c*peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*cows_c*age_c	0.05	0.00	0.99
17	hours_c*~peak_emp_c*~marital_c*~size_c*gen_cc*~tenure_c*~age_c	0.04	0.00	0.98
18	hours_c*~peak_emp_c*~marital_c*~size_c*~tenure_c*cows_c*~age_c	0.04	0.00	0.98
19	~peak_emp_c*~marital_c*~size_c*gen_cc*~tenure_c*cows_c*~age_c	0.04	0.00	0.98
20	hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c	0.06	0.00	0.99
21	~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*age_c	0.06	0.00	0.99

Solution coverage: 0.17; solution consistency: 0.98

Note: Using the tough CSE screen as an outcome, it can be found that the combination of young, not a dairy farmer, and low tenure for both males and females is an early indicator of low CSE, but this combination is insufficient by itself to identify low CSE.
Model: neg_cse_scre_c ≥ f(hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.98.

P4 Receives Support: Farmographic Configurations Indicate High and Low Job Strains

Table 10a includes eight farmographic models indicating high job strain. Only one of the eight models includes dairy farming as an ingredient. Horticulture, mixed farming, and beef/sheep each appear more often in models than dairy farming. Surprising to the two researchers (authors), young farmer (not old) appears in all eight models. Young farm manager is a local necessity for high strain but an insufficient ingredient by itself for indicating high strain. Seven of the eight models include the negation of peak employment (i.e., hiring for seasonal employment): a second major surprise in the study.

Older farm manager is an ingredient in 8 of 12 models for indicating low job strain cases in Table 10b versus not appearing even once in Table 10a. Young farm manager does appear as an ingredient in 4 of the 12 models in Table 10b. These findings support the perspective that asking whether the association between age and job strain is positive or negative is shallow; the more useful question to ask is when does older versus younger age occur as an ingredient in farm managers with high versus low job strain. Asymmetric framing asks when, not if, and examines age's role in both high and low job strain separately.

P5 Receives Support: Farmographic Configurations Indicate Both High and Low Job Stress

Table 11a includes seven models of farmographic configurations indicating overall high job stress. Six of seven of these models include the negation of horticultural farming while five of the seven include beef/sheep farming. Surprisingly for the researchers, six of seven models include short hours. The a priori expectation was that working long hours associates with high stress. The symmetric findings in Fig. 3 support this expectation; in Fig. 3 working hours has a statistically significant positive correlation with three of the six stress factors (Table 11b).

The evidence that the asymmetric test indicates working hours is a negative ingredient most of the time for case outcomes with high stress while the symmetric test indicates working hours relates positively to stress supports the perspective that researchers need to adopt a case-based approach to enable case-based implications. Even though the symmetric variable relationships are highly significant ($p < .001$), their effect sizes are small, which means that a substantial number of cases occur where farmers who work a low number of hours have high stress. As Trafimow and Marks (2015) and Hubbard (2016) indicate, the reporting of findings from NHSTs is more rubbish than substance – worse than rubbish; NHST findings are often misleading if the researcher is interested in explaining, describing, and predicting outcomes.

Table 10a. Testing P4a for Farmographics Identifying High Job Strain.

	Model	raw coverage	unique coverage	consistency
1	~mixed_c*horticult_c*~bf_sheep_c*~hours_c*peak_emp_c*~size_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.04	0.02	0.95
2	~mixed_c*horticult_c*~bf_sheep_c*~hours_c*~peak_emp_c*~marital_c*~size_c*gen_cc*~tenure_c*~cows_c*~age_c	0.03	0.01	0.97
3	mixed_c*~horticult_c*~bf_sheep_c*~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.04	0.00	0.97
4	mixed_c*~horticult_c*~bf_sheep_c*~hours_c*~peak_emp_c*marital_c*~size_c*~gen_cc*tenure_c*~cows_c*~age_c	0.04	0.00	0.97
5	~mixed_c*~horticult_c*~bf_sheep_c*hours_c*~peak_emp_c*~marital_c*size_c*~gen_cc*~tenure_c*cows_c*~age_c	0.04	0.01	0.94
6	mixed_c*~horticult_c*~bf_sheep_c*~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*~tenure_c*~cows_c*~age_c	0.03	0.00	0.96
7	~mixed_c*~horticult_c*bf_sheep_c*hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*~age_c	0.03	0.01	0.94
8	~mixed_c*~horticult_c*bf_sheep_c*~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*cows_c*~age_c	0.03	0.00	0.96
Solution coverage: 0.10; solution consistency: 0.90				

Note: Young and not a dairy farmer is an ingredient in seven of eight models indicating high job strain. The combination of young and not a dairy farmer is insufficient by itself for indicating farmers having high job strain.
Model: strain_c = f(mixed_c, horticult_c, bf_sheep_c, hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.94.

Table 10b. Testing P4b for Farmographics Indicating Low Job Strain.

	Model	raw coverage	unique coverage	consistency
1	~mixed_c*horticult_c*~bf_sheep_c*~hours_c*~peak_emp_c*marital_c*~size_c*~gen_cc*~cows_c*age_c	0.03	0.01	0.98
2	mixed_c*~horticult_c*~bf_sheep_c*hours_c*~peak_emp_c*marital_c*~size_c*gen_cc*~tenure_c*cows_c*~age_c	0.02	0.00	0.99
3	~mixed_c*~horticult_c*bf_sheep_c*~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*cows_c*~age_c	0.02	0.00	0.99
4	~mixed_c*~horticult_c*bf_sheep_c*hours_c*~peak_emp_c*~marital_c*~size_c*gen_cc*tenure_c*~cows_c*age_c	0.02	0.00	0.98
5	~mixed_c*horticult_c*~bf_sheep_c*hours_c*peak_emp_c*~marital_c*~size_c*gen_cc*tenure_c*~cows_c*age_c	0.02	0.00	0.98
6	mixed_c*~horticult_c*~bf_sheep_c*~hours_c*~peak_emp_c*marital_c*~size_c*gen_cc*tenure_c*cows_c*age_c	0.02	0.00	0.99
7	~mixed_c*~horticult_c*bf_sheep_c*~hours_c*~peak_emp_c*marital_c*~size_c*gen_cc*tenure_c*cows_c*age_c	0.02	0.00	1.00
8	mixed_c*~horticult_c*bf_sheep_c*hours_c*~peak_emp_c*marital_c*size_c*gen_cc*tenure_c*~cows_c*~age_c	0.02	0.00	1.00
9	mixed_c*~horticult_c*bf_sheep_c*~hours_c*~peak_emp_c*marital_c*size_c*gen_cc*tenure_c*~cows_c*age_c	0.02	0.00	0.99
10	~mixed_c*horticult_c*~bf_sheep_c*hours_c*~peak_emp_c*marital_c*size_c*gen_cc*tenure_c*~cows_c*age_c	0.02	0.01	0.99
11	mixed_c*~horticult_c*~bf_sheep_c*~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*age_c	0.02	0.00	0.99
12	mixed_c*~horticult_c*~bf_sheep_c*hours_c*peak_emp_c*marital_c*size_c*gen_cc*tenure_c*cows_c*~age_c	0.03	0.01	0.98
Solution coverage: 0.08; solution consistency: 0.97				

Note: Eight of 12 models include older farmer as an ingredient and 6 of 12 include dairy farmer as an ingredient in models for low-strain farm manager.
Model: notstrain_c = f(mixed_c, horticult_c, bf_sheep_c, hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.98.

Table 11a. Testing P5a: Farmographic Configurations Indicating High Stress.

	Model	raw coverage	unique coverage	consistency
1	~mixed_c*horticult_c*~bf_sheep_c*~hours_c*peak_emp_c*~marital_c*~size_c*~gen_cc*~tenure_c*~cows_c*~age_c	0.06	0.00	0.90
2	~mixed_c*~horticult_c*bf_sheep_c*~hours_c*~peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*cows_c*~age_c	0.08	0.00	0.91
3	~mixed_c*~horticult_c*bf_sheep_c*~hours_c*peak_emp_c*marital_c*size_c*~gen_cc*tenure_c*~cows_c*age_c	0.09	0.01	0.89
4	~mixed_c*~horticult_c*bf_sheep_c*~hours_c*~peak_emp_c*marital_c*~size_c*gen_cc*tenure_c*cows_c*age_c	0.08	0.01	0.89
5	mixed_c*~horticult_c*bf_sheep_c*hours_c*~peak_emp_c*marital_c*size_c*gen_cc*tenure_c*~cows_c*~age_c	0.06	0.00	0.90
6	mixed_c*~horticult_c*bf_sheep_c*~hours_c*~peak_emp_c*marital_c*size_c*gen_cc*tenure_c*~cows_c*age_c	0.07	0.01	0.91
7	mixed_c*~horticult_c*~bf_sheep_c*~hours_c*peak_emp_c*~marital_c*size_c*gen_cc*tenure_c*cows_c*age_c	0.08	0.01	0.89

Solution coverage: 0.11; solution consistency: 0.69

Note: Four of seven models include no dairy farmers (i.e., no cows) and six of seven include high tenure in these high stress outcome models. However, not dairy farming is insufficient by itself as an indicator of high stress.

