UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ

Colegio de Administración y Economía

A Times Series Analysis of Government Regulation in Ecuador from 2008 to 2017

Proyecto de Investigación

.

Juan José Achig Andrango

Economía

Trabajo de titulación presentado como requisito
para la obtención del título de
Economista

Quito, 06 de diciembre de 2018

UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ

COLEGIO DE ADMINISTRACIÓN Y ECONOMÍA

HOJA DE CALIFICACIÓN DE TRABAJO DE TITULACIÓN

A Times Series Analysis of Government Regulation in Ecuador from 2008 to 2017

Juan José Achig Andrango

Calificación:

Nombre del profesor, Título académico: Santiago José Gangotena, PhD.

Firma del profesor ______________________________

Quito, 06 de diciembre de 2018

Derechos de Autor

Firma del estudiante: ____________________________________

Nombres y apellidos: Juan José Achig Andrango

Código: 00125540

Cédula de Identidad: 1719691592

Lugar y fecha: Quito, 06 de diciembre de 2018

AGRADECIMIENTOS

A Dios por darme todas las oportunidades y permitirme concluir esta etapa que apenas es el comienzo de toda la jornada. A mis padres, Laura y Eddy, por su apoyo incondicional durante todos estos años. A mi abuela, Laura, por brindarme la fuerza y motivación para cumplir todas mis metas. A mi hermano, Santiago, por siempre ser ejemplo e inspiración en mi vida. A mis grandes amigos por haber sabido estar en toda circunstancia; Adri, Sebas, Navas, mil gracias. Finalmente, a Santiago José Gangotena por haber fomentado mi gusto por la investigación y por su apoyo en la realización de este proyecto.

RESUMEN

Este trabajo tiene como objetivo el realizar un estudio de series de tiempo al flujo regulatorio del Ecuador en la última década. Para este objetivo se plantean modelos univariados de series de tiempo y la metodología ARIMA estacional para poder caracterizar correctamente el flujo mensual y trimestral de regulación del 2008 al 2017. Como contribución principal se busca sentar las bases para un posterior estudio multivariado de series de tiempo con el cual se establezca el efecto de la regulación sobre variables macroeconómicas.

Palabras clave: Regulación, Teoría Macroeconómica, Crecimiento Económico, Análisis de series de tiempo, Modelos Univariados, ARIMA estacional.

ABSTRACT

The main objective of this research project is to conduct a time series study of the Ecuadorian regulatory flow in the last decade. For this purpose, time series univariate models and seasonal ARIMA methodologies are proposed to correctly characterize the monthly and quarterly flow of regulation from 2008 to 2017. The main contribution is to lay the foundations for a subsequent multivariate time series study which establishes the effect of regulation on macroeconomic variables.

Key words: Regulation, Macroeconomic Theory, Economic Growth, Time Series analysis, Univariate models, Seasonal ARIMA.

TABLA DE CONTENIDO

ÍNDICE DE TABLAS

ÍNDICE DE FIGURAS

1 INTRODUCTION

Ecuador has been suffering an increase in the flow of regulation over the past decade and the aggregate effects of this phenomenon has not been considered. Alcívar (2017) quantified the monthly flow of regulation for the period from 2008 to 2017 with the objective of creating a tool for further macroeconomic studies. Macroeconomic theory does not establish a framework to study the effects of regulation; nevertheless, there have been several papers that have quantified the general effects of regulation. Dawson & Seater (2013) proposed a cointegrated time series process in order to quantify this effect; however, before conduct cointegrated methods, a characterization of observations must be done. The use of filters, univariate and multivariate models are appropriate techniques that could give us the same results as a cointegration approach, but with different time series variables.

The Moving Average and the Hodrick & Prescott filters are commonly used in order to transform non-stationary data into a stationary data. Additionally, econometric theory uses univariate and multivariate techniques to model time series and obtain the best fit. Therefore, stationarity along with autocorrelation represent the major challenges for the analysis of any time series. Before conducting any multivariate process where causality relations could be obtained, the univariate models provide the first insights into the behavior of the flow of regulation for Ecuador.

In this sense, the present paper presents the first time series study of the monthly and quarterly flow of regulation in Ecuador. The main model that will be conducted is a seasonal ARIMA model, that fits monthly data, but the quarterly data could not be fitted because of data scarcity. The structure of the present paper goes as follows: Section 2 establishes the literature review that will set the ground for Section 3 in which methodology is deployed. Section 4 presents the main results and conducts the main tests and models into the data. Finally, Section

5 presents the economic discussion of the seasonal ARIMA models found and Section 6 discuss the main conclusion of this study.

2 LITERATURE REVIEW

Economic growth rates vary between countries because of education, productivity, foreign aid, values, among other social indicators; moreover, there is a field in which scholars have agreed that causes and slowdowns economic activity: Government Regulation. Goff (1996) has been recognized as the pioneer of the macