Relationship between cost savings achieved through inventory policies in pharmacies and food and nutrition services, and supply chain success factors

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Outline

Motivation

Inicio | El 86% de farmacias de hospitales, con problemas de abastecimiento

Profesión ·

estudio de 'European Association of Hospital Pharmacist'

El 86% de farmacias de hospitales, con problemas de abastecimiento

(a) Pharma

01 de septiembre 2020

Junaeb admite atrasos en abastecimiento de canastas de alimentación

Por Prensa Radio Agricultura | 47 Visitas

(b) FNS

CONICYT
Comisión Nacional de Investigación
Científica y Tecnológica

CERTIFICADO ADJUDICACIÓN
INICIACIÓN EN INVESTIGACIÓN

14 de octubre de 2019

Alejandra Vidales Carmona, Directora del Programa Fondo Nacional de Desarrollo Científico y Tecnológico (FONDECYT) de la Comisión Nacional de Investigación Científica y Tecnológica (CONICYT), certifica que Don/ña **FERNANDO ALONSO ROJAS ZUÑIGA**, de nacionalidad **CHILE**, ha aprobado el proyecto **11190004** en el Concurso FONDECYT de tipo **INICIACIÓN EN INVESTIGACIÓN - 2019**, titulado **SAVINGS IN INVENTORY COSTS OF PHARMACIES AND FOOD AND NUTRITION SERVICES OBTAINED THROUGH STOCHASTIC DEMAND MODELS FOR THE SUPPLY AND ITS RELATIONSHIPS WITH SUCCESS FACTORS IN THE SUPPLY CHAIN**, con una duración de **2** años a partir de **01/11/2019** hasta el **31/10/2021**. Dicho proyecto es patrocinado por **UNIVERSIDAD DE VALPARAISO**.

La distribución de recursos asignados es la siguiente:

ITEM PRESUPUESTARIO	AÑO 1	AÑO 2
PERSONAL	$ 18.000.000	$ 18.000.000
VIAJES	$ 1.850.000	$ 2.100.000
VIAJES COOP.INTERNACIONAL	$ 0	$ 0
GASTOS DE OPERACION	$ 2.850.000	$ 2.850.000
BIENES DE CAPITAL	$ 1.300.000	$ 0
APOYO INFRAESTRUCTURA	$ 540.000	$ 508.000
GASTOS DE ADMINISTRACION	$ 3.060.000	$ 2.881.000
TOTAL	**$ 27.600.000**	**$ 26.339.000**

Se extiende el presente certificado a petición del/de la interesado/a, para los fines que estime conveniente.

General objective

To evaluate relationships between cost savings achieved through inventory policies in pharmacies and food and nutrition services, and supply chain success factors.

Background

- The particularities of the supply management in pharmacies and food and nutrition services (FNS) make necessary the adaptation of useful models to optimize this process in these industries and quantify performance measures as savings in costs, see [Moons et al., 2018], [Wanke et al., 2016], [Rojas et al., 2015],[Rojas and Leiva, 2016] and [Rojas et al., 2019]
- [Rojas et al., 2019] have collected these particularities, formulating stochastic inventory models that lead to minimize total costs (TC) of inventory in cases applied to these areas, lead savings in TC (order, purchase, holding and shortage).
- [Toba et al., 2008] showed that indicated savings in total inventory costs can be related to success factors in the supply chain of these areas, such as: purchase agreed between technical and supply staff, group purchasing organization and data management technology for supply.

Background

- In order to describe the demand per unit time (DPUT) of in a stochastic programming (SP) problem to solve an stochastic inventory model adequately, it is needed to consider the possible temporal dependence, intermittence and statistical dependence in the modeling of the DPUT, see [Rojas, 2018].
- [Benjamin et al., 2003] proposed a GLM version of ARMA models known as the generalized ARMA (GARMA), which considers ARMA components by transforming the data mean through a link function as in GLM. Very advantage: Flexibility, Multiple statistical distributions (under GAMLSS approach extended [Stasinopoulos and Rigby, 2007] can considered continuous, count and mixture statistical distribution, for diverse degree of intermittency, skewness, kurtosis of DPUTs).