Model: stress_screen_c ≥ f(mixed_c, horticult_c, bf_sheep_c, hours_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), consistency cutoff: 0.89.

Table 11b. Testing P5b: Farmographics Indicating Low Stress.

	Model	raw coverage	unique coverage	consistency
1	~mixed_c*horticult_c*~bf_sheep_c*marital_c*~size_c*gen_cc*~cows_c*age_c	0.15	0.05	0.95
2	~mixed_c*horticult_c*~bf_sheep_c*not_hrs_c*marital_c*~size_c*gen_cc*~tenure_c*~cows_c	0.10	0.01	0.97
3	~mixed_c*~horticult_c*~bf_sheep_c*~not_hrs_c*~peak_emp_c*marital_c*size_c*~tenure_c*cows_c*~age_c	0.13	0.01	0.98
4	~mixed_c*~horticult_c*~bf_sheep_c*~peak_emp_c*marital_c*~size_c*gen_cc*~tenure_c*cows_c*~age_c	0.12	0.02	0.99
5	~mixed_c*~horticult_c*~bf_sheep_c*~not_hrs_c*marital_c*size_c*gen_cc*~tenure_c*cows_c*~age_c	0.12	0.01	0.97
6	~mixed_c*~horticult_c*~bf_sheep_c*~not_hrs_c*~peak_emp_c*marital_c*~size_c*gen_cc*tenure_c*age_c	0.09	0.01	0.99
7	~mixed_c*horticult_c*~bf_sheep_c*~not_hrs_c*peak_emp_c*marital_c*~size_c*gen_cc*tenure_c*~cows_c	0.05	0.00	0.99
8	~mixed_c*~horticult_c*~bf_sheep_c*~not_hrs_c*~peak_emp_c*marital_c*gen_cc*tenure_c*cows_c*age_c	0.09	0.00	0.98
9	mixed_c*~horticult_c*~bf_sheep_c*not_hrs_c*~peak_emp_c*marital_c*gen_cc*tenure_c*~cows_c*age_c	0.04	0.01	0.97
10	mixed_c*~horticult_c*~bf_sheep_c*~not_hrs_c*marital_c*size_c*gen_cc*tenure_c*~cows_c*age_c	0.03	0.01	0.95
11	~mixed_c*~horticult_c*bf_sheep_c*~peak_emp_c*marital_c*size_c*gen_cc*tenure_c*~cows_c*age_c	0.05	0.01	0.96
12	~mixed_c*~horticult_c*bf_sheep_c*~not_hrs_c*marital_c*size_c*gen_cc*tenure_c*~cows_c*age_c	0.05	0.00	0.96
13	~mixed_c*~horticult_c*~bf_sheep_c*peak_emp_c*marital_c*size_c*gen_cc*tenure_c*cows_c*age_c	0.08	0.01	0.98
14	~mixed_c*~horticult_c*bf_sheep_c*~not_hrs_c*~peak_emp_c*marital_c*size_c*gen_cc*~tenure_c*~cows_c*~age_c	0.03	0.01	0.99
15	~mixed_c*~horticult_c*~bf_sheep_c*not_hrs_c*peak_emp_c*marital_c*size_c*~gen_cc*~tenure_c*cows_c*~age_c	0.05	0.02	0.99

Solution coverage: 0.48; solution consistency: 0.96

Model: not_stress_c ≥ f(mixed_c, horticult_c, bf_sheep_c, not_hrs_c, peak_emp_c, marital_c, size_c, gen_cc, tenure_c, cows_c, age_c), frequency cutoff: 4, consistency cutoff: 0.95.

P6 Receives Support: High Scores on CSE Screens Indicate High Job Satisfaction

The model of the easy CSE screen indicating high scores on job satisfaction is only marginally useful. While coverage is high (0.75), the model's consistency is equal to 0.77 for the easy CSE screen in Fig. 4. Even at this relatively low consistency level, the odds are 2.3 to 1 that a case with a score above 0.6 has a score above 0.5 on job satisfaction. On using the tough CSE screen, the odds increase dramatically to 6.5 to 1. Fig. 4 presents the details. These findings confirm and radically extend the findings in symmetric tests that CSE is a variable associating positively with job satisfaction. The present study appears to be the first to show that cases high in CSE are high in job satisfaction consistently.

P7 Receives Support: High Scores via the CSE Screens Indicate Low Job Strain

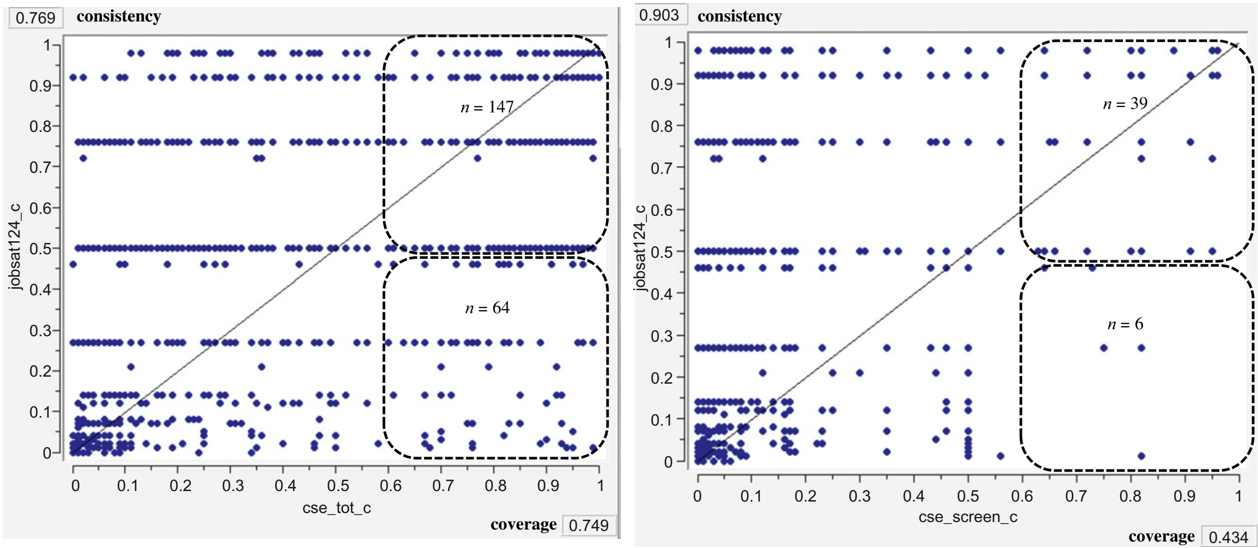
The two XY plots and simple antecedent models in Fig. 5 support P7: high scores for the easy and tough CSE screens indicate farm managers with low job strain. On using the easy CSE screen, the odds are 7 to 1 that a high score in the CSE screen indicates a low job strain outcome, whereas on using the tough screen, the odds increase to 8 to 1 that a high score on the CSE screen indicates a low score on job strain.

Note that fewer cases manage to have calibrated scores above 0.75 using the tough versus easy screen in Fig. 5. Thus, fewer high outcome cases are identifiable using the tough screen but the tough screen identifies substantially fewer "false positives," that is, farmers high on the (tough versus easy screen) but who do not have high scores on low job strain. The false positive cases decreases from 21 to 8 as appearing in Fig. 5.

P8 Receives Support: High Scores via the CSE Tough Screen Indicate Low Job Stress

Fig. 6 presents the XY plot for the SPOT for P8. The findings provide strong support for P8: 55 of 60 cases with scores above 0.6 on the CSE tough screen (i.e., requirement of membership scores above 0.90 for each of the four CSE sub-traits) are above 0.6 for the negation of job stress. Thus, the odds are 11 to 1 that a farm manager has low job stress if she or he has high scores for all four CSE sub-traits.

