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A CUSTOMER COMPLAINT FROM A TELECOMMUNICATION COMPANY: A BAYESIAN DATA ANALYSIS

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ABSTRACT

This study considers a customer complaint dataset due to the technical services provided by a telecommunications company collected for 134 consecutive weeks from the first week of January 2018 up to the year 2019. The total count of weekly complaints is the sum of different causes, which characterizes compositional data. The data was analyzed assuming a Poisson regression model for the weekly total complaint count data in presence of a random factor and compositional models both under a Bayesian approach using existing MCMC (Monte Carlo Markov Chain) to get the posterior summaries of interest. The obtained results are of great importance to improve the service quality of the company.

Keywords: quality of services; complaint counts; Poisson regression models; compositional data; Bayesian approach

1. INTRODUCTION

Telecommunication companies usually have many customer complaints due to technical services provided by the company. Discovering possible causes of complaints is of great interest to improve quality of services in telecommunication companies (Anderson, Fornell & Mazvancheryl, 2004; Claro et al., 2014; Coelho et al., 2016; Fornell & Wernerfelt, 1987; Luo, 2007, 2009; Romani, Grappi & Dalli, 2012; Singh & Wilkes, 1996; Singh, 1988). The study was developed in a telecommunications company located in the central region of the São Paulo state.

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The main goal is to discover if time effect affects the increase or decrease in repair complaints in the telecommunication company and if the composition of complaint counts is changing during the follow-up period. The company has been operating since 2014 with the Optic Fiber product with VOIP, Broadband and DTH/IPTV TV products.

Figure 1 shows the plot of the weekly total counts of complaints from the company customers for the assumed period of 134 weeks. Table A1 in an appendix at the end of the manuscript shows the complaint counts corresponding to that period.

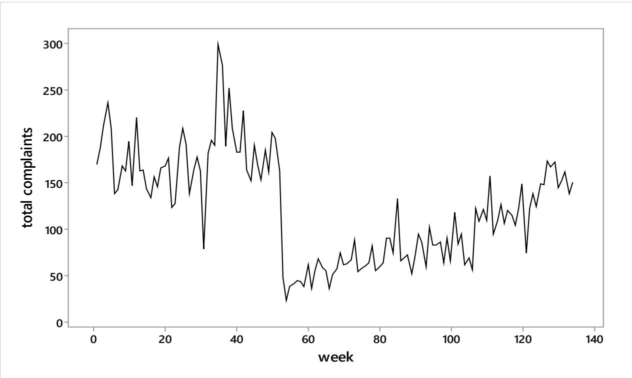

Figure 1: Weekly total counts of complaints

Figure 1 and Table A1 show that the weekly counts of complaints have a change-point at the beginning of the year 2019 (close to the week 48) with a great decreasing in the customer complaints. From this month, there is the beginning of another period of increasing in the customer complaint. From month 8 (august) of 2018, there is a trend for the number of complaints to increase until the end of the follow-up period. Figure 2 shows the box-plots of the customer complaints in the years 2018, 2019 and 2020, from where we observe a decreasing of complaints in the year 2019 when compared to the year 2018 and an increasing of complaints in the year 2020 when compared to the year 2019.

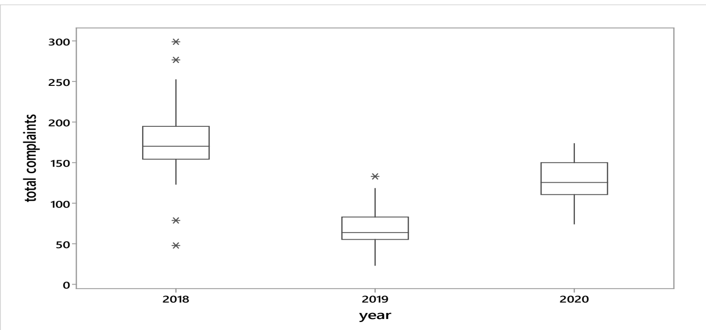

Figure 2: Box-plots of customer complaints in years 2018, 2019 and 2020

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Figure 3 shows the plots of the percentage of complaints due to different causes during the period of 134 weeks. These total week customer complaints is the sum of complaints due to different causes: field complaints, canceled service complaints, massive complaints, other causes complaints, withheld complaints and system complaints.

