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Application of Structural Equation Modeling (SEM) in restructuring state intervention strategies toward paddy production development

Shahin Shadfar1*, Iraj Malekmohammadi1

1 Department of Agricultural Development, Science and Research Branch, Islamic Azad University, Tehran – Iran

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Abstact

To structure state interventions policies into rice production development in Iran; by studying state intervention policies in major rice producing countries; a theoretical model was proposed. To test the fitness of the model by real data from the field, and to evaluate state intervention policies, CFA and SEM application have used. Convergent Validity (CV), Discriminate Validity (SD) and Construct Reliability (CR) of the model were assessed by applying appropriate tests and measurement indices, including SIC and AVE. Despite little is known about the Multicollinearity (MC) in SEM; extra care was taken; proper diagnosis and treatment for MC in SEM was practiced. The outcome is totally new structure for intervention policies, can be taken by state to boost rice production in Iran. The same procedure can be applied into agricultural development of other states.

Keywords: Structural equation modeling, rice production development, state intervention strategies

Introduction

The researches on the role of the state in the development have generated many debates and countless pages of writings. Albeit, the new millennium poses new challenges for policy makers; government, private sectors and social segments together must set the development agenda of tomorrow to meet the diverse and changing needs. The appropriate role of government in the new millennium, in particular, appears to be an interesting and challenging one. Thus, if the future of modern economies and societies needs to be very different from the past, it will require a much sharper focus on radical development policy agendas (Karagiannis and Madjd-Sadjadi, 2007). The state concept and roles have been drastically changed in last five decades. In recent years, expectations from government to play special role has been significantly increased. The general mood is changing to have different type of

* Corresponding author: e-mail: shahin.shadfar@gmail.com

state plans in very new perspectives, new structures and new attitudes to develop economy and sub sectors. Therefore, it is crucial to understand how stronger, more interventionist states will interact with today's highly globalized international economy (Ohnesorge et al, 2010). This is why some economists like Evans believes that sterile debates about 'how much' states intervene have to be replaced with arguments about different kinds of involvement and their effects. Contrasts between 'dirigiste' and 'liberal' or 'interventionist' and 'noninterventionist' states; focus attention on degree of departure from ideal-typical competitive markets. They confuse on the basic issues. In the contemporary world, withdrawal and involvement [of the state] are not the alternatives. State involvement is a given. The appropriate question is not 'how much' but 'what kind' (Evans, 1995). Many studies have conceded the role of state in economic changes and achieved development goals (Chang & Rowthorn, 2009, Madden & Cytron, 2003). Ever since the states have started to make developmental policies and intervene into agricultural development; scientist try to answer key questions on what would be pros and cons of the state interventions. Failure of invisible hands of the market to deliver developmental desires; in light of understanding development mechanism, rules and processes; have made modeling state interventions policies, an interesting and challenging task for the policymakers. In country like Iran, by decades of policymaking history on state interventions and state willing and passion to interfere into agriculture sector; structure the policies of state to intervene into this sector is crucial and necessary, yet difficult and strategic topic. It is widely accepted that Iran state who has absolute controlling power, coming from making rules and using monetary tools; directly and indirectly acts as driver force to re-structure the developmental policies (Sinayiee, 2005). Having said that the state is the tailwind toward development in Iran, many questions are posed on special role of the government in agricultural development. Notwithstanding, like many other Asian countries, as staple food for the overwhelming majority of the population, rice is ultimately a food security concern in Iran (it is the second staple food item after wheat). Therefore, government's responsibility to provide substantial intervention in terms of both regulation and support is indispensable. However, from the other rice producing countries experiments, it has been revealed that the state interventions are to ensure the continued viability of rice production and guaranteed sufficient number of farmers would continue to plant enough rice to feed the population. Having said that, Obanil & Dano (2005) have shown under the framework of continuing state intervention, options for developing rice production to meet domestic requirements are not very much different. Therefore, finding the appropriate formula comprising production related and market-based interventions by the state, determine whether the goal of achieving self-sufficiency [strategic goal for many Asian countries as well as Iran] would ultimately be realized.

Global rice data shows Iran was the 4^{th} biggest rice importer country in the world in 2010 by over 985,000 T imported rice, which was accounted for 3.4% of total exported rice (Rice International Conference & Exhibition, 2011). Giving this situation, rice production in Iran has challenges which can be named few; natural resources degradations, low pace in rural growth and development, limited farmers participation to set the policies and make decisions, existing powerful and effective traditional local-social structures, high risk and cost of production, deficiency in rice industry and lands leveling, fragmented farms, and change of land usage to project businesses (Fallah, 2007). Notwithstanding, state agencies in Iran are inattentively planning and executing projects mostly without rice farmers' involvement and participations. Due to lack of belief in farmers effective role in development, most of the Iranian state plans and programs in this section had been developed without feasibility studies and scientific background (Najafi, 2000). Consequently, the rice farmers are disengaged and inattentive to government projects and plans. They are not willing to follow state planned goals in regards to rice production (Fallah, 2007). Therefore, organizational structure and current complex of state plans and projects toward agricultural development could not respond to this section needs and priorities; and as result; government cannot analyze challenges and issues in rice production business to develop suitable solutions (Anonymous, Iran Ministry of Agriculture think-tank, 2009). This is why the state and rice farmers have totally different priorities, goals, preferences, expectations and even separate action plans, which leave issues untreated; problems unresolved and might create even more issues. Knowing this fact that every year, Iran's government spends millions of dollars to achieve rice self-sufficiency goal and develop rice production; makes studying state interventions policies in rice sector merit and strategic topic; to plan state interventions in a manner that brings the highest benefits to the targeted group in line with the intended development path. To this end, state intervention policies should be re-structured again; fit the agro-ecological and socio-economical policy environment of Iran. Such interfering developmental programs would then have greater chance of being accepted and practiced in more sustainable manner than programs based on temporary incentives or coercive pressure.

To address these challenges and increase the productivity and growth in business of rice production; this paper, as part of the PhD dissertation entitled: Designing the Structure of State Interventions for Developing Rice Production in Northern Region of Iran Based on Framers' Preferences; is aimed to re-structure the state intervention policies in Iran rice sector. The study has reviewed state policies in regards to rice production development in major rice producing countries to propose state intervention structure (Malekmohammadi et al, 2011) and accordingly has identified areas that state should take the plunge to develop the rice production. Following that, Structural Equation Modeling (SEM) techniques has been applied to re-model state strategies, policies and plans, given this fact that identify underplaying factors and constructs could help the state to allocate its rare resources more effectively in this section.