Fig. 7 helps to answer an additional question about CSE and job stress. Is a high score on the negation of CSE a necessary condition for high job stress? The XY plot in Fig. 7 supports an affirmative answer. Fig. 7 includes no cases



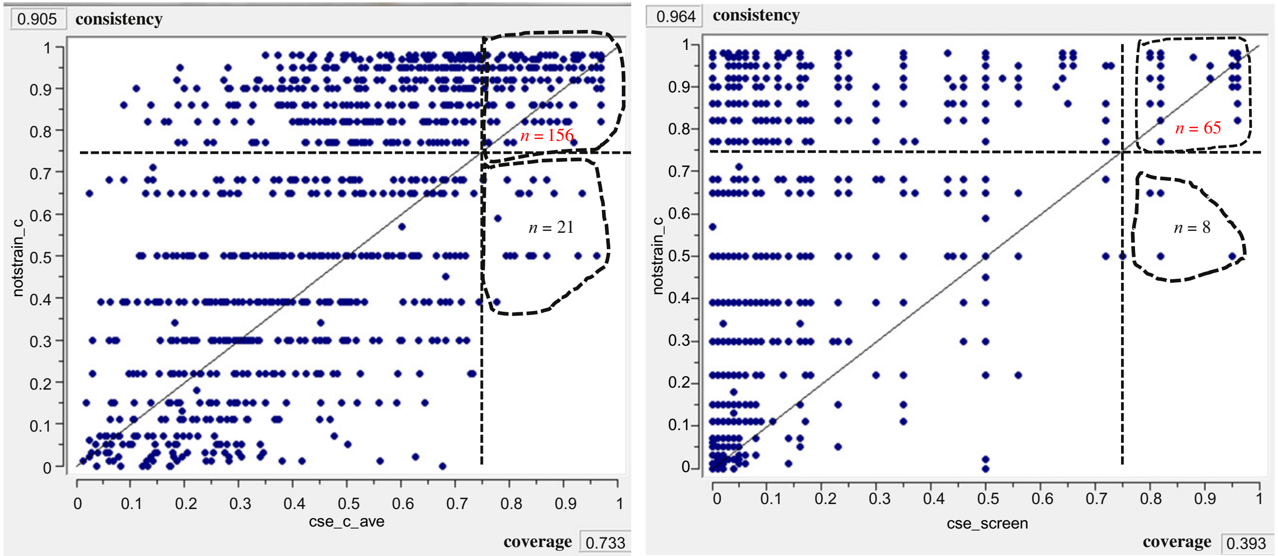
(A) Model: Job satisfaction (JS) ≥ CSE sum calibrated

Note: Odds of JS ≥ 0.50 is 2.3 to 1.

(B) Model: Job satisfaction ≥ CSE four traits' screen

Note: Odds of JS ≥ 0.50 is 6.5 to 1.

Fig. 4. (P6) Core Self-Evaluations Sum Scores Calibrated versus Screen of Four Core Self-Evaluation Traits Calibrated: Consistency in Identifying High Job Satisfaction. *Note*: Identifying high consistency to be equal or greater than 0.85, model B provides high consistency though the coverage of model A is higher than B. Dots indicate cases; a specific dot may represent more than one case.



(A) Easy Screen Model: Low job strain ≥ CSE sum calibrated

Note: Odds are 7 to 1 if high in CSE_c_ave, farmer is high in negation of job strain

(B) Tough Screen Model: Low job strain ≥ CSE four traits' screen

Note: Odds are 8 to 1 if high in CSE tough screen, farmer is high in negation of job strain.

Fig. 5. (P7) Core Self-Evaluation Using Easy versus Tough Screens to Indicate Low Job Strain. *Note*: Identifying high consistency to be equal or greater than 0.75, model B provides higher consistency though the coverage of model A is higher than B. Applying the tough versus easy screen decreases the number of false positives but also decreases the number of farmers identified as high in low job strain. (Dots sometimes include two or more cases at the same dot location.)

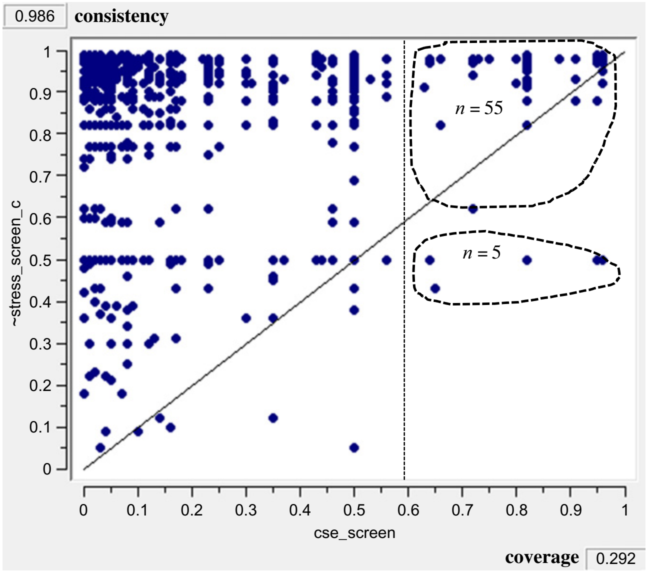


Fig. 6. Findings for P8: CSE Tough Screen Configuration Indicating Negation of Job Stress. *Note*: The high consistency (0.986) confirms that high CSE indicates high negation of job stress. Odds are more than 11 to 1 that a score above 0.60 on the CSE screen will be above 0.80 on the negation of stress screen.

with stress scores above 0.6 and negative CSE below 0.5. This XY plot shows that high scores in the negation of CSE (i.e., cases low in stress) are necessary but insufficient for high job stress.

All 24 correlations for the four CSE sub-traits and job stress are negative (rough dotted rectangle in Fig. 3) and statistically significant. However, the Fig. 7 XY plot indicates that the relationship between CSE and job stress is asymmetric, not symmetric. Most farm managers who are low in CSE are not high in job stress. Managers who are high in the tough CSE screen are high in job stress. Dropping the tools of symmetric testing via correlation and MRA and picking-up and using the tools of asymmetric testing via XY plots, configurational analysis, and fsQCA enable the researcher to move from a variable-based theory-analysis mismatch to a case-based theory-analysis match (cf., Fiss, 2007).

P9 Receives Moderate Support: High Job Stress Configurations Predict High Job Strain

Fig. 8 is the XY plot for overall job stress as an indicator of job strain. The applicable consistency index is equal to 0.78 for this plot. This consistency and

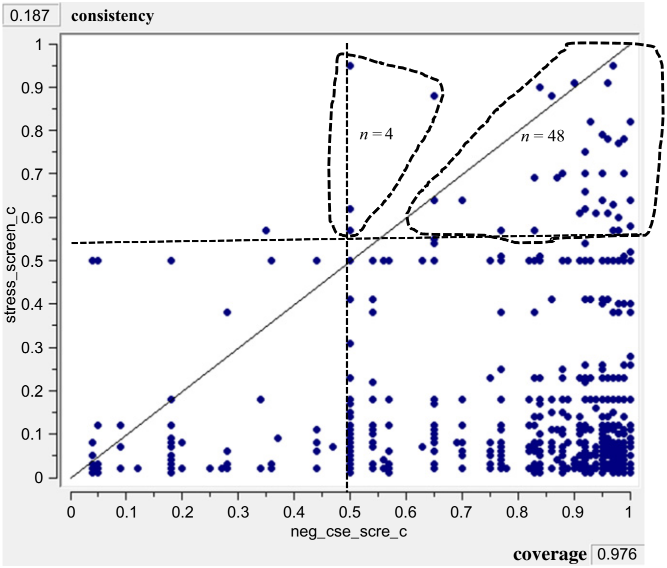


Fig. 7. Low CSE (Using Tough Screen): (P8) A Necessary but Insufficient Condition for High Stress. *Note*: Most farm managers low on the CSE screen are low in stress. However, almost all farm managers high in stress are low on the CSE screen. The pattern shows low CSE is a necessary but insufficient condition for high stress.

the plot itself supports a marginal usefulness of high overall stress indicating high overall strain. The additional details of findings in Table 12 help to increase understanding about how job stress affects job strain. Note in the three models for high job strain in Table 12a that high financial stress is a local necessity condition – financial stress is an ingredient in all three conditions. Model 2 in Table 12a includes three high-scoring conditions and two low-scoring conditions; this configuration produces more than 2 to 1 odds in identifying high versus low job strain – the most useful model.

Does low job strain associate with configurations that include low job stress factors? The findings in Table 12b support an affirmative answer. Note in Table 12b that high financial stress is an ingredient in four of the ten models but always with three or four additional negations of other stress factors. The highly useful question is not whether or not high financial stress is a cause of high job strain but when does high financial stress indicate high versus low job strain. Outcome-centered research addresses this deeper question while directional-variable-centered research does not.

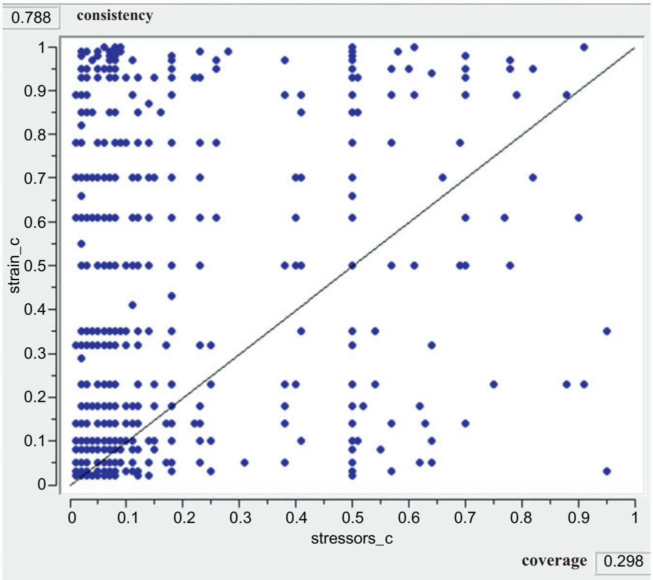


Fig. 8. (P9) High Stress as an Indicator of High Strain. *Note*: The consistency (0.79) indicates a model of marginal usefulness for indicating high strain.

Table 12a. Job Stressor Configurations Indicating High Strain.

Model	raw coverage	unique coverage	consistency
1 ~hazards_c*time_c*finan_c	0.37	0.13	0.78
2 ~unpredict_c*~hazards_c*pol_proc_c*isola_c*finan_c	0.20	0.01	0.84
3 ~unpredict_c*pol_proc_c*~isola_c*time_c*finan_c	0.25	0.04	0.81
Solution coverage: 0.42; solution consistency: 0.76			

Model: strain_c = f(unpredict_c, hazards_c, pol_proc_c, isola_c, time_c, finan_c), frequency cutoff: 3, consistency cutoff: 0.84.

Findings Do Not Support P10: High Job Stress Cases Do Not Consistently Indicate Low Job Satisfaction

The XY plots in Fig. 9 show that only one farm manager with very high job stress also exhibits high job satisfaction, while nine farm managers with very high job stress exhibit very low job satisfaction. However, the consistency index (0.77) for the XY data plot in Fig. 9b provides only marginal support for the

Table 12b. Job Stressor Configurations Indicating Low Strain.

	Model	raw coverage	unique coverage	consistency
1	~unpredict_c*~time_c*~finan_c	0.51	0.03	0.88
2	~unpredict_c*~pol_proc_c*~isola_c	0.47	0.02	0.86
3	~hazards_c*~isola_c*~time_c*~finan_c	0.45	0.01	0.91
4	~hazards_c*~pol_proc_c*~time_c*~finan_c	0.41	0.00	0.90
5	~unpredict_c*~hazards_c*~pol_proc_c*~time_c	0.40	0.01	0.89
6	~pol_proc_c*~isola_c*time_c*finan_c	0.19	0.01	0.86
7	~hazards_c*~isola_c*time_c*finan_c	0.20	0.01	0.85
8	hazards_c*pol_proc_c*~isola_c*~time_c*finan_c	0.16	0.01	0.91
9	~unpredict_c*~isola_c*~time_c	0.51	0.01	0.87
10	~unpredict_c*~hazards_c*~isola_c*finan_c	0.22	0.00	0.86
Solution coverage: 0.71; solution consistency: 0.82				

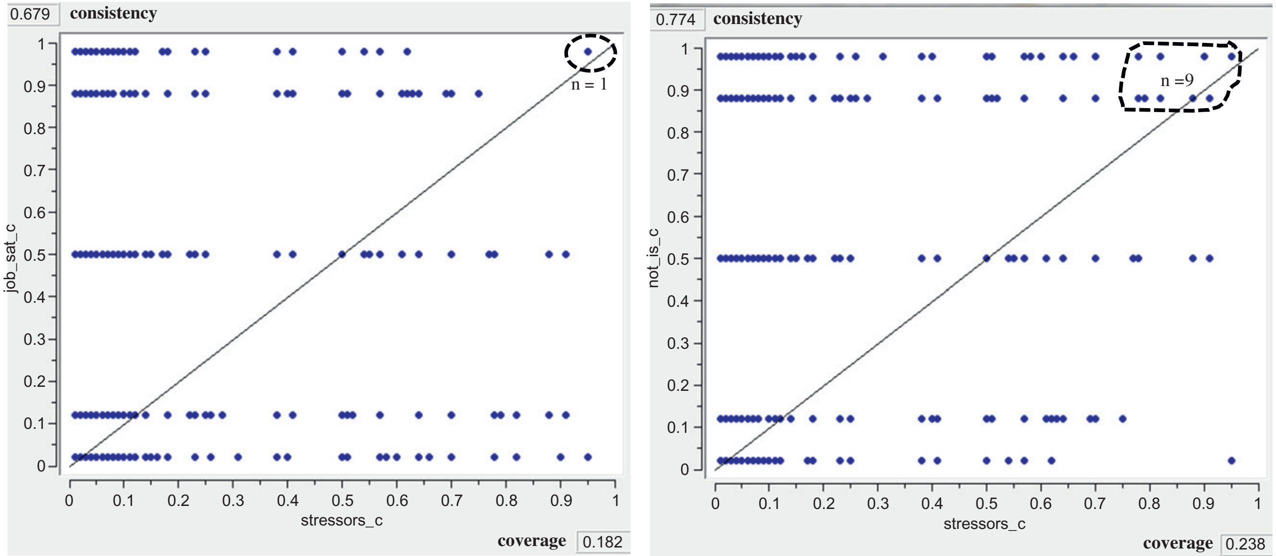
Model: notstrain_c = f(unpredict_c, hazards_c, pol_proc_c, isola_c, time_c, finan_c), frequency cutoff: 4, consistency cutoff: 0.89.

proposition that high job stress indicates high negation in job satisfaction. While job stress may be useful as an ingredient in complex antecedent conditions indicating high job satisfaction, the simple condition of high job stress is insufficient for predicting low job satisfaction.

Findings Do Not Support P11: High Job Strain Cases Do Not Consistently Indicate Low Job Satisfaction

The scatter of cases in the XY plots in Fig. 10 are similar to the ones in Fig. 9. Very high job strain identifies 18 farm managers having high scores in the negation of job satisfaction (Fig. 10b) as well as 9 farm managers with very high scores in job satisfaction (Fig. 10a). These numbers indicate that farm managers having high job strain are 2 to 1 more likely to be highly dissatisfied versus highly satisfied in their jobs.

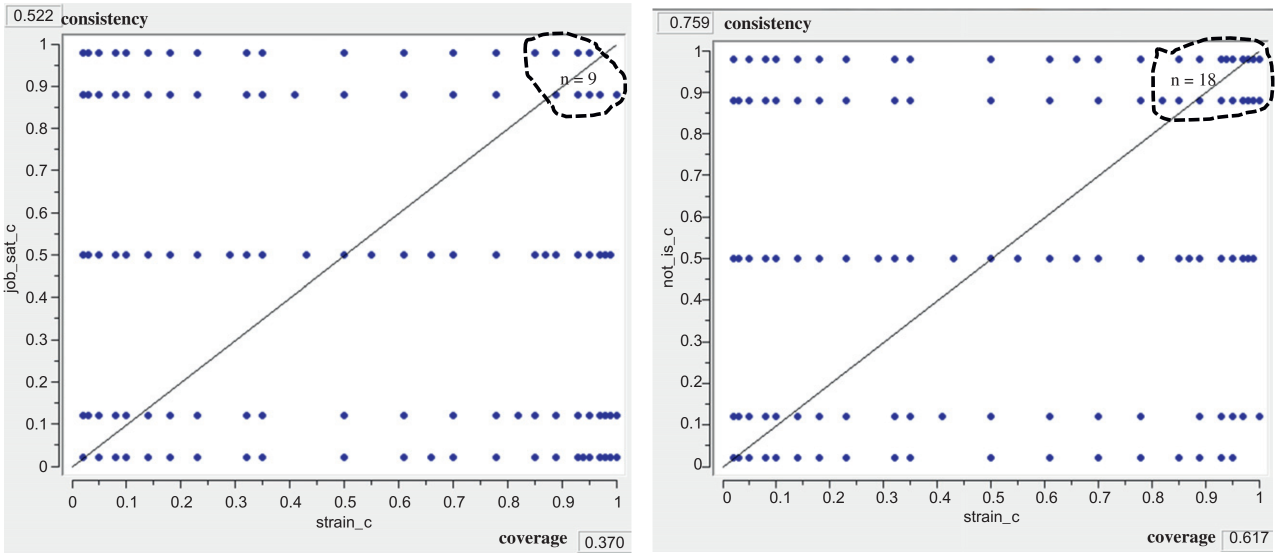
However, the consistency index equal to 0.76 supports the conclusion that the high job strain is only marginally an indicator of high scores in low job satisfaction. Consistency indexes above 0.84 indicate the odds are greater than 2 to 1 that high scores in the simple or complex antecedent condition indicate high scores in the simple or complex outcome condition. Consider adopting the rule that consistency needs to be above 0.84 for concluding a specific model to be useful for identifying cases high for an outcome condition.



(a) High Job Stress Indicating Farmers with High Job Satisfaction

(b) High Job Stress Indicating Farmers with Low Job Satisfaction

Fig. 9. (P10) High Job Stress as an Indicator of High versus Low Job Satisfaction. *Note*: The consistency indexes indicate that the somewhat precise outcome test (SPOT) for model B is marginally accurate but model A is inaccurate. However, the accuracy of each of these models indicates the high job stress is a sufficient indicator of either high or low job satisfaction. Deep descriptions are possible to prepare for the single case (#898) high in job stress and high in job strain as well as the nine cases in job stress and high in the negation of job satisfaction.



(a) High Job Strain as Indicator of High Job Satisfaction **(b) Job Strain as an Indicator of Low Job Satisfaction**

Fig. 10. (P11) High Job Strain as an Indicator of High versus Low Job Satisfaction. *Note*: High job strain is more often an indicator of high negation versus high job satisfaction. Model B is marginally useful as an indicator of farm managers having low job satisfaction. Model A is not useful as a predictor of high job satisfaction. "Feel the burn" or "no pain, no gain" are tropes that might come to mind for the nine farmers high in job strain and high in job satisfaction as appearing in the XY plot for model A.

Findings Support General Composite Models of Farmographics, CSE, Job Stress, Job Strain, as Indicators of High (Low) Job Satisfaction

Embracing the assumption that farm managers' psychological conditions occur in specific farmographic, job strain, and job stress conditions, the study includes performing additional theory construction and data analysis to learn whether highly informative composite models of these conditions can explain and predict high job satisfaction − and whether additional models can explain and predict the negation of job satisfaction. Configurations including possibly up to nine simple conditions were created and tested; the nine simple conditions included job tenure, farm size, four industry categories, the tough CSE screen, job stress, and job strain. The composite analyses did not include additional farmographic conditions but additional analyses including these additional conditions (e.g., gender, peak seasonal hiring, and marital status) support the general conclusions appearing below.

The general composite models deliver high consistencies and high solution coverages of farm managers for high job satisfaction − and additional models deliver the same for low job satisfaction. Details appear in Table 13, parts a and b. Note in Table 13a that high scores in the CSE tough screen appears in three of the nine models. Negation scores for the tough CSE screen appears in five of the nine models because only a relatively few farm managers in the study have high scores in the CSE screen but still have high job satisfaction. Some farm managers do achieve high job satisfaction without having high scores on the tough CSE screen. How do they do so? They do so by having low scores for job stressors and job strain along with certain configurations of farmographic conditions.

Validation of CSE Tough Screen Indicating High Job Satisfaction

To examine the consistency of the findings for different samples, four subsamples were formed without replacement and the simple model was tested that high farm managers scores on the CSE tough screen indicates high job satisfaction. The consistency findings in the four XY plots in Fig. 11 confirm the predictive validity of the model. The consistencies are 0.87, 0.88, 0.88, and 0.89 for plots A, B, C, and D, respectively. The coverages are quite high as well (range: 0.38 to 0.43). The findings appearing in Fig. 11 apply for five crisp membership scores for job satisfaction − ranging from 0.00 to 0.02.

DISCUSSION

Adopting a broad view for a moment, the present study contributes by its additional evidence from a national survey of farm managers of CSE's association

Table 13a. Composite Model of High Job Satisfaction.

	Model	raw coverage	unique coverage	consistency
1	~mixed_c*~horticult_c*~bf_sheep_c*dairy_c*~strain_c*~stressors_c*cse_screen	0.23	0.01	0.90
2	~tenure_c*~size_c*~mixed_c*~horticult_c*bf_sheep_c*~dairy_c*~stressors_c*~cse_screen	0.04	0.01	0.84
3	~tenure_c*size_c*~mixed_c*~horticult_c*bf_sheep_c*~dairy_c*~strain_c*~stressors_c	0.07	0.02	0.89
4	~tenure_c*size_c*~mixed_c*~horticult_c*~bf_sheep_c*dairy_c*~strain_c*~cse_screen	0.21	0.08	0.84
5	~size_c*~mixed_c*horticult_c*~bf_sheep_c*~dairy_c*~strain_c*~stressors_c*cse_screen	0.08	0.04	0.87
6	tenure_c*size_c*~mixed_c*horticult_c*~bf_sheep_c*~dairy_c*~stressors_c*~cse_screen	0.04	0.01	0.83
7	tenure_c*~mixed_c*~horticult_c*bf_sheep_c*~dairy_c*~strain_c*~stressors_c*cse_screen	0.06	0.02	0.94
8	~tenure_c*~size_c*~mixed_c*horticult_c*~bf_sheep_c*~dairy_c*~strain_c*stressors_c*~cse_screen	0.04	0.01	0.84
9	tenure_c*size_c*mixed_c*~horticult_c*~bf_sheep_c*~dairy_c*~strain_c*~stressors_c*~cse_screen	0.07	0.05	0.85
Solution coverage: 0.52; solution consistency: 0.83				

Model: job_sat_c = f(tenure_c, size_c, mixed_c, horticult_c, bf_sheep_c, dairy_c, strain_c, stressors_c, cse_screen), frequency cutoff: 2, consistency cutoff: 0.84.

Table 13b. Composite Model of Low Job Satisfaction.

	Model	raw coverage	unique coverage	consistency
1	strain_c*~cse_screen*~mixed_c*horticult_c*~bf_sheep_c*~dairy_c*~size_c	0.16	0.10	0.85
2	~cse_screen*stress_all_c*~mixed_c*horticult_c*~bf_sheep_c*~dairy_c*~size_c*~tenure_c	0.06	0.00	0.91
3	strain_c*~cse_screen*~stress_all_c*~mixed_c*~horticult_c*bf_sheep_c*~dairy_c*~size_c	0.05	0.03	0.87
4	strain_c*~cse_screen*~stress_all_c*~mixed_c*~horticult_c*~bf_sheep_c*dairy_c*~size_c	0.22	0.14	0.83
5	~cse_screen*stress_all_c*~mixed_c*~horticult_c*~bf_sheep_c*dairy_c*size_c*~tenure_c	0.10	0.01	0.81
6	~cse_screen*~stress_all_c*~mixed_c*horticult_c*~bf_sheep_c*~dairy_c*size_c*tenure_c	0.05	0.01	0.92
7	strain_c*~cse_screen*stress_all_c*~mixed_c*~horticult_c*~bf_sheep_c*dairy_c*size_c	0.11	0.00	0.86
Solution coverage: 0.43; solution consistency: 0.82				

Model: not_js_c = f(strain_c, cse_screen, stress_all_c, mixed_c, horticult_c, bf_sheep_c, dairy_c, size_c, tenure_c), frequency cutoff: 2, consistency cutoff: 0.84.

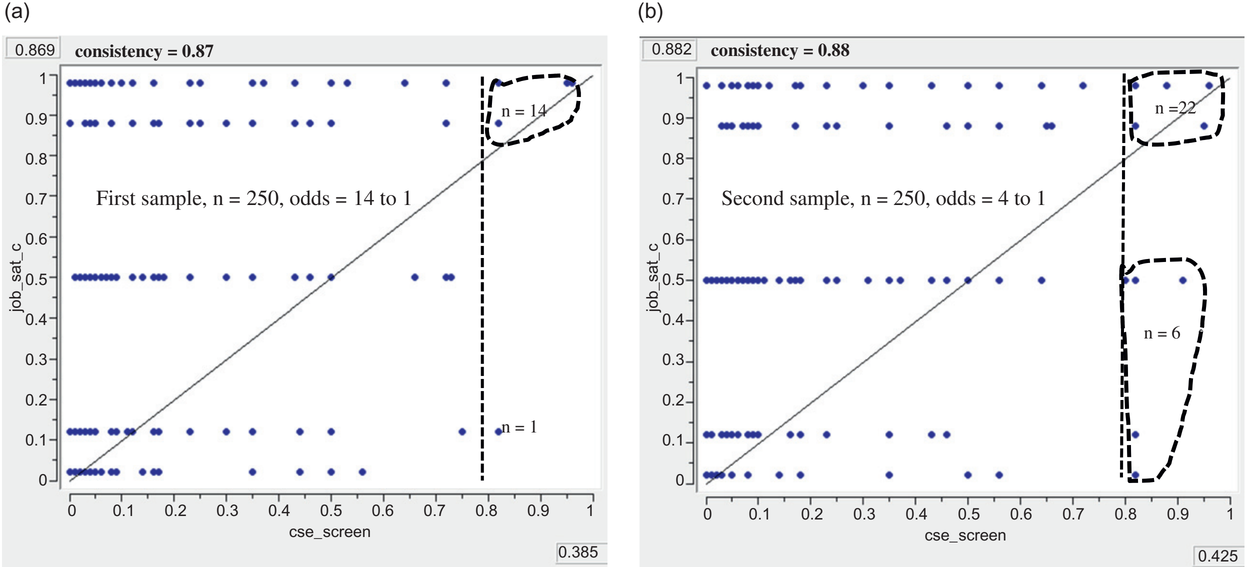


Fig. 11. Validation Replications for CSE Screen ≤ Job Satisfaction: Four Samples ($n = 250$, 250, 250, 264) Created from Total Sample ($n = 1{,}014$).

