SPATIAL PRICE TRANSMISSION, TRANSACTION COSTS, AND ECONOMETRIC MODELLING

AND

MODELLING SALMONELLA SPREAD IN BROILER PRODUCTION

By

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Abstract: Transaction costs are major determinants of price transmission across space and must be accounted for when modelling price transmission. This article contributes to literature by evaluating the impact of not properly accounting for transaction cost variation on price transmission parameters using a Monte Carlo experiment and a real world application. We show that when transaction costs are variable and nonstationary, threshold vector error correction models assuming fixed thresholds provide biased inference, while the flexible threshold specification accounting for transaction cost variation is able to provide unbiased estimates on market performance indicators.

In the second essay, we identify determinants and control strategies for *Salmonella* in broiler production. The presence of *Salmonella spp.* in broiler production is a concern as the bacterium can be transmitted to humans via contaminated meat and derived products. A longitudinal study using official results of *Salmonella spp.* isolation from drag swabs collected at the end of the grow-out period was performed to determine risk factors related to farm and broiler house characteristics and management practices, as recorded by a Brazilian integrated broiler enterprise. A Bayesian hierarchical spatio-temporal model revealed significant spatial and time influence and significant effects of size of broiler house and total housing area per farm, type of broiler house and litter recycles on the odds of isolating *Salmonella spp.* from litter, allowing the implementation of measures to reduce the risk of persistence of the bacterium in the broiler production chain. We find evidence of a principal-agent problem while setting strategies to control the bacteria in litter and suggest the adoption of incentives aiming to reduce prevalence in the integrated enterprise. The possibility of implementing optimal control measures by extending recorded data is discussed.

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SPATIAL PRICE TRANSMISSION, TRANSACTION COSTS AND ECONOMETRIC MODELLING: HOW INFERENCE CAN BE IMPROVED WHEN ACCOUNTING FOR INFORMATION ON TRANSACTION COST

Abstract

Transaction costs are major determinants of price transmission across space and must be accounted for when modelling price transmission. This article contributes to literature by evaluating the impact of not properly accounting for transaction cost variation on price transmission parameters using a Monte Carlo experiment and a real world application. We show that when transaction costs are variable and nonstationary, threshold vector error correction models assuming fixed thresholds provide biased inference, while the flexible threshold specification accounting for transaction cost variation is able to provide unbiased estimates on market performance indicators.

Keywords: Transaction cost, Threshold Vector Error Correction Model, Monte Carlo experiment, threshold cointegration, time-varying cointegration.

JEL codes: C15, Q11, Q13

Introduction

Spatial price transmission and market efficiency has long been of interest for agricultural commodities with studies mostly focusing on evaluating market integration and the degree and speed of transmission of prices across markets (Lo and Zivot 2001a; Barrett 2001; Hassouneh, Serra and Gil 2010; Goodwin 2006; Brosig et al. 2011; Esposti and Listorti 2013). Spatial price transmission theory is mostly based on the concept of "Law of One Price (LOP)", which should be a theoretical condition for markets to be integrated (Goodwin 2006). According to the LOP, prices of a homogeneous good must be the same across markets, net of transaction costs. When there is price difference between regions greater than costs of transporting and selling goods from one market to another, arbitrage becomes profitable so that prices are driven back to an equilibrium where differences are equal or lower than transaction costs (Sexton, Kling, and Carman 1991). Therefore, in order to study price transmission and market efficiency, it is imperative to account for transaction costs (Mcnew and Fackler 1997), although in reality, transaction costs and trade flow data are not easily available.

To overcome the problem of unobserved transaction costs, a class of nonlinear model has been extensively used, namely threshold vector error correction model (TVECM). This modelling framework allows for the presence of thresholds in the cointegrating vector, which is expected to account for the transaction cost effect in the price transmission process.

Therefore, when price differences are greater than the estimated threshold, prices are expected to correct faster towards the established long-run equilibrium, as arbitrage would be profitable. Similarly, when price differences are lower than the threshold, corrections would be slower or even inexistent (Fackler and Goodwin 2001; Listorti and Esposti 2012).

Although the TVECM framework is expected to address limitations of the linear error correction model, particularly accounting for the transaction cost effect, previous studies argue that the standard TVECM could lead to biased results because actual transaction cost is omitted from the equations , and transference cost is frequently not constant over time (Barrett 2001). Barrett and Li (2002) evaluate the role of incorporating transaction costs and trade flow data in price transmission analysis using a maximum likelihood estimation of a mixture distribution model. Authors demonstrated that at least one assumption among stationary transfer costs, and constant and unidirectional trade was violated in every direction-specific market pair, underscoring the need for incorporating transaction costs and using more flexible methods to model price transmission.

Despite its popularity in the price transmission literature, some recent work has demonstrated that the TVECM is fragile as determination of thresholds depends heavily on the methodology used and may not truly address the limitation of the linear models when transaction costs are not available (Frey and Manera 2007; Goodwin, Holt and Prestemon 2011). In addition, corrections towards the long run equilibrium may not be immediate, as in most TVECMs, but rather smooth.

Even though several modelling methods have been proposed to better adjust price behavior to specific markets' characteristics, it is still unclear how the dynamics of transaction costs impacts spatial price transmission. Few studies have explicitly incorporated transaction cost data into the modelling framework or have dealt with the issue of varying transaction costs. Bekkerman, Goodwin and Piggott (2009), revisiting the work of Goodwin and Piggott (2001) specifying a variable transaction costs framework, show that the asymmetric variable thresholds model outperformed the alternative constant and symmetric thresholds specification.

Formal evaluations of the impact of omitting transaction cost information on inference in price transmission under the TVECM framework is still to be described. Lence, Moschini and Santeramo (2018) evaluate the performance of a Band-TVECM through a Monte Carlo experiment and show that the model underestimates transaction costs, while counterintuitively providing poor inference on possible trade occurrence, biasing downwards the speed of price transmission and suggesting lower-than-expected market integration.

Although underscoring the weaknesses of the Band-TVECM, the authors did not evaluate any alternative econometric modelling which could theoretically better represent the dynamics of the transaction costs and the price correction mechanism (e.g. the assumption of time-varying co-integration). The addition of potential sources of observed transaction costs into the modelling framework was not assessed either.

Our study contributes to literature by modelling a TVECM with and without the incorporation of transaction cost information and comparing the performance of a constant threshold model specification and a time varying threshold model specification using Monte Carlo experiments.

Our results show that when transaction cost is stationary and exogenously determined, TVECM provides correct inference. However, when transportation cost is endogenously determined and nonstationary, the standard TVECM results in incorrect inferences on price adjustment to the long run equilibrium and frequency of spatial arbitrage due to the assumption of constant transaction cost. Letting the threshold be a function of lagged transportation costs significantly improved inference.

Our paper follows with a literature review explaining the theory behind the TVECM and its use to evaluate spatial price transmission in agricultural markets. We then provide detailed specification on econometric modelling, data generation and results from our Monte Carlo experiments, concluding with a real-world application to the Brazilian hog industry and directions for future research.

Literature Review

Most spatial price analyses are based on the assumption of LOP, which states that the price, net of transaction costs, of a given commodity must be the same across regions. Therefore, the LOP is a consequence of spatial arbitrage and also one possible explanation for cointegration (Goodwin and Schroeder 1991). The concept of cointegration, on the other hand, relates to the property of a function of a given pair of nonstationary variables to be stationary. For the case of price series, cointegration means that the difference of two nonstationary price seires share a common long run mean, to which prices tend to return.

Methodologies based on cointegration have been widely used to evaluate market integration and price transmission in agricultural and other commodities markets (Frey and Manera 2007). As price series tend to be nonstationary, cointegration models are able to represent how cointegrated non-stationary variables are linked by a stationary long-run relationship, allowing them to diverge from it in the short run. This provides the distinction between short and long run dynamics of the prices of interest.

One of the most popular methodologies used to model cointegrated prices is the vector error correction model (VECM). In the VECM, a long run relationship is established by the presence of cointegration between the analyzed prices. If this hypothesis is not confirmed, then the dependence of prices is limited to short run responses to shocks (Listorti and Esposti 2012). This long run relationship expresses the LOP, which assumes the price spreads to be constant or in constant proportions. The assumption of constant price spreads (proportions) may be regarded as a caveat of the methodology, once prices may not be cointegrated in given integrated markets, and transaction costs and other factors contributing to price differences could be nonstationary and time varying (Barrett 1996; Listorti and Esposti 2012).

The identification of thresholds in the error correction term has partially overcome the assumption of constant price spreads. In the presence of thresholds, the model assumes a nonlinear form (or stepwise linear), in which the price correction mechanism depends on the estimated thresholds: prices are expected to converge faster to the long run equilibrium if the price spread lies outside of the interval given by the threshold. The thresholds would then, represent the minimum profitable price difference for arbitrage to occur, illustrating the concept of LOP. These models are described as Threshold Vector Error Correction Models (TVECM).

Most works describing spatial price transmission in agricultural markets have accounted for transaction costs using threshold autoregressive (TAR) and TVECM models (Brosig et al. 2011; Lo and Zivot 2001b; Meyer 2004; Serra, Gil and Goodwin 2006; Listorti and Esposti 2012; Greb et al. 2013). Lo and Zivot (2001) used TVECM to detect threshold type cointegration for several tradable goods, including agricultural commodities, assuming the existence of a constant threshold.

Meyer (2004) applied a three regime TVECM to account for transaction costs in spatial price transmission in European pig markets, considering symmetric adjustment towards the long run equilibrium by allowing the existence of two thresholds of equal magnitude. Brosig et al. (2011) applied a similar methodology to study wheat market integration in Turkey, using the determined threshold to infer on a minimum level of transaction costs, which would impede full market integration. Chen and Lee (2008), use a similar methodology to study integration and deviations from the LOP in Taiwanese pig markets assuming symmetric transaction costs. Common limitations of these papers are restrictions on symmetrical adjustment and on assuming constant transaction costs.

Another potential limitation for using TVECM to model transaction costs and evaluate market integration and efficiency is the absence of trade flow variables. While such information may be valuable to study market integration, it may not be necessarily needed to study market performance, as reported by Stephens et al. (2012). They find that intermarket price adjustments occurs both in presence and absence of physical trade, with larger and more rapid adjustments occurring in periods without physical trade flows.

Following a similar rationale, Lence, Moschini and Santeramo (2018) developed a data generating process (DGP) which accounted for expectations of decision makers and delivery lags in the price determination. Under this framework, existence of price differences greater than transaction costs were fully consistent with market equilibrium, as authors showed that price movements due to trade decisions were made before shocks on supply and demand were realized on the terminal markets. Arbitrage is allowed and leads to price correction in the following period. This provides a useful condition to evaluate the performance of the TVECM, as the researcher knows the exact transaction costs preventing or encouraging arbitrage, speed of price adjustment and number of observations of price differences falling within each of the trade regimes occurring under different scenarios of interest.

Besides the study of Lence, Moschini and Santeramo (2018), we did not find in recent literature other studies that had formally evaluated the performance of the TVECM and evidenced the implication of its assumptions in terms of inference. Some common limitations of the previously mentioned studies relate to the problem of estimation of the thresholds, and the assumption of constant and symmetric thresholds.

Although some of those limitations were already addressed, it is not yet clear how the assumption of constant transaction costs may affect inference when transaction costs are in fact variable, and whether incorporating information about transaction costs in the model can improve inference. We address this issue in the following way: we extend the study of Lence, Moschini and Santeramo (2018) by evaluating the performance of a Band-TVECM under the assumption of constant and variable transaction costs.

To specify a variable TVECM, we follow with procedures described by Park, Mjelde and Bessler (2007), which consist in obtaining price series filtered by the effects of time variation through the use of variables which influence prices that have a known time pattern, and using these series to follow with the inference procedure and estimate the TVECM. We use metrics commonly used to evaluate market performance such as the speed of price adjustment, the threshold values (or the band of inactivity) and the frequency of violations to spatial arbitrage to compare the estimated results under the two different modelling frameworks with the corresponding true values. We also apply the TVECM under the two mentioned specifications to study price transmission within Hog Markets in Brazil, as a real world case study, and show in this real world example, the implications of a potentially mispecified model.

Methodology

To evaluate the performance of the TVECM and the role of incorporating information about transaction costs in the modelling framework, we first generate non-stationary cointegrated price series based on true transaction costs, speed of price adjustment, and percentage of violations of spatial equilibrium using the Monte Carlo experiment method. Then, TVECMs with various specifications are estimated using these price series with and without incorporating transaction cost, and estimation results are compared to the underlying true values. Finally, regional price and transaction data from the Brazilian hog producers are applied to the TVECM.

Monte Carlo Experiments

To generate nonstationary but cointegrated data, we specify a two-region equilibrium model where prices are determined according to stochastic supply and demand conditions in each market. The model assumes that the product is perishable, and that no storage is allowed. This data generating process (DGP) draws on Lence, Moschini and Santeramo (2018), which has the advantage of accounting for delivery lags and rational expectations.

The inverse demand functions are written as:

(1) $$P_t^i = \delta_t^i \left(C_t^i\right)^{-\frac{1}{\varepsilon_i}},$$

where P_t^i is the price in region i at time t, δ^i is a demand scaling factor, C_t^i represents total consumption in region i, and ε_i is the own price elasticity of demand for region i. The model is also built under a complementarity slackness condition that implies that the expected price differential is exactly equal to transfer cost when there is a positive shipment between regions. The equilibrium prices and shipped quantities between regions are determined according to the following equations:

(2) $$\bar{P}_t^i = \delta_t^i[(1-\bar{x}_t^{ij})S_t^i + \bar{x}_t^{ji}S_t^j]^{-\frac{1}{\varepsilon_i}},$$

(3) $$\bar{P}_t^j = \delta_t^j[\bar{x}_t^{ij}S_t^i + (1-\bar{x}_t^{ji})S_t^j]^{-\frac{1}{\varepsilon_j}},$$

where $\bar{P}_t^{i,j}$ is the equilibrium price in regions i, j at time t, $\bar{x}_t^{ij}$ and $\bar{x}_t^{ji}$ are the equilibrium proportions of supply transported from regions $i(j)$ to region $j(i)$, S_t^i and S_t^j are supply quantities in regions i and j, which are exogenously determined, and $\varepsilon_{i,j}$ is the own price elasticity of demand in each region.

For our simulations, we considered the simplest case of constant supply, e.g. $S^{i,j} = 1$, which makes production in each region stationary.[1] To generate prices integrated of order one, I(1), demand is then assumed to be subject to exogenous I(1) shocks, generating price series exhibiting threshold cointegration by construction.

Demand shocks in each region can be specified by:

(4) $$\ln(\delta_t^i) = \ln(\delta_{t-1}^i) + u_t^i ,$$

Where u_t^i is an i.i.d. $N(-0.5\epsilon_i^2, \epsilon_i^2)$ random shock to the demand at the terminal market, which is realized after shipping decisions are made.

The equilibrium price process at every period t, given process (4) and given the equilibrium quantity shipments $\bar{\mathrm{x}}_t^{\mathrm{ij}}$, can be represented as:

[1] Several DGP were evaluated in Lence, Moschini and Santeramo (2018). For simplicity, we follow this specification to evaluate our different modelling approaches.

(5) $$\overline{EP}_t^i = \exp\left(u_t^i\right) \delta_{t-1}^i [\left(1 - \bar{x}_t^{ij}\right) S_t^i + \bar{x}_t^{ji} S_t^j]^{-\frac{1}{\varepsilon_i}},$$

(6) $$\overline{EP}_t^j = \exp\left(u_t^j\right) \delta_{t-1}^j [\bar{x}_t^{ij} S_t^i + \left(1 - \bar{x}_t^{ji}\right) S_t^j]^{-\frac{1}{\varepsilon_j}},$$

where $\overline{EP}_t^{i,j}$ is the realized equilibrium price in regions i, j at period t.

To account for time varying transaction costs, we considered two scenarios of transaction cost variation following Lence, Moschini and Santeramo (2018): exogenous time varying per unit costs, and endogenous time-varying per unit costs.

For the exogenous time varying per unit cost, transfer cost DGP is given by:

(7) TC_t^{ij} i.i.d. Beta(12,12,0.025,0.075).

For the endogenous per unit transfer costs, the supply function is given by:

(8) $$TC_t^{ij} = 0.05 + 0.26 x_t^{ij} S_t^i$$

where TC_t^{ij} is transfer cost between regions. In this model, transference cost is the only cost for arbitrage, and can therefore be defined as transaction cost, a broader term that normally involves other sources of unmeasured costs like opportunity costs for arbitrage.