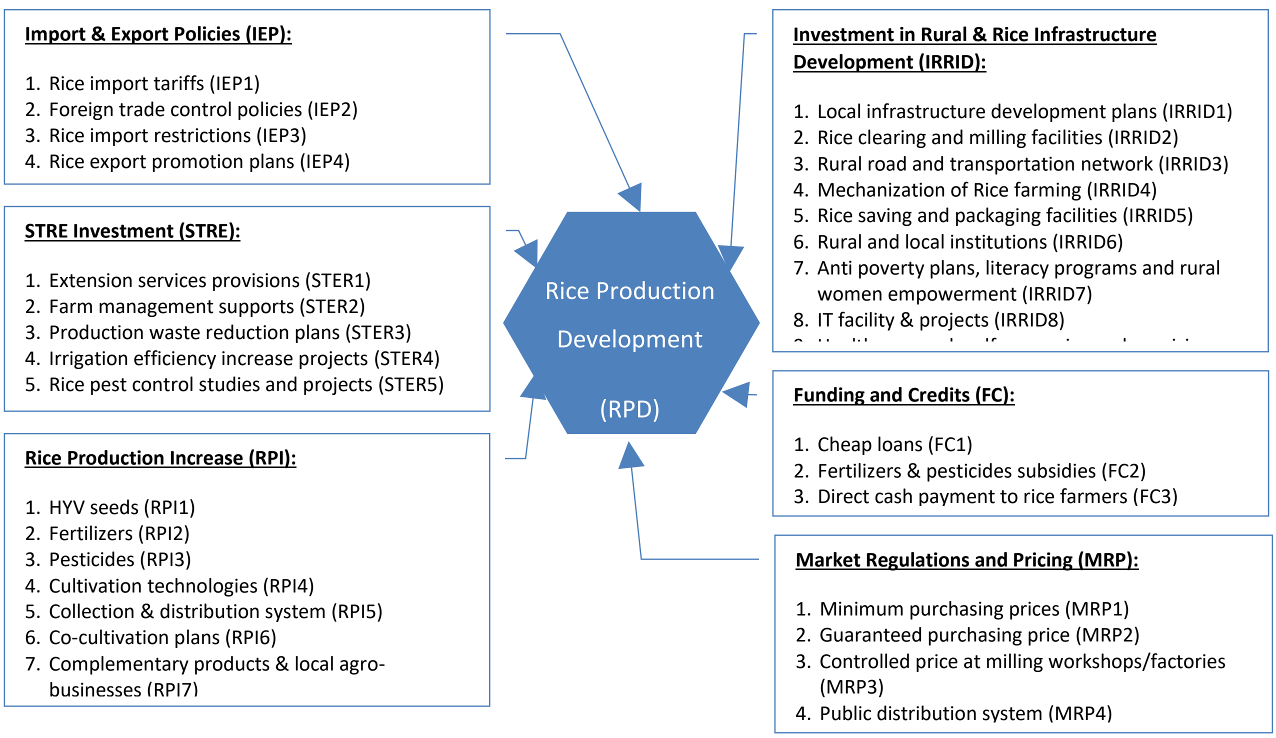
Theoretical Method

According to Workman (2008), Asian countries enjoy a prohibitive lead in farming rice, China and India, together, accounted for over half of the world's rice supply in 2006. Empirical studies have shown several factors contributing to the rice production across major rice producing countries (i.e. in Asia) that among them, main factors are the adoption of modern varieties (HYVs), use of inorganic fertilizers, availability of irrigation facilities, and government commitment to support rice production. However, according to Rice Trade (2010) there has been a major decline in world rice production since late 2007 due to many eternal & out of control factors, including climatic conditions in many major rice producing countries as well as policy decisions affected rice export by the governments of countries with considerable rice production. Nevertheless, according to the Food and Agriculture Organization (FAO) of the U.N., 80% of the world rice production comes from 6 countries including, China, India, Indonesia, Vietnam, Thailand, Myanmar and Philippines (Ibid). To define a theoretical model for analyzing and evaluating policies of the states in rice sector in Iran, commonalties of the state intervention policies in major rice producing countries (table 1) have studied [summery of common areas that state have interfered is reported in table 2 in appendices]. The output of this study was a globalized structure model of policies (fig 1) that states of major rice producing countries across the world have been taking to tackle key issues in rice production. The initial assumption was, in the absence of any analytical model that can simplify the complexity of rice production involving factors and serve as an alternative analytical model; the efforts of interventions by the governments in successful countries (i.e. major rice producing countries) can be duplicated as role model.

Table 1: Rice Production in Major Rice Producing Countries

Country	Rice Production (Million Ton)	Global Production Share (%)
China	182.0	28.80
India	136.5	21.60
Indonesia	54.4	8.60
Vietnam	35.8	5.70
Thailand	29.6	4.60
Philippines	15.3	2.40

Fig. 1: Theoretical Model to Structure State Interventions Policies to Develop Rice Production



United States	8.8	1.40
South Korea	6.3	1.00
Malaysia	2.2	0.30

Source: Workman, 2008

Such a model then can be used further to understand the intricacies of the system and to study in advance the effects of changes in various internal and external variables in the system (Gupta and Kortzfleisch, 1987). Another assumption of developing this theoretical model was this fact that positive effects of these policies already have been approved by enormous amount of rice these countries are producing. Therefore, following same path might help to build up and implement the same structure to ensure desired result; which is increase in rice output and ultimately developing rice production in Iran. The wide range of policies have been experienced in these countries (see table 2), clearly points to state intervention as crucial factor for the success of increase in rice production. The type of intervention is, however, just as important – if not more important. Nevertheless, common areas in intervention policies by states in these countries can be summarized & re-structured as below:

1. Investment in Rural and Rice Infrastructure Development (IRRID)
2. Rice Production Increase (RPI)
3. Science, Technology, Research and Extension Investment (STRE)
4. Funding and Credits Policies (FC)
5. Market Regulations and Pricing Policies (MRP)
6. Import and Export Policies (IEP)

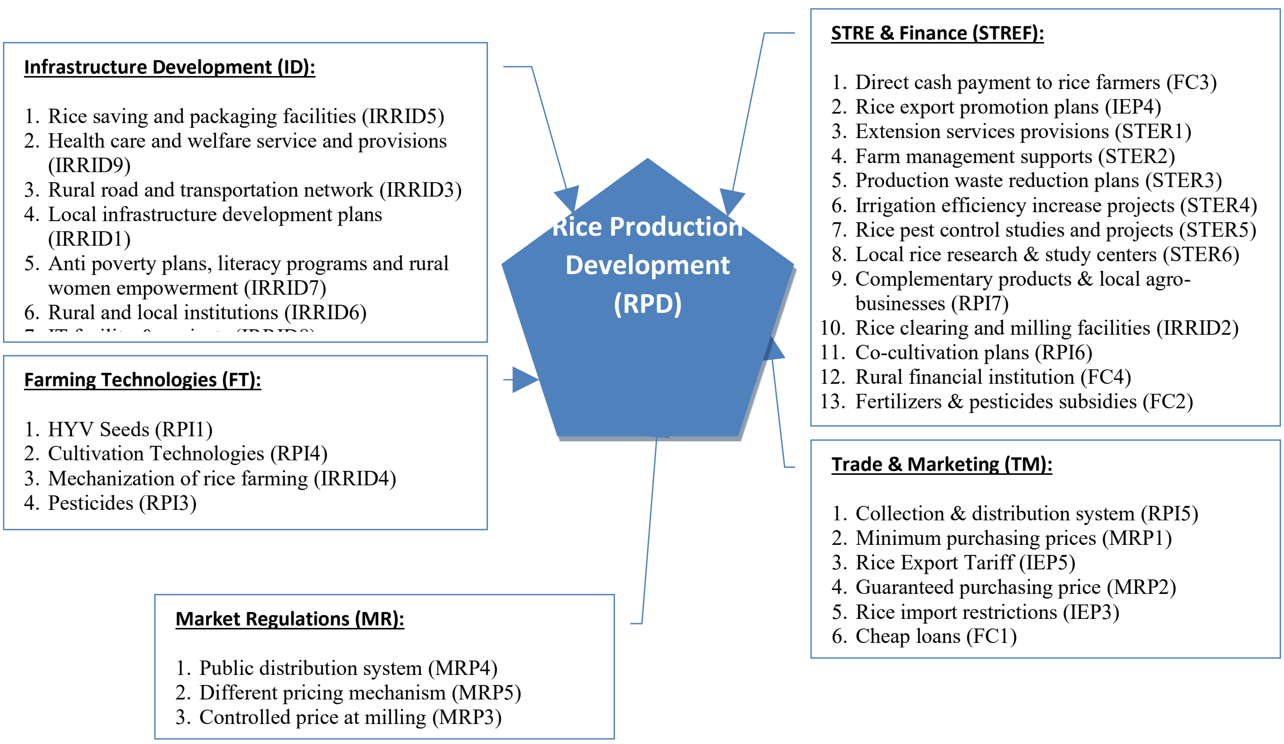
This structure describes the policy environment that have helped shape the viability of the rice sector and the affordability and reliability of rice supply, specifying the institutional details of state interventions as well as the strategic policies that drive them. It also could help to establish parameters to the design and implement proper structure of the state rice supportive and developmental policies in Iran.

Analyzing Method

To measure the effects of super-variables (constructs) of proposed theoretical model for state interventions, all rice farmers in the state of Mazandaran (N = 176,792, n = 385) as biggest rice producing province in Iran have approached. Questionnaire with different type of statements (in total 147 statements) implemented in Likert scale have been developed to collect the necessary data. Validity and internal reliability of questionnaire measured by Cronbach's alpha coefficient ($\alpha = 0.90$), Theta coefficient ($\theta = 0.96$) and AVE (= 0.93). By using innovative variable refinery technique (Malekmohammadi, 2008) some of statements and variables which could create bias omitted as well. In the next step, measurements of all sub-area policies (IVs) of model run into exploratory factor analysis (Shadfar and Malekmohammadi, 2011a) to see the loading of variables and reduce the number of parameters in the model as well as finding the structure of relationships among variables in each proposed areas. Consequently, factor analysis has identified five major components within data set, accounted for 67.54% of total variance. Consequently, operational model for this study (fig. 2) has created which is shrank version of initial proposed theoretical model for state interventions by totally new IVs and sub-areas compartments.

Having two definitions and scales for rice production development as Dependent Variable (DV) of this study, ordinal regression for dichotomous definition of DV and multinomial logistic regression for categorical definition of DV have applied. Model goodness-of-fit parameters showed multicollinearity (MC) among IVs, which was needed proper treatment by calculating VIF & Tolerance (Shadfar and Malekmohammadi, 2013b). Consequently, three IVs; *Infrastructure Development (ID), Trade & Marketing (TM)* and *STRE & Finance (STREF)*; detected as cause of multicollinearity. However, due to importance of these constructs in

Fig. 2: Operational Model of State Interventions for Rice Production Development

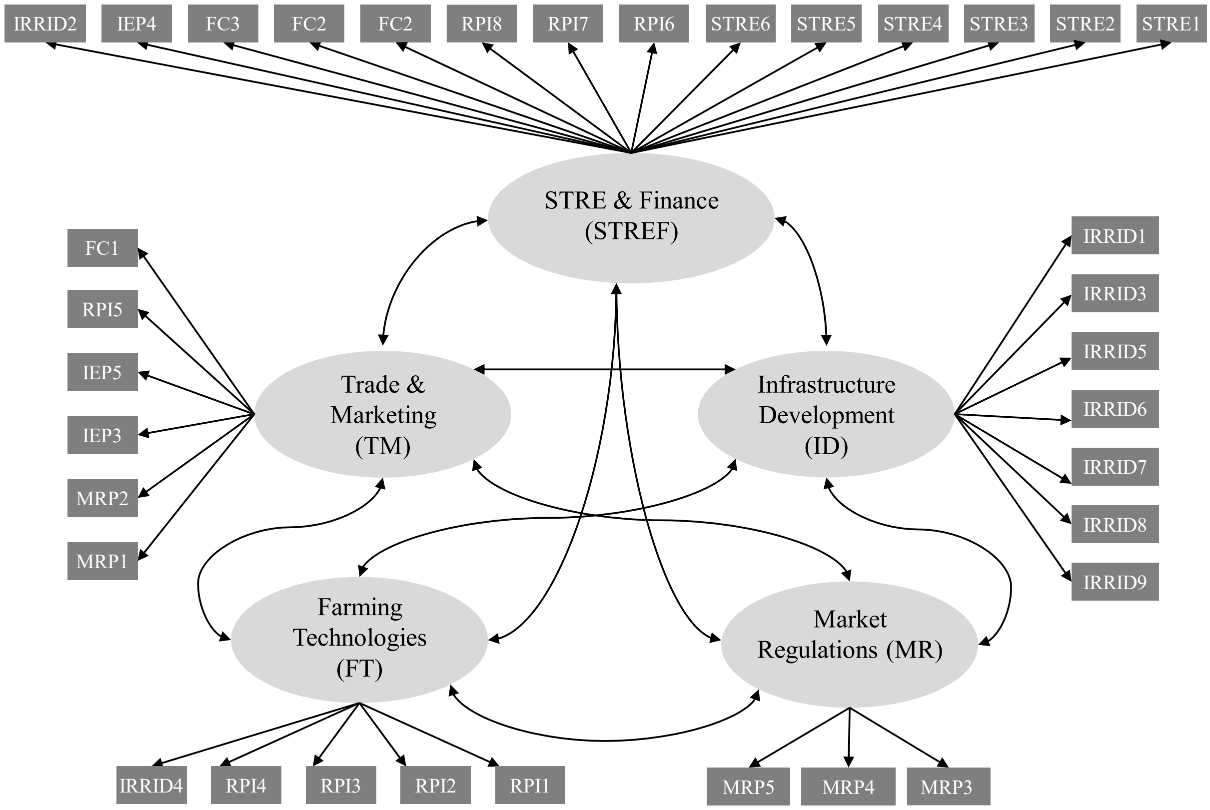


model, it was decided to keep them in the model for further analysis. Having results of exploratory factor analysis and application of ordinal and multinomial logistic regressions, the model has finally new five super-variables now, while multicollinearity also diagnosed and at the final stage, study relationships among and between IVs & DV, as well as measuring the fitness of the proposed model is due to identified by application of SEM.

Structural Equation Modeling (SEM)

Researchers can use SEM for purposes of analyzing potential mediator and moderator effects. In addition, by conducting SEM analysis, the researcher can model observed variables, latent variables (i.e., the underlying, unobserved construct as measured by multiple observed variables), or some combination of the two. Regardless of the specific variables the researcher uses, SEM is a confirmatory technique where analyses typically involve testing at least one a priori, theoretical model, and unlike many other statistical techniques, when using SEM the researcher can test the entire theoretical model in one analysis. As part of the analysis, the researcher can test both the specific hypothesized relationships among his or her variables and the plausibility of the overall model (i.e., the fit of the model). Clearly, SEM has a number of benefits for the researcher interested in studying relatively complex theoretical models (Martens and Haase, 2006). SEM grows out of and serves purposes similar to multiple regressions, but in a more powerful way which takes into account the modeling of interactions, nonlinearities, correlated independents, measurement error, correlated error terms, multiple latent independents each measured by multiple indicators, and one or more latent dependents also each with multiple indicators. SEM can be used as a more powerful alternative to multiple regression, path analysis, factor analysis, and analysis of covariance. That is, these procedures may be seen as special cases of SEM, or, to put it another way, SEM is an extension of the general linear model (GLM) of which multiple regression is a part. Advantages of SEM compared to multiple regression include more flexible assumptions (particularly allowing interpretation even in the face of multicollinearity), use of confirmatory factor analysis to reduce measurement error by having multiple indicators per latent variable, the attraction of SEM's graphical modeling interface, the desirability of testing models overall rather than coefficients individually, the ability to test models with multiple dependents, the ability to model error terms, the ability to test coefficients across multiple between-subjects groups. Moreover, where regression is highly susceptible to error of interpretation by misspecification, the SEM strategy of comparing alternative models to assess relative model fit makes it more robust (Garson, 2011a). In addition, with initial theoretical model, SEM can be used inductively by specifying a corresponding model and using collected data to estimate the values of free parameters; construct latent variables which cannot be directly measured; and explicitly capture the unreliability of measurement in the model, which in theory allows the structural relations between latent variables to be accurately estimated. SEM centers around two steps; validating the measurement model and fitting the structural model. The former is accomplished primarily through confirmatory factor analysis, while the latter is accomplished primarily through path analysis with latent variables. In fact, use of SEM software for a model in which each variable has only one indicator is a type of path analysis. Use of SEM software for a model in which each variable has multiple indicators but there are no direct effects (arrows) connecting the variables is a type of factor analysis (Ibid). In this study, SEM by AMOS 18 as widely accepted software of SEM application has practiced.

Fig. 3: Graphical Display of fiveConstructs in Measurement Model



Results and Discussions

Measurement Model

Measurement model of this study; extended from the operational model of state intervention policies in rice production development; is illustrated in fig. 3; represents models constructs, indicator variables and interrelationships in the model. There is no point in proceeding to the structural model [in SEM] until validity of measurement model is satisfactory (Paswan, 2009). This can be done by Confirmatory Factor Analysis (CFA). By CFA, factor structure on basis of a good theory can be specified. CFA can also provide quantitative measures that assess the validity and reliability of proposed theoretical model. Basically two broad approaches available to assess the measurement model validity by CFA. First is examining Goodness-of-fit (GOF) indices and the second is evaluate the construct validity and reliability of the specified measurement model (Ibid). SEM has no single statistical test that best describe the strength of model's prediction. Instead, different type of measures, have developed by researchers; in combination assess the results. In this study GOF indices are presented first and later validity and reliability of measurement model is discusses. The initial measure of GOF is SRMS (Standardized Root Mean Square Residual), which is the average difference between the predicted and observed variances and covariances in the model, based on standardized residuals. Standardized residuals are fitted residuals [residual covariance]. The smaller the SRMR, the better the model fit. SRMR = 0 indicates perfect fit, value less than .05 is widely considered good fit and below .08 is adequate fit (Garson,2011a). Despite in the literature cutoff at larger than < .10, .09, .08 also found; SRMS of this study sample calculated by Amos was 0.0644 which is in range of adequate fit.