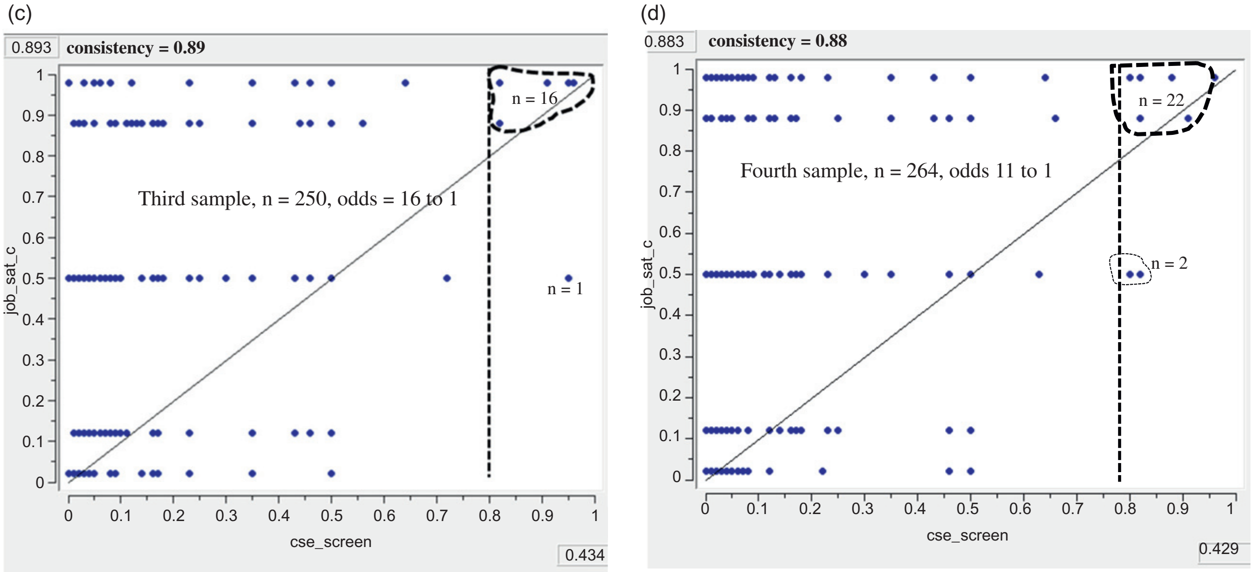


Fig. 11. (*Continued*)

with job satisfaction. The evidence here supports Judge and Bono's (2001) findings in a meta-analysis that all four CSE sub-traits display statistically significant positive correlations with job satisfaction. The present study further contributes by using complexity theory to model the conditions when low scores for CSE indicate high job satisfaction (i.e., Table 13a findings) and high scores for CSE indicate low job satisfaction (i.e., Table 13b findings). Thus, the theory and empirical findings in the present study do more than complement and extend Judge and Bono's (2001) conclusion from their meta-analysis that CSE and CSE sub-traits have nonzero correlations of similar magnitude with job satisfaction. Complexity theory, asymmetric configurational analysis using Boolean algebra to identify specific outcomes are the bases for case-based modeling and analysis in the present study rather than the currently pervasive use of linear model of independent terms in regression models using matrix algebra. Fiss (2007) correctly observes that independent terms in regression models pose variables as rivals in attempting to account for their individual influences on a dependent variable. Given that the independent terms in a regression model are rarely independent – as the positive correlations among the four CSE sub-traits bear witness – the attempt to measure the independent contribution of each term in a linear regression model is an attempt to answer a bad question. Relevant here is Cohen's (1997, p. 1000) conclusion, "'Discovering' in the population that a difference between two means is not precisely zero, or that a correlation between two variables is not precisely zero, are trivial findings."

While a problem, the lack of independence of variables assumed to be independent in symmetric tests may be less serious than ignoring the contrarian cases that almost always occur in studies relying on symmetric tests – this statement is another way of expressing the point that relationships among variables are almost never symmetrical (an exception is creating a few questions of the same construct in a multi-item scale). The following steps illustrate such a finding. For both antecedent and outcome conditions, dividing the cases by quintiles from very low, low, middle, high, and very high and cross-tabbing the two conditions (i.e., variables) usually results in the presence of cases in all 25 cells. For example, Fig. 12 is the cross-tab of the quintiles for the summed average CSE scores and job satisfaction for the data in the present study.

Cross-tabulations of cases by quintiles is a case-based procedure recommended by McClelland (1998) as a step in constructing algorithms. Before doing so, McClelland (1998) was frustrated by the failure to achieve high predictive validation (using data from new samples of cases) via symmetric tests (MRA models). Fig. 12 illustrates McClelland's (1998) use of quintiles to achieve distinguishes information from noise. The support of the overall symmetric relationships between the CSE and JS in Fig. 12 is clear only at the two extreme quintile cross-tab levels: low-low and high-high. These two cells include the greatest number of cases in the cross-table (85 + 109 = 194) or close to 20% of the total respondents. Cases in cells contrary to the symmetric

	Job Satisfaction					
CSE Group	**Very low**	**Low**	**Middle**	**High**	**Very High**	**Total**
Very low	85	53	39	20	8	205
Low	32	49	74	28	20	203
Middle	16	42	74	33	38	203
High	13	22	78	50	53	216
Very high	2	5	30	27	109	173
Total	148	171	295	158	228	1000

7.6% of the total cases

4.2% of the total cases

Phi = 0.63, $p < .001$

= the number in the box indicates the most frequent number of cases in the row.

= the number in the dotted-line boundary are cases contrary to the highly significant statistically positive linear relationship indicated by phi = 0.63; the contrarian cases have very low and low CSE scores but very high and high in job satisfaction or cases having high and very high CSE scores but low or very low job satisfaction scores.

Fig. 12. Cross-Tabulation of Quintiles of Cases for Core Self-Evaluations (Summed CSE Averages) and Job Satisfaction.

relationship also are present in Fig. 12. These cases appear inside the dotted areas of Fig. 12. Close to 12% of the cases in the study indicate a relationship of either low CSE with high JS or high CSE with low JS. Rather than ignore such cases, case-based theory and data analysis attempt to explain and predict their occurrence by examining the complex conditions in which they appear. Though McClelland's study has an annual citation-count close to 50 since 1998, the two steps that he took – testing for predictive validity (not just fit validity) using case-based algorithms – continue to be ignored pervasively in applied psychology. The present study contributes by applying (and recognizing) McClelland's successful and seemingly simple, yet radical, paradigm shift from variable-based, symmetric, directional-relationship theory construction and testing to case-based, asymmetric, outcome-identification theory construction and testing.

Prior and current environmental conditions are likely to influence the extent that managers work with low or high CSE as a dispositional trait. The present study contributes by proposing and examining the perspective that farmographic configurations (including specific categories of farm industries) influence farm managers' psychological self-concept. To answer this question from a particularly useful case research stance, the present study contributes by taking the following three steps: (1) adopting complexity theory in applied psychology to offer (2) a case-based, contextual, farmographic configurational explanations of managers with high CSEs, and (3) conducting an empirical study that provides evidence to confirm or reject the theory. Because of the relevancy of causal asymmetry tenet in complexity theory, the present study takes the related but separate steps for identifying the managers with low CSEs. The reported study provides substantial evidence supporting the theoretical perspective that farmographics including working in specific industries affect farm managers' positive or negative self-concepts (i.e., cases high or low in CSE).

Bart Simpson's advice, "Don't have a cow, man!" implies that having cows associates with high psychological strain and high stress. The findings in the present study do not support this implication. In fact, dairy farming appears much more frequently in farmographic configurations indicating low psychological strain (Table 10) and low stress (Table 11) rather than Simpson's implication. Possibly, similar to pets, cows may be given names (e.g., Betsy) more often than sheep, beef, or horticultural crops. Given that research (Allen, Shykoff, & Izzo, 2001; Siegel, 1990) includes evidence that ownership versus non-ownership of pets, dogs especially, associates with lower stress among the elderly (humans) and the present study's findings, "Have a cow, man!" is likely to be sounder than Simpson's advice for reducing stress.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Limitations of the study include the possibility of self-report bias for each of the items in the survey. Self-generated validity issues (Feldman & Lynch, 1988) whereby the questions answered early affect answers given later in the survey is a concern. Respondents' abilities to know themselves sufficiently to give valid answers to their real-life psychological dispositions (Wilson, 2004) is a related question that the present study does not try to answer. As a step to probing this issue, further development of implicit dispositions, indirect questioning, via thematic apperception testing (TAT) of CSE sub-traits is appropriate for future research on job stressors, job strain, and job satisfaction. Just as McClelland, Koestner, and Weinberger (1989) observed for implicit versus self-attributed motives, implicit and self-attributed CSE sub-traits may differ substantially among some respondents and matching versus mismatching is likely to affect the accuracy of identifying specific outcomes by specific individuals. The high nomological validity in the patterns of correlations (Fig. 3) and in the abilities of the case-based models in predicting outcomes accurately in some, but not all, propositions supports the general conclusion that the method's limitations do not indicate fatal flaws. The study does offer several advances in theory and useful empirical findings.

The study is limited by not including job performance questions. Prior research (Hsiao et al., 2015) demonstrates that job satisfaction relates to job performance asymmetrically. Case-based examinations of the configurations of CSE sub-traits, both high and low job satisfaction, job stress, and job strain impact high versus low job performance await the attention of future researchers.

The study's examination of managers in one industry in one (highly developed) nation is a limitation. Additional studies are necessary that replicate and extend the present study to inform theory as to whether or not the specific case-based models are generalizable to other nations and additional industries. Performing such research seeking "statistical sameness" in findings is a necessary step for advancing good (i.e., accurate) science (cf. Hubbard, 2016).

IMPLICATIONS FOR HRM THEORY CONSTRUCTION AND PRACTICE

The findings and discussion in the present study clarifies a dilemma raised by Judge and Bono (2001, p. 86), "On the basis of these results [symmetric test findings], when one is interested in predicting job satisfaction or job performance, it is not clear whether researchers should use one or more of these [CSE] traits." The present study indicates that researchers should include all four CSE sub-traits in their study and if researchers do seek to predict individual outcomes, two additional steps are necessary. First, researchers need to move beyond the use of symmetric MRA to the use of algorithms, as done by McClelland (1998). Second, researchers need to test for predictive validity using additional samples of respondents, as done by McClelland (1998). The present study shows that for the following algorithm to be a model high in predictive accuracy for high job satisfaction, the requirement is that managers score above the 90th percentile across each of the four CSE sub-traits. This model is asymmetric; the model says nothing about low scores on job satisfaction. Many of the managers not surpassing the four-trait screen have high scores in job satisfaction and many have low scores in job satisfaction. Additional models are necessary to identify managers below the four-trait algorithm model for identifying those with high job satisfaction. The equifinality tenet and the additional tenets in complexity theory are relevant for advancing HRM theory and research.

Most researchers in the behavioral sciences mostly use symmetric tests such as MRA. Almost all of these studies test the resulting MRA models using fit validation only (Gigerenzer & Brighton, 2009). High fit validities of MRA models are illusions as Armstrong (2012) explains – seemingly useful models by fit validity can be accomplished using a table of random numbers for data as Armstrong (2012) demonstrates. While MRA models are usually more accurate than simpler algorithmic models in fit validation because they over fit the models to account for idiosyncratic impacts of values of variables in the models, the reverse finding occurs for predictive validation (Marewski, Gaissmaier, & Gigerenzer, 2010). Essays in the relevant literature periodically recognize the necessity of achieving accurate point estimation rather than the current dominant practice of providing (context-free) relationship directionalities (Andreski, 1972; Edwards & Berry, 2010; Gigerenzer, 2004; Hubbard, 2016; Meehl, 1967; McCloskey, 2002; Woodside, 2014).

Given the rising number of studies using configurational analysis that provide findings from SPOT rather than findings from tests for nonzero directional relationships via NHSTs, hope springs. Criticism of the use of NHST focusing on reporting findings of nonzero directional relationships has been robust: Hubbard (2016) counted 4,359 citations to 19 articles and books describing the failures of NHST. "This [citation impact] would make them seemingly impossible to ignore in academic circles. Yet ignored they are when it comes to changing statistical analysis and reporting habits" (Hubbard, 2016, p. 234). Given a practice is so ingrained as NHST to enable the continuation of the lack of recognition of its bad practice, critics need to produce theory and show findings that provide point (outcome) estimates. Criticism alone is insufficient to cause a paradigm shift. Such paradigm shift studies are available (Fiss, 2011; Hsiao et al., 2015; McClelland, 1998; Ordanini et al., 2014; Wu et al., 2014). Advancing this paradigm shift from NHST to SPOT represents the not so hidden subtext of the present study.

REFERENCES

Alegre, A., Mas-Machuca, M., & Berbegal-Mirabent (2014). Antecedents of employee job satisfaction: Do they matter? *Journal of Business Research*, *69*(4), 1390−1395.

Allen, K., Shykoff, B., & Izzo, J. (2001). Pet ownership, but not ACE inhibitor therapy, blunts home blood pressure responses to mental stress. *Hypertension*, *38*(4), 815−820.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. ~~*Psychological Bulletin*, *103*(3), 411−423~~.

Andreski, S. (1972). *Social science as sorcery*. New York, NY: St. Martin's Press.

Anscombe, F. J. (1973). Graphs in statistical analysis. *American Statistician*, *27*(1), 17−21.

Armstrong, J. S. (2012). Illusions in regression analysis. *International Journal of Forecasting*, *28*, 689−694.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: W. H. Freeman.

Bascand, G. (2009). *Labour Market Statistics: 2008*. Wellington: Statistics New Zealand.

Brayfield, A. H., & Rothe, H. F. (1951). An Index of Job Satisfaction. *Journal of Applied Psychology*, *35*(5), 307−311.

Brazil, S. (Ed.) (2008). *New Zealand official yearbook* (p. 357). Statistics New Zealand. ISBN 978-1-86953-717-3.

Chang, C., Ferris, D. L., Johnson, R. E., Rosen, C. C., & Tan, J. A. (2012). Core self-evaluations: A review and evaluation of the literature. *Journal of Management*, *38*, 81−128.

Cohen, J. (1977). *Statistical power analysis for the behavioral sciences (Rev. ed.)*. New York, NY: Academic Press.

Costa, P. T., Jr., & McCrae, R. R. (1988). Personality in adulthood: A six-year longitudinal study of self-reports and spouse ratings on the NEO Personality Inventory. *Journal of Personality and Social Psychology*, *54*(5), 853–863.

Deary, I. J., Willock, J., & McGregor, M. (1997). Stress in farming. *Stress Medicine*, *13*(2), 131–136.

Edwards, J. R., & Berry, J. W. (2010). The presence of something or the absence of nothing: Increasing theoretical precision in management research. *Organization Research Methods*, *13*(4), 668–689.

Feldman, J. M., & Lynch, Jr. J. G. (1988). Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *Journal of Applied Psychology*, *73*(3), 421–435.

Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *The Academy of Management Review*, *32*(2), 1180–1198.

Fiss, P. C. (2011). Building better casual theories: A fuzzy set approach to typologies in organizational research. *Academy of Management Journal*, *54*(2), 393–420.

Fiss, P. C., Marx, A., & Cambré, B. (2013). Configurational theory and methods in organizational research: Introduction. In P. C. Fiss, B. Cambré, & A. Marx (Eds.), *Configurational theory and methods in organizational research* (Vol. 38). Bingley: Emerald.

Fogarty, G. J., Machin, M. A., Albion, M. J., Sutherland, L. F., Lalor, G. I., & Revitt, S. (1999). Predicting occupational strain and job satisfaction: The role of stress, coping, personality, and affectivity variables. *Journal of Vocational Behavior*, *54*(3), 429–452.

Frösén, J., Luoma, J., Jaakkola, M., Tikkanen, H., & Aspara, J. (2016). What counts versus what can be counted: The complex interplay of market orientation and marketing performance measurement. *Journal of Marketing*, *80*(3), 60–78.

Gardner, D. G., & Pierce, J. L. (2009). The core self-evaluation scale: Further construct validation evidence. *Educational and Psychological Measurement*, *70*, 291–304.

Gigerenzer, G. (1991). From tools to theories: A heuristic of discovery in cognitive psychology. *Psychological Review*, *98*(2), 254–267.

Gigerenzer, G. (2004). Mindless statistics. *Journal of Socio-Economics*, *33*(5), 587–606.

Gigerenzer, G. (2010). *Rationality for mortals: How people cope with uncertainty*. Oxford: Oxford University Press.