The two variable transaction cost assumptions explicitly represent constant and variable transaction cost cases. However, endogenous transaction costs are likely to be more realistic, as this specification implies that the supply of transfer services is not infinitely elastic. Furthermore, Behrens and Picard (2011) show that endogenous freight rates respond to trade imbalances (the so called backhaul problem). In this case, it is postulated that larger shipment volumes would have to bid away resoruces from other uses, resulting in a per unit transfer cost increase (Lence, Moschini and Santeramo 2018).

Regional price series are generated under two assumptions: (1) equal demand elasticities in both regions (demand elasticity of 0.7) and (2) inelastic demand (0.7) in one region and more elastic demand (1.5) in the other region. The demand elasticities used in this study are from previously reported empirical applications (Azzam and Wellman 1992).

We generate 500 samples with 520 observations each under assumptions of stochastic exogenous transfer cost with equal and different demand elasticities between regions, and stochastic endogenous transfer cost with equal and different demand elasticities between regions. Although some empirical applications generate data with more than 2000 observations (e.g., daily price series for 10 year period), we used 520 observations in our Monte Carlo experiments to reduce computational burden as other studies use even smaller sample sizes (Greb et al. 2013; Lence, Moschini and Santeramo 2018).

Under each of the assumptions above, we generate 500 samples with 3 price regimes (two thresholds) and 500 samples with 2 price regimes (one threshold).

For a given pair of two prices, say p_t^a and p_t^b, a long run relationship is established by:

(9)

$$ECT_t = z_t = p_t^a - \alpha_0 - \alpha_1 p_t^b ,$$

where the error term z_t represents the deviations from the long run equilibrium between the two price series at time t, also defined as the error correction term (ECT). In our study, we assume $\alpha_0 = 0$ for brevity.

To allow for time varying thresholds, so that variable transaction costs can be accounted for, Following Park, Mjelde and Bessler (2007), filtered price series are specified as:

(10) $$p_t^i = \alpha_0 + \alpha_1 TC_{t-1}^{ij} + \alpha_2 TC_{t-1}^{ji} + \varepsilon_t^i$$

where TC_{t-1}^{ij} is the lagged transportation cost from region i to region j, α_0 is a constant term and α_1 and α_2 are coefficients associated with lagged transportation costs, for i,j $\in$ a, b. The term ε_t^i

will then represent the price in each region after considering the effect of transportation cost in the previous period, as decisions on shipment made on period t will effectively induce price changes on period t+1.

Model Specifications

The error correction model conditional on one threshold value may be specified as:

(11)

$$\begin{pmatrix}\Delta p_t^a\\ \Delta p_t^b\end{pmatrix} = \begin{pmatrix}\mu_{1a}\\ \mu_{1b}\end{pmatrix} + \begin{pmatrix}\vartheta_{1a}\\ \vartheta_{1b}\end{pmatrix} ECT_{t-1} + \begin{pmatrix}\sum_{n=1}^{j} \pi_{1na}\Delta p_{t-n}^a\\ \sum_{n=1}^{j} \pi_{1n}\ \Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}\sum_{n=1}^{j} \rho_{1nb}\Delta p_{t-n}^b\\ \sum_{n=1}^{j} \rho_{1na}\Delta p_{t-n}^a\end{pmatrix} + \begin{pmatrix}u_{1t}\\ u_{1tb}\end{pmatrix}$$

If $ECT_{t-1} \leq \psi$, Regime 1

$$\begin{pmatrix}\Delta p_t^a\\ \Delta p_t^b\end{pmatrix} = \begin{pmatrix}\mu_{2a}\\ \mu_{2b}\end{pmatrix} + \begin{pmatrix}\vartheta_{2a}\\ \vartheta_{2b}\end{pmatrix} ECT_{t-1} + \begin{pmatrix}\sum_{n=1}^{j} \pi_{2na}\Delta p_{t-n}^a\\ \sum_{n=1}^{j} \pi_{2nb}\Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}\sum_{n=1}^{j} \rho_{2nb}\Delta p_{t-n}^b\\ \sum_{n=1}^{j} \rho_{2na}\Delta p_{t-n}^a\end{pmatrix} + \begin{pmatrix}u_{2ta}\\ u_{2tb}\end{pmatrix}$$

If $ECT_{t-1} > \psi$, Regime 2,

where Δ is the first difference operator, ϑ_i represents the speed of adjustment towards the long run equilibrium for each regime, π_{in} and ρ_{in} represent the short run relationships between the two markets a and b, ψ is the threshold value to be estimated, and u_{it} is an error term assumed to be i.i.d. and normally distributed. The Schwarz Information Criterion is employed to determine the appropriate lag structure of equation (11).

When deviations, ECTs, are below the threshold value (ψ), the price transmission process is defined by Regime 1, and arbitrage is not expected to happen, as the regime represents spatial price efficiency. As a consequence, no significant price adjustment is expected to be observed, or the speed of adjustment, as viewed through coefficient ϑ_{1a} and ϑ_{1b} is expected to be smaller than that for ϑ_{2a} and ϑ_{2b}. In Regime 2, the outer regime represents situations where the spatial equilibrium is broken, allowing profitable arbitrage and driving prices faster towards the long run equilibrium.

Greb et al. (2013) describe some restrictions on the coefficients ϑ that ensures that p^a and p^b are cointegrated. It is expected that (i) $-1 \leq \vartheta_{2a} < 0$, (ii) $0 < \vartheta_{2b} < 1$, (iii) $0 < (|\vartheta_{2a}| + \vartheta_{2b}) < 1$. Condition (i) ensures that p^a is reduced when spatial equilibrium is violated, while condition (ii) ensures that p^b increases. Both conditions ensure that changes in p^a and p^b will restore the spatial equilibrium. Condition (iii) ensures that there is no overshooting in price correction. The same rationale is valid for the model specification with two thresholds. The only difference is that there are two conditions in which spatial equilibrium is violated: $p^a - p^b$ is lower than the lower threshold and $p^a - p^b$ is greater than the upper threshold, which are related to trade in both directions. A three regime TVECM with two thresholds can be specified as:

(12)

$$\begin{pmatrix}\Delta p_t^a\\ \Delta p_t^b\end{pmatrix} = \begin{pmatrix}\mu_{1a}\\ \mu_{1b}\end{pmatrix} + \begin{pmatrix}\vartheta_{1a}\\ \vartheta_{1b}\end{pmatrix} ECT_{t-1} + \begin{pmatrix}\sum_{n=1}^{j} \pi_{1n} \ \Delta p_{t-n}^a\\ \sum_{n=1}^{j} \pi_{1nb}\Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}\sum_{n=1}^{j} \rho_{1nb}\Delta p_{t-n}^b\\ \sum_{n=1}^{j} \rho_{1n} \ \Delta p_{t-n}^a\end{pmatrix} + \begin{pmatrix}u_{1ta}\\ u_{1tb}\end{pmatrix} \ ;$$

If $ECT_{t-1} < \psi_1$, Regime 1

$$\begin{pmatrix}\Delta p_t^a\\ \Delta p_t^b\end{pmatrix} = \begin{pmatrix}\mu_{2a}\\ \mu_{2b}\end{pmatrix} + \begin{pmatrix}\vartheta_{2a}\\ \vartheta_{2b}\end{pmatrix} ECT_{t-1} + \begin{pmatrix}\sum_{n=1}^{j} \pi_{2n} \ \Delta p_{t-n}^a\\ \sum_{n=1}^{j} \pi_{2nb}\Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}\sum_{n=1}^{j} \rho_{2nb}\Delta p_{t-n}^b\\ \sum_{n=1}^{j} \rho_{2na}\Delta p_{t-n}^a\end{pmatrix} + \begin{pmatrix}u_{2ta}\\ u_{2tb}\end{pmatrix}$$

If $\psi_1 \leq ECT_{t-1} \leq \psi_2$, Regime 2.

$$\begin{pmatrix}\Delta p_t^a\\ \Delta p_t^b\end{pmatrix} = \begin{pmatrix}\mu_{3a}\\ \mu_{3b}\end{pmatrix} + \begin{pmatrix}\vartheta_{3a}\\ \vartheta_{3b}\end{pmatrix} ECT_{t-1} + \begin{pmatrix}\sum_{n=1}^{j} \pi_{3na}\Delta p_{t-n}^a\\ \sum_{n=1}^{j} \pi_{3nb}\Delta p_{t-n}^b\end{pmatrix} + \begin{pmatrix}\sum_{n=1}^{j} \rho_{3nb}\Delta p_{t-n}^b\\ \sum_{n=1}^{j} \rho_{3na}\Delta p_{t-n}^a\end{pmatrix} + \begin{pmatrix}u_{3ta}\\ u_{3tb}\end{pmatrix}$$

If $\psi_2 < ECT_{t-1}$, Regime 3.

Under specification (12), regimes 1 and 3 are compatible with spatial arbitrage, therefore coefficients $\vartheta_1$and ϑ_3 are expected to be significant and greater thanϑ_2. Same restrictions described for the one threshold model are applied to the two threshold specification.

Equation (12) is commonly estimated by using the profile likelihood estimator, where for each possible pair of threshold values $\psi = (\psi_1, \psi_2)$, the remaining parameters in the likelihood function corresponding to equation (12) are replaced by their maximum likelihood estimates. Then, the pair of thresholds that maximizes the resulting profile likelihood function is selected

(Hansen and Seo 2002; Lo and Zivot 2001a; Greb et al. 2013). The R software with package *tsDyn* is used for estimation.

To obtain variable thresholds, instead of using p_t^i, we used the filtered price series $\widehat{\varepsilon_t^i}$, as defined in equation (10). It follows from equation (12), taking the middle regime, that time varying thresholds can be obtained from the relationship:

(14) $$\psi_1 \leq \widehat{\varepsilon_t^a} - \widehat{\varepsilon_t^b} \leq \psi_2$$

where $\widehat{\varepsilon_t^a} = p_t^a - \widehat{\alpha_0^a} - \widehat{\alpha_1^a} TC_{t-1}^{ab} - \widehat{\alpha_2^a} TC_{t-1}^{ba}$, as well as $\widehat{\varepsilon_t^b} = p_t^b - \widehat{\alpha_0^b} - \widehat{\alpha_1^b} TC_{t-1}^{ba} - \widehat{\alpha_2^b} TC_{t-1}^{ab}$.

Therefore, from algeabric manipulation we obtain that daily threshold values based on transportation costs are:

(15) $$\psi_{1t} = \psi_1 + (\widehat{\alpha_0^a} + \widehat{\alpha_1^a} TC_{t-1}^{ab} + \widehat{\alpha_2^a} TC_{t-1}^{ba} - \widehat{\alpha_0^b} - \widehat{\alpha_1^b} TC_{t-1}^{ba} - \widehat{\alpha_2^b} TC_{t-1}^{ab})$$

(16) $$\psi_{2t} = \psi_2 + (\widehat{\alpha_0^a} + \widehat{\alpha_1^a} TC_{t-1} + \widehat{\alpha_2^a} TC_{t-1}^{ba} - \widehat{\alpha_0^b} - \widehat{\alpha_1^b} TC_{t-1}^{ba} - \widehat{\alpha_2^b} TC_{t-1}^{ab})$$

Using daily values of transaction cost in equations 15 and 16 provide the time varying thresholds. This approach allows one to consider the effect of different transaction cost according to the transportation route (backhaul problem), which is more likely to happen and well described in transportation problems (Behrens and Picard 2011).

Finally, for each one of the four evaluated scenarios, after fitting models according to the known spatial price regimes, we compare the number of correct classifications of observations within and outside the band of inaction under the fixed and flexible threshold specifications and the estimated transaction cost using a two sample t-test, as well as the mean speed of price adjustment using a one sample t-test.

Empirical Application to Brazilian Hog Industry

A real world application is carried out using daily farm gate hog prices of six different regions of the State of Parana, Brazil: Cascavel, Curitiba, Maringa, Ponta Grossa, Londrina, and Toledo. Time series price data from the period comprising Jan 2006 until November 2015 (2,575 observations) was obtained from Parana State Agriculture and Supplies Bureau website. These price series are specifically interesting to study because the State of Parana is the second largest hog producing state in Brazil, with the majority of production localized in one specific region, allowing studying the transmission of prices from a central market to more peripheral markets.

The transportation cost data used in this study are the national freight cost index compiled by the Department of Economics of NTC&Logistica (National Association of Breakbulk Freight and Logistics from Brazil). This index is corrected monthly according to surveyed fixed and variable costs faced by transportation firms in Brazil, including the studied regions, like labor specific costs, diesel prices, truck depreciation, insurance, and accounts for variations in costs specifically by transportation route.

The monthly index is disaggregated into daily series to work with daily price observations using the procedure developed by Chow and Lin (1971). The procedure uses daily diesel prices of each region as a high frequency indicator to disaggregate the monthly series. Region specific diesel prices series are obtained from the National Agency for Oil, Natural Gas and Biofuels, Brazil.

Each of the price series is tested for stationarity using the Augmented Dickey-Fuller (ADF) and DF-GLS (Elliott, Rothenberg and Stock 1996) tests and the KPSS (Kwiatkowski et al. 1992) test. The lag length to be used in the ADF and DF-GLS tests is obtained using the Schwarz criterion.

Linear cointegration between each pair of price series is evaluated using both the Johansen's approach (Johansen 1992a; Johansen 1992b; Johansen 1995) and the ADF test. According to Hansen (1997), the conventional test used to test for linearity in the ECT is not appropriate given that the null hypothesis of linearity in the *AR* process does not follow a standard distribution. Therefore, to test for linearity and the presence of one or two thresholds, three versions of the Hansen (1997; 1999b) tests are used: Hansen's F_{12} (F_{13}, F_{23}) test postulates a null hypothesis of one (one,two) regime(s) versus an alternative of two (three, three) regimes. The test is performed sequentially: first F_{12} is performed. If the null of one price regime is rejected, then F_{23} is performed. If F_{23}'s null is rejected, the sample is inferred to have 3 price regimes. If F_{12}'s null is not rejected, then F_{13} is performed to distinguish samples with one price regime and 3 price regimes.

After defining the appropriate number of price regimes, we use specifications described in (12) and estimate models using the Regularized Bayesian (RB) estimator. Under this methodology, the selection of thresholds is done using the integral calculus, which does not require arbitrary trimming as in the PL[2], and also provides a way to account for inherent variability of estimates. The posterior median is a function used to choose optimal threshold values over the grid of ECTs (Greb et al. 2014) as:

(17) $$\int_{\min(ECT_{t-1})}^{\hat{\psi}_i} P_{RB}(\psi_i \,|\Delta P, X) d\psi_i = 0.5, for\ i = 1,2\ ,$$

where P_{RB} is the posterior distribution, ΔP is the dependent variable, and X is a *n x d* matrix containing columns of ECTs, intercepts and values of lagged terms. As noted by Serebrennikov and Götz (2015), P_{RB} is well defined in the whole threshold parameters space T = $\{\psi_1, \psi_2 |\ \min(\gamma' p_t) < \psi_1 < \psi_2 < \max(\gamma' p_t)\}$. Computation is based on a prior $P_{RB}(\psi|X) \propto I(\psi \in \mathrm{T})$ forψ, where $I(\cdot)$ is an indicator function providing switching between regimes. R software with *nlme* package is used to estimate the model in this study.

[2] A limitation of the profile likelihood estimator is that the minimum number of observations in each outer regimes has to be arbitrarily selected (trimming parameters), which biases the estimation of parameters (either when the number of observations is not large enough, or when the differences between the true thresholds is not large enough). In our MC study, all of our generated samples had sufficient number of observations in outer regimes and true values of parameters were known. Therefore we used the PL estimator as it is less computationally intensive than the RB.

Results

Objectives of our study are to examine if TVECM can be improved by accounting for the variation of transaction costs in its model specification. This section presents results of our Monte Carlo experiments and an empirical application to the Brazilian hog industry.

For the results of Monte Carlo experiments, we report results of both fixed and flexible threshold specification to show the effect of accounting for time varying cointegration in estimated parameters that are commonly used to assess market integration and deviations from the spatial equilibrium. We finally present results of applying our procedures to a spatial analysis of price transmission in the Brazilian hog industry. The empirical application is expected to provide implications of assuming constant transaction cost when there is evidence of significant transaction cost variation in the spatial price analysis.

Monte Carlo Experiments

On tables 1 to 5, results of parameters used to compare a fixed threshold model (TVECM-F) and a flexible threshold model (TVECM-L) are summarized.

The following parameters are estimated and compared with the true values:

- Violations of spatial price equilibrium: is the percentage of observations defined to be greater than the estimated threshold for the one threshold scenario, or greater than the upper or smaller than the lower threshold for the two-threshold scenario.
- Threshold values and band of inaction: for the case of one threshold, the estimated threshold value is compared. For the case of two thresholds, the total value obtained by $\psi_2 - \psi_1$ (from equation 12) is computed, which represents the interval where price differences are not expected to be corrected to the long run equilibrium, therefore defined as the band of inaction.

- Adjustment to the long-run equilibrium: obtained by the estimated coefficients of the ECTt-1, as defined in equations 11 and 12.

Starting with the case of two regimes (one threshold), when data is generated under the specification of exogenously determined stochastic transaction cost, TVECM-F provides downward biased estimation of violations of spatial price equilibrium, but other evaluated parameters are not significantly affected. By accounting for variation in transfer cost, using the TVECM-L, such biased estimation is not observed. Differences in price elasticity seem not to affect inference.

Still on the two regimes case, when data is generated under the specification of endogenously determined stochastic transfer cost, TVECM-F provides downward biased estimation of both violations of spatial price equilibrium and speed of adjustment, at least at the 10% level. TVECM-L, on the other hand, is able to recover estimates similar to the true value, underscoring the need to account for variable transaction costs. Again, differences in price elasticity seem to slightly affect inference, improving estimated value of speed of adjustment for the case of equal demand elasticity under TVECM-F.

For the three regimes case (two thresholds), when true underlying data generating process was exogenously determined stochastic transaction cost, both TVECM-F and TVECM-L provided upward biased estimates of violations of spatial equilibrium. Other parameters were not affected by model specification or different price elasticity.

Analyzing together tables 1 and 3, it is clear that when transaction cost is stationary and exogenously determined, either specifications of TVECM is able to recover true values of speed of price adjustment, threshold values and inaction bands. TVECM-L, on the other hand, was able to recover true values of violations of spatial price equilibrium for the two-regime case, suggesting that the flexible threshold specification is preferred over the fixed. Although true values of violations of spatial price equilibrium could not be recovered under either model specifications for the case of three regimes, this parameter may be considered of less importance when analyzing market performance, as discussed by Stephens et al. (2012) and Lence, Moschini and Santeramo (2018). A more reliable parameter will be speed of price adjustment, as it will measure how fast prices adjust to the established long-run equilibrium, reflecting efficiency of not only arbitrage, but also corrections of price expectations.

The last case we evaluated was data generated under the specification of endogenously determined stochastic transfer cost, the case of three regimes. Under this specification, estimates obtained under TVECM-F and TVECM-L of violations of spatial price equilibrium are upward biased, while estimates of inaction bands are downward biased.

Speed of adjustment, however, could be correctly recovered when estimated under the TVECM-L framework, while it was downward biased when transaction costs were assumed to be constant. The case of equal demand elasticity was found to slightly improve estimation for the TVECM-F.

Taken together, our results clearly show that, when transaction costs are stationary and exogenously determined, under the presence of one threshold (two price regimes), standard TVECM (assuming constant transaction costs) still provides reliable estimates of speed of price adjustment and threshold values. However, estimates of violations of spatial price equilibrium are biased, which could lead to misinterpretation of market integration if this parameter is used to infer higher arbitrage opportunities and less integrated markets.

Such misinterpretation is even worse when the assumption of fixed transaction costs is violated and the true data generating process of the transaction cost series is nonstationary: both violations of spatial price equilibrium and speed of adjustment are biased, which will lead to a poor inference about market performance.

Similarly, in the case of three regimes (two thresholds), not accounting for transaction cost variations when this cost is stationary, leads to biased estimates of violations of spatial price equilibrium, but still reliable estimates of speed of price adjustment and inaction band. However, when transaction costs are in fact nonstationary, but assumed to be constant, the degree of misinterpretation is worsened under the presence of two thresholds, as all parameters will be biased. Accounting for transaction costs variation under this scenario still provided biased estimates of band of inaction and violations of spatial price equilibrium, but unbiased estimates of speed of adjustment, which may be considered a more reliable indicator of market performance. A poor performance of different TVECM under the case of three regimes has been documented by Lence, Moschini and Santeramo (2018) and Greb et al. (2013).

Spatial Price Transmission in the Brazilian Hog Industry

Our Monte Carlo experiment results show that the TVECM with the flexible threshold specification (TVECM-L), incorporating transaction cost information, outperforms the TVECM with the fixed threshold specification (TVECM-F). Therefore, the TVECM-L is applied to the Brazilian hog industry data for an empirical application.

Summary statistics for the price series used, as well as route specific freight index series are shown in tables 5 and 6. On table 5, we see that hog prices ranged between 1.0 Brazilian real (BRL) per kilogram to up to 4.85 for some regions, showing a coefficient of variation of up to 31%. Freight cost index (Table 6) ranged from 2.969 to 5.478, with a variation of up to 19.1%.

Hog prices as well as freight cost indices were found to be I(1) in levels (ADF-test and KPSS test). Cointegration was further evaluated and confirmed for the filtered price series. Results for cointegration tests are reported in table 7.

ADF-test with the null of a unit root is employed on the spatial price differential (zt) of each price pairs. Johansen trace test statistic is also used, with the null hypothesis that the cointegrating vector has rank $r = 0$. The null hypothesis that $r = 1$ could not be rejected (not shown on table 7).

Table 8 reports that Hansen's test indicates that the three-regime specification better represents price transmission behavior between regions. As transit between regions is unrestricted and both hog farms and processing plants are close to each other or located at each of the evaluated regions, we understand that transmission of prices may happen in both ways for each regional pair.

We have selected Toledo as the central market, as it concentrates most of hog production and processing in the state of Parana and is a reference center nationwide. Cascavel is located 50km from Toledo and is the second largest producing center in the state. Ponta Grossa is also an important production and processing center (448km from Toledo) while Maringa (324km from Toledo), Londrina (413km from Toledo) and Curitiba (541km from Toledo) may be considered marginal markets in terms of production and processing as compared to regions of Toledo, Cascavel, and Ponta Grossa. Results of the threshold test in Table 9 confirm threshold cointegration for all price pairs with two thresholds at least at the 10% level.

Parameter estimates of TVECM for each pair of regional hog prices are shown in tables 10-14. To understand price transmission behavior between regions, we focus our analysis on the size and significance of the adjustment coefficients (ϑ_i), and the total adjustment ($\vartheta_{ib} - \vartheta_{ia}$) observed in each regime, especially Regimes 1 and 3, which will be compatible with spatial arbitrage. As we relax the assumption of constant and symmetric thresholds, we are able to identify asymetric price adjustment dynamics and how price shocks in a peripheral or central market are expected to be dissipated as price correction takes place in one or both regions. This may be evindenced by examining the significance of the coefficient ϑ_i, to determine if deviations from the long-run equilibrium are corrected by adjustments of either or both p_t^a and p_t^b (Granger 1988). This causal impact of the lagged error correction term that impacts on the long-run relationship of the dynamic cointegrated process may be generally understood as a long-run Granger causality (Woo, Lee, and Shum 2017). The short-run Granger causality can be tested by evaluating the joint significance of the short-run coefficients (ρ_i) from equation 12, using standard Wald statistics (Li 2006), allowing a more comprehensive understanding of price adjustments towards equilibrium and the directions of non-linear Granger causality.

From table 9, we see that in Regime1, only Cascavel prices are adjusting to the long-run equilibrium, while in regime 3, only Toledo prices are adjusting. As we defined $\mathrm{ECT}_{t-1} = \mathrm{Tol}_{t-1} - \mathrm{Cas}_{t-1}$, in Regime 1 the interpretation of the results are that when filtered prices in Cascavel (Toledo) increase (decrease), leading to an absolute difference greater than 0.542, only prices in Cascavel adjust to the long-run equilibrium, reducing at a rate of 1.678. Similarly, in Regime 3, prices in Toledo adjust downwards at a rate of 0.932 when filtered price difference between regions exceeds 0.507. In other words, it is possible to identify that price increases in Cascavel (Toledo) will trigger price decreases in Toledo (Cascavel) if the filtered prices exceed the lower and upper threshold, which are not symmetric in absolute values (a greater difference is needed to trigger adjustment in Cascavel than in Toledo and the rate of adjustment is also different). In regime 2, adjustment occurs in both regions, and total adjustment in regime 2 (0.017+0.065=0.082), obtained by calculating ($\vartheta_{ib} - \vartheta_{ia}$), is lower than in regime 1 (1.776) and regime 3 (0.932), as expected. Short-run Granger causality was evidenced only in regime 3, meaning that when price differences between Toledo and Cascavel are greater than the upper threshold, Cascavel was found to Granger cause Toledo.

Interpretation of results for other region pairs follow the same rationale and are summarized in table 14. It was evidenced that prices in Tol seem to adjust to the long-run equilibirum when transmission is evaluated for non-hog producing regions (Mar, Lon and Cur), whereas the pattern of adjustment seem to be similar for Cas and PG (both Cas and PG adjust in Regime 1, while Tol adjusts in Regime 3), other important hog producing regions.

Short-run Granger causality was found to depend on price regimes and was bivariate only for Tol-Mar price pair in regime 1. For all other identified short-run causalities, prices in Tol seemed to be Granger caused by other regions, which is consistent with past research that shows causality flows up with the marketing channel (Haigh and Bessler 2004) and Tol was defined as our central market due to the concentration of production and processing facilities.

Different transaction costs, as viewed through threshold values, were determined for each price pairs, which were not necessarily proportional to distance between regions, e.g. we observed an inaction band ($\psi_2 - \psi_1$) of 1.049 for a short distance (50km) pair Toledo-Cascavel, while for a longer distance (324km) specific price pair (Toledo-Maringa), the inaction band was determined as 0.42. This observation may be explained by the market structure of the regions in question and the interpretation of thresholds not only as costs of transport and restrictions to trade, but also to the so called sunk costs of arbitrage, as discussed in O'Connell and Wei (2000) and in Ihle and Cramon-Taubadel (2008). Toledo and Cascavel, although being closely located, have their own market structure, with cooperatives and contracted producers, which may prevent entry from other parties and increase the potential transaction cost needed to trigger price transmission. This information, nevertheless, must be carefully interpreted, as the threshold values seem not to truly represent transaction costs, as shown in our MC study, although commonly used in literature as estimates of transaction costs. A better indicator of market integration may be the adjustment speed, which is expected to be greater, the closely related markets are. Furthermore, this estimate was found to be unbiased in our MC experiment.

To illustrate the findings of our MC experiment with our real world case study, we also fit two thresholds and three regimes TVECM using unfiltered prices, assuming constant transaction costs. We restrict the comparison of results to the adjustment coefficients, as shown in table 15.

Overall, results observed for the empirical application are similar to those evidenced in our MC study: when considering time-varying thresholds, adjustment to the long-run equilibrium was greater (faster) as compared to the fixed threshold scenario, which is related to more integrated markets. Given the non-stationarity of freight indices, it is unlikely that the assumption of constant thresholds will hold for our empirical case. Therefore, we understand that the estimation obtained under flexible threshold specification better represents the behavior of price transmission for the evaluated markets. Additionally, coefficients observed for Regimes 1 and 3, and consequently, total adjustment are more reasonable in terms of spatial price transmission theory (favoring market integration), given the information on market structure.

Conclusion

In the current paper, we show using a Monte Carlo experiment, that the standard TVCEM assuming fixed transaction costs provides misleading inference when the actual transaction costs are variable and non-stationary. Although the model still provides reliable results when transaction cost data is stationary, the assumption of constant and stationary transaction costs were already pointed as problematic by other researchers. It is unlikely, especially when evaluating extensive time series data, that transaction cost will be stationary. We show that failing to account for transaction cost variation leads to biased estimates of violations of spatial equilibrium, threshold values and speed of adjustment, especially when evaluating price series with two thresholds. Such biased estimate would lead to misleading inference on market performance and integration. Specifying a variable threshold model, accounting for transaction cost variation, improved inference and provided unbiased estimates of both adjustment to the long run equilibrium and estimation of transaction costs, especially when modelling transmission on the presence of one threshold, as compared to the case of two thresholds.

Further research to extend this work will involve extension of the empirical applications (either evaluating more regions and different commodities), as well as estimating half-lives of price shocks and potential explanatory variables for delayed price transmission. Other forms of modelling time variation on the absence of transference cost data may also help to improve inference, as it is unlikely that a fixed threshold will hold in empirical applications, especially when evaluating large time series data.

The modelling alternative incorporating freight indices as a source of variation in transaction cost sounds appealing concerning spatial price transmission theory. One disadvantage, however, is that it requires some source of knowledge about how transaction costs behave over time. Different modelling alternatives able to account for time variable cointegration when data on transference cost is unavailable remains to be further developed.

Table 1.1. Difference between true and estimated parameters from TVECM with fixed and flexible threshold specifications when samples are generated with *exogenously* determined stochastic transfer cost: *the case of three regimes*

Demand elasticity	Parameter	Specification	Mean	S.D.	Mean Difference
Different: $\varepsilon_i \neq \varepsilon_j$	Violations of spatial price equilibrium	Fixed threshold	0.683	0.197	0.127***
		Flexible threshold	0.712	0.181	0.156***
		True value	0.556	0.114	-
	Speed of adjustment	Fixed threshold	0.830	0.274	-0.170
		Flexible threshold	0.846	0.266	-0.154
		True value	1	0	-
	Inaction band	Fixed threshold	0.077	0.061	-0.023
		Flexible threshold	0.074	0.067	-0.026
		True value	0.100	0.000	-
Same: $\varepsilon_i = \varepsilon_j$	Violations of spatial price equilibrium	Fixed threshold	0.712	0.192	0.168***
		Flexible threshold	0.717	0.187	0.173***
		True value	0.544	0.108	-
	Speed of adjustment	Fixed threshold	0.824	0.258	-0.176
		Flexible threshold	0.829	0.255	-0.171
		True value	1	0	-
	Inaction band	Fixed threshold	0.070	0.056	-0.030
		Flexible threshold	0.069	0.058	-0.031
		True value	0.100	0.000	-

*** Denotes significant difference from the true value at 1%.

Table 1.2. Difference between true and estimated parameters from TVECM with fixed and flexible threshold specifications when samples are generated with *exogenously* determined stochastic transfer cost: *the case of two regimes*

Demand elasticity	Parameter	Specification	Mean	S.D.	Mean Difference
Different: $\varepsilon_i \neq \varepsilon_j$	Violations of spatial price equilibrium	Fixed threshold	0.329	0.205	-0.163***
		Flexible threshold	0.491	0.285	-0.001
		True value	0.492	0.039	-
	Speed of adjustment	Fixed threshold	0.933	0.371	-0.067
		Flexible threshold	0.932	0.377	-0.068
		True value	1	0	-
	Threshold value	Fixed threshold	0.049	0.020	-0.001
		Flexible threshold	0.048	0.020	-0.002
		True value	0.050	0.000	-
Same: $\varepsilon_i = \varepsilon_j$	Violations of spatial price equilibrium	Fixed threshold	0.365	0.212	-0.129***
		Flexible threshold	0.494	0.289	0.000
		True value	0.494	0.038	-
	Speed of adjustment	Fixed threshold	0.965	0.374	-0.035
		Flexible threshold	0.946	0.352	-0.054
		True value	1	0	-
	Threshold value	Fixed threshold	0.048	0.020	-0.002
		Flexible threshold	0.048	0.020	-0.002
		True value	0.050	0.000	-

*** Denotes significant difference from the true value at 1%.

Table 1.3. Difference between true and estimated parameters from TVECM with fixed and flexible threshold specifications when samples are generated with *endogenously* determined stochastic transfer cost: *the case of three regimes*

Demand elasticity	Parameter	Specification	Mean	S.D.	Mean difference
Different: $\varepsilon_i \neq \varepsilon_j$	Violations of spatial price equilibrium	Fixed threshold	0.693	0.174	0.216***
		Flexible threshold	0.689	0.203	0.212***
		True value	0.477	0.079	-
	Speed of adjustment	Fixed threshold	0.410	0.284	-0.590***
		Flexible threshold	0.640	0.285	-0.360
		True value	1	0	-
	Inaction band	Fixed threshold	0.101	0.065	-0.047***
		Flexible threshold	0.060	0.067	-0.088***
		True value	0.148	0.036	-
Same: $\varepsilon_i = \varepsilon_j$	Violations of spatial price equilibrium	Fixed threshold	0.687	0.175	0.209***
		Flexible threshold	0.701	0.200	0.223***
		True value	0.478	0.077	
	Speed of adjustment	Fixed threshold	0.474	0.274	-0.526*
		Flexible threshold	0.634	0.283	-0.366
		True value	1	0	-
	Inaction band	Fixed threshold	0.092	0.056	-0.046***
		Flexible threshold	0.056	0.061	-0.082***
		True value	0.138	0.031	

*** Denotes significant difference from the true value at 1%.

* Denotes significant difference from the true value at 10%.

Table 1.4. Difference between true and estimated parameters from TVECM with fixed and flexible threshold specifications when samples are generated with endogenously determined stochastic transfer cost: the case of two regimes

Demand elasticity	Parameter	Specification	Mean	S.D.	Mean Difference
Different: $\varepsilon_i \neq \varepsilon_j$	Violations of spatial price equilibrium	Fixed threshold	0.340	0.191	-0.160***
		Flexible threshold	0.497	0.274	-0.003
		True value	0.500	0.033	-
	Speed of adjustment	Fixed threshold	0.344	0.331	-0.656**
		Flexible threshold	0.883	0.302	-0.117
		True value	1	0	-
	Threshold value	Fixed threshold	0.170	0.064	-0.001
		Flexible threshold	0.170	0.062	-0.001
		True value	0.171	0.054	
Same: $\varepsilon_i = \varepsilon_j$	Violations of spatial price equilibrium	Fixed threshold	0.339	0.196	-0.161***
		Flexible threshold	0.492	0.280	-0.008
		True value	0.500	0.032	-
	Speed of adjustment	Fixed threshold	0.417	0.350	-0.583*
		Flexible threshold	0.902	0.337	-0.098
		True value	1	0	-
	Threshold value	Fixed threshold	0.147	0.059	-0.003
		Flexible threshold	0.150	0.058	0.000
		True value	0.150	0.046	-

*** Denotes significant difference from the true value at 1%.

** Denotes significant difference from the true value at 5%.

* Denotes significant difference from the true value at 10%.

Table 1.5. Descriptive statistics of farm gate hog prices (Brazilian Real) for six regions

Region	Mean	SD[1]	CV[2]	Minimum	Maximum
Cascavel	2.336	0.672	0.288	1.000	4.020
Curitiba	2.518	0.781	0.310	1.000	4.850
Londrina	2.548	0.723	0.284	1.100	4.800
Maringa	2.561	0.732	0.286	1.100	4.850
Ponta-Grossa	2.494	0.760	0.305	1.000	4.850
Toledo	2.324	0.627	0.270	1.200	3.850

[1]Standard Deviation.

[2]Coefficient of Variation.

Table 1.6. Freight Cost Index for Each Specific Route

Route Freight Cost Index	Mean	SD[1]	CV[2]	Minimum	Maximum
Toledo-Cascavel	3.992	0.762	0.191	2.969	5.437
Toledo-Curitiba	4.036	0.742	0.184	3.033	5.478
Toledo-Londrina Toledo-PontaGrossa Toledo-Maringa	3.963	0.717	0.181	2.989	5.344
Cascavel-Toledo	3.992	0.762	0.191	2.969	5.435
Curitiba-Toledo	4.036	0.741	0.184	3.033	5.452
Londrina-Toledo	3.962	0.716	0.181	2.989	5.324
PontaGrossa- Toledo	3.963	0.717	0.181	2.982	5.342
Maringa-Toledo	3.962	0.715	0.180	2.989	5.347

[1]Standard Deviation.

[2]Coefficient of Variation.

Table 1.7. ADF-test statistic on z_t and Johansen cointegration test for price pairs

Price pair	ADF-test statistic on z_t[1]	Johansen (Trace statistic)[1]
Toledo-Cascavel	-6.616***	109.50***
Toledo-Curitiba	-6.252***	109.39***
Toledo-Londrina	-6.117***	100.17***
Toledo-Maringa	-6.336***	93.01***
Toledo-Ponta Grossa	-5.985***	86.30***

*** denotes the rejection of H_0 at 1% level.

[1] H_0 of no cointegration, H_1 of cointegration.

Table 1.8. Hansen's threshold test for error correction terms

Price pair	Lag	Type	Test statistic	*p*-Value[4]
Toledo-Cascavel	2	1 vs. 2[1]	29.33	<0.001
		1 vs. 3[2]	57.35	<0.001
		2 vs. 3[3]	27.71	0.002
Toledo-Curitiba	2	1 vs. 2[1]	38.57	<0.001
		1 vs. 3[2]	51.75	<0.001
		2 vs. 3[3]	13.10	0.051
Toledo-Londrina	2	1 vs. 2[1]	78.80	<0.001
		1 vs. 3[2]	90.68	<0.001
		2 vs. 3[3]	15.45	0.072
Toledo-Maringa	4	1 vs. 2[1]	56.09	<0.001
		1 vs. 3[2]	83.69	<0.001
		2 vs. 3[3]	27.01	<0.001
Toledo-Ponta Grossa	3	1 vs. 2[1]	63.34	<0.001
		1 vs. 3[2]	105.16	<0.001
		2 vs. 3[3]	40.82	0.004

[1] H_0 of the presence of no threshold effect (1 regime), against H_1 of one threshold (two regimes).
[2] H_0 of the presence of no threshold effect (1 regime), against H_1 of two thresholds (three regimes).
[3] H_0 of the presence of one threshold (2 regimes), against H_1 of two thresholds (three regimes).
[4] *p*-Value was obtained after 1000 bootstrap replications.

Table 1.9. Parameter estimates of TVECM, Toledo – Cascavel

	Regime 1		Regime 2		Regime 3	
	$(ECT_{t-1} < -0.542)$		$(-0.542 \leq ECT_{t-1} \leq 0.507)$		$(ECT_{t-1} > 0.507)$	
Variables	ΔTol	ΔCas	ΔTol	ΔCas	ΔTol	ΔCas
ECT_{t-1}	-0.098	1.678**	-0.065**	0.017**	-0.932**	0.000
	(0.154)	(0.119)	(0.009)	(0.005)	(0.123)	(0.078)
ΔTol_{t-1}	1.270	0.196	-0.238**	0.002	2.963**	0.086
	(1.019)	(0.999)	(0.020)	(0.012)	(0.763)	(0.620)
ΔTol_{t-2}	0.964	0.311	-0.084**	-0.007	2.205**	0.723
	(1.024)	(1.011)	(0.019)	(0.012)	(0.755)	(0.664)
ΔCas_{t-1}	-0.544	-0.126	0.043	0.044**	-1.202**	-0.372
	(0.976)	(0.966)	(0.030)	(0.018)	(0.423)	(0.285)
ΔCas_{t-2}	0.824	0.055	-0.026	-0.020	1.816	0.179
	(1.224)	(1.220)	(0.030)	(0.018)	(1.528)	(1.512)
$Wald_{SR}$	0.696	0.124	2.754	0.476	8.058**	2.927

Tol and *Cas* are Toledo and Cascavel filtered prices, respectively.
Numbers in parentheses are standard errors.
$Wald_{SR}$ refer to the standard Wald statistic used to test short-run Granger causality in the equations of Tol and Cas with two degrees of freedom.
**Indicate significance at the 5% level.

Table 1.10. Parameter estimates of TVECM , Toledo – Londrina

	Regime 1 $(ECT_{t-1} < -0.644)$		Regime 2 $(-0.644 \leq ECT_{t-1} \leq 0.605)$		Regime 3 $(ECT_{t-1} > 0.605)$	
Variables	ΔTol	ΔLon	ΔTol	ΔLon	ΔTol	ΔLon
ECT_{t-1}	-0.720** (0.143)	0.024 (0.142)	-0.065** (0.008)	0.008 (0.008)	-0.592** (0.060)	0.013 (0.059)
ΔTol_{t-1}	0.832** (0.192)	-0.090 (0.191)	-0.260** (0.020)	-0.018 (0.019)	0.723** (0.099)	-0.035 (0.097)
ΔTol_{t-2}	-0.129 (0.191)	-0.091 (0.190)	-0.075* (0.020)	-0.013 (0.019)	0.408** (0.077)	-0.048 (0.076)
ΔLon_{t-1}	-0.363** (0.102)	-1.062** (0.100)	0.013 (0.020)	0.015 (0.020)	-0.257 (0.291)	-0.669** (0.291)
ΔLon_{t-2}	-0.005 (0.471)	0.287 (0.468)	0.025 (0.019)	0.049** (0.019)	-0.012 (0.412)	0.196 (0.408)
$Wald_{SR}$	12.79**	0.283	1.903	1.056	0.796	0.401

Tol and *Lon* are Toledo and Londrina filtered prices, respectively.
Numbers in parentheses are standard errors.
$Wald_{SR}$ refer to the standard Wald statistic used to test short-run Granger causality in the equations of Tol and Lon with two degrees of freedom.
**Indicate significance at the 5% level.

Table 1.11. Parameter Estimates of TVECM, Toledo – Curitiba

	Regime 1 ($ECT_{t-1} < -0.639$)		Regime 2 ($-0.639 \leq ECT_{t-1} \leq 0.537$)		Regime 3 ($ECT_{t-1} > 0.537$)	
Variables	ΔTol	ΔCur	ΔTol	ΔCur	ΔTol	ΔCur
ECT_{t-1}	-0.553**	-0.002	-0.073**	-0.002	-0.074	-0.005
	(0.273)	0.272)	(0.008)	(0.008)	(0.048)	(0.046)
ΔTol_{t-1}	-0.231	-0.005	-0.255**	-0.006	0.983**	0.017
	(0.432)	(0.432)	(0.020)	(0.019)	(0.121)	(0.116)
ΔTol_{t-2}	-0.444	0.001	-0.074**	0.001	0.006	0.013
	(0.345)	(0.345)	(0.020)	(0.019)	(0.080)	(0.077)
ΔCur_{t-1}	-0.134	-0.033	-0.008	-0.042**	-7.142**	0.435
	(0.432)	(0.432)	(0.021)	(0.020)	(1.430)	(1.383)
ΔCur_{t-2}	0.093	0.029	0.000	0.030	5.846**	-0.009
	(0.432)	(0.431)	(0.021)	(0.020)	(0.667)	(0.641)
$Wald_{SR}$	0.143	0.001	0.1291	0.107	82.711**	0.039

Tol and *Cur* are Toledo and Curitiba filtered prices, respectively.
Numbers in parentheses are standard errors.
$Wald_{SR}$ refer to the standard Wald statistic used to test short-run Granger causality in the equations of Tol and Cur with two degrees of freedom.
**Indicate significance at the 5% level.

Table 1.12. Parameter Estimates of TVECM , Toledo – Ponta Grossa

	Regime 1 ($ECT_{t-1} < -0.508$)		Regime 2 ($-0.508 \leq ECT_{t-1} \leq 0.501$)		Regime 3 ($ECT_{t-1} > 0.501$)	
Variables	ΔTol	ΔPG	ΔTol	ΔPG	ΔTol	ΔPG
ECT_{t-1}	-0.036	0.120**	-0.057**	0.004	-0.377**	0.001
	(0.035)	(0.030)	(0.008)	(0.007)	(0.058)	(0.051)
ΔTol_{t-1}	-0.724**	0.019	-0.248**	0.023	0.025	0.030
	(0.098)	(0.085)	(0.020)	(0.017)	(0.128)	(0.113)
ΔTol_{t-2}	-0.481**	0.036	-0.097**	0.021	0.076	-0.004
	(0.083)	(0.072)	(0.021)	(0.018)	(0.103)	(0.091)
ΔTol_{t-3}	-0.167*	-0.060	-0.081**	0.008	-0.008	-0.005
	(0.094)	(0.082)	(0.020)	(0.017)	(0.082)	(0.072)
ΔPG_{t-1}	-0.026	0.987**	0.065**	0.110**	2.951**	0.256
	(0.368)	(0.331)	(0.023)	(0.020)	(0.500)	(0.455)
ΔPG_{t-2}	1.641**	1.079**	0.013	0.059**	3.222**	0.512
	(0.361)	(0.323)	(0.023)	(0.020)	(0.682)	(0.640)
ΔPG_{t-3}	-1.029**	0.912**	0.016	0.002	-1.761**	0.089
	(0.324)	(0.288)	(0.023)	(0.020)	(0.658)	(0.613)
$Wald_{SR}$	33.634**	0.846	9.388**	2.45	95.835**	0.094

Tol and *PG* are Toledo and Ponta Grossa filtered prices, respectively.
Numbers in parentheses are standard errors.
$Wald_{SR}$ refer to the standard Wald statistic used to test short-run Granger causality in the equations of Tol and PG with three degrees of freedom.
**Indicates significance at the 5% level.
*Indicates significance at the 10% level.

Table 1.13. Parameter Estimates of TVECM , Toledo – Maringa

	Regime 1 ($ECT < -0.242$)		Regime 2 ($-0.242 \leq ECT \leq 0.178$)		Regime 3 ($ECT > 0.178$)	
Variables	ΔTol	ΔMar	ΔTol	ΔMar	ΔTol	ΔMar
ECT	-0.119**	0.015	-0.034**	0.022*	-0.081**	-0.016
	(0.016)	(0.014)	(0.014)	(0.012)	(0.013)	(0.011)
ΔTol_{t-1}	-0.274**	-0.053*	-0.311**	0.027	-0.145**	-0.005
	(0.034)	(0.029)	(0.029)	(0.024)	(0.033)	(0.028)
ΔTol_{t-2}	-0.132**	-0.094**	-0.028	0.012	-0.179**	-0.018
	(0.034)	(0.029)	(0.032)	(0.027)	(0.030)	(0.025)
ΔTol_{t-3}	-0.130**	-0.033	-0.094*	0.028	-0.152**	0.009
	(0.032)	(0.027)	(0.031)	(0.026)	(0.032)	(0.027)
ΔTol_{t-4}	-0.133**	-0.008	0.109*	0.018	-0.267**	0.028
	(0.033)	(0.028)	(0.028)	(0.024)	(0.031)	(0.026)
ΔMar_{t-1}	0.027	-0.001	-0.041	-0.068*	-0.005	-0.004
	(0.046)	(0.040)	(0.028)	(0.024)	(0.052)	(0.046)
ΔMar_{t-2}	-0.182**	-0.246**	0.006	0.037	-0.095 *	-0.015
	(0.047)	(0.041)	(0.028)	(0.023)	(0.052)	(0.046)
ΔMar_{t-3}	-0.059	0.111**	-0.034	0.025	-0.148**	0.020
	(0.053)	(0.047)	(0.027)	(0.023)	(0.055)	(0.048)
ΔMar_{t-4}	0.047	0.187**	-0.006	0.032	0.026	0.106**
	(0.054)	(0.047)	(0.027)	(0.022)	(0.054)	(0.047)
$Wald_{SR}$	16.394**	11.095**	3.480	2.397	10.572**	1.796

Tol and *Mar* are Toledo and Maringa filtered prices, respectively.
Numbers in parentheses are standard errors.
$Wald_{SR}$ refer to the standard Wald statistic used to test short-run Granger causality in the equations of Tol and Mar with four degrees of freedom.
**Indicates significance at the 5% level.
*Indicates significance at the 10% level.

Table 1.14. Comparison of TVCEM Parameters and Test Results for Pairwise estimations.

Price Pair (distance)	Regime 1			Regime 3		
	Total Adj.	LR Adj.	SR Granger Causality	Total Adj.	LR Adj.	SR Granger Causality
Tol-Cas (50km)	1.776	Cas	-	0.932	Tol	Cas→Tol
Tol-PG (448km)	0.156	PG	PG→Tol	0.378	Tol	PG→Tol
Tol-Mar (324km)	0.134	Tol	Tol→Mar Mar→Tol	0.065	Tol	Mar→Tol
Tol-Lon (413km)	0.744	Tol	Lon→Ton	0.605	Tol	-
Tol-Cur (541km)	0.555	Tol	-	0.069	-	Cur→Tol

Tol, Cas, PG, Mar, Lon and Cur are Toledo, Cascavel, Ponta Grossa, Maringa, Londrina and Curitiba prices, respectively.
Total Adj. refers to total Adjustment obtained by $(\vartheta_{ib} - \vartheta_{ia})$.
LR Adj refers to the price that adjusts to the long run equilibrium (significance of ϑ_i coefficient).
SR GC refers to short run Granger Causality and indicates the obtained causality direction.