In reference to model fit, researchers use numerous goodness-of-fit indicators to assess a model. Some common fit indices are the Normed Fit Index (NFI), Non-Normed Fit Index (NNFI, also known as TLI), and Incremental Fit Index (IFI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). The wellness of different indices with different samples sizes, types of data, and ranges of acceptable scores are the major factors to decide whether a good fit exists (Hu & Bentler, 1999; Mac-Callum et al, 1996). In general, TLI, CFI, and RMSEA for one-time analyses are preferred (Schreiber et al, 2006). However, this study reports most of goodness-of-fit measures can be found in Model Fit Summary output of AMOS.

Starting with relative chi-square CMIN/DF, also called *normal chi-square*, *normed chi-square*, or simply *chi-square to df ratio*, is the chi-square fit index divided by degrees of freedom. This norming is an attempt to make model chi-square less dependent on sample size.

Table 3: Likelihood Ration Chi-Square

Model	NPAR	CMIN	Df	P	CMIN/DF
Default	80	2134.9	550	.000	3.88
Saturated	630	.000	0		
Independent	35	11146.3	595	.000	18.73

Carmines and McIver (1981) state that relative chi-square should be in the 2:1 or 3:1 range for an acceptable model. Ullman (2001) says 2 or less reflects good fit. Kline (1998) says 3 or less is acceptable. Some researchers allow values as high as 5 to consider a model adequate fit (ex., by Schumacker & Lomax, 2004) while others insist relative chi-square should be 2 or less. Less than 1.0 is poor model fit. Paswan (2009) says a value below 2 is preferred but between 2 and 5 is considered acceptable. Relative chi-square (CMIN/DF) for default model (measurement model) of this study is 3.88 (table 3), which is acceptable. However, Garson (2011) have discussed four ways in which the chi-square test may be misleading. Because of these reasons, many researchers who use SEM believe that with a reasonable sample size (ex., > 200), other fit tests (ex., NNFI, CFI, RMSEA) also should be considered to avoid of blindly acceptance or modify the model. Since GFI and AGFI tests can yield meaningless negative values, they are not any more preferred indices of goodness-of-fit and no more reported (Ibid). However, the cutoff for these two is > 0.90. But, GFI & AGFI of this study reported by AMOS are 0.730 & .0.690, respectively which could not pass cutoff.

Table 4 shows CFI, TLI, IFI, RFI and NFI for this study. The Comparative Fit Index, CFI, also known as the Bentler Comparative Fit Index compares the existing model fit with a null model which assumes the indicator variables (and hence also the latent variables) in the model are uncorrelated (the "independence model"). CFI varies from 0 to 1. CFI close to 1 indicates a very good fit.

Table 4: Baseline Comparison

Model	NFI Delta 1	RFI rho1	IFI Delat 2	TLI Rho 2	CFI
Default	.808	.793	.850	.838	.850
Saturated	1.000		1.000		1.000
Independent	.000	.000	.000	.000	.000

By convention, CFI should be equal to or greater than 0.90 to accept the model, indicating that 90% of the covariation in the data can be reproduced by the given model. Note Raykov (2000, 2005) and Curran et al. (2002) have argued that CFI, because as a model fit measure based on noncentrality, is biased. However, CFI of this study model is 0.850. Incremental Fit Index (IFI) also should be equal to or greater than 0.90 to accept the model. IFI is relatively independent of sample size and is favored by some researchers for that reason. IFI of this study is reported at 0.850. Normed Fit Index (NFI) was developed as an alternative to CFI, but one which did not require making chi-square assumptions. "Normed" means it varies from 0 to 1, with 1 = perfect fit. NFI reflects the proportion by which the researcher's model improves fit compared to the null model (uncorrelated measured variables). Reported NFI for in this study is 0.808. Tucker-Lewis Index (TLI) or Non-Normed Fit Index, is similar to NFI, but penalizes for model complexity. Marsh et al. (1988, 1996) found TLI to be relatively independent of sample size. TLI close to 1 indicates a good fit. Rarely, some authors have used the cutoff as low as 0.80 since TLI tends to run lower than GFI. However, more recently, Hu and Bentler (1999) have suggested TLI >= 0.95 as the cutoff for a good model fit and this is widely accepted (ex., by Schumacker & Lomax, 2004) as the cutoff. TLI values below 0.90 indicate a need to respecify the model. As shown in table 4, TLI of this study model is 0.838 and therefore, the model has to be respecified. Relative Fit Index (RFI), also known as RHO1, is not guaranteed to vary from 0 to 1. However, RFI close to 1 indicates a good fit. Reported RFI for this model is 0.793. Parsimony-Adjusted Measures Index (PNFI) also shown in table 5. There is no commonly agreed-upon cutoff value for an acceptable model for this index. By arbitrary convention, PNFI>0.60 indicates good parsimonious fit (though some authors use >0.50). In case of this study, PNFI is 0.747 which is acceptable.

Table 5: Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default	.924	.747	.786
Saturated	.000	.000	.000
Independence	1.000	.000	.000

Root Mean Square Error of Approximation (RMSEA) given in table 6 is also called RMS or RMSE or discrepancy per degree of freedom. RMSEA is a popular measure of fit, partly because it does not require comparison with a null model. It is one of the fit indexes less affected by sample size, though for smallest sample sizes it overestimates goodness of fit (Fan, Thompson, and Wang, 1999). By convention (ex., Schumacker & Lomax, 2004) there is good model fit if RMSEA is less than or equal to 0.05, there is adequate fit if RMSEA is less than or equal to 0.08. More recently, Hu and Bentler (1999) have suggested RMSEA less than or equal to ≤ .06 as the cutoff for a good model fit.

Table 6: Root Mean Square Error of Approximation

Model	RMSEA	LO 90	HI 90	PCLOSE
Default	.087	.083	.091	.000
Independence	.215	.211	.218	.000

There appears to be universal agreement that RMSEA of .10 or higher is poor fit. RMSEA is normally reported with its confidence intervals. In a well-fitting model, the lower 90% confidence limit includes or is very close to 0, while the upper limit is less than 0.08. Reported values for RMSEA in table 6, support model fit, as RMSEA is 0.087.

Hoelter's critical N, also called the Hoelter index, is given in table 7 and is used to judge if sample size is adequate.

Table 7: Hoelter Indices

Model	Hoelter 0.05	Hoelter 0.01
Default	109	114
Independence	23	24

By convention, sample size is adequate if Hoelter's N is greater than > 200. However Hoelter's N under 75 is considered unacceptably low to accept a model by chi-square. Two N's are output, one at the 0.05 and one at the 0.01 levels of significance. This throws light on the chi-square fit index's sample size problem. In case of this study, Hoelter index is acceptable as it is in range (200 – 75).

Assessing the Measurement Model

One of the biggest advantages of CFA is its ability to quantitatively assess the construct validly of proposed measurement theory. Construct validity is made up of four components including; Face Validity (the extent to which the content of the items is consistent with construct definition, based solely on the researcher's judgment);

Table 8: Standardized Regression Weights

Construct			Estimate
STRE1	<---	STREF	0.816
STRE2	<---	STREF	0.853
STRE3	***<---***	***STREF***	***0.574***
STRE4	<---	STREF	0.723
STRE5	<---	STREF	0.845
STRE6	<---	STREF	0.769
RPI6	***<---***	***STREF***	***0.680***
RPI7	<---	STREF	0.829
RPI8	<---	STREF	0.856
FC2	***<---***	***STREF***	***0.550***
FC3	<---	STREF	0.808
FC4	<---	STREF	0.717
IEP4	<---	STREF	0.833
IRRID2	<---	STREF	0.771
MRP1	<---	TM	0.745
MRP2	<---	TM	0.792
IEP3	***<---***	***TM***	***0.677***
IEP5	***<---***	***TM***	***0.605***
RPI5	<---	TM	0.840
FC1	<---	TM	0.886
IRRID1	***<---***	***ID***	***0.687***
IRRID3	<---	ID	0.703
IRRID5	<---	ID	0.731
IRRID6	<---	ID	0.763
IRRID7	<---	ID	0.843
IRRID8	<---	ID	0.768
IRRID9	***<---***	***ID***	***0.609***
RPI1	***<---***	***FT***	***0.670***
RPI2	<---	FT	0.766
RPI3	***<---***	***FT***	***0.591***
RPI4	<---	FT	0.884
IRRID4	<---	FT	0.834
MRP3	<---	MR	0.866
MRP4	***<---***	***MR***	***0.448***
MRP5	***<---***	***MR***	***0.638***

Convergent Validity (CV), Discriminant Validity (DV) and Nomological Validity (NV) (Paswan, 2009). Since major goodness-of-fit test for this model did not support good fit, therefore it merits to find out whether indicator variables of the model measure the same concept. In this study, convergent validity (the extent to which indicators of a specific construct ‘converge’ or share a high proportion of variance in common) is measured by factor loadings, Average Variance Extracted (AVE) (Fornell and Larcker, 1981) and reliability. For this purpose, all standardized loadings in Standardized Regression Weights in AMOS output (table 8); as rule of thumb, should be 0.5 or higher and ideally 0.7 or higher (Garson,2011a). By deep look into table 8, examining loading values, having all *p*-values significantly higher than 0.05 in Regression Weights (table 9); only one construct is detected by loading lower than 0.5 (MRP4 = 0.448) and ten constructs lower than 0.7 (marked in **bold** *Italic*). Therefore, all these eleven constructs will be deleted in the next run of the model.

Table 9: Regression Weights

Construct	S.E.	C.R.	P	L
STRE1<---STREF	2.245	0.13	***	par_1
STRE2<---STREF	1.989	0.11	***	par_2
STRE3<---STREF	0.692	0.06	***	par_3
STRE4<---STREF	0.881	0.06	***	par_4
STRE5<---STREF	4.107	0.22	***	par_5
STRE6 <---STREF	1.023	0.06	***	par_6
RPI6<---STREF	0.848	0.06	***	par_7
RPI7<---STREF	3.712	0.21	***	par_8
RPI8<---STREF	2.073	0.11	***	par_9
FC2<---STREF	0.635	0.06	***	par_10
FC3<---STREF	1.135	0.07	***	par_11
FC4<---STREF	1.685	0.11	***	par_12
IEP4<---STREF	1.179	0.07	***	par_13
IRRID2<---STREF	1		***	
MRP1<---TM	0.29	0.02	***	par_14
MRP2<---TM	0.342	0.02	***	par_15
IEP3<--- TM	0.285	0.02	***	par_16
IEP5<--- TM	0.261	0.02	***	par_17
RPI5<--- TM	0.593	0.03	***	par_18
FC1<---TM	1		***	

IRRID1<---ID	1.196	0.11	***	par_19
IRRID3<---ID	1.247	0.11	***	par_20
IRRID5<---ID	2.309	0.20	***	par_21
IRRID6<---ID	1.308	0.11	***	par_22
IRRID7<---ID	4.71	0.36	***	par_23
IRRID8<---ID	1.417	0.12	***	par_24
IRRID9<---ID	1		***	
RPI1<---FT	0.162	0.01	***	par_25
RPI2<---FT	0.346	0.02	***	par_26
RPI3<---FT	0.145	0.01	***	par_27
RPI4<---FT	0.916	0.04	***	par_28
IRRID4<---FT	1		***	
MRP3 <---MR	1.56	0.12	***	par_29
MRP4 <---MR	1.042	0.14	***	par_30
MRP5 <---MR	1		***	

L = Label

Discriminate validity (the extent to which a construct is truly distinct from other constructs) is measured by AVE. In this method, the researcher concludes that constructs are different if the average variance extracted (AVE) for one's constructs is greater than their shared variance (Garson, 2011b). AVE estimates the amount of variance captured by a construct in relation to the variance due to random measurement error. AVE varies from 0 to 1, and it represents the ratio of the total variance that is due to the latent variable. According to Bagozi (1991), a variance extracted of greater than 0.50 indicates that the validity of both the construct and the individual variables is high. AVE can be calculated from below formula (Paswan, 2009):

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}$$

In this formula, λ^2 is Squared Factor Loadings and *n* is number of items. Having squared factor loadings for all constructs and *n* for ach latent variable, AVE can be calculated. For STREF, calculated AVE = 0.585, for TM = 0.582, for ID = 0.536, for FT = 0.572 and for MR = 0.452. An AVE of less than 0.5 indicates that on average, there is more error remaining in the items than there is variance explained by latent factor structure have been imposed on the measure (Ibid). Therefore, items by AVE lower than cutoff can be dropped from the model.

Construct reliability also is computed from the sum of factor loadings. In Paswan (2009) given formula, λi is squared factor loadings, squared for each construct and the sum of error variance terms for a construct (δi = 1 – squared factor loading which is called item reliability). Error variance also called delta.

$$CR = \frac{(\sum_{i=1}^{n} \lambda_i)}{(\sum_{i=1}^{n} \lambda_i)^2 + (\sum_{i=1}^{n} \delta_i)}$$

Having all measures to calculate construct reliability for each construct, the rule of thumb for a construct reliability estimate is that values of 0.7 or higher suggest good reliability. Reliability between 0.6 and 0.7 may be acceptable provided that other indicators of a model's construct validity are good. High construct reliability indicates that internal consistency is exists. This means measures all are consistently representing something (Ibid). Calculated CR for STREF = 0.95, for TM = 0.89, for ID = 0.88, for FT = 0.86 and for MR = 0.69, which appear Market Regulations construct has boor reliability. Having AVE & CR for model, although some loadings are below 0.5 & 0.7, Discriminant Validity (DV) also examined. DV by definition is the extent to which a construct is truly distinct from other constructs. Rule of thumb for this measure is all construct AVE estimates should be larger than the corresponding Squared Interconstruct Correlation (SIC) estimates. If they are, this indicates the measured variables have more in common with construct they are associated with than they do with the other constructs.

Table 10: Constructs Correlation Estimates

Interconstruct Correlation (IC)	Estimate
TM <--> ID	0.930
ID <--> MR	0.779
FT <--> MR	0.637
TM <--> FT	0.746
ID <--> FT	0.756
TM <--> MR	0.884
STREF <--> FT	0.803
STREF <--> MR	0.713
STREF <--> ID	0.835
STREF <--> TM	0.910

To calculate SIC, correlation estimates shown in correlation table should be squared and compare with AVE estimates for each constructs (see table 10).

Table 11: AVE & SIC Comparison

Constructs	SIC	AVE	V
	0.645		
STREF	0.508	0.585	×
	0.697		

	0.828		
TM	0.865 0.557 0.781 0.828	0.585	×
ID	0.607 0.572 0.697 0.865	0.536	×
FT	0.406 0.572 0.557 0.645	0.572	×
MR	0.607 0.406 0.781 0.508	0.452	×

V = Validity × = Not Valid

Comparison between AVE and SIC for each constructs is given in table 11. As clearly shown in this table, none of constructs in this study could pass the discriminant validity test, as AVE values are not greater than SICs. However, as final step in assessing construct validity of measurement model, Nomological Validity (NV) of the model also examined. NV is tested by examining whether the correlations between the constructs in the measurement model make sense. To assess nomological validity, all *p*-values in covariance table (table 12) should be significant, and correlation estimates (table 10) of constructs also has to be positive (Paswan, 2009).

Table 12: Constructs Covariances

Constructs	S.E.	C.R.	P
TM<-->ID	0.212	9.462	***
ID<-->MR	0.053	7.555	***
FT<-->MR	0.426	7.549	***
ID<-->FT	1.558	10.113	***
TM<-->MR	0.434	8.533	***
STREF<-->FT	0.212	9.278	***
STREF<-->MR	0.553	9.965	***
STREF<-->ID	0.063	8.147	***
STREF<-->TM	0.067	8.742	***

Note: Estimate column is deleted by author.

By looking into goodness-of-fit indices, particularly, TLI (0.838), CFI (0.850) and RMSEA (0.087); it can be concluded that model fitting is under question overall, as two out of three goodness-of-fit indices do not meet the cutoff. In regards to validity of the model:

- Factors by loadings greater than 0.7 has to be removed (in total 11 factors).
- Calculated AVEs for model constructs are fine, except for MR (0.452).

- Construct Reliability measures also for all constructs in the model are acceptable, except for MR (0.69).
- Model failed to pass Discriminant Validity tests (i.e. AVE > SIC).
- Nomological Validity of the model is significant at the acceptable level.

Therefore, it can be said that overall the model has some internal problems, because those indices which are dependent to the sample size could meet the cutoff range of acceptance (e.g. RMSEA & Hoelter Indices) whereas indices like CMIN/DF, IFI and TLI which are independent of sample and because of that are more interested could not.

Diagnosing Measurement Model Problems

The Multicollinearity (MC) in the model already has been diagnosed by application of Ordinal Regression (ORD) & Multinomial Logistic Regression (RMULT). Therefore, poor fitness of model have shown by goodness-of-fit measures were not surprising. Especially, three constructs; *Infrastructure Development (ID)*, *Trade & Marketing (TM)* and *STRE & Finance (STREF)*; had high value of VIF and low value of Tolerance showing cause of multicollinearity. In addition, multinomial logistic regression results recommended that as treatment of multicollinearity, these three constructs (ID, TM & STREF) should be dropped from the model. However, due to importance of these IVs (theoretical reason); it was decided to keep these IVs, and instead of omitting by regression measures; try to omit constructs by looking deep inside the construct components and drop those which accounted for majority of problem. As instructed by Paswan (2009), in addition to evolution goodness-of-fit, following diagnostic measures for confirmatory factor analysis should be checked.

- Path estimates – the completely standardized loadings (AMOS = standardized regression weights) that link the individual indicators to a particular construct. The recommended minimum is = 0.7; but loadings at 0.5 are also acceptable. Variables with insignificant or low loadings should be considered for deletion. --> Looking into Standardized Regression Weight (table 8); 11 items with loading factors lower than 0.7 (marked in **bold** *Italic*) has to be dropped. Since the model had complexity with multicollinearity, therefore, it is wise to put strict standards and drop all factor loadings lower than 0.7.
- Standardized residuals – the individual differences between observed covariance terms and fitted covariance terms. The better the fit the smaller the residual – these should not exceed |4.0|. --> Checking Standardized Residual Covariance table in AMOS output showed only one residual (RPI2 & MRP4) have value (4.168) greater than 4.0. Interestingly, MRP4 has the lowest loading factor among the factors by 0.448 and already is in the elimination list. Having outraged residual with MRP4; put this one also in elimination list (for abbreviation meanings and factors' name, please refer to fig 1 & fig. 2).
- Modification indices – the amount the overall Chi-square value would be reduced by freeing (estimating) any single particular path that is not currently estimated. That is, if you add or delete any path what would be the impact on the Chi-square. --> Modifying indices would help to decrease the Chi-square and fit the model. However, it should be done if consistent with theory and face validity.

Nevertheless, as discussed earlier, all 11 factors with loading values lower than 0.7 dropped from the model. Since after that Market Regulations constructs left by only one component

(MRP3), due to co-loading of this component on Trade & Marketing constructs and elimination of Market Regulations, MRP3 was jointed to Trade & Marketing. Doing this, Chi-square significantly improved and decreased from 2134.9 (df = 550) to 1043.7 (df = 203), showing substantial increase in goodness-of-fit.

Model Trimming

Modifying the model is an important step in SEM. One may first adds paths one at a time based on the Modification Indices (MI), then drops paths one at a time based on the chi-square difference test or Wald tests of the significance of the structural coefficients. However, when this process has gone as far as judicious, then the researcher may erase one arrow at a time based on non-significant structural paths, taking theory into account in the trimming process. More than one cycle of building and trimming may be needed before the researcher settles on the final model (Garson, 2011a). However, it was decided to repeat the steps have been taken during measurement model building, start by dropping all construct with loading lower than 0.7. Doing this, only IRRID3 diagnosed by loading = 0.691 and dropped from the model. Consequently, model Chi-square decreased further (927.8, df = 183), shown improvement in fitness.

Treatment of Multicollinearity

Grewal et al (2004) reaffirmed the difficulty of diagnosing and treatment of multicollinearity in SEM. They indicated that, review of the literature shown that we know relatively little about the conditions that lead to multicollinearity problems in SEM. Although we do have tools for detecting when multicollinearity may be affecting estimates, these techniques are often ambiguous. Lastly, there are some remedial actions that can be taken when multicollinearity exists, but they may be difficult to implement, and in general the evidence regarding their practical effectiveness is limited. However, Kaplan (1994) has called all these methods “more or less ad hoc.” Nonetheless, sometimes even having good fit in a model can be misspecified. One indicator of this occurring is if there are high modification indexes in spite of good fit [like case of this study]. Complete multicollinearity is assumed to be absent, but correlation among the independents may be modeled explicitly in SEM. However, high modification indexes indicate multicollinearity in the model and/or correlated error (Garson, 2011a). Knowing at least three of IVs in the model are the cause of multicollinearity (Shadfar & Malekmohammadi, 2013b); pushed the model and raised the flag to find proper treatment for multicollinearity at this stage. The problem of multicollinearity is closely related to the issue of discriminant validity. If constructs are too highly correlated, they lack discriminant validity as seen in the first run of the model. Researchers who use SEM usually conduct measurement analyses prior to testing structural relationships, and often assess discriminant validity by testing whether the correlations (corrected for measurement error) among constructs differ from one. If this is not the case, multicollinearity is probably extreme, and the researcher will most likely respecify the model because the distinct conceptual status of the constructs in question is questionable (Anderson and Narus 1984). Therefore, a model can be theoretically identified but still not solvable due to such empirical problems as high multicollinearity in any model, or path estimates close to 0 in non-recursive models.

However, Garson (2011a) is given four signs for multicollinearity in the model; among them is Standard Errors of the Unstandardized Regression Weights; in which when there are two nearly identical latent variables, and these two are used as causes of a third latent variable, the difficulty in computing separate regression weights may well be reflected in much larger standard errors for these paths than for other paths in the model, reflecting high multicollinearity of the two nearly identical variables. Also, in Covariances of the parameter estimates, where the same difficulty in computing separate regression weights may well be reflected in high covariances of the parameter estimates for these paths, estimates much higher than the covariances of parameter estimates for other paths in the model. Signs of multicollinearity can be found in Variance estimates and Standardized Regression Weights as well. However, looking into Regression Weights (table 13) of the model; again like convergent validity assessment, all loading values have *p*-values significantly higher than 0.05. Having said that some of paths shown much larger Standard Errors (S.E.) and estimates (marked in **bold** *Italic*) than for others in the model. Therefore, those components with high S.E. & estimates had to be dropped from the model. Following this, STRE5 (S.E. = 0.226), RPI7 (S.E. = 0.209), IRRID7 (S.E. = 0.172), STRE1 (S.E. = 0.129), FC4 (S.E. = 0.114), RPI8 (S.E. = 0.113) and STRE2 (S.E. = 0.109) which shown higher S.E. & estimates than the other components path dropped from the model, yielded highly significant decrease in Chi-square value from 1043.37 (df = 203) to 435 (df = 84). Deleting paths with high estimated covariance made no difference into model rather increased Chi-square and reduced the fitness of the model. Checking the Standardized Residual Covariance also showed no residual greater than |4.0|. The largest residual is 2.946 (MRP1 & MRP3). Using the modification indexes (recommended add regression paths or remove covariances paths) were not theoretically sound. Therefore, the model was accepted as final trimmed version, as no more sign of multicollinearity also detected.