Success factors in SCM

Based in [Toba et al., 2008], the success factors of the supply chain raised in the research correspond to:

- a) SF1: the purchase of products and raw materials agreed between the technical staff-supplier,
- b) SF2: a successful association with a group purchasing organization and
- c) SF3: the existence of synchronized supply data management technology integrated with the purchasing system.

Two problems: Multilevel relationships and endogeneity.
[Kim and Frees, 2007] propose a generalized method of moments (GMM) technique for addressing endogeneity in multilevel models without the need of external instrumental variables. This approach uses both, the between and within variations of the exogenous variables, but only assumes the within variation of the variables to be endogenous [Gui et al., 2020].

Mixed effect model

i = product
j = category of product
k = institution
SavingTC$_{ijk}$ =

$$E(\Delta TC_{ijk}) = \mu_{ijk} = \beta_0+\beta_1 SF1_{ijk}+\beta_2 SF2_{ijk}+\beta_3 SF3_{ijk}+\beta_4 factor(Category)+\beta_5 factor(Institution)+$$

b$_{0i}$ + $\beta_{1i} SF1_{ijk} + b_{2i} SF2_{ijk} + b_{3i} SF3_{ijk}$
where, $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are fixed effects compatible with endogeneity at the second and third level (category and institution, respectively), and here, the products (i) vary in average savings both in their intercept (b_{0i}) and in their slope (b_{1i}, b_{2i}, b_{3i}), which together make up the total variance in said saving TC attributable to the variation between products. This individual contribution is quantified using an intercept and random slope model with normal distribution (N). The variation between individuals in intercept and slope is $\sigma^2_{b_0}, \sigma^2_{b_1}, \sigma^2_{b_2}, \sigma^2_{b_3}$.The covariance between the intercept and the slope is given by $\sigma_{b_0 b_1 b_2 b_3}$. Then, $\Delta TC_{ijk} \sim N(\mu_{ijk}, \sigma^2_{\Delta TC})$

$$\begin{pmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{pmatrix} \sim N(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{b_0} & \sigma_{b_0 b_1} & \sigma_{b_0 b_2} & \sigma_{b_0 b_3} \\ \sigma_{b_0 b_1} & \sigma^2_{b_1} & \sigma_{b_1 b_2} & \sigma_{b_1 b_3} \\ \sigma_{b_0 b_2} & \sigma_{b_1 b_2} & \sigma^2_{b_2} & \sigma_{b_2 b_3} \\ \sigma_{b_0 b_3} & \sigma_{b_1 b_3} & \sigma_{b_2 b_3} & \sigma^2_{b_3} \end{bmatrix})$$

`https://www.rdocumentation.org/packages/REndo/versions/1.1/topics/multilevelIV`

Stochastic inventory model

Parameters		Variables	
t:	Period index of the decision stage in the planning time horizon ($t = 1, \ldots, T$).	Z_t:	Binary variable indicating whether a purchase is carried out in period t or not.
C_t:	Purchase budget in period t.	Q_t:	Quantity of units to be purchased in period t .
u_t:	Unitary cost of purchase in period t.	I_t:	Stock level at the end of period t.
o_t:	Fixed order cost in period t.	I_0:	Initial stock level.
h_t:	Holding cost at the end of period t .	S_t:	Shortage level at the end of period t.
s_t:	Shortage cost at the end of period t.		
p_t^ω:	Probability of occurrence of the scenario ω in period t of the decision stage.		

To obtain the observed values of a forecast DPUT y_t^ω of Y_t, their probabilities p_t^ω, and E(TC) see [Rojas et al., 2019]

The corresponding SP framework used to minimize the expected TC –E(TC)– of the inventory model can be formulated as [Raa and Aghezzaf, 2005]

$$\min\{\mathrm{E(TC)}\} = \min\left\{\sum_{\omega\in\Omega}\sum_{t=T}^{T+1} o_t Z_t + u_t Q_t + p_t^\omega(h_t I_t^\omega + s_t S_t^\omega)\right\}, \tag{1}$$

subject to

$$\begin{array}{rcl} Q_t + (I_{t-1}^\omega - S_{t-1}^\omega) - (I_t^\omega - S_t^\omega) & = & y_t^\omega, \\ Q_t & \leq & C_t Z_t, \end{array} \tag{2}$$

$$\forall t \in T, \quad \forall \omega \in \Omega, \quad Q_t \geq 0, \quad I_t^\omega \geq 0, \quad S_t^\omega \geq 0, \; y_t^\omega \geq 0, \quad p_t^\omega \in [0,\, 1], \quad Z_t \in \{0,\, 1\},$$

where Ω is the set of selected possible demand scenarios and ω is a specific scenario, with a fixed number of scenarios in each period of the decision stages. The objective function defined in Eq. (1) attains a solution that minimizes E(TC) over all scenarios. This minimization can be carried out through the addition of sharing cuts for feasibility and optimality at the resource function, whenever this function or its constraints contain stochastic coefficients that exhibit inter-stage dependency of ARMA type in a multi-stage problem [Infanger and Morton, 1996].

Figure: Register

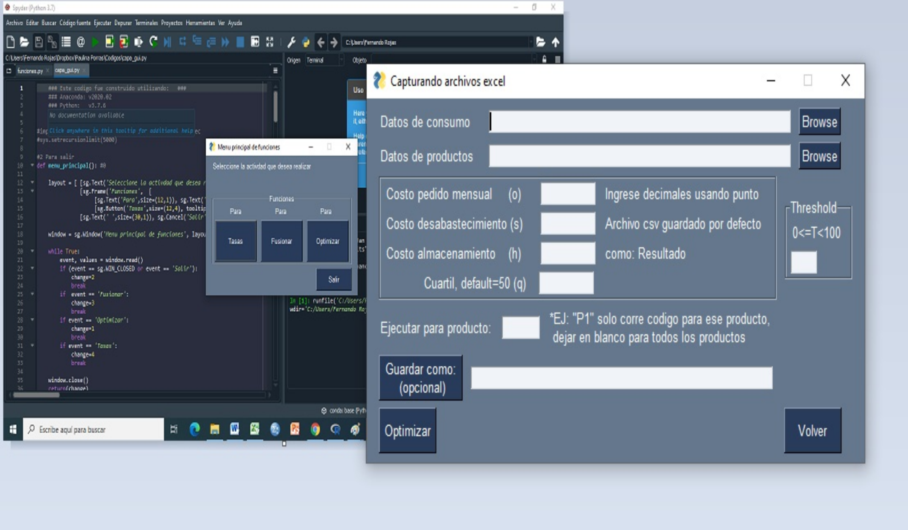

Figure: Functions

Savings and SFs

In order to quantify performance measures as savings in TC obtain from the purchase plan of the stochastic inventory model obtained from SP models based on generation of scenarios, it is possible to compare this results with actual TC. This savings in TC (Δ) is computed as

$$\Delta = (\mathrm{AC} - \mathrm{SPC})/\mathrm{SPC},$$

where AC and SPC are the TCs obtained under actual case and SP, respectively.
Success factors of interest in supply ($SF_1=$ Agreed purchase between technical and supply staff, 3 items vector {5=fully accomplished,...,1=Not accomplished},$SF_2=$ successful partnership with a group purchasing organization, 3 items vector {5=fully accomplished,...,1=Not accomplished},$SF_3=$ existence of supply data management technology synchronized and integrated with the purchase system, 3 items vector {5=fully accomplished,...,1=Not accomplished}.
At a second level: the products that make up the FNSs inventory were divided into 5 categories called: 1 groceries, 2 dairy products, 3 fruits, 4 vegetables and 5 meats. The products that make up the inventory of public pharmacies were categorized as 6 drugs.
At a third level, the institutions participating in the study were 1: FNS and 2: Pharmacies.

Results

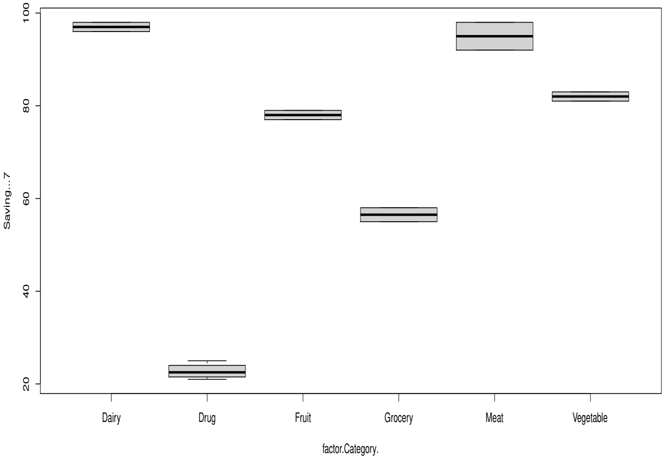

Figure: Boxplots of Savings segmented by Category

Results

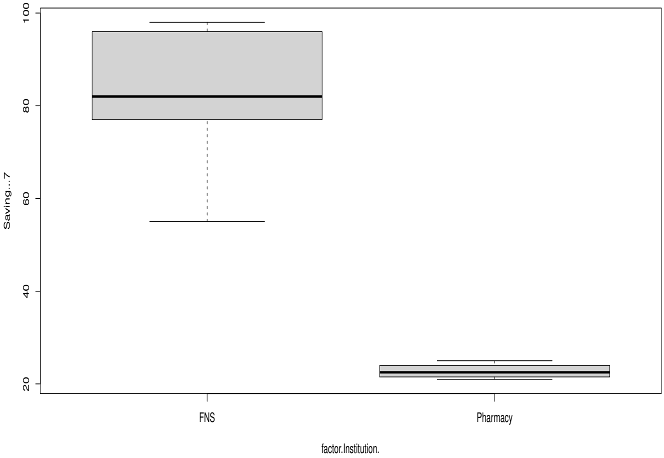

Figure: Boxplots Savings by Institution

Results

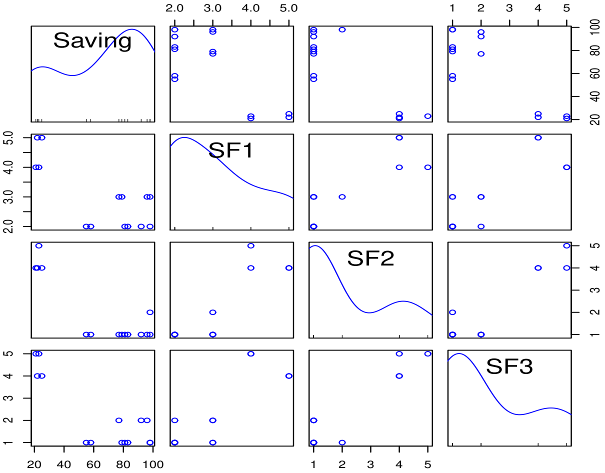

Figure: Scatter plot matrix of savings and success factors

Results

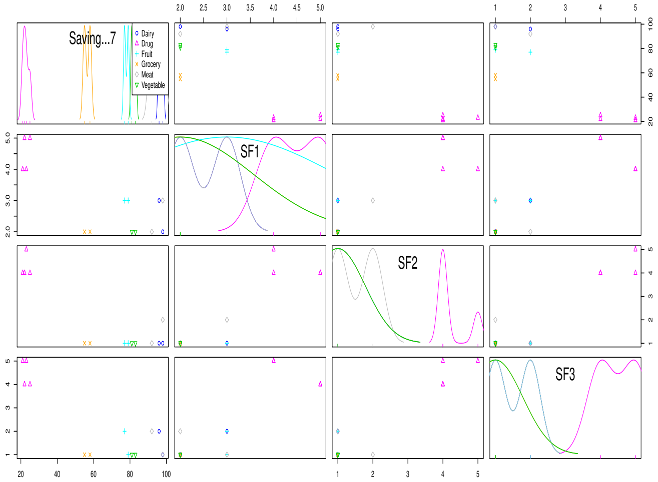

Figure: Scatter plot matrix of savings and success factors by Category

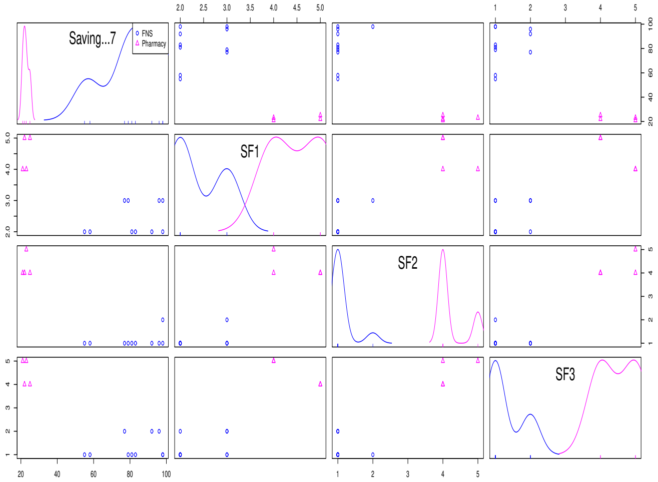

Figure: Scatter plot matrix of savings and success factors by Institution

Results

Table: Correlation Spearman's Matrix between Savings and Success Factors

	Saving	SF1	SF2	SF3
Saving	1.00	-0.58	-0.61	-0.64
SF1	-0.58	1.00	0.83	0.78
SF2	-0.61	0.83	1.00	0.75
SF3	-0.64	0.78	0.75	1.00

Results: Exploring fixed and random effect with lmer()

Table: Fixed effect of Linear mixed model fit by REML lmer() function in R software. Model: Saving $\sim$ SF1 + SF2 + SF3 + factor(Category)+factor(Institution)+(SF1 | Category) + (SF2 | Category) + (SF3 | Category) + (SF1 | Institution) + (SF2 | Institution) + (SF3 | Institution)

	Estimate	Std. Error	t value
(Intercept)	96.56	5.72	16.88
SF1	0.56	1.19	0.47
SF2	2.60	1.35	1.93
SF3	-2.37	1.07	-2.23
factor.Institution.[T.Pharmacy]	-76.70	8.47	-9.05
factor.Category.[T.Fruit]	-19.28	4.13	-4.67
factor.Category.[T.Grocery]	-41.41	4.19	-9.87
factor.Category.[T.Meat]	-3.30	4.14	-0.80
factor.Category.[T.Vegetable]	-15.91	4.19	-3.79

In lmer() in R, the fixed effects are specified without parentheses, the random effects are specified with parentheses, and error just gets added on.

Results: Exploring fixed and random effect with lmer()

Table: Random effect of Linear mixed model fit by REML lmer() function in R software. Model: Saving $\sim$ SF1 + SF2 + SF3 + factor(Category)+factor(Institution)+(SF1 | Category) + (SF2 | Category) + (SF3 | Category) + (SF1 | Institution) + (SF2 | Institution) + (SF3 | Institution)

Group	Name	Std.Dev.	Corr
Category	Intercept	1.510e+00	
Category	SF3	1.640e-13	1.00
Category	Intercept	1.510e+00	
Category	SF2	3.117e-14	-1.00
Category	Intercept	1.510e+00	
Category	SF1	5.499e-13	-1.00
Institution	Intercept	1.510e+00	
Institution	SF3	1.572e-12	-1.00
Institution	Intercept	1.510e+00	
Institution	SF2	1.870e-13	1.00
Institution	Intercept	1.510e+00	
Institution	SF1	4.173e-14	1.00
Residual		1.510e+00	

In lmer() in R, the fixed effects are specified without parentheses, the random effects are specified with parentheses, and error just gets added on.