Table 1.15. Adjustment coefficients obtained for Empirical Evaluations of Price Transmission for Each Region Pair.

	(Δp)	ϑ_1	ϑ_2	ϑ_3	Adj1[1]	Adj2[1]	Adj3[1]
Flexible Threshold	Tol.	-0.098	-0.065	-0.932	1.779	0.082	0.932
	Cas.	1.678	0.017	0.000			
Fixed Threshold	Tol.	0.020	-0.064	-0.430	0.327	0.077	0.476
	Cas	0.347	0.013	0.046			
Flexible Threshold	Tol.	-0.553	-0.073	-0.074	0.551	0.071	0.069
	Cur.	-0.002	-0.002	-0.005			
Fixed Threshold	Tol.	-0.042	-0.051	-0.034	0.080	0.070	0.049
	Cur	0.038	0.019	0.015			
Flexible Threshold	Tol.	-0.720	-0.065	-0.592	0.744	0.073	0.605
	Lon.	0.024	0.008	0.013			
Fixed Threshold	Tol.	-0.017	-0.054	-0.026	0.029	0.051	0.033
	Lon.	0.012	-0.003	0.007			
Flexible Threshold	Tol.	-0.119	-0.034	-0.081	0.134	0.056	0.065
	Mar.	0.015	0.022	-0.016			
Fixed Threshold	Tol.	-0.052	-0.041	-0.033	0.062	0.039	0.040
	Mar.	0.010	-0.002	0.007			
Flexible Threshold	Tol.	-0.036	-0.057	-0.377	0.156	0.061	0.378
	PG.	0.120	0.004	0.001			
Fixed Threshold	Tol.	-0.055	-0.045	-0.028	0.096	0.057	0.041
	PG.	0.041	0.012	0.013			

ϑ_i denotes the adjustment coefficient for the i-th regime.
Flexible thresholds are average recovered values reported.
[1]Refers to total adjustment ($\vartheta_{ib} - \vartheta_{ia}$) for each regime.

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CHAPTER II

MODELLING *SALMONELLA* SPREAD IN BROILER PRODUCTION: IDENTIFYING DETERMINANTS AND CONTROL STRATEGIES

Abstract

The presence of *Salmonella spp.* in broiler production is a concern as the bacterium can be transmitted to humans via contaminated meat and derived products.

A longitudinal study using official results of *Salmonella spp.* isolation from drag swabs collected at the end of the grow-out period was performed to determine risk factors related to farm and broiler house characteristics and management practices, as recorded by a Brazilian integrated broiler enterprise. A Bayesian hierarchical spatio-temporal model revealed significant spatial and time influence and significant effects of size of broiler house and total housing area per farm, type of broiler house and litter recycles on the odds of isolating *Salmonella spp.* from litter, allowing the implementation of measures to reduce the risk of persistence of the bacterium in the broiler production chain. We find evidence of a principal-agent problem while setting strategies to control the bacteria in litter and suggest the adoption of incentives aiming to reduce prevalence in the integrated enterprise. The possibility of implementing optimal control measures by extending recorded data is discussed.

Keywords: Salmonella, Broiler chicken, risk analysis, Bayesian hierarchical model

Introduction

Poultry meat is currently the world's most consumed and affordable meat type among animal-source. For the coming decade, per capita consumption is expected to increase by 5.5% worldwide, highlighting the importance of this commodity to food security and protein availability (Anon 2018). However, consumption of contaminated poultry meat was reported to cause 20.6% of foodborne diseases in the US between 1998 and 2008, among which *Salmonella spp.* was one of the main etiological agents (Painter et al., 2013).

Salmonella is a natural inhabitant of the gastrointestinal tract (GIT) of birds and can be introduced into the production system through several ways like contaminated feed or water, live vectors, contaminated litter, and even humans via contaminated boots or tools (Wales, Allen and Davies 2010). Therefore, to effectively control the bacteria within a poultry enterprise, many critical control points involving different production stages must be properly observed from the parent stock, feed production, transportation, on-farm interventions and finally at the processing plant. In this regard, major efforts must be directed to reducing the bacterial load entering the processing plant, as cross contamination is a major source of bacterial detection at this level (Cox and Pavic 2010; Volkova et al. 2010; Singer et al. 2007).

Several authors have performed risk analyses to identify factors linked to a higher likelihood of salmonella detection in chicken carcasses, e.g. at the processing plant (Singer et al. 2007; Volkova et al. 2010; Vandeplas et al. 2010).

Hygiene practices targeting bacterial elimination from production sites and prevention of contamination are constantly found to be interventions providing the greatest benefits in reducing prevalence at the processing plant (Tessari et al. 2009; Rose et al. 2000).
Epidemiological models have been used to model the spread of salmonella in many livestock production systems (Hill, R. R. L. Simons, et al. 2016; Gavin et al. 2018; Crabb et al. 2018; Binter et al. 2011; Nielsen and Nielsen 2012; Nielsen and Dohoo 2011). Most of these studies, however, have not account for dynamic decisions within the production system and are unable to estimate important parameters related to transmission and prevalence of diseases because they tend to rely heavily on assumptions, which makes the results fragile from an applied perspective. Furthermore, the lack of information from field controlled trials or field observations collected in a consistent manner is a major drawback when attempting to model a real-life scenario (Bucher et al. 2012), underscoring the need to incorporate field data into a modelling framework. Such a task, however, is not trivial once not all firms keep a consistent scheme of data collection or are willing to disclose information.

When it comes to modelling the spread of salmonella within a broiler enterprise, it is crucial to have data of bacterial presence from different stages of production, and which is traceable across different production units, that is, repeated measurements from different farms throughout the processing plant. Such information allows the estimation of the likelihood of detecting the bacteria as a function of determined risk factors, aiming to further improve the control and ultimately eradicate the infection with evidence based decision making. This information can be further applied to a commonly used epidemiological model to assess the optimal control measures given a set of available alternatives applicable to the specific enterprise. However, when dealing with repeated measurements across time to identify risk factors related to the occurrence of salmonella, temporal and spatial autocorrelation must be accounted for. It is intuitive that a positive poultry house is more likely to remain positive if disinfection protocols are not properly applied, which will be translated into time autocorrelation. Similarly, one negative poultry house located closer to one that is positive for *Salmonella spp.* is more likely to be contaminated by vectors or fomites than poultry houses that are more spatially isolated. This neighborhood effect will ultimately be a cause of spatial autocorrelation.

The presence of spatial and temporal autocorrelation are problematic when fitting logistic regressions as the assumption of independent and identically distributed (i.i.d.) errors is violated, which especially affects the significance of risk factor estimates. Furthermore, when evaluating risk factors for a determined biological agent, it may be of interest to identify and account for spatial patterns across time. Most studies evaluating risk factors for the presence of *Salmonella spp.* in livestock tend to consider random effects attributed to the farm or one specific region (Namata et al. 2009; Rose et al. 1999; Volkova et al. 2010; Le Bouquin et al. 2010). Few studies use longitudinal data, and most studies do not account explicitly for spatial autocorrelation.

Our study defines risk factors among farm characteristics and management practices consistently controlled by an integrated broiler enterprise related to the isolation of *Salmonella spp.* from litter in the grow-out period. We estimate a spatio-temporal Bayesian hierarchical binomial logistic regression model using field data of *Salmonella spp.* isolation in broiler houses from different farms in the south region of Brazil. The model captures the spatial and temporal patterns in Salmonella occurrence via random effects, while setting conditional autoregressive (CAR) priors. The probability of salmonella detection is then defined to be a function of covariates pertaining to consistently recorded farm characteristics and practices and the random spatio-temporal effects. The article contributes to literature by determining the effect of farm characteristics like size of broiler house and type of broiler house, as well as management practices like litter recycle, on the probability of isolating *Salmonella spp.* from litter, while explicitly accounting for spatial and temporal sources of variations

Model estimates are used to calculate odds ratio for each of the relevant risk factors to identify determinants of *Salmonella spp.* spread and draw control strategies for policy implications. We add a discussion about drawing optimal control measures from estimated parameters and expected probabilities and show the effect of interventions related to litter recycles on the enterprise expected return using a partial budget.

Literature Review

Salmonella contamination in broiler production is of concern because of the possibility of bacterial carry over from the production sites to the processing units with consequent contamination of carcasses, potentially leading to foodborne diseases (Hardie et al. 2019). Food poisoning cause by Salmonella, denominated Salmonellosis, is caused by non-typhoidal Salmonella enterica serotypes and is normally characterized by a self-limiting gastroenteritis syndrome (dyarrhoea, fever and abdominal pain), with an incubation period between 4 and 72h, rarely causing mortality (Antunes et al. 2016). Disease is more common in infants and elderly people, which are more susceptible to low infective doses (Chen et al. 2013).

Healthy poultry frequently harbor Salmonella and the transmission of the bacteria from meat and contaminated eggs is suggested as the main risk factor for human contamination. Effort involving surveillance, biosecurity and vaccination is related to substantial reduction in salmonellosis cases in Europe, highlighting the importance of adopting effective control measures in poultry and egg production, focusing primarily on serotypes related to human diseases like Salmonella Enteritidis and Salmonella Typhimurium (Hugas and Beloeil 2014).

Several risk analysis and modelling frameworks were performed to identify and suggest control measures for the risk of foodborne disease caused by Salmonella from broiler chicken (Rajan, Shi and Steven C. Ricke 2017; Kloska et al. 2017; Namata et al. 2009a) layers (Namata et al. 2008), pigs (Hill, R. L. Simons, et al. 2016; Gavin et al. 2018; Binter et al. 2011) and dairy cattle (Nielsen and Dohoo 2011; Nielsen and Nielsen 2012).

On farm risk assessment in broiler chicken performed by Le Bouquin et al.(2010) show that risk of bacterial infection increased when neighbors helped in the placement of day-old-chicks and decreased when proper cleaning and disinfection of equipment was performed and when farms used acetic acid for water sanitation and discarded dead birds in a proper container. Kloska et al. (2017) shows that a risk orientated hygiene analysis in Germany, targeting disinfection of critical points like water lines and feed lines, wall, air system and house environment was effective in eradicating Salmonella JAVA. Similar control strategies based in risk factors were also described in Doyle and Erickson (2006), and relate to sanitation practices to prevent contamination on the farm and during transportation and elimination of the pathogen from water and feed.

Modelling frameworks used to identify risk factors normally use logistic regressions, generally incorporating random effects to relax the i.i.d. residuals assumption (Combelles et al. 2019; Namata et al. 2009a; Hue et al. 2011). Combelles et al. (2019) lists several studies used to identify livestock disease risk factors and the outcome related to risk detection and finds that about 18 out of 36 studies evaluated from 2006 to 2016 used logistic models. Few of these studies, however, use longitudinal data or account for sources of spatial variation. Leroux, Lei, and Breslow (2000) define a mixed model to estimate disease rates in small areas while accounting for spatial dependence. Napier et al. (2016) describes a Bayesian hierarchical model to estimate the impact of changes in MMR vaccine uptake in measles susceptibility in Scotland, using the a spatial structure similar to that described by Leroux, Lei, and Breslow (2000), and adding a time specific component to control for autocorrelation.

In our study, we specify a similar Bayesian hierarchical modelling framework as that discussed in Napier et al. (2016), accounting for specific space and time autocorrelation. The advantage of the hierarchical Bayesian approach in mixed modelling, especially in mixed logistic models, relates to the theoretical advantage over the classical procedure of obtaining a consistent, asymptotically normal and efficient estimator using less stringent conditions, as described in Train (2001). Furthermore, as the Bayesian procedure provides exact information about the posterior distribution, while the classical procedure only approximates the posterior (having the error approximation disappearing asymptotically), there is the ability to make statements from small samples as well as large.

In the next section, we describe in detail how data was collected and processed, as well as how we identify spatial and temporal autocorrelation and how model is specified to account for those effects.

Materials and Methods

Data

The dataset comprises results of isolation of *Salmonella spp.* in litter of 417 different broiler flocks, from 139 broiler houses serving a vertically integrated company located in a south region of Brazil. The data of *Salmonella spp.* isolation were recorded from 3 consecutive flocks of each broiler house, accounting for a total evaluation time of 195 days. Drag swabs samples were collected from the litter of every broiler house 15 days before slaughter (average rearing time was 45 days). The collection was made by a trained field technician following standard protocols and analyzed by an accredited laboratory according to the recommendations described in the Ordinance 126 of November 3rd, 1995 (BRASIL 1995), and following the program establish by the Brazilian Ministry of Agriculture to control *Salmonella spp.* in broiler chickens and turkeys (Brasil 2016).

Briefly, the sampling procedure consists in dragging an assembly of at least three separate moistened 10cm x 10cm surgical gauze swabs, attached to a string stapled to a wooden spatula over the litter along the length of the broiler house, using the water and feeder lines as sectioning guides(Carrique-Mas and Davies 2008). The samples are then placed in transport media and immediately sent for analysis.

Spatial location of each broiler house was recorded using global positioning system (GPS) coordinates. The coordinates were then used to identify neighbors of every poultry house by Euclidean distance, using a circle of 20km from each broiler location as a cutoff point. Under this specification, the obtained neighborhood matrix reveals an average number of links of 33.71 for each broiler house. Three broiler houses were the most connected with 63 links, while 2 were the least connected with only 1 link. Average link distance was 11.45km, and median distance was 11.89km.

Table 1 summarizes the farm characteristics adopted as covariates, used by the enterprise to characterize broiler houses, farms and the practice of recycling litter. Size of broiler house relates to the total area of the broiler house in thousands of square meters. This is a continuous variable and ranges from 900 m^2 to 5400 m^2, with mean value across all farms of 2230 m^2. Number of broiler houses per farm was also a continuous variable ranging from 1 to 4, with mean 1.52, which records the number of different broiler houses under the same farm unit. A dummy variable to indicate whether the broiler house was located on a farm with a single broiler house (0) or on a farm with multiple broiler houses (1) was included to identify possible management effects, as multipole broiler house farms tend to be more specialized. Total housing size is a continuous variable that the enterprise uses to measure the total broiler production area, in square meters, of the farm and is obtained by summing the areas of broiler houses in that particular farm. This variable ranged from 1200 m^2 to 14400 m^2, with mean value of 3940 m^2.

Type of broiler house is a categorical variable used to characterize broiler houses across farms and is related to the structure and age of the building, type of equipment and isolation. Type 1 and type 2 broiler houses are conventional houses, with lateral curtains for insulation and ventilation, sprinklers, fans, automatic feeders and drinkers. Main difference between types 1 and 2 houses relates to the age of the building, which is greater than 5 years for type 1 and lower than 5 years for type 2. Type 3 houses are those with negative pressure and controlled environment, with evaporative panels, automatic drinkers and feeders.

Number of litter recycles is a continuous variable that indicates the number of times the litter used in one flock is treated in the between flock period and used on the next flock, with little or no addition of new litter. The average number of recycles was 5.72, ranging from 1 to 22 recycles. Wood shavings are used as bedding material in this enterprise and compose the litter. Other variables recorded are categorical and relate to the presence (1) or absence (0) of livestock, dogs or crop areas in the farm where the broiler house is located.

Out of the 139 evaluated broiler houses, 45, 74 and 77 were positive for *Salmonella spp.* at the end of the first, second and third rearing cycles, accounting for an estimated raw prevalence of 32.37%, 53.32% and 55.39%, respectively.

Model specification

Each of the broiler houses in this study is considered a unique spatial unit *k,* with $k = 1, \ldots,$ K=139, defined by a GPS location. Data on presence or absence of *Salmonella spp.* at the end of each $t = 1, ., , T$=3 rearing periods is recorded for every unit. Denoting by θ_{kt}, the probability of detecting *Salmonella spp.* in litter of the *k-th* broiler house at time *t*, a Bayesian hierarchical logit model is described as:

(1)

$$\ln\left(\frac{\theta_{kt}}{1-\theta_{kt}}\right) = \boldsymbol{X}'_{kt}\boldsymbol{\beta} + \varphi_{kt} + \delta_t$$

The logit probabilities of *Salmonella spp.* detection are modelled as a liner combination of a $p \times 1$ vector of covariates $\boldsymbol{X}_{kt}$, and spatial φ_{kt} and temporal δ_t random effects, where p represents covariates described in table 1, and their respective vector of regression parameters $\boldsymbol{\beta}$.

It is assumed that $\boldsymbol{\beta}$ follows a multivariate normal distribution and a diffuse multivariate normal prior distribution is specified: $\boldsymbol{\beta} \sim N(0, 1000\mathbf{I})$, where $\mathbf{I}_{p\times p}$ is the identity matrix.
The spatial random effect φ_{kt} and temporal random effect δ_t model spatial and temporal trends and autocorrelation in the data after accounting for the covariate effects. Spatial autocorrelation is controlled by a symmetric $K \times K$ neighborhood weight matrix $\boldsymbol{W} = (w_{kj})$, where w_{kj} represents spatial closeness between spatial units (S_k, S_j), and w_{kj} is non-zero if they share a common

border and zero otherwise, and $w_{kk} = 0$ for all *k*. Temporal autocorrelation is controlled by a binary $N \times N$ temporal neighborhood matrix $\boldsymbol{D} = (d_{tj})$, where $d_{tj} = 1$ if $|j-t|=1$ and $d_{tj} = 0$ otherwise.

It is specified that:

(2) $$\varphi_t \sim N(0, \tau_t^2 \boldsymbol{Q}(\boldsymbol{W}, \rho_S)^{-1}) for\ t = 1, \dots, N,$$

where $\varphi_t = (\varphi_{1t}, \dots, \varphi_{kt})$ is the vector of all spatial random effects at period *t*, and the spatial autocorrelation in the data is modelled by the matrix $\boldsymbol{Q}(\boldsymbol{W}, \rho_S) = [\rho_S(\text{diag}(\boldsymbol{W1}) - \mathbf{W}) + (1 - \rho_S)\mathbf{I}]$, where 1 is a $K \times 1$ vector of 1's, so that diag(**W1**) is a diagonal matrix with diagonal elements equal to the row sums of **W. W** and $\mathbf{I}_{K \times K}$ are the neighborhood and identity matrices, respectively. The full conditional specification of φ_{kt} is then :

(3) $$\varphi_{kt} | \boldsymbol{\varphi}_{-k}, \boldsymbol{W}, \rho, \tau_t^2 \sim N\left(\frac{\rho_S \sum_{j=1}^{K} w_{kj}\varphi_{jt}}{\rho_S \sum_{j=1}^{K} w_{kj} + 1 - \rho_S}, \frac{\tau_t^2}{\rho_S \sum_{j=1}^{K} w_{kj} + 1 - \rho_S}\right),$$

Where $\boldsymbol{\varphi}_{-kt} = (\varphi_{1,t}, \dots, \varphi_{k-1,t}, \varphi_{k+1,t}, \dots, \varphi_{K,t})$. ρ_S measures the strength of spatial autocorrelation and is assumed to be constant over time, as variances τ_t^2 are allowed to change temporally, thus capturing changes on spatial variability.

For the temporal random effect, it is specified that:

(4) $$\delta_t | \boldsymbol{\delta}_{-t}, \boldsymbol{D} \sim N\left(\frac{\rho_T \sum_{j=1}^{N} d_{tj}\delta_j}{\rho_T \sum_{j=1}^{N} d_{tj} + 1 - \rho_T}, \frac{\tau_T^2}{\rho_T \sum_{j=1}^{N} d_{tj} + 1 - \rho_T}\right),$$

where $\boldsymbol{\delta} = (\delta_1, \dots, \delta_N)$. ρ_T measures the strength of temporal autocorrelation and the temporal random effects capture the overall temporal trend in the probability of isolating *Salmonella spp.* in litter across all broiler houses. The spatial random effects model was proposed by Leroux et al. 2000), while the temporal random effects were described in Besag, York and Molliie (1991) .

The following priors are specified for parameters from equations 3 and 4:

(5) $$\tau_1^2, \dots, \tau_N^2, \tau_T^2, \sim \text{Inverse} - \text{Gamma}(1, 0.01)$$

$$\rho_S, \rho_T \sim \text{Uniform}(0,1).$$

Those distributions and parameter values are chosen because they provide flat and conjugate priors, as described in Lee, Rushworth and Napier (2018).

Sampling from the posterior distributions is obtained using Markov Chain Monte Carlo simulation with Gibbs sampling and Metropolis-Hastings algorithms. Computations are made in the R software, using package *CARBayesST*.

Spatial dependence is evaluated by first fitting the Bayesian hierarchical model specified in equation (1) without including random effects. Residuals are recovered and used to compute Moran's I (Moran 1950) statistics, performing permutation tests on the residuals separately for each year. The null hypothesis tested is of no spatial autocorrelation and the alternative hypothesis is of positive spatial autocorrelation. Temporal autocorrelation at lag 1 was also computed from the residuals using a Lagrange multiplier test for serial correlation (Breusch 1978) across all locations (null hypothesis of no serial autocorrelation, and alternative hypothesis of autocorrelation of order 1).

In order to select relevant covariates, we first estimate equation (1) including all variables in table 1 with relevant interactions. These covariates are included to represent the standard poultry environment in Brazil to incorporate risk factors that are frequently examined in previous studies (Le Bouquin et al. 2010; Nauta, Van de Giessen and Henken 2000; Altekruse et al. 2006).

To determine the model specification, we started with all covariates in Table 1 and their interactions, and variables with insignificant estimates were removed from model specification. Model was then re-estimated without the covariate. This exercise was done iteratively until the final model was obtained. The Deviance Information Criterion (DIC), an information criterion that accounts for model goodness of fit while penalizing complexity (Spiegelhalter et al. 2014) was also used to compare different specifications. DIC can be easily calculated from posterior samples and is preferred over other information criteria (like Akaike information criterion and Schwarz-Bayes information criterion) for being more appropriate in hierarchical models. This model selection approach is commonly applied in the literature of epidemics (Volkova et al. 2010; Vandeplas et al. 2010; Le Bouquin et al. 2010).

Results and Discussion

In this section, we will describe step by step the results obtained after model estimation and graphical representations, including a discussion and providing economic implications.

Table 2 shows the presence of positive spatial autocorrelation in second and third rearing cycles based on Moran's I test statistics (Table 2), confirming the adequacy of a spatial model. Temporal autocorrelation was also detected (0.22 on average across all locations – not shown in tables), suggesting the presence of positive autocorrelation at lag 1.

Model estimates were obtained after generation of 200,000 samples, following a burn-in period of 50,000 samples. Convergence for the chain of each posterior distribution was assessed to have been reached using Geweke's statistics (Geweke 1991), which is based on the normal approximation and measures the sampled mean value of the first 10% of the chain as compared to the last 50%. If the calculated statistic is greater than |1.96|, there is evidence of poor convergence, as calculated sample means at the beginning of the chain are substantially different than calculated mean at the end of the chain. Subsequently, 150,000 samples were generated, where every 10th draw was stored and the rest discarded to remove the autocorrelation, leaving inference based on 15,000 samples.

The Bayesian posterior medians and 95 % credible intervals for equation (1), reported in Table 3, show that all covariates except the number of broiler houses per farm and the dummy variable indicating a single or multiple broiler house per farm, presence of livestock, dogs or crops significantly affected the probability of isolating *Salmonella spp.* from litter. In a Bayesian setting, the posterior density is used to asses if an independent variable has a non-zero effect over the response by defining the 2.5% and 97.5% limits for the distribution, which is normally defined as the 95% credible interval. If this credible interval does not contain zero, then the effect of the independent variable may be understood as "significant" or non-zero. Interactions between type of broiler house and each of the numerical variables were also evaluated and found to be insignificant (results not shown for brevity).[3]

To allow for non-linear responses of the numeric variables, a quadratic term was included, and was found to be significantly different from zero only for size of broiler houses and litter reutilization as shown in table 3[4].

Table 3 shows the posterior median and credible intervals for all covariates listed in table 1, as well as Geweke statistics. The effect of number of broiler houses per farm (N_houses) and whether the farm has one or multiple broiler houses (single) was not different from zero. The same was true for the presence of livestock, dogs or crops. Geweke statistics for all posterior distributions reveal good mixing of samples and provide evidence of converge of the chains. Random effect estimates are not shown in table 3 for brevity, but were also accounted for during model selection.

After excluding insignificant covariates shown in table 3 and re-estimating the model from equation 1, the DIC from Table 4 indicates that the new specification is indeed preferred over the latter, once the calculated value is lower (530.01 for model from Table 4 *vs* 535.97 for model from Table 3) .

Table 4 reports that a quadratic effect between the size of broiler house and the number of litter reutilizations were identified, but with opposite responses: size of broiler house was found to increase the odds of isolating *Salmonella spp.* in litter, peaking for broiler houses between 4000 m^2 and 5000m^2 and decreasing thereof. Note that the average size is 2230 m^2. This effect is better observed from figure 1, where the posterior distribution of the calculated Odds Ratio (O.R.) of size of broiler house, with respect to the mean value, is graphed.

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[3] DIC for model including interactions was 549.66.

[4] The quadratic functional form was also tested for number of broiler houses and total housing size, but was not preferred over the linear functional form. DIC for model presented in table 3, including quadratic terms for all numeric variables was 536.46. For brevity, estimates s are not shown in table 3.

Size of broiler house, also named house area in other studies (Rose et al. 2000; Rose et al. 1999; Chriél, Stryhn and Dauphin 1999), significantly influenced probability of detection of *Salmonella spp*. This covariate did not significantly affect the response in those studies, while it was linked to increase in O.R. in other studies in laying hens (Huneau-Salaün et al. 2009; Namata et al. 2009b). From a transmission perspective, it might be possible that bigger houses, housing a greater number of birds, would be more likely to, given a potential contamination, favor pathogen amplification. In the present study, although density could not be effectively recorded, the same average number of birds per square meter are housed for different types and sizes of broiler houses[5] in the enterprise. Furthermore, interactions between type and size of broiler house did not reveal significant effects, reducing the likelihood of a potential confounding between these variables.

Number of litter recycles, as opposed to the size of broiler house, decreased the odds of isolating *Salmonella spp.* in litter, being lower between 5 and 6 recycles, and increasing thereof, while the average number of recycles is 5.72 times. The posterior distribution with credible intervals of the calculated O.R. of number of litter recycles, with respect to the mean value, is graphed in figure 2 for better reference.

Litter reutilization may be classified as a factor affecting persistence of contamination, because every broiler house's litter is commonly treated inside it in the between-flock period and hardly is exchanged with other broiler houses, even when in the same farm. Persistence of *Salmonella spp.* in litter is well studied (Kloska et al. 2017; Voss-Rech et al. 2019) and known to be affected by moisture levels, temperature and ammonia levels during fermenting or composting, so that in aged litter (more recycled) higher levels of these factors are required to properly eliminate the bacterium (Wilkinson et al. 2011; Singh, Kim and Jiang 2012; Kim et al. 2012). This behavior is reflected in the O.R. obtained for litter recycle, where a reduction on O.R. was

[5] Normally, type 3 broiler houses, which have a controlled environment and more stable temperature and moisture conditions tend to accommodate higher densities, but this information was not fully disclosed for this study.

observed with a subsequent increase. The initial reduction may be due to interactions of *Salmonella spp.* with other microorganisms colonizing litter in the early reutilizations: as less stablished is the microbiome of the litter, the less effect of competitive exclusion is observed, accounting for a relative higher presence of *Salmonella* on first recycles, summed to the impacts of fermentation. At a certain point, however, fermentation starts to lose efficiency and persistence of *Salmonella spp.* is encouraged, as demonstrated in Kim et al. (2012).

Total housing size had a linear negative effect on the log of odds of isolating *Salmonella spp.* in litter, as viewed by the negative value of the posterior median for this variable (table 4). To better understand this effect, we calculate the posterior distribution and plot median values and credible intervals of the O.R. of the total housing size value with respect to the mean value (3940 m^2) and depict the response in figure 3.

It is clear that farms with bigger housing capacity, not necessarily bigger houses, are less likely to be tested positive for *Salmonella spp.* in litter than farms with smaller capacity. One possible explanation for this effect may be that farms with more housing area tend to be more specialized, leading to better management practices during and between the rearing period. Although technical support is provided by the integrator, every farmer is responsible for carrying out husbandry and disinfection procedures under regular supervision of a qualified technician, which can ultimately lead to differences not only on the odds of isolating *Salmonella spp.*, but also on performance parameters.[6]

Categorical variables for broiler house type reduced the probability of detection of *Salmonella spp*. Odds ratio (O.R.) calculated for a type 2 broiler house reveals that the odds of isolating *Salmonella spp.* from litter of this type of building is 68% lower (O.R.≅0.32) than from a type 1 building, with credible intervals ranging from 18% (O.R.≅0.82) to 89% (O.R.≅0.11).

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[6] Data related to performance parameters, like feed efficiency, daily gain and mortality could help clarifying the reason why farms with larger housing area, but not necessarily with more houses, were less likely to have the bacterium isolated from litter. However, due to confidentiality issues, this data could not be provided.

Similarly, the odds of isolating *Salmonella spp*. from type 3 buildings is 85% lower (O.R.≅0.15), with credible intervals ranging from 50% (O.R.≅0.5) to 96% (O.R.≅0.04). These relationships are graphed in figure 4, where the posterior distributions of the calculated O.R. with respect to type 1 houses, with median values and 95% credible intervals are shown in violin plots.

Regarding type of broiler house, in this study, conventional broiler houses (with lateral curtains used to control temperature and air flow) were classified into two categories: type 1 and type 2. The main difference attributed between both relates to the age of the building, that for type 1 houses was greater than 5 years, while for type 2 houses was lower than 5 years. Type 3 houses, however, are broiler houses without curtains, but with evaporative cooling systems, which means that there is no direct contact with outdoor environment and the entrance of wild birds or rodents is markedly reduced. This more stable and isolated environments were expected to reduce contamination from external sources vectored by birds, rodents or dust, which are constantly pointed as risk factors for *Salmonella spp.* contamination (Volkova et al. 2010; Vandeplas et al. 2010; Rajan, Shi and Steven C Ricke 2017). This fact, linked to a potential greater commitment of the integrated producer on a higher fixed investment may be an explanation for the observed effect and may also explain the difference on O.R. between old and new buildings (types 1 and 2, respectively). Old buildings and old equipment are harder to disinfect, as they become worn out and with fixtures, favoring the accumulation of dirt, litter and feces. Such effects, linked to a higher need for maintenance (replacing curtains, nets, disabling and cleaning equipment) could lead to both an increased persistence of contamination, as well as an increased susceptibility for contamination from external sources (Doyle and Erickson 2006; Rose et al. 2000; Marin, Hernandiz and Lainez 2009). A similar explanation applies for the effect of total housing size and was already discussed.

The estimated time specific effects (δ_t) revealed a positive trend on the probability of isolating *Salmonella spp.* in litter, as observed on the graphical representation from figure 5 of the estimated probability of isolating *Salmonella spp.* in litter for each type of broiler house across the evaluation period.

The figure clearly shows a similar increase in estimated probability of isolating *Salmonella spp.* from litter of all types of broiler houses, but also highlights the difference in probability between houses, which seems to remain similar throughout the study. When looking at posterior median, type 3 broiler houses calculated probabilities were 60 to 70% lower than type 1, while calculated probabilities for type 2 houses were 36 to 50% lower than type 1. This finding indicates that one possible measure taken by the integrator to significantly reduce *Salmonella spp.* prevalence and potential losses at the end of the production chain will be to incentivize contracted producers to invest in new broiler houses or eventually contract with producers who have types 2 and 3 broiler houses.

Posterior median of correlation coefficients and variances (table 4) show evidence of positive spatial autocorrelation (ρ_S = 0.2247) and time autocorrelation ($\rho_T = 0.3808$). Estimates for spatial variation for every time period (τ_t^2) were very similar, suggesting no significant differences on variance of the probability of detection of *Salmonella spp.* across space.
For comparison purposes, we show the covariate estimates without accounting for temporal or spatial autocorrelation in table 5. Although the comparison of Bayesian estimates with estimates obtained using the frequentist approach are not appropriate, we observe that estimated coefficients were overall smaller than the obtained posterior medians when assuming residuals are i.i.d., and the coefficients for litter recycles were only marginally significant. This will carry much uncertainty on the determination of relevant risk factors and especially for the case of litter recycles, will lead to unreliable standard errors and consequent estimation of confidence intervals for O.R.

Implications and economic analysis

Using a spatio-temporal Bayesian hierarchical binomial logistic regression model, this study shows that the probability of detecting *Salmonella spp.* in litter of broiler houses in the grow-out period is significantly affected by size of broiler house, total housing area/farm, type of broiler house, and number of litter recycles. To the author's best knowledge, it is the first study evaluating risk factors related to *Salmonella spp.* isolation in broiler chicken litter in Brazil, and also using data routinely and consistently collected by a broiler enterprise. Some authors assess the prevalence of specific *Salmonella* serotypes in the same region, but use pooled data (without accounting for spatial or time autocorrelation) from different enterprises and report values between 5% and 11% (Voss-Rech et al. 2015; Giombelli and Gloria 2014; Pandini et al. 2015). More recently, Voss-Rech et al. (2019) evaluating 9 broiler houses in the same region, shows that non-typhoidal *Salmonella* tend to persist in contaminated farms, but did not link the results to risk factors.

In this study, covariates were selected according to the classification used by the enterprise, which may have aggregated various factors affecting *Salmonella* transmission or persistence into one variable. This classification, however, is made according to several requirements on standard biosecurity practices, and potential variations on these factors would be exceptions to the established requirement. Therefore, the covariates adopted in this study are effectively eligible to be changed by the enterprise, although some variables such as type and size of broiler houses may be more difficult to change than others like litter recycle.

An expected profit maximizing decision maker would choose the type and size of broiler house, total housing area per farm and number of litter recycles. This research provides a key component of the optimization: the probability of isolating *Salmonella spp*. Given the dynamic nature of the problem, where a decision taken at time t will impact outcomes at times $t+i$, with $i=1, \ldots, T$, the decision maker has to estimate the expected proportion of contaminated flocks at times $t+i$,…, $t+T$, given the chosen control variables and respective costs. Because of the delay between the timing of costs and payoffs, the expected profit is discounted using a discount factor r. The combinations of factors that provide the highest net present value are therefore understood to be optimal.

To allow the exercise of optimal control, the decision maker has to know the set of relevant choices to choose from and the distribution of the expected outcomes. This study has identified the most relevant covariates to be used in optimal control of *Salmonella spp.*, and also clearly showed the role of spatial and time patterns, which must be accounted for when simulating bacterial diffusion. One next step is to define a transmission model incorporating the spatial structure and time effects, which allows for a more reliable forecast of the expected probabilities of isolating *Salmonella spp*. Based on our findings, this model may be specified by defining a stochastic state-space transmission model, similar to that described in Hooker et al. (2011), where the transmission parameter between broiler houses is a function of distance between houses and type and size of broiler house and litter recycle. Both effects would then account for the parameter governing the transition of a broiler house from susceptible to infected, and vice-versa.

Economic loss of having positively tested flocks should also be considered. If a flock tests positive for *Salmonella spp.* 2 weeks before slaughter, this flock will be processed differently at the slaughter house to reduce the risk of carcass contamination (Brasil 2016) and cannot be used to manufacture of products with more added value (processed products) but mostly directed to fresh or frozen products. This leads to revenue loss for the integrator as well as an increase in costs because *Salmonella spp.* positive flocks sometimes are held at the farm to be slaughtered at the end of the day to minimize risk of infecting negative flocks. Depending on the prevalence recorded for the integrator, flocks can be held even until one determined day (e.g. end of a given week), leading to significant increases in feed costs. Following the directives of the ministry of agriculture for the surveillance and control of *Salmonella*, based on World

Organisation for Animal Health [OIE] (2010), every flock must be surveilled at least once before slaughter and this information is further used for risk assessment by the veterinary authority. Therefore, data on *Salmonella spp.* occurrence is available for the integrator, but may not be always stored in a way that allows effective data analysis, or is misused in terms of risk assessment.

With a proper system of data collection and an accurate model, it is possible to estimate the potential losses arising from *Salmonella spp.* contamination, unrelated to foodborne diseases. The detection on the pre-slaughter period and adoption of control measures markedly decreases this risk (Brasil 2016), but the costs of implementing different processing strategies, slaughter segregation and restricted access to different markets have not been defined. To the author's best knowledge, there is no such a description in literature. Therefore, we use production cost and revenue estimates reported by Miele et al. (2010) for an integrated broiler enterprise in the studied region and provide an example of how the model estimates and Odds Ratios can be translated into economic terms. We use the costs of litter replacement and total labor costs as a proportion of total working costs[7], and expected return over total capital costs[8] calculated considering a 6% annual return rate, as determined in Miele et al. (2010). We use these figures to compare the impact of positive flocks on expected return over total working costs, assuming that positive flocks will have a 40% discount on total return, which will be transferred to the farmer according to the proportion of produced positive flocks if litter is recycled more than 6 times. The expected return is calculated adopting a baseline scenario for each type of broiler house, assuming that litter will be completely replaced after 6 cycles, a common practice considered for the expected return and working costs calculation per flock (Miele et al. 2010). On the integrated system, the cost of litter replacement is a responsibility of the producers. Therefore, to increase return, there

[7] Total working costs are defined by the author as the sum of labor, litter, wood and electricity, maintenance, insurance, propane, paper for housing chicks, quick lime, extras (including other utilities), depreciation and environmental costs (licenses).
[8] This cost includes previously reported costs plus investment in buildings and equipment.

may be an incentive to recycle litter in order to reduce working costs and therefore increase profit.

Our goal is to calculate the proportion of positive flocks, assuming that litter recycles is the only risk factor responsible for *Salmonella spp*. transmission and persistence, and show how the dynamics of potential cost reduction may affect incentives to recycle litter, considering a two year interval.

We first calculate the probabilities of detecting salmonella in litter according to the number of litter recycles, using posterior distributions for the covariates Litter_use and Litter_use^2 (presented in Table 4) and calculating posterior densities of the probabilities for values of litter use ranging from 1 to 12. Table 6 reports the calculated posterior medians and 95% credible intervals for the probabilities.

The calculated probabilities on table 6 reflect the O.R. relationship depicted in figure 2. It is clear from table 6 and figure 2 that setting the number of recycles in 6 provides the lowest probability of isolating *Salmonella spp.*

Table 7 reports the cost calculations related to litter recycles for each type of broiler house evaluated in this study, and reported in Miele et al. (2010). Costs and returns are expressed as a proportion of total working cost per broiler house. Different cost structures for each broiler house indicates that there might be different incentives to recycle litter.

The problem faced by the producer may be defined by:

(6) $$\max_{st} \sum_{t=1}^{12} \frac{NR_t}{(1+r)^t}$$

Where st is a discrete choice related to the strategy to be chosen of recycle litter more than 6 times or follow the recommendation of the integrator, NR_t is the net return at cycle *t* described in Table 8 for each of the broiler houses, and r is the discount rate.

For our example, we assume the enterprise does not discount revenue for positive flocks if litter is replaced at the sixth rearing cycle. After that, we assume a 40% discount on revenue coming from positive flocks, and consider an additional 6 recycles, to simulate approximately one additional year of cycles (number of flocks per year is usually 6 to 6.5) in which the producer will be able to dilute the cost with litter replacement into 12 cycles (including first 6 cycles to which no penalty was applied). Such distribution of costs is clear when we observe cost/flock of litter replacement, which decreases for all types of houses, but is numerically greater for type 3 houses.

Looking at expected net returns, our baseline scenario assumes that the producer will receive full compensation for the 6 first cycles until litter replacement, so expected return for the 6 cycles is constant. At the 7^{th} cycle, if litter is not replaced, a penalty is applied for positive flocks. From a min-max selection criteria, considering that producers will choose to have the best possible performance in the worst case (Aissi, Bazgan and Vanderpooten 2009), the expected net return for all subsequent cycles after cycle number 6 is lower than the baseline scenario. This would discourage risk-averse producers to recycle litter with the objective of maximizing expected returns.

However, as this kind of extreme risk aversion does not always hold (Rabin and Thaler 2001), it is possible that some producers would chose to maximize net present value, using the posterior median of expected returns as an estimate of payments, and ignore the issue of return variation. Under this decision rule, the problem faced by the producer is to choose between 12 consecutive payments equal to the baseline scenario, or 6 baseline consecutive payments followed by 6 variable payments according to each expected return. Using a discount rate of 1% per cycle, and considering the baseline scenario as $100 for each type of broiler houses, we see that for broiler houses of types 1 and 3, producers will choose to extend recycle until 12 rearing cycles, as the calculated net present value (NPV), will be greater than 12 equal payments (Table 8).

This simple example highlights the importance of defining the risk factors related to *Salmonella spp.* occurrence and its respective cost share to allow effective control strategies and explains why producers choose strategies that would lead to greater risk of *Salmonella spp.*

occurrence. It is interesting to note that type 1 broiler houses were characterized in this study as riskier than types 2 and 3 with respect to *Salmonella spp.* isolation, and the economic incentive to recycle more litter may bring even more risk to the enterprise. Similarly, while type 3 broiler houses owners are incentivized to recycle more litter, this type of broiler house had the lowest probability of being contaminated with the bacterium.

The presented result is highly dependent on how the decision maker parametrizes the problem, in terms of assumption of decision rules (risk aversion), cost determination, cost share and incentives. If the penalty applied for positive flocks is greater, the result will be different (in favor of adopting the proposed replacement scheme), as well as if instead of a penalty, a premium is paid for negative flocks, especially on the first 6 cycle period (aiming to reduce contamination or persistence of the bacterium), the risk for litter recycle on *Salmonella spp.* isolation may be reduced. These types of incentives clearly relate to an attempt to solve the principal-agent problem that is frequently described in agricultural cooperatives (Ortmann and King 2007), as the producer and the enterprise manager may not share the same objective, which in this case is minimize *Salmonella spp.* occurrence.

Our study is also important to shed light on the benefits for the enterprise of using official data linked to a systematic classification of broiler farms to identify risk factors related to occurrence of *Salmonella*, the importance of accurate cost determination and the use of incentives to induce producers adopting procedures related to the elimination of the bacterium. The advantages for the enterprise include understanding the probable causes of outbreaks and, given a more detailed follow up, the costs and benefits involved in prevention and control of the infection and the adoption of optimal control strategies.

Conclusion

This longitudinal study is the first Brazilian study using official data recorded from a broiler enterprise to establish risk factors related to farm characteristics and management strategies affecting the probability of isolating *Salmonella spp.* at the end of the grow-out period. We show evidence of spatial and time autocorrelation, which were accounted for by means of a Bayesian hierarchical model. Factors potentially related to the horizontal transmission of *Salmonella*, like type of broiler house, size of broiler house and total housing size significantly affected the probability of isolating the bacterium in litter. The number of litter recycles, likely related to the persistence of infection within broiler houses, and also affected such probability.

We show how the risk for *Salmonella spp.* isolation increases as each of the risk factors change and we give an example of scenarios in which the producers will chose litter recycles strategies that will lead to increased probability of *Salmonella spp.* occurrence and discuss the role of establishing economic incentives to avoid the principal-agent problem and reduce the risk for positive flocks. Although the modelled scenarios may vary according to the cost and incentives adopted, it clearly shows an example of principal –agent problem and how it may impact *Salmonella spp.* persistence in the enterprise.

Future studies including more cycles and different covariates may clarify the dynamics of bacterial spread and allow for the establishment of optimal control strategies. Relationship of *Salmonella spp.* presence and production performance may also help clarify the effect of house size and farm capacity while allowing for a more accurate calculation of costs and returns for each evaluated farm.

Our study sheds light on the importance to use official data and systematic classification of farms and broiler houses to define risks for the isolation of *Salmonella* using a reliable model specification. Extending data collection and using it to parameterize a diffusion model is a promising alternative for the enterprise to establish optimal control measures.

Table 2.1. Description of farm characteristics and practices adopted as covariates.

Covariate	Type	Code	Description
Size of broiler house ($1000m^2$)	continuous	House size	Min=0.90, average=2.23, max=5.40
Number of Broiler houses/farm	continuous	N_houses	Min=1.00, average=1.52, max=4
Single house	categorical	single	Dummy variable taking the value of 0 if farm has only one broiler house and 1 if farm has 2 or more broiler houses
Total housing size ($1000m^2$)	continuous	Total Housing Size	Min=1.20, average=3.94, max=14.40
Type of broiler house	Categorical with three levels	Type1, Type2, Type3	1-Old building with curtains, 2-New building with curtains, 3-New building with climate control
Number of litter recycles	continuous	Litter_use	Min=1.00, average=5.72, max=22.00
Presence of livestock	categorical	Livestock	1- if present, 0- otherwise
Presence of Dogs	categorical	Dogs	1- if present, 0- otherwise
Presence of crop areas	categorical	Crops	1- if present, 0- otherwise

Table 2.2. Test results for spatial autocorrelation at each rearing cycle (time period).

Rearing cycle	Observed Rank	Test Statistic[1]	p-value
1	1252	-0.023	0.874
2	1243	0.024**	0.048
3	9513	0.027**	0.033

[1]Moran's I test statistic was obtained after 10000 simulations. H_0=no spatial autocorrelation, H_1=positive spatial autocorrelation.

**denote significance at the 5% level.

Table 2.3. Bayesian hierarchical logit posterior medians and credible intervals including all covariates described in Table 1[1]. Dependent variable is the isolation of *Salmonella spp.* in litter (n=417).

Variable	parameter	Median	2.5%	97.5%	Geweke[2]
Intercept	β_0	-2.823	-4.852	-0.608	0.3
House size	β_1	3.043	1.340	4.651	-0.6
House size^2	β_2	-0.314	-0.557	-0.058	0.7
Litter_use	β_3	-0.209	-0.452	0.006	1.9
Litter_use^2	β_4	0.017	0.001	0.036	-1.9
Total Housing size	β_5	-0.349	-0.536	-0.185	0.3
Type2	β_6	-1.169	-2.172	-0.129	0.3
Type3	β_7	-1.890	-3.186	-0.457	0.4
N_houses	β_8	0.392	-0.336	1.094	-0.6
Single	β_9	-0.261	-1.168	0.621	0.6
Livestock	β_{10}	-0.723	-1.597	0.113	0.2
Dogs	β_{11}	0.555	-0.231	1.364	-0.3
Crops	β_{12}	0.000	-0.661	0.648	0.8
			DIC[3]= 535.97		

[1]Random effects estimates are not shown.
[2]Geweke diagnostic: values lower than |1.96| suggest good mixing
[3]Deviance information criterion

Table 2.4. Bayesian hierarchical logit posterior medians and credible intervals including only significant covariates and specific random effects. Dependent variable is the isolation of *Salmonella spp.* in litter (n=417).

variable	parameter	Median	2.5%	97.5%	Geweke[1]
Intercept	β_0	-2.427	-4.285	-0.685	0.9
House size	β_1	2.921	1.385	4.541	-0.9
House size^2	β_2	-0.310	-0.543	-0.077	0.9
Litter_use	β_3	-0.227	-0.458	-0.017	0.2
Litter_use^2	β_4	0.018	0.002	0.037	-0.1
Total Housing size	β_5	-0.281	-0.419	-0.159	0.6
Type2	β_6	-1.154	-2.193	-0.200	0.6
Type3	β_7	-1.921	-3.275	-0.697	0.8
Rearing cycle1	δ_1	-0.518	-0.884	-0.124	-0.6
Rearing cycle2	δ_2	0.189	-0.038	0.481	-0.3
Rearing cycle3	δ_3	0.312	0.038	0.617	0.7
Spatial var1	τ_1^2	0.005	0.001	0.028	0.5
Spatial var2	τ_2^2	0.005	0.001	0.037	-0.3
Spatial var3	τ_3^2	0.005	0.001	0.033	-1.1
Time var	τ_T^2	0.113	0.010	0.807	0.0
Spatial autocorrelation	ρ_S	0.224	0.011	0.691	0.7
Time autocorrelation	ρ_T	0.380	0.021	0.896	0.3
			DIC[2]= 530.01		

[1]Geweke diagnostic: values lower than |1.96| suggest good mixing
[2]Deviance information criterion

Table 2.5. Logit estimates with covariates and interaction terms without accounting for spatial and temporal effects (n=417).

Covariate	Estimate[1]	Std. error	*p*-value
Intercept	-2.263**	0.912	0.013
House size	2.723***	0.779	0.001
House size^2	-0.290**	0.115	0.012
Total Housing size	-0.263***	0.063	<0.001
Type2	-1.055**	0.479	0.027
Type3	-1.785***	0.625	0.004
Litter_use	-0.186*	0.109	0.086
Litter_use^2	0.014*	0.008	0.097

[1]Maximum likelihood estimation obtained under the generalized linear model framework with logit link function.

***denote significance at the 1% level.

**denote significance at the 5% level.

*denote significance at the 10% level.

Table 2.6. Posterior medians and credible intervals for the calculated probabilities of isolating *Salmonella spp.* from litter according to the number of litter recycles. (n=15000 samples).