Table 13: Regression Weights (Trimmed Model)

Regression Path	Est.	S.E.	C.R.	P
STRE1<---STREF	***2.260***	***0.129***	***17.469***	*****
STRE6<---STREF	1.035	0.063	16.315	***
RPI7<---STREF	***3.696***	***0.209***	***17.713***	*****
RPI8<---STREF	***2.098***	***0.113***	***18.572***	*****
FC3<---STREF	1.144	0.066	17.272	***
FC4<---STREF	***1.676***	***0.114***	***14.643***	*****
IEP4<---STREF	1.185	0.066	17.85	***
IRRID2<---STREF	1			
MRP1<---TM	0.286	0.016	17.48	***
MRP2<---TM	0.344	0.017	20.187	***
RPI5<---TM	0.592	0.026	22.443	***
FC1<---TM	1			

IRRID6<---ID	0.883	0.052	16.884	***
IRRID7<---ID	***3.117***	***0.172***	***18.163***	*********
IRRID8<---ID	1			
RPI4<---FT	0.92	0.049	18.852	***
IRRID4<---FT	1			
STRE4<---STREF	0.879	0.059	15.006	***
STRE2<---STREF	***2.018***	***0.109***	***18.489***	*********
STRE5<---STREF	***4.112***	***0.226***	***18.201***	*********
MRP3<---TM	0.317	0.018	17.567	***

Notes:
- Label column is deleted by author.
- Est. = Estimate

Comparison Goodness-of-Fit

Comparing goodness-of-fit indices for the trimmed model to complex model (table 14), shows tremendous changes in model fit, yielded to simpler model by better fit indexes. The goal in this stage wasn't to find the most parsimonious model which is not significantly different from the saturated model, which fully but trivially explains the data; rather the goal was to find the most parsimonious model which is well-fitting by a selection of goodness of fit tests, many of them based on the given model's model-implied covariance matrix not be significantly different from the observed covariance matrix. Knowing all correlation ratio of parameters has to be significant at 0.05 (>1.96); and by looking into critical ratios for differences between parameters in the model; those components in which have non-significant value should be dropped.

Table 14: Goodness-Of-Fit Indices Comparison

GOF Indices	Complex Model	Trimmed Model
CMIN	2134.905	434.958
DF	550	84
p	.000	000
SRMR*	0.0644	0.0519
CMIN/DF	3.822	5.178
GFI	0.700	0.860
AGFI	0.690	0.801
CFI	0.850	0.917
TLI	0.838	0.896
IFI	0.850	0.917
RFI	0.793	0.874

Rho1		
NFI Delta1	0.808	0.900
PNFI	0.747	0.720
RMSEA	0.087	0.104
Helter 0.05	109	94
Helter 0.01	114	104

*Standardized RMS

Therefore, FC1 & MRP3 diagnosed by three non-significant correlation ratio values have dropped from the model, yielded significant increase in goodness-of-fit indices and fitness of the final model.

Comparing Validity Indices

Comparing CR & AVE (table 15) calculated indices for components and constructs of the trimmed model to complex model also shows higher validity in new trimmed model. As is seen in this table, it can be concluded that overall, validity indexes are at much higher level in trimmed model rather than complex model, means trimmed model is better fit to measure items actually designed to measure. Therefore, latent constructs that proposed theoretically are capable to measure what they intended to measure; would yield better assessment which is closer to reality.

Table 15: CR & AVE Comparison, Trimmed vs. Complex Models

Construct	Complex Model		Trimmed Model	
	CR	AVE	CR	AVE
STREF	0.951	0.585	0.940	0.599
TM	0.892	0.583	0.888	0.603
ID	0.889	0.536	0.648	0.678
FT	0.868	0.572	0.921	0.757
MR	0.453	0.453	Elim.	Elim.

Elim. = Eliminated

SEM Analysis of Rice Production Development

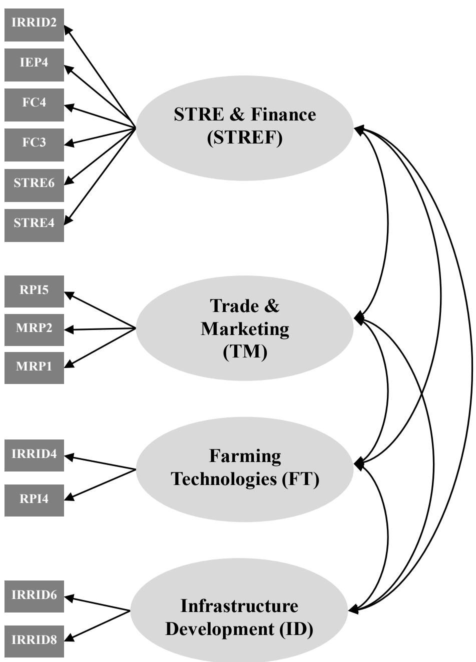
Yielded model of confirmatory factor analysis (fig 4) now can be run into SEM to check entire theoretical model in one analysis. As part of the analysis, test both of the specific hypothesized relationships among variables and the plausibility of the overall model (i.e., the fit of the model) is tested.

Table 16: GOF Indices for SEM on RPD

GOF Indices	Complex Model
CMIN	280.113
DF	68
p	.000
SRMR*	0.0442
CMIN/DF	4.119
GFI	.904
AGFI	.852
CFI	.937
TLI	.915
IFI	.937
RFI Rho1	.891
NFI Delta1	.919
PNFI	.686
RMSEA	.090
Helter 0.05	121

*Standardized
RMS

Fig. 4: Final Measurement Model



This is because, SEM has a number of benefits are interested in studying interrelations and prediction of model components on Rice Production Development (RPD). Model fitting information is given in table 16. As shown in table 18, STREF, ID and FT has positive effect on RPD, while TM effect is negative. The highest effect is from ID. Interestingly, MR which in theory supposed to have influence on RPD was eliminated during CFA.

Table 17: Constructs Correlation Estimates

Interconstruct Correlations (IC)	Estimates
MRP1 <--- TM	0.705
MRP2 <--- TM	0.758
RPI5 <--- TM	***0.861***
RPI4 <--- FT	***0.897***
IRRID4 <---FT	0.842
IRRID6 <--- ID	0.807
IRRID8 <---ID	***0.840***
STRE4 <--- STREF	0.739
STRE6 <--- STREF	0.745
FC3<--- STREF	0.826
FC4 <--- STREF	0.706
IEP4 <--- STREF	***0.848***
IRRID2 <---STREF	0.768

Standardized Regression Weights also is given in table 17. Standardized Total Effect Size also shown in table 18. As shown in this table, IRRID8 is the most influenced factor among ID constructs on rice production. Similarly, the most effective

Table 18: Standardized Total Effects

Components	STREF	ID	FT	TM
RPD	0.216	0.248	0.092	-0.448
IRRID8		***0.840***		
IRRID6		0.807		
IRRID4			0.842	
RPI4			***0.897***	
RPI5				***0.861***
MRP2				0.758
MRP1				0.705
IRRID2	0.768			
IEP4	***0.848***			
FC4	0.706			
FC3	0.826			
STRE6	0.745			
STRE4	0.739			

factor on rice production among FT components is RPI4, Whereas, RPI5 is the most effective factor on rice production among from TM constructs. IEP4 also is considered the greatest effective factor on rice production among six components of STREF.