Results: multilevelIV() RE and FE plot by Institution

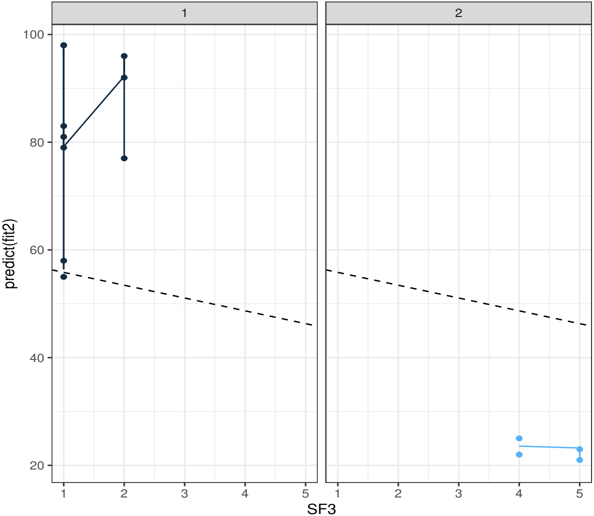

Figure: Example multilevelIV() RE and FE plot by Institution. SF3 Example

Results: multilevelIV() RE and FE plot by Category

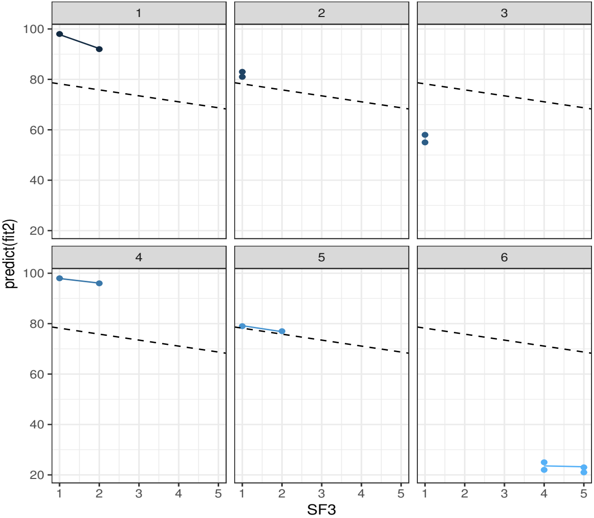

Figure: Example multilevelIV() RE and FE plot by Category. SF3 Example

Results: multilevelIV() function

Table: Mixed effects for model Saving $\sim$ SF1+SF2+SF3 + factor.Category. + factor.Institution. + (1 | Category) + (1 | Institution) | endo(SF1,SF2,SF3)

Variable	Estimate	Std. Error	z-score	$Pr(> \|z\|)$
(Intercept)	96.56	4.83	20.00	0.00
SF1	0.56	1.19	0.47	0.64
SF2	2.60	1.35	1.93	0.05
SF3	-2.38	1.07	-2.23	0.03
factor.Institution.[T.Pharmacy]	-76.70	7.28	-10.54	0.00
factor.Category.[T.Fruit]	-19.28	2.71	-7.11	0.00
factor.Category.[T.Grocery]	-41.41	2.81	-14.71	0.00
factor.Category.[T.Meat]	-3.30	2.73	-1.21	0.23
factor.Category.[T.Vegetable]	-15.91	2.81	-5.65	0.00

The test results GMM level 3 and 2 vs random effects in level 3 and 2 (p-value 0.636) provide support that the random effects of level 3 and 2 should be used, and that effectively SF are endogenous variables.

Results: Check RE, Correlation SF vs residuals RE

Table: Check RE, Correlation SF vs residuals RE

	SF1	SF2	SF3	resREF
SF1	1.00	0.87	0.84	-0.00
SF2	0.87	1.00	0.93	-0.00
SF3	0.84	0.93	1.00	-0.00
resREF	< -0.001	< -0.001	< -0.001	1.00

Discussion

-The analysis of our main result shown in Table 4 indicates that both SF2 and SF3 of the pharmacy supply chains and FNSs are related to the savings obtained from the use of stochastic inventory models, in turn.
-We once confirmed that SFs are endogenous variables respect to savings of inventories.
-SF2 has a positive relationship, that is, the greatest savings achieved are related to higher scores in SF2, this is a successful partnership with a group purchasing organization. However, SF3 operates in an inverse manner, that is, greater savings are achieved from low values of evaluation for the existence of supply data management technology synchronized and integrated with the purchase system. Both results are expected.
-Pharmacies achieve lower inventory savings than FNSs, which is explained by their greater technological development and good logistical practices evidenced. Saving in Dairy > Vegetable > Fruit > Grocery > Drugs.

Acknowledgements

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