Number of recycles	Median	2.5%	97.5%
1	0.448	0.396	0.496
2	0.406	0.316	0.494
3	0.374	0.260	0.495
4	0.351	0.222	0.497
5	0.337	0.199	0.497
6	0.333	0.188	0.501
7	0.336	0.187	0.509
8	0.347	0.196	0.519
9	0.367	0.213	0.555
10	0.397	0.239	0.585
11	0.437	0.270	0.626
12	0.488	0.303	0.682

Table 2.7. Calculated costs of litter replacement per flock, expected returns, gains, losses and net return for each type of broiler house according to the number of litter recycles.

Type of broiler house	Cost/Flock of Litter replacement[1]	Number of recycles	Expected Return[2]	Expected Loss from positive flocks[3]	Expected Net Return[4] [min , median]
Type 1	12.32%	6 (baseline)	14.25%	-	[14.25% , 14.25%]
	11.91%	7	14.65%	1.97%	[10.56% , 12.68%]
	10.59%	8	15.97%	2.22%	[11.37% , 13.75%]
	9.57%	9	17.00%	2.50%	[11.97% , 14.50%]
	8.74%	10	17.82%	2.83%	[12.42% , 14.99%]
	8.07%	11	18.49%	3.23%	[12.68% , 15.26%]
	7.51%	12	19.05%	3.72%	[12.74% , 15.33%]
Type 2	11.73%	6 (baseline)	15.18%	-	[15.18% , 15.18%]
	11.34%	7	15.57%	2.09%	[11.28% , 13.48%]
	10.08%	8	16.83%	2.34%	[11.98% , 14.49%]
	9.10%	9	17.81%	2.61%	[12.54% , 15.19%]
	8.32%	10	18.59%	2.95%	[12.95% , 15.64%]
	7.68%	11	19.23%	3.36%	[13.19% , 15.87%]
	7.15%	12	19.76%	3.86%	[13.22% , 15.90%]
Type3	14.61%	6 (baseline)	15.36%	-	[15.36%, 15.36%]
	13.10%	7	16.86%	2.27%	[12.15% , 14.59%]
	11.54%	8	18.43%	2.56%	[13.12% , 15.87%]
	10.32%	9	19.65%	2.88%	[13.84% , 16.76%]
	9.35%	10	20.62%	3.27%	[14.37% , 17.35%]
	8.55%	11	21.42%	3.74%	[14.69% , 17.67%]
	7.89%	12	22.08%	4.31%	[14.77% , 17.77%]

[1]Cost estimated as a percentage of total working cost for each type of broiler house.
[2]Expected return calculated considering total capital cost and a 6% annual rate, and expressed as a percentage of total working cost according to the type of broiler house.
[3]Expected loss from positive flocks calculated by the product of the posterior median of the probability of isolating *Salmonella* (percentage of positive flocks) and the 40% revenue discount for positive flocks.
[4]Posterior distribution of net returns obtained by subtracting the expected return and the expected Loss related to litter recycles. Minimum and Median values are displayed.

Table 2.8. Net present value calculated for expected returns obtained for each type of broiler house.

Type of broiler house	Number of recycles	Expected net Return[1]	Expected net return[2] ($)	NPV (baseline)[3]	NPV (baseline + recycles)
Type 1	6 (baseline)	14.25%	100		
	7	12.68%	88.98		
	8	13.75%	96.49		
	9	14.50%	101.75	$1125.51	$1131.38
	10	14.99%	105.19		
	11	15.26%	107.08		
	12	15.33%	107.58		
Type 2	6 (baseline)	15.18%	100		
	7	13.48%	88.80		
	8	14.49%	95.45		
	9	15.19%	100.06	$1125.51	$1121.95
	10	15.64%	103.03		
	11	15.87%	104.54		
	12	15.90%	104.74		
Type3	6 (baseline)	15.36%	100		
	7	14.59%	94.98		
	8	15.87%	103.32		
	9	16.76%	109.11	$1125.51	$1171.36
	10	17.35%	112.95		
	11	17.67%	115.04		
	12	17.77%	115.69		

[1]Median value of expected net return described in Table 7.

[2]Expected return in monetary terms assuming baseline value as $100.

[3]Net present value calculated using a discount rate of 1% per period and 12 equal payments of $100.

[4]Net present value calculated using a discount rate of 1% per period, 6 equal payments of $100 and the expected monetary returns depicted in column 4 for each type of broiler house.

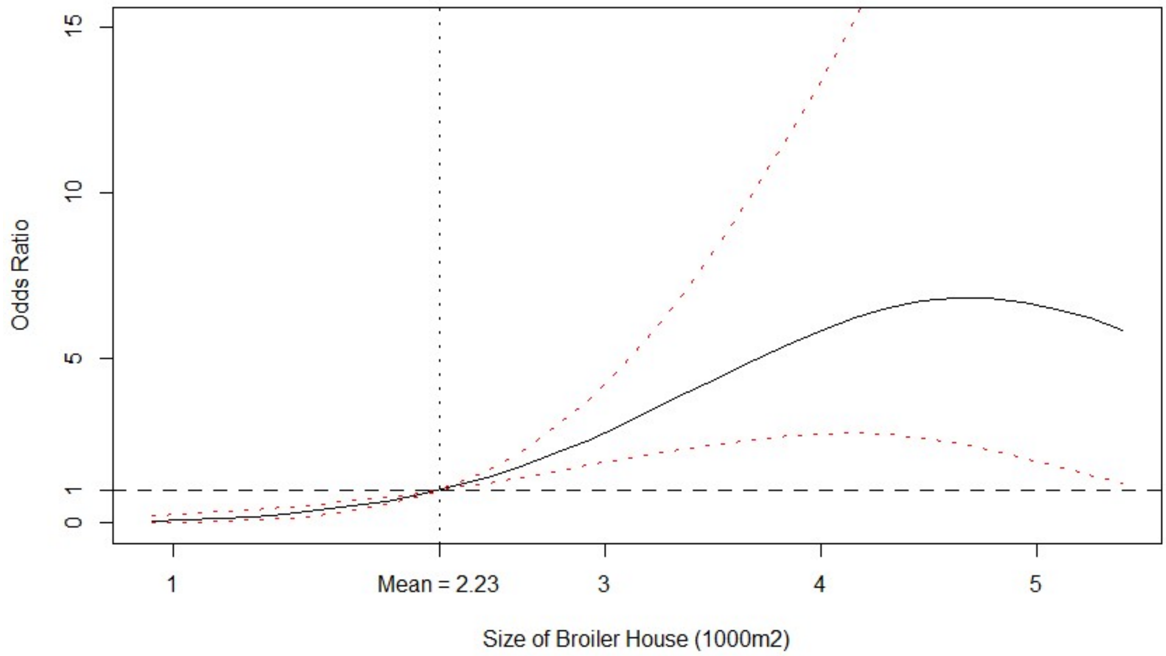

Figure 1. Odds ratio relationship between size of broiler house (1000m^2) and Probability of isolating *Salmonella spp.* from litter. Odds ratio is relative to the mean value, which is shown by the vertical dashed line. Solid line is the posterior median odds ratio and red dashed lines are 95% credible intervals. Horizontal dashed line shows odds ratio=1 for reference.

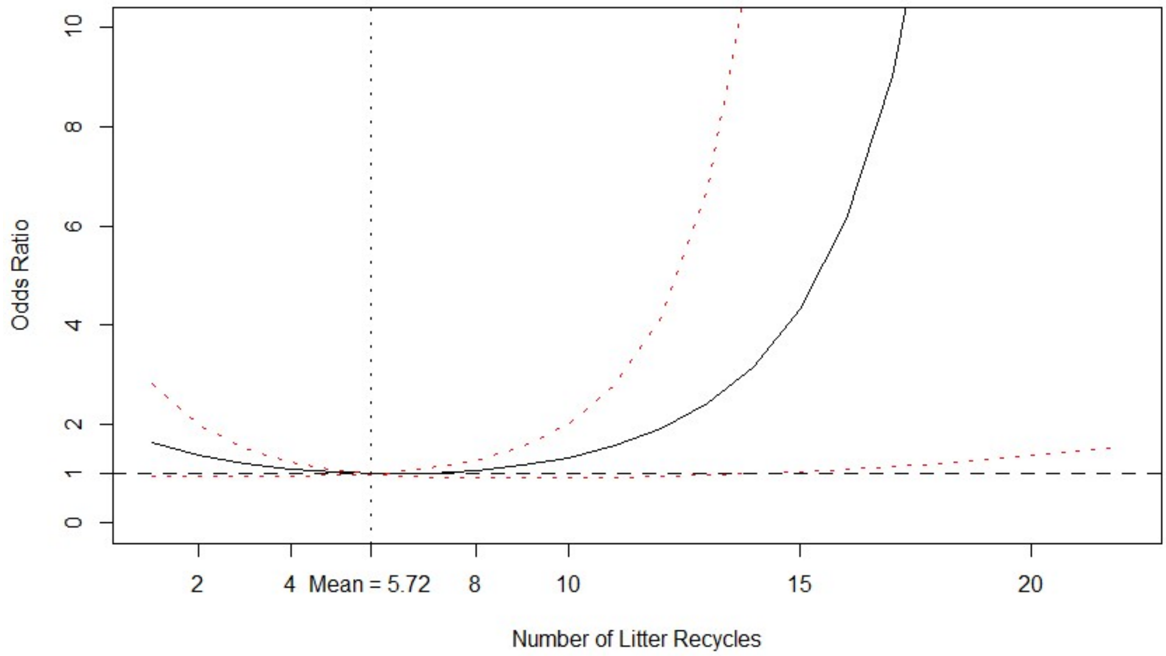

Figure 2. Odds ratio relationship between number of litter recycles and probability of isolating *Salmonella spp.* from litter. Odds ratio is relative to the mean value, which is shown by the vertical dashed line. Solid line is the posterior median odds ratio and red dashed lines are 95% credible intervals. Horizontal dashed line shows odds ratio=1 for reference.

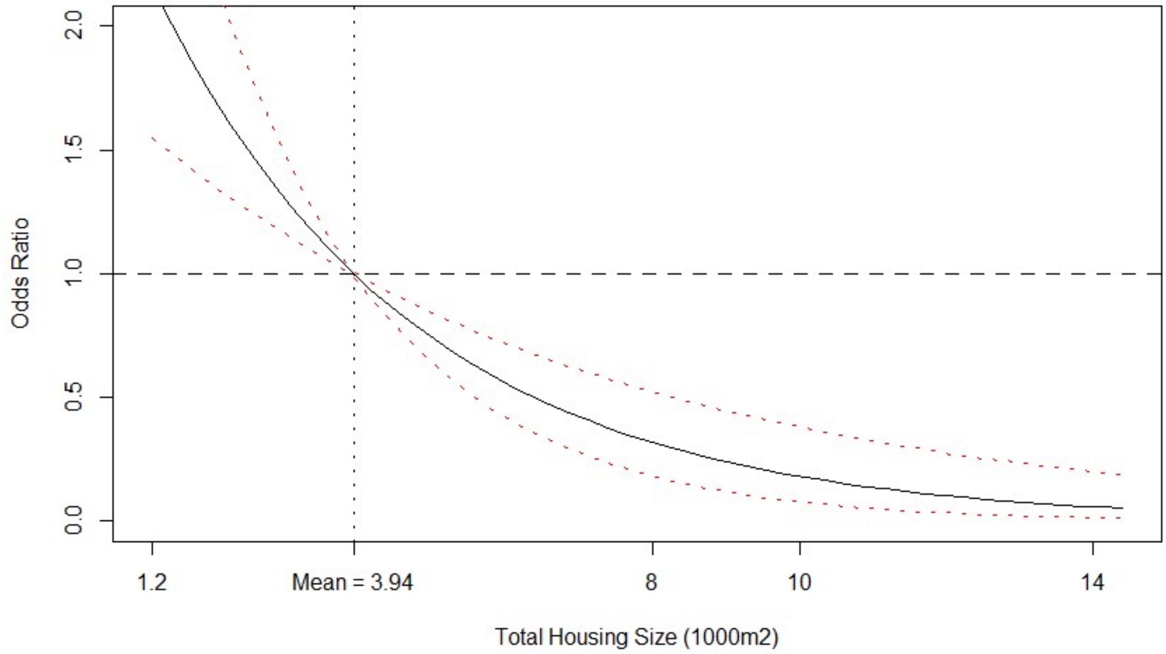

Figure 3. Odds ratio relationship between Total housing size (1000m^2) and probability of isolating *Salmonella spp.* from litter. Odds ratio is relative to the mean value, which is shown by the vertical dashed line. Solid line is the posterior median odds ratio and red dashed lines are 95% credible intervals. Horizontal dashed line shows odds ratio=1 for reference.

Figure 4. Violin plots showing the posterior density of the estimated Odds Ratio relationship between types of broiler house 2 and 3 with respect to type1 and probability of isolating *Salmonella spp.* from litter. Horizontal lines inside plots represent posterior medians and 95% credible intervals.

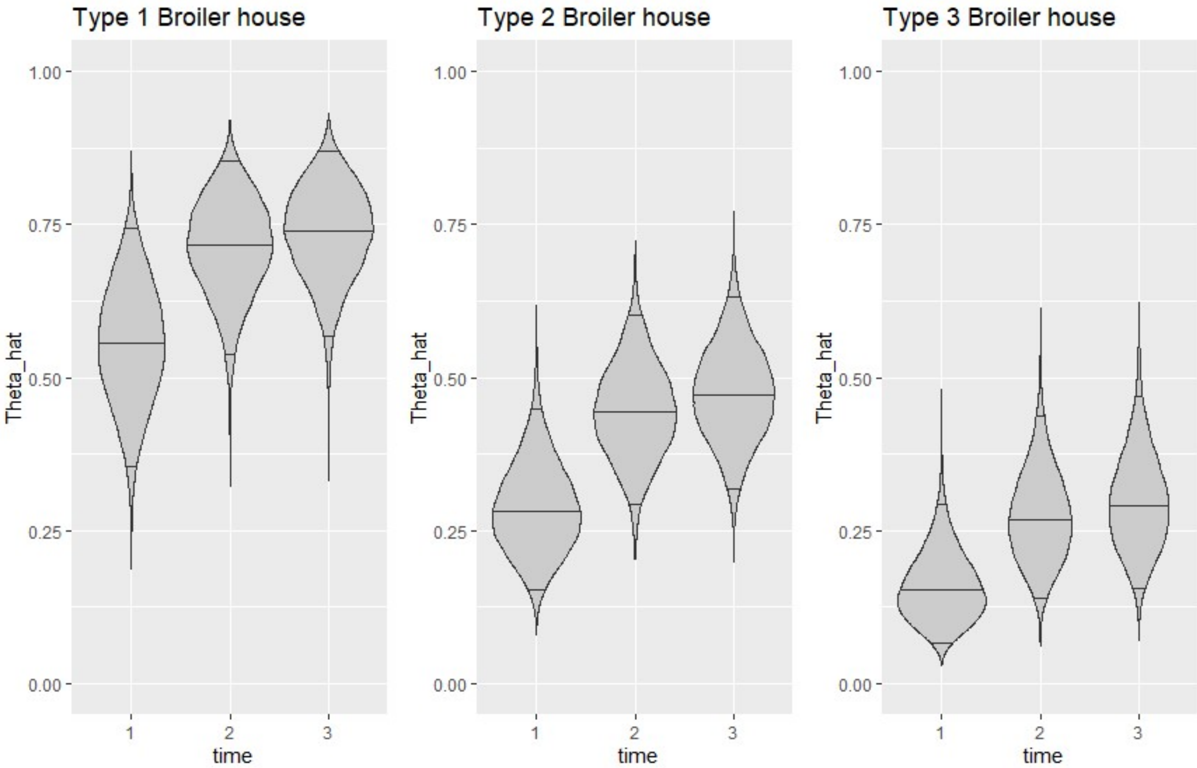

Figure 5. Violin plots showing the posterior density of the average estimated probability of isolating *Salmonella spp.* at the end of each time point for all types of broiler houses. Horizontal lines inside plots represent posterior medians and 95% credible intervals. Theta_hat= $\widehat{\theta_t} = \frac{exp(\bar{X}_t^T\beta+\delta_t)}{1+exp(\bar{X}_t^T\beta+\delta_t)}$**, for** $\bar{X}_t = \frac{\sum_{k=1}^{K} X_{kt}}{K}$ **.**

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