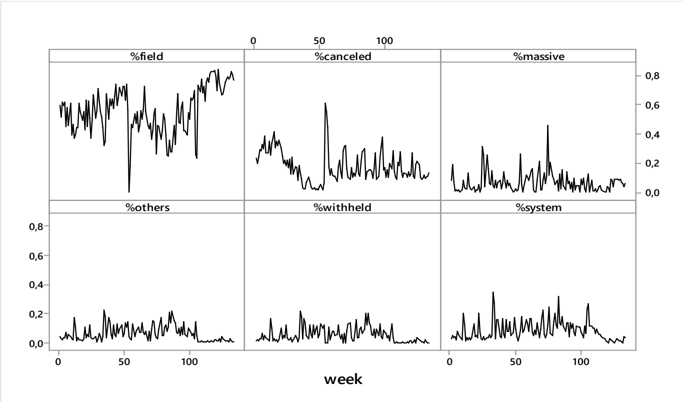

Figure 3: Complaint percentage time series due to different causes

The causes of complaints due to missed deadlines are:

- **Field**: missed deadlines due to non-compliance by the technician or technical support team that was unable to end a service within its proposed service schedule (SLA). These unfulfilled deadlines can occur due to a mistake in the calculation of the technician's time or even an extra situation where an equipment does not configure due to systemic intermittence and the technical support takes a long time to signal for an opening call and thus interrupting the repair.
- **Canceled:** canceled repairs after losing the proposed SLA. Either canceled repairs can be due by the customer or by the telecommunications company itself; however, if the cancellation action is due by the customer or by the company after the expiration of the term, this repair is out of time even canceled. Repairs that are in the systemic system and that are canceled not affecting the service schedule; there is often a delay in the support team to make the decision to cancel.
- **Massive**: repairs that lose time within massive events. Massive events are those that have a widespread problem in a region. These problems can be, for example, from a hardware firmware failure, a service distribution cabinet that goes offline or even theft of cables or cable breakage caused by trucks with very high loads. These repairs are pending the closure of the massive event and nothing could be done until the event

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closes. Often, the massive closure exceeds the final repair time and this causes the deadline for this defect ticket to be lost.

- **Others**: here there are several causes, such as, for example, the customer's internal network is malfunctioning which has an impact on the technician's dealings to meet the repair request within the proposed period. As a special case, this situation occur when the manager of an apartment building takes time to release the technician's authorization to enter or customers absent at the time the technician goes to do the repair. They are causes of less impact in their context, but which in general cause great impacts to the service indicators.

- **Retained (withheld):** repairs that lose their retention period. Retention is a sector that receives a possible intention from the customer to cancel and this sector tries to reverse the situation so that there is no further customer complaint for the same problem. Sometimes it is an intermittent problem when the client feels that the problem can be solved by itself and therefore cancels the repair. This retention sector has the function of contacting the customer and explaining that it is better to be attended by the technician to avoid problems in the future. However, if the process of this retention action is not agile, the term will be out of SLA and even if the customer maintains the decision to cancel the technical visit, the term will already be considered as out of the SLA.

- **System**: repairs that lose time due to an error or systemic failure. These occurrences happen when a technician is at the service point (customer's home) and is unable to finish the service due to technical system issues. These issues vary from the platform that provides the customer service to be slow to the technical support tools with intermittent operation. When these systemic failures occur, the technician and support team to reverse the situation can do little. Sometimes a platform update can cause major systemic impacts and cause several SLA's lost due to this action. If a systemic “Rollback” is needed (action to undo the update and return to the previous version), the impact on the deadline may be even greater

From Figure 3 we have some preliminary conclusions:

- The percentages of complaints due to field is approximately constant during the period of 134 weeks showing a small increasing at the end of the follow-up period.
- The percentages of complaints due to canceled decreases at the beginning of the period with a sharp increasing close to the week 50; from this week the percentages are approximately constant until the end of the period.
- The percentages of complaints due to massive do not show great changes in the follow-up period, but there are some peaks in some weeks.
- The percentages of complaints due to others do not show great changes in the follow-up period, but there is a decreasing at the end of the follow-up period.
- The percentages of complaints due to withheld and system show similar behavior as seen for the percentages of complaints due to others.

1.1. Goals of the study

The main goals of this study are:

- To verify statistically if there is change on the customer complaint counts in the different years (2018, 2019 and 2020) assuming an appropriate statistical model. We assume a Poisson regression model.
- To use existing compositional models in the presence of the covariate year for the percentages of complaint counts due to different causes to verify possible changes in the behavior of the percentages during the follow-up period.
- To get prediction for the customer complaint counts that can assist the company to make better decisions.

The article is organized as follows: section 2 presents a brief review of service quality related to customer complaints; section 3, presents the proposed methodology; section 4 presents the obtained results; section 5 presents some concluding remarks.

2. A BRIEF LITERATURE REVIEW ON CUSTOMERS COMPLAINTS

Usually consumer complaints could affect the reputation of a company (Claro et al., 2014; Martins & Julio, 2013; Coelho et al., 2016; Anderson, Fornell & Mazvancheryl, 2004; Pimentel & Aguiar, 2012) leading to very negative images (Matos & Rossi, 2008; Singh & Wilkes, 1996; Trusov, Bucklin & Pauwels, 2009). Some studies relate consumer complaint

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counts to the market value of the company (Hevalier & Mayzlin, 2006; Goldenberg et al., 2007; Mittal, Ross & Baldasare, 1998; Romani, Grappi & Dalli, 2012).

In the service sector of a telecommunication company is very important to have good technical services since the customers expect good quality of service and technical assistance. With good services, the companies improve their image, attract and retain customers (Kotler & Armstrong, 2003, p. 475). Decreasing customer complaints is an important task to be achieved by all companies, as observed in many studies presented the literature. Consumers in recent years have increasing access to the internet where negative or positive information reports at any time could affect the reputation of each corporation (Martins & Julio, 2013; Coelho et al., 2016; Anderson, Fornell & Mazvancheryl, 2004). The use of social networks is becoming common for the customers to conduct research on quality certification of services and products prior to purchase (Pimentel & Aguiar, 2012).

Negative images for companies usually are linked to customer dissatisfaction (Matos & Rossi, 2008; Singh & Wilkes, 1996; Trusov, Bucklin & Pauwels, 2009); another negative aspect for telecommunication companies is a great number of complaints in public agencies (Singh, 1988) such as ANATEL in Brazil, the regulatory agency that deals with all telecommunication problems in Brazil (Luo, 2009; Winchester, Romaniuk & Bogomolova, 2008).

It is important to point out that the behavior of complaints (Richins, 1983; Singh & Wilkes, 1996) can have direct linear effect on the company's market value (Chevalier & Mayzlin, 2006; Goldenberg et al., 2007; Mittal, Ross & Baldasare, 1998; Romani, Grappi & Dalli, 2012; Sousa, 2011; Mahfood, 1994). In this direction, the literature introduces different statistical or mathematical models in the data analysis of customer complaint data (Fornell & Wernerfelt, 1987).

In recent years, with the technological advance, almost all companies have large amount of customer complaint data reported daily, weekly or monthly in the computers of the companies. The statistical analysis of customer complaint data, as considered in the present study, is very important to companies to improve the quality of services, which is essential to better company performance or even, survival in the large competitive world of companies.

3. METHODOLOGY

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In this section, we present the statistical models, used in the data analysis of the customer complaint count data in the telecommunication company considered in this study.

3.1. Poisson regression model

Longitudinal Poisson data is usual in many applications, where the counts are reported for each sample unit in different times as observed in the count data set of customer complaints introduced in Table A.1. From the results of Table 1, we observe that the sample means are different of the sample variances for the combinations year × count, which is an indication of extra-Poisson variability (year 2018, sample average = 176.55; sample variance = 1738.52; year 2019, sample average = 67.38; sample variance = 437.87; year 2020, sample average = 131.79; sample variance = 610.03). The Poisson distribution assumes that the mean is equal to the variance (Montgomery & Runger, 2011).

To incorporate the dependence among the count data and the extra-Poisson variability, the literature introduces a random effect or “frailty” in regression models (Clayton, 1991) for the parameter of the Poisson distribution. Many authors (Albert & Chib, 1993; Crouchley & Davies, 1999; Dunson, 2000, 2003; Jorgensen et al., 1999; Henderson & Shimakura, 2003; Dunson & Herring, 2005) consider the use of a random effect or a “frailty” to analyze longitudinal discrete data. Some authors (Moustaki, 1996; Sammel, Ryan & Legler, 1997; Moustaki & Knott, 2000) consider generalized linear mixed models with normally distributed random effects.

The Poisson distribution assumed when the behavior of a random variable represents the number of occurrences of events in a time interval or in space (surface or volume) has probability function given by,

$$P(X = x) = e^{-\lambda} \lambda^{x} / x! \qquad (1)$$

$x = 0, 1, 2, 3. . .$; $e = 2.71828...$; λ is the parameter of the distribution representing the mean number of occurrences of the event in time or space unit. The mean and the variance are both equal to the λ parameter. Let us define two “dummy” variables : (year 2018 is assumed as reference): $\delta_1 = 1$ for the year 2019; $\delta_1 = 0$ for the other years 2018 and 2020; $\delta_2 = 1$ for the year 2020; $\delta_2 = 0$ for the other years 2018 and 2019.

Thus, we have:

- $(\delta_1 , \delta_2) = (1, 0)$ for the year 2019.

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- $(\delta_1, \delta_2) = (0, 1)$ for the year 2020.
- $(\delta_1, \delta_2) = (0, 0)$ for the year 2018.

In this way, we assume the regression model for the parameter λ in the Poisson distribution (1) given by,

$$\lambda_i = \exp(\beta_0 + \beta_1 \delta_{1i} + \beta_2 \delta_{2i} + w_i) \qquad (2)$$

for i = 1, 2, ..., 134; w_i is a random effect (latent unobserved variable) that captures the dependence between the week counts, assumed with a normal distribution $N(0, \sigma_w^2)$.

Remarks:

(1) If $(\delta_1, \delta_2) = (0,0)$ (year 2018) we have $\lambda_{2018} = \exp(\beta_0)$

(2) If $(\delta_1, \delta_2) = (1,0)$ (year 2019) we have $\lambda_{2019} = \exp(\beta_0 + \beta_1)$

(3) If $(\delta_1, \delta_2) = (0,1)$ (year 2020) we have $\lambda_{2020} = \exp(\beta_0 + \beta_2)$

That is, with $\gamma = \exp(\beta_0)$ as a base, we have multiplicative effects $\exp(\beta_1)$ and $\exp(\beta_2)$ in the consumer complaint means in the years 2019 and 2020 relative to the reference year 2018:

- Mean for the year 2018: $\lambda_{2018} = \gamma$
- Mean for the year 2019: $\lambda_{2019} = \gamma\exp(\beta_1)$ (3)
- Mean for the year 2020: $\lambda_{2020} = \gamma\exp(\beta_2)$

We assume a hierarchical Bayesian analysis for the model considering normal prior distributions for the regression parameters β_0, β_1 and β_2 with known hyperparameter values. For the second stage of the hierarchical Bayesian analysis, it is assumed a gamma prior distribution for the inverse of the variance σ_w^2 of the latent variable w_i, that is, $\zeta_w = 1/\sigma_w^2 \sim G(a_w,b_w)$ where $G(a,b)$ denotes a gamma distribution with mean a/b and variance a/b^2 ; a_w and b_w are known hyperparameters. Further, we assume prior independence among the parameters.

3.2. Compositional regression model

Compositional data that usually are common in geology, economics and biology are a very special case of data given by vectors of G proportions. Let us denote $\mathbf{x} = (x_1, x_2,\ldots, x_G)$ to be a compositional vector, where $x_i > 0$, for $i = 1,\ldots, G$ and $x_1 + x_2 +\ldots + x_G = 1$. In this situation,

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usual statistical methods for multivariate data under the usual assumption of normal multivariate distribution (Johnson & Wichern, 1998) are not appropriate for analyzing compositional data, since the compositional have constraints. For the statistical analysis of compositional data we could consider a Dirichlet distribution, but this model requires that the correlation structure be negative, an unobserved fact for compositional data where some correlations are positive (Aitchison, 1982, 1986).

Aitchison and Shen (1985) introduced a simple model approach for compositional data analysis with the transformation of the vector of G components **x** into a vector **y** into R^{G-1} considering an additive ratio log (ALR) function (see also, Rayens & Srinivasan, 1991). Other model approach is introduced in the literature considering the isometric log-ratio (ILR) transformation (Egozcue et al., 2003; Martin-Fernandez, Daunis-Estadella & Mateu-Figueras, 2015), but the inverse transformation to get the proportions in each class is more complex and the obtained results are similar to the results assuming the ALR transformation (Martinez et al., 2019). A simple way to get inferences for the ALR model is the use of a Bayesian approach (Iyengar & Dey, 1996, 1998; Tjelmeland & Lund, 2003), especially considering Markov Chain Monte Carlo (MCMC) methods (Gelfand & Smith, 1990; Roberts & Smith, 1993).

The compositional data introduced in Table A.1 related to the causes of customer complaints are denoted by x_{1i} = % field, x_{2i} = % canceled, x_{3i} = % massive, x_{4i} = % others, x_{5i} = % withheld and x_{6i} = % system. Let us assume a model with additive ratio log (ALR) transformation given by $y_{1i} = \log(x_{2i}/x_{1i})$, $y_{2i} = \log(x_{3i}/x_{1i})$, $y_{3i} = \log(x_{4i}/x_{1i})$, $y_{4i} = \log(x_{5i}/x_{1i})$, $y_{5i} = \log(x_{6i}/x_{1i})$ given by,

$$
\begin{aligned}
y_{1i} &= \beta_{11} + \beta_{12}(\text{year}_i - 2018) + w_i + \varepsilon_{1i} \\
y_{2i} &= \beta_{21} + \beta_{22}(\text{year}_i - 2018) + w_i + \varepsilon_{2i} \\
y_{3i} &= \beta_{31} + \beta_{32}(\text{year}_i - 2018) + w_i + \varepsilon_{3i} \\
y_{4i} &= \beta_{41} + \beta_{42}(\text{year}_i - 2018) + w_i + \varepsilon_{4i} \\
y_{5i} &= \beta_{51} + \beta_{52}(\text{year}_i - 2018) + w_i + \varepsilon_{5i}
\end{aligned} \tag{4}
$$

where i=1,2,...,134; β_{11}, β_{12}, β_{21}, β_{22}, β_{31}, β_{32}, β_{41}, β_{42}, β_{51} and β_{52}, w_i is a random effect (latent variable unobserved) that captures the dependence between the proportions and ε_{ji} are independent assumed errors with normal distributions $N(0, \sigma_j^2)$, j = 1, 2, 3, 4, 5. We assume a normal distribution $N(0, \sigma_w^2)$ for the random effects w_i, i = 1, 2, …, 134.

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For a hierarchical Bayesian analysis of the model, we assume normal prior distributions for the regression parameters with known hyperparameter values. For the second stage of the hierarchical Bayesian analysis, it is assumed a gamma prior distribution for the inverse of the variance σ_w^2 of the latent variable w_i, that is, $\zeta_w \sim G(a_w,b_w)$. Further, we assume prior independence among the parameters.

Posterior summaries of interest for the Poisson regression and the compositional models were obtained using simulated samples of the joint posterior distribution for the model parameters using MCMC methods (Chib & Greenberg, 1995). The simulation algorithm to get samples for the joint posterior distribution for the model parameters is obtained from the complete conditional posterior distributions for each parameter. A major simplification in the simulation procedure is to use some existing Bayesian simulation software. One such software is the Openbugs software (Lunn et al, 2009), where it is only needed to specify the joint distribution for the observations and the prior distributions for the parameters of the assumed model.

4. RESULTS

In this section, we present the Bayesian inference results assuming both models presented in section 3.The posterior summaries of interest were obtained using the OpenBugs software.

4.1. Use of a Poisson regression model for the longitudinal total complaint count data

In this section we present the inference results assuming the Poisson regression model (1) and (2) for the total customer complaints in each week of the follow-up period. We assume approximately non-informative prior distributions for the parameters, that is, $\beta_0 \sim N(0,10)$, $\beta_1 \sim N(0,1)$, $\beta_2 \sim N(0,0.1)$ and $\zeta_w = 1/\sigma_w^2 \sim G(0.1,0.1)$. Table 1 shows the posterior summaries of interest obtained using the OpenBugs software (burn-in sample of size 11.000; 1000 simulated Gibbs samples obtained choosing each 100th simulated in 100.000 simulated samples).The convergence of the simulation algorithm was verified from trace plots.

Table 1: Posterior summaries (Poisson regression model)

	Mean	Sd	Lower 95% ci	Upper 95% ci
β_0	5.139	0.03623	5.068	5.211
β_1	-0.9654	0.05493	-1.076	-0.853
β_2	-0.2714	0.06187	-0.3941	-0.1476
λ_{2018}	170.7	6.182	158.8	183.2
λ_{2019}	65.0	2.574	60.07	69.95

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λ_{2020}	130.2	6.445	117.5	143.7
mult.eff.2019	0.3814	0.02094	0.3411	0.4262
mult.eff.2020	0.7638	0.04726	0.6743	0.8627
$\zeta_w = 1/\sigma_w^2$	15.76	2.365	11.51	20.62

Table 1 shows that the covariates ("dummy" variables) δ_1 (year 2019) and δ_2 (year 2020) have significative effects on the year means of customer count complaintes related to the reference year 2018 since the value zero in not included in the 95% credible inervals for the regression parameters β_1 and β_2. Since the Bayesian estimators for β_1 and β_2 have negative values, there is a decreasing in the customer complaint means in the years 2019 and 2020 in relation to the year 2018.

The posterior means for the Poisson distribution (1) parameters related to the years 2018, 2019 and 2020 are given respectively by 170.7, 65.0 and 130.2, values that are close to the estimated sample means (176.55, 67.38 and 131.79) indicating good fit of the model for the data.The multiplicative effects for the years 2019 and 2020 related to the year 2018 have Bayesian estimators given, respectively by, 0.3814 and 0.7638.

4.2. Use of a compositional regression model for the longitudinal percentages components of the total complaint count data

In this section, a Bayesian analysis for the percentages of customer complaints due to different causes assuming the compositional model (4) is presented assuming normal independent prior distributions N(0,1) for the regression parameters β_{11}, β_{12}, β_{21}, β_{22}, β_{31}, β_{32}, β_{41}, β_{42}, β_{51} and β_{52} and gamma distributions G(1,1) for the inverse of the variances σ_j^2, j = 1, 2, 3, 4, 5 of the errors ε_{1i}, ε_{2i}, ε_{3i}, ε_{4i} and ε_{5i}.

We also assume another gamma prior distribution G(1,1) for the inverse of the variance σ_w^2 of the latent variable W_i, i = 1,…,n. Table 2, shows the posterior summaries of interest (Monte Carlo estimators for the posterior means, posterior standard deviations and 95% credibility intervals) based on 1000 simulated Gibbs samples (every 100th simulated sample among 100,000 generated Gibbs samples to get an approximately uncorrelated sample) of the joint posterior distribution for all model parameters obtained using Openbugs software and considering a burn-in sample of size 11,000 discarded to eliminate the effect of the initial parameter values needed for the MCMC algorithm. Convergence of the MCMC simulated samples also was monitored by traceplots of the generated Gibbs samples.

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From the results presented in Table 2, we observe that the year has significative effect (zero not included in the 95% credibility intervals) in the following situations:

Table 2: Posterior summaries (compositional regression model)

	Mean	Sd	Lower 95% ci	Upper 95% ci
β_{11}	-1.07	0.2006	-1.455	-0.6801
β_{12}	-0.07112	0.1814	-0.4261	0.293
β_{21}	-2.504	0.4279	-3.343	- 1.651
β_{22}	-0.8077	0.3844	-1.562	- 0.06352
β_{31}	-1.733	0.1772	- 2.075	-1.374
β_{32}	-0.6748	0.1568	-0.9821	-0.3494
β_{41}	-1.601	0.3592	-2.267	-0.8335
β_{42}	-2.632	0.3237	-3.228	-1.967
β_{51}	-1.504	0.2623	-2.019	-0.9839
β_{52}	-0.769	0.2226	-1.196	-0.3352
$\zeta_w = 1/\sigma_w^2$	0.5441	0.08239	0.4017	0.7155
$\zeta_1 = 1/\sigma_1^2$	0.8984	0.144	0.6582	1.204
$\zeta_2 = 1/\sigma_2^2$	0.08072	0.01021	0.06245	0.1038
$\zeta_3 = 1/\sigma_3^2$	2.849	0.8626	1.571	5.047
$\zeta_4 = 1/\sigma_4^2$	0.1191	0.01473	0.09251	0.15
$\zeta_5 = 1/\sigma_5^2$	0.3301	0.04225	0.2552	0.4236

- Response $y_1 = \log(x_2/x_1)$ where x_1 = %field and x_2 = %canceled: the 95% credible interval for the regression parameter β_{12} includes the zero value; that is, year does not show statistically differences for the response $y_2 = \log(x_3/x_1) = \log(x_3) - \log(x_1)$ where x_1 = %field is considered as reference.

- Response $y_2 = \log(x_3/x_1)$ where x_1 = %field and x_3 = %massive: the 95% credible interval for the regression parameter β_{22} does not include the zero value; that is, year shows statistical effect on the response $y_2 = \log(x_3/x_1) = \log(x_3) - \log(x_1)$ where x_1 = %field is considered as reference. Since β_{22} is estimated by a negative value, the difference $\log(x_3) - \log(x_1)$ is decreasing during the period.

- Response $y_3 = \log(x_4/x_1)$ where x_1 = %field and x_4 = %others: the 95% credible interval for the regression parameter β_{32} does not include the zero value; that is, year shows statistical effect on the response $y_3 = \log(x_4/x_1) = \log(x_4) - \log(x_1)$ where x_1 = %field is considered as reference. Since β_{32} is estimated by a negative value, the difference $\log(x_4) - \log(x_1)$ is decreasing during the period.

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- Response $y_4 = \log(x_5/x_1)$ where x_1 = %field and x_5 = %withheld: the 95% credible interval for the regression parameter β_{42} does not include the zero value; that is, year shows statistical effect on the response $y_4 = \log(x_5/x_1) = \log(x_5) - \log(x_1)$ where x_1 = %field is considered as reference. Since β_{42} is estimated by a negative value, the difference $\log(x_5) - \log(x_1)$ is decreasing during the period.

- Response $y_5 = \log(x_6/x_1)$ where x_1 = %field and x_6 = %system: the 95% credible interval for the regression parameter β_{52} does not include the zero value; that is, year shows statistical effect on the response $y_5 = \log(x_6/x_1) = \log(x_6) - \log(x_1)$ where x_1 = %field is considered as reference. Since β_{52} is estimated by a negative value, the difference $\log(x_6) - \log(x_1)$ is decreasing during the period.

Figure 4 shows the plots of the responses $y_{1i} = \log(x_{2i}/x_{1i})$, $y_{2i} = \log(x_{3i}/x_{1i})$, $y_{3i} = \log(x_{4i}/x_{1i})$, $y_{4i} = \log(x_{5i}/x_{1i})$, $y_{5i} = \log(x_{6i}/x_{1i})$ versus time (134 weeks) which confirms the obtained results of the compositional model fit.

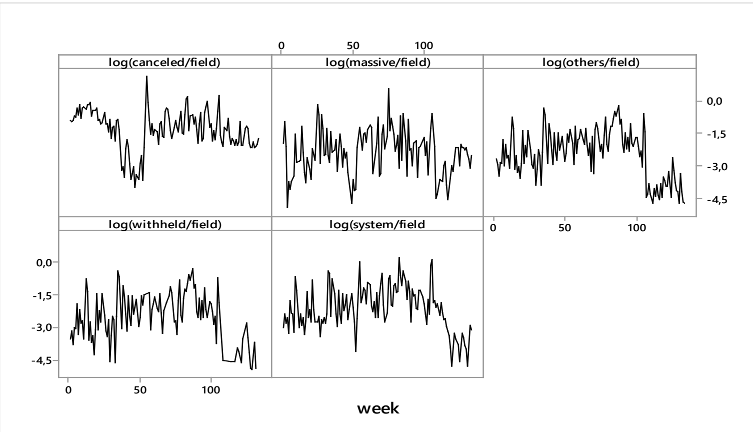

Figure 4: Plots of the responses y_{1i}, y_{2i}, y_{3i}, y_{4i} and $y_{5i} = \log(x_{6i}/x_{1i})$ versus weeks

5. CONCLUDING REMARKS

The obtained results from the different statistical analyzes associated with the telecommunications company complaint counts can be of great interest to the company.

The Poisson regression model for the total count of complaints showed that although there was a decreasing of complaints from the year 2018 to the year 2019, we observe an increasing in the total count complaints for the year 2020, which is a cause for concern for the company.

The compositional model approach for the week complaints due to different causes was important to show where the percentage components (related to the complaints of different causes) is changing in the specified follow-up period. These results are of great interest to improve the quality service provided by the telecommunications company.

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APPENDIX A

Table A.1 Complaint count data

week	year	total complaints	field	canceled	massive	others	withheld	system
1	2018	171	102	40	14	7	3	5
2	2018	188	97	37	36	5	4	9
3	2018	212	130	51	16	4	3	8
4	2018	237	141	69	1	8	7	11
5	2018	209	129	59	3	7	6	5
6	2018	138	62	45	1	10	9	11
7	2018	143	83	43	2	4	3	8
8	2018	168	77	65	0	10	9	7
9	2018	163	99	44	3	7	6	4
10	2018	195	76	53	16	6	5	39
11	2018	147	68	51	4	3	2	19
12	2018	221	81	56	5	38	37	4
13	2018	163	64	54	4	18	17	6
14	2018	164	72	61	22	3	2	4
15	2018	144	64	60	6	5	4	5
16	2018	134	82	41	3	3	2	3
17	2018	157	87	55	2	4	3	6
18	2018	146	72	47	5	2	1	19
19	2018	166	91	59	0	5	4	7
20	2018	168	72	50	3	18	17	8
21	2018	177	112	44	3	6	5	7
22	2018	124	56	24	6	7	6	25
23	2018	128	80	28	0	6	5	9
24	2018	189	96	34	6	24	23	6
25	2018	209	78	46	65	8	7	5
26	2018	192	94	32	49	5	4	8
27	2018	138	92	31	5	4	3	3
28	2018	164	83	20	42	7	6	6
29	2018	178	99	42	28	2	1	6
30	2018	163	116	20	9	5	4	9
31	2018	79	49	14	4	5	4	3
32	2018	182	100	31	27	8	7	9
33	2018	196	101	16	8	2	1	68
34	2018	191	85	34	5	8	7	52
35	2018	300	96	40	23	67	66	8
36	2018	277	97	25	9	51	50	45
37	2018	190	128	5	13	7	6	31
38	2018	253	127	6	21	44	43	12
39	2018	209	134	4	5	30	29	7
40	2018	183	109	12	11	11	10	30
41	2018	183	117	19	25	6	5	11
42	2018	228	131	16	16	29	28	8
43	2018	164	108	6	5	10	9	26
44	2018	152	112	3	12	7	6	12
45	2018	191	114	4	8	25	24	16
46	2018	169	109	5	10	11	10	24
47	2018	153	110	2	4	15	14	8
48	2018	185	122	4	0	23	22	14
49	2018	162	117	3	1	7	6	28
50	2018	205	149	8	4	13	12	19
51	2018	198	125	10	2	27	26	8
52	2018	163	121	3	2	18	17	2
53	2018	48	27	3	3	7	6	2
54	2019	23	0	14	6	1	0	2
55	2019	38	7	21	2	1	0	7
56	2019	41	19	18	0	1	0	3
57	2019	45	20	8	2	6	5	4
58	2019	43	23	5	5	2	1	7
59	2019	38	18	6	4	3	2	5
60	2019	62	34	7	5	6	5	5
61	2019	36	15	4	4	4	3	6
62	2019	55	25	6	8	4	3	9
63	2019	68	38	5	11	5	4	5
64	2019	58	29	10	1	8	7	3
65	2019	55	31	12	0	4	3	5

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66	2019	36	26	5	0	2	1	2
67	2019	51	28	5	4	4	3	7
68	2019	57	26	16	12	1	0	2
69	2019	74	32	23	1	6	5	7
70	2019	62	29	20	1	1	0	11
71	2019	63	23	10	5	6	5	14
72	2019	67	28	7	9	10	9	4
73	2019	88	47	8	5	13	12	3
74	2019	54	31	9	6	3	2	3
75	2019	57	15	6	26	2	1	7
76	2019	61	28	8	7	2	1	15
77	2019	64	29	7	13	6	5	4
78	2019	82	30	12	9	14	13	4
79	2019	55	23	14	5	3	2	8
80	2019	58	31	7	3	3	2	12
81	2019	64	32	7	4	7	6	8
82	2019	90	35	18	7	11	10	9
83	2019	91	23	25	1	7	6	29
84	2019	74	18	22	9	8	7	10
85	2019	133	47	12	3	28	27	16
86	2019	66	18	9	10	9	8	12
87	2019	69	19	10	3	15	14	8
88	2019	72	33	11	1	11	10	6
89	2019	52	17	8	7	7	6	7
90	2019	71	38	10	4	5	4	10
91	2019	95	64	9	7	6	5	4
92	2019	86	41	14	2	9	8	12
93	2019	59	28	16	4	3	2	6
94	2019	102	59	9	0	11	10	13
95	2019	83	51	9	8	5	4	6
96	2019	83	35	20	1	12	11	4
97	2019	86	36	27	4	5	4	10
98	2019	64	25	24	3	3	2	7
99	2019	90	49	14	0	9	8	10
100	2019	66	33	11	6	6	5	5
101	2019	118	76	12	6	9	8	7
102	2019	84	53	13	8	4	3	3
103	2019	95	61	10	2	6	5	11
104	2019	62	43	12	0	2	1	4
105	2019	69	18	11	5	10	9	16
106	2019	56	13	16	7	3	2	15
107	2020	123	90	18	0	1	0	14
108	2020	109	75	11	9	1	0	13
109	2020	121	94	11	1	2	1	12
110	2020	110	75	22	1	1	0	11
111	2020	158	115	29	3	1	0	10
112	2020	95	59	26	0	1	0	9
113	2020	110	83	16	2	1	0	8
114	2020	127	99	13	5	2	1	7
115	2020	107	81	14	5	1	0	6
116	2020	120	97	15	2	1	0	5
117	2020	115	95	12	1	2	1	4
118	2020	104	86	14	0	1	0	3
119	2020	122	102	13	0	3	2	2
120	2020	149	119	18	6	3	2	1
121	2020	75	52	20	2	1	0	0
122	2020	123	103	13	0	2	1	4
123	2020	139	104	13	12	4	3	3
124	2020	125	88	24	10	1	0	2
125	2020	149	99	31	5	7	6	1
126	2020	148	100	28	13	4	3	0
127	2020	174	131	18	15	3	2	5
128	2020	167	130	15	15	2	1	4
129	2020	173	137	16	14	2	1	3
130	2020	145	112	17	13	1	0	2
131	2020	152	120	14	10	4	3	1
132	2020	162	134	16	9	2	1	0
133	2020	138	111	15	5	1	0	6
134	2020	150	115	20	9	1	0	5