Table 19: Latent Constructs Standardized Regression Weights

Latent Constructs	Estimates
RPD <--- STREF	0.216
RPD <--- ID	***0.248***
RPD <--- TM	***-0.448***
RPD <--- FT	0.092

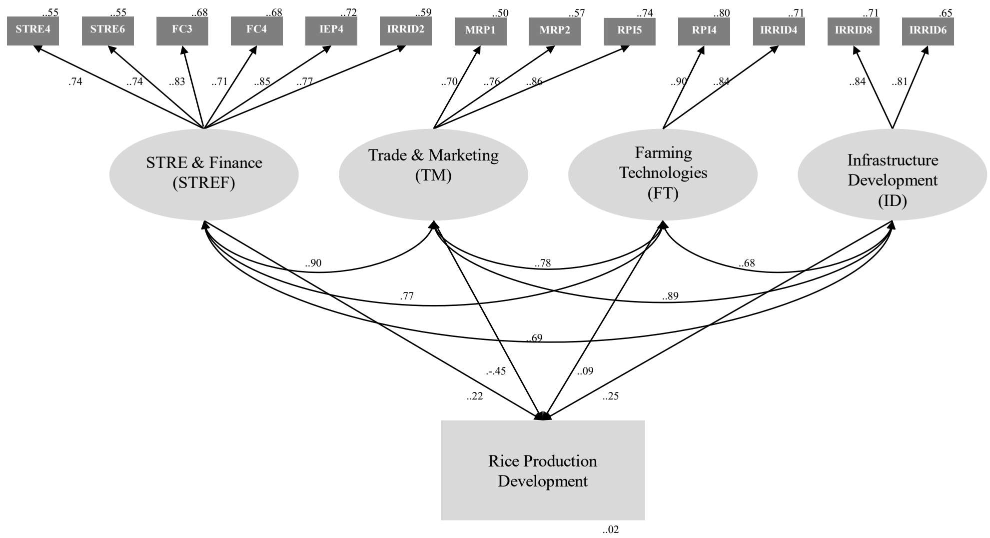
Notes:
- RPD = Rice Production Development
- STREF = Science, Technology, Research, Extension and Finance
- ID = Infrastructure Development
- TM = Trade & Marketing
- FT = Farming Technologies

As can be seen in second row in table 19, the most effective constructs on rice production development, overall is Infrastructure Development, whereas, surprisingly; Trade & Marketing has the negative effect.

Conclusion

Complexity of agricultural practices, ever changing nature of business of rice, state passion to intervene into this business; blended by rice farmers needs and priorities, have demanded re-structuring the state intervention policies. To do this, policies of major rice producing countries in the world who were accountable for more than 80% of global rice production studied. Commonalities among practiced effective policies on rice business re-structured into theoretical model; re-forming 35 practical and strategic intervention policies which underneathed under 6 super independent variables (fig. 1). This theoretical model later, tested in biggest rice producer province in Iran (Mazandaran) and empirical data in regards to effectiveness of this bunch of policies run into confirmatory factor analysis and later SEM analysis. The outcome consist of 13 most effective policies shrank into four policy areas (super independent variables) in which the effectiveness and inter-relations among and between

Fig. 5: SEM Analysis of State Interventions into Rice Business



them is measured by SEM (fig. 5). Now it can be said, likelihood of success of the state to boost rice business is at the maximum level in Iran, if the state undertake policies is summarized into this model, having eye on all in-between and inter-correlations among and between involving policies.

However, many studies re-confirmed effectiveness of final model compartments. For instance, in regards to FC3 compartment, which is "direct cash payment to rice farmers"; Kazukauskas *et al* (2011) have found some evidences in their studies that land reduction and disinvestment intensity increased for those exiting farms that were 'policy-treated' by decoupling direct payments in Europe. Sipilainen & Kumbhakar (2010) also in their study have concluded that, direct payment as subsidy has positive effect; indicating the direct link between the amount of subsidy and total output. More specifically in regards to STRE4 compartment in the model which is "irrigation efficiency increase projects"; Abasolo *et al* (2007) attempted to measure the impact of infrastructure support, especially road and irrigation - on the technical efficiency of rice production in Mindanao, Philippines. Based on their findings, they have recommended that authorities must prioritize the pavement of roads given their crucial role in improving technical efficiency of rice production. They also have recommended that the Department of Agriculture, through the National Irrigation Administration, must fast-track the construction of additional small-scale irrigation systems to allow farmers a greater degree of control over their irrigation water. Another example is in regards to IRRID6 compartment which is "rural & local institution"; where Motamed (2010) in his study on the role of cooperative companies in sustainable rice production and poverty alleviation in Gilan state of Iran have concluded that cooperative companies have a basic role in achievement sustainable rice production and reduction of poverty, thus cooperative companies should be organized and supported by government. Forssell (2009) have studies state rice price policies in Thailand. He is concluded that price policy have been taken by the state; has undermined the market forces and therefore also negatively affected the integration of the rice market. If the policy was sustained with high pledging prices [guaranteed prices], there was a risk of large negative effects in the long run since farmers' incentives to reduce costs and become more effective might be harmed. His finding is reaffirming effectiveness of MRP2 compartment in the final model which is "guaranteed purchasing prices' (more references on effectiveness of theoretical model compartment is give in "*More to Read*" in *Appendices* section).

Nevertheless, like many other developing countries, the state role in Iran; is and has been extensive. Having said that, state in Iran does not seems to stop interfering into strategic business like rice. Interestingly, in this study Market Regulations as one of the key areas that state is active; was omitted from the model by rice farmers. That means state should not intervene into the market. Giving this fact, still Iran's government main driving policy in rice business is substantial intervention into the rice market by regulatory policies, such as high importing tariff, ban on rice imports from some certain countries that has cheaper prices than Iran's and price subsidies for local production. However, if the state would like to have maximum ROI (return-on-investment) on millions of dollars annually spending in this section; it should have clear view on where investment has to be done and how it shod be done; having in mind; taking any kind of these policies in complexity of rice production development, would trigger chain reactions among all other involving factors; is given in this study model.

Appendices:

Table 2: Comparison of the State Intervention Policies in Rice Sector in Major Rice Producing Countries

Country (World Rice Production Share %)	Areas of State Intervention					
	Investment in Rice & Rural Infrastructure Development	Rice Production Increase	STRE Investment	Funding Credits	Market Regulations and Pricing	Import and Export Policies
China (28.8%)	1. Expenditure for agricultural infrastructure to expand irrigated areas 2. Rural anti poverty programs	1. Subsidized inputs 2. Support of modern varieties (including hybrid rice), cultivation technologies, and heavy application of chemical fertilizer and pesticides	1. State budget for agricultural infrastructure, science and technology studies, and rural relief funds 2. Government support for research and support services	1. Subsidized credit 2. Secured flow of funds to rural financial institutions	1. Monopolized rice procurement through the procurement contract system 2. Determined rice production volume 3. Price support programs	1. Procurement and price level control 2. Foreign trade control policies 3. Quantitative restrictions and export subsidies policies
India (21.6%)	1. Rural people betterment plans 2. Irrigation development schemes	1. Subsidized seeds 2. Subsidized fertilizers 3. Subsidized pesticides	Rural research, education and extensions programs	1. Regional Local Banks 2. Production credits	1. Public distribution system 2. Minimum support prices	1. Export restrictions 2. Quantitative control on import & export 3. Export tariff 4. Export subsidies
Indonesia (8.6%)	1. Irrigation facilities and rehabilitation of existing ones	1. Promotion of high yielding varieties and marketing support	N/A	Government support on credit	Three type rice prices	Rice import tariff

	2. State support for infrastructure such as roads and ports	2. Fertilizer and pesticide subsidies				
Vietnam (5.7%)	Strengthening cooperatives and other rural institutions	1. Equal access to land 2. Subsidies on Fertilizer & seeds	Greater focus on research and development	Subsidies on credit	N/A	1. Import tariffs 2. Export subsidies
Thailand (4.6%)	Upgrading the country's road network	The vast area planted to rice	Land utilization	N/A	N/A	Export duties
Philippine (2.4%)	1. Funding supports on irrigation projects development 2. Encouraging farmers to raise their fertilizer usage from current levels	Encourage hybrid seeds	1. Adoption of more efficient technology and machinery suitable for rice farmers 2. Expand knowledge intensive technologies	Providing credits	N/A	N/A
United States (1.4%)	Broader and more modernized infrastructure	1. Better institutions, facilities, equipment, investments 2. Commodity and income support	Risk management and related programs	Farm credit	Direct Payments to Farmers	Export promotion
South Korea (1%)	N/A	1. Production incentives for farmers 2. Collecting and distribution mechanism	N/A	N/A	Government pricing mechanisms	N/A

Malaysia (0.3%)	1. Investments in building drainage and irrigation facilities 2. State investments to improve physical infrastructure such as roads, irrigation & drainage systems	1. Fertilizer subsidy and price support 2. Subsidies for such inputs as fertilizers, pesticides and seeds 3. Mechanization program	1. Undertakes active research and development studies in rice 2. Research and development studies on high yielding seeds and varieties 3. Provision of extension services and marketing	N/A	Guaranteed Minimum Price (GMP) Controlled prices at milling, wholesaling and retailing	Monopoly on imports

More to Read (Effectiveness of Policies in the Theoretical Model of the State Intervention in Rice Production Development):

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