Gigerenzer, G., & Brighton, H. (2009). Homo heuristics: Why biased minds make better inferences. *Topics in Cognitive Science*, *1*(1), 107–143.

Gladwell, M. (2000). *The tipping point: How little things can make a big difference*. New York, NY: Little, Brown.

Goldberg, D. P., & Williams, P. (1991). A user's guide to the *General Health Questionnaire*. *Acta Psychiatrica Scandinavica*, *84*, 125–129.

Hiller, N., & Hambrick, D. C. (2005). Conceptualizing executive hubris: The role of (hyper-) core self-evaluations in strategic decision-making. *Strategic Management Journal*, *26*(4), 297–319.

Hsiao, J. P.-H., Jaw, C., Huan, T. C., & Woodside, A. G. (2015). Applying complexity theory to solve hospitality contrarian case conundrums: Illuminating happy-low and unhappy-high performing frontline service employees. *International Journal of Contemporary Hospitality Management*, *27*(4), 608–647.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Model: A Multidisciplinary Journal*, *6*(1), 1–55.

Hubbard, R. (2016). *Corrupt research: The case for reconceptualizing empirical management and social science*. Thousand Oaks, CA: Sage.

Hutching, B. Ed. (2006). *New Zealand official yearbook*. Statistics New Zealand.

Joreskog, K. G. (1993). Testing structural equation models. In K. A. Bolen & J. C. Long (Eds.), *Testing structural equation models* (pp. 294–316). Newbury Park, CA: Sage Publisher.

Judge, T. A., & Bono, J. E. (2001). A rose by any other name: Are self-esteem, generalized self-efficacy, neuroticism, and locus of control indicators of a common construct. In B. W.

Roberts & R. Hogan (Eds.), *Personality psychology in the workplace: Decade of behavior* (pp. 93–118). Washington, DC: American Psychological Association.

Judge, T. A., Erez, A., & Bono, J. E. (1998). The power of being positive: The relation between positive self-concept and job performance. *Human Performance*, *11*(2-3), 167–188.

Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2003). The core-self-evaluations scale: Development of a measure. *Personnel Psychology*, *56*, 303–331.

Judge, T. A., & Hurst, C. (2008). How the rich (and happy) get richer (and happier): Relationship of core self-evaluations to trajectories in attaining work success. *Journal of Applied Psychology*, *93*(4), 849–863.

Judge, T. A., & Kammeyer-Mueller, J. D. (2011). Happiness as a societal value. *Academy of Management Perspectives*, *25*, 30–41.

Judge, T. A., Locke, E. A., & Durham, C. C. (1997). The dispositional causes of job satisfaction: A core evaluations approach. *Research in Organizational Behavior*, *19*, 151–188.

Kalliath, T. J., O'Driscoll, M. P., & Brough, P. (2004). A confirmatory factor analysis of the General Health Questionnaire, 12, 11–20.

Kokkinos, C. (2007). Job stressors, personality and burnout in primary school teachers. *British Journal of Educational Psychology*, *77*(1), 229–243.

Locke, E. A., McClear, K., & Knight, D. (1996). Self-esteem and work. *International Review of Industrial/Organizational Psychology*, *11*, 1–32.

Marewski, J. N., Gaissmaier, W., & Gigerenzer, G. (2010). Good judgements do not require complex cognition. *Cognitive Processing*, *11*(2), 103–121.

McClelland, D. C. (1998). Identifying competencies with behavioral-event interviews. *Psychological Science*, *9*(5), 331–339.

McClelland, D. C., Koestner, R., & Weinberger, J. (1989). How do self-attributed and implicit motives differ? *Psychological Review*, *96*(4), 690–702.

McCloskey, D. (2002). *The secret sins of economics*. Chicago, IL: Prickly Paradigm Press.

Meehl, P. E. (1967). Theory-testing in psychology and physics: A methodological paradox. *Philosophy of Science*, *34*, 103–115.

Meehl, P. E. (1978a). Theoretical risks and tabular asterisks: Sir Karl, Sir Ronald, and the slow progress of soft psychology. *Journal of Consulting and Clinical Psychology*, *46*(4), 806–834.

Misangyi, V. F., Greekhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2016). Embracing causal complexity: The emergence of a neo-configurational Perspective. *Journal of Management*, *42*(7), 1–28.

Nguyen, N., & Borteyrou, X. (2016). Core self-evaluations as a mediator of the relationship between person–environment fit and job satisfaction among laboratory technicians. *Personality and Individual Differences*, *99*, 89–93.

Ordanini, A., Parasuraman, A., & Rubera, G. (2014). When the recipe is more important than the ingredients: A qualitative comparative analysis (QCA) of service innovation configurations. *Journal of Service Research*, *17*(2), 134–149.

Products from New Zealand (2016). Retrieved from https://productsfromnz.com/1821+Economy+of+New+Zealand. Accessed on November 29, 2016.

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

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and Applied*, 80(1, Whole No. 609).

Schinkel, S., van Dierendonck, D., & Anderson, N. (2004). The impact of selection encounters on applicants: An experimental study into feedback effects after a negative selection decision. *International Journal of Selection and Assessment*, *12*, 197–205.

Siegel, J. M. (1990). Stressful life events and use of physician services among the elderly: The moderating role of pet ownership. *Journal of Personality and Social Psychology*, *58*(6), 1081–1086.

Simon, H. (1990). Invariants of human behavior. *Annual Review of Psychology*, *41*(1), 1–19.

Soyer, E., & Hogarth, R. (2012). The illusion of predictability: How regression statistics mislead experts. *International Journal of Forecasting*, *28*(3), 695–711.

Spector, P. E., Dwyer, D. J., & Jex, S. M. (1988). Relation of job stressors to affective, health, and performance outcomes: A comparison of multiple data sources. *Journal of Applied Psychology*, *73*(1), 11–19.

Spector, P. E., & Jex, S. M. (1998). Development of four self-report measures of job stressors and strain: Interpersonal conflict at work scale, organizational constraints scale, quantitative workload inventory, and physical symptoms inventory. *Journal of Occupational Health Psychology*, *3*(4), 356–367.

Sprietzer, G. M., Kizilos, M. A., & Nason, S. W. (1997). A dimensional analysis of the relationship between psychological empowerment and effectiveness, satisfaction, and strain. *Journal of Management*, *23*(5), 679–704.

Trafimow, D. (2014). Editorial. *Basic and Applied Social Psychology*, *36*, 1–2.

Trafimow, D., & Marks, M. (2015). Editorial. *Basic and Applied Social Psychology*, *37*(1), 1–2.

Walker, L. S., & Walker, J. L. (1987). Stressors and symptoms predictive of distress in farmers. *Family Relations*, *36*(4), 374–378.

Wall, T. D., Jackson, P. R., Mullarkey, S., & Parker, S. K. (1996). The demands-control model of job strain: A more specific test. *Journal of Occupational and Organizational Psychology*, *69*(2), 153–166.

Weick, K. E., & Sutcliffe, K. M. (2007). *Managing the unexpected: Resilient performance in and age of uncertainty* (2nd Ed.). San Francisco, CA: Jossey-Bass.

Wilson, T. D. (2004). *Strangers to ourselves*. Cambridge, MA: Harvard University Press.

Winefield, H. R., Goldney, R. D., Winefield, A., & Tiggemann, M. (1989). The general health questionnaire: Reliability and validity for Australian youth. *Australian & New Zealand Journal of Psychiatry*, *23*, 53–58.

Woodside, A. G. (2013a). Proposing a new logic for data analysis in marketing and consumer behavior: Case study research of large-N survey data for estimating algorithms that accurately profile X (extremely high-use) consumers. *Journal of Global Scholars of Marketing Science*, *22*, 277–289.

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

Woodside, A. G. (2014). Embrace•perform•model: Complexity theory, contrarian case analysis, and multiple realities. *Journal of Business Research*, *67*(12), 2495–2503.

Woodside, A. G. (2016). *Replacing null hypothesis statistical testing (p < .05): Computing with words, applying complexity theory, and somewhat precise outcome testing (SPOT)*. Working Paper No. 2016-1. Curtin School of Marketing, Curtin University, Perth, Australia.

Wu, P.-L., Yeh, S. S., Huan, T. C., & Woodside, A. G. (2014). Applying complexity theory to deepen service dominant logic: Configural analysis of customer experience-and-outcome assessments of professional services for personal transformations. *Journal of Business Research*, *67*(8), 1647–1670.

Zadeh, L. (1996). Fuzzy logic: Computing with words. *IEEE Transactions on Fuzzy Systems*, *4*(2), 103–111.

Zellner, A. (2001). Keep it sophisticatedly simple. In H. Keuzenkamp & M. McAleer (Eds.), *Simplicity, inference, and modelling: keeping it sophisticatedly simple* (pp. 242–261). Cambridge: Cambridge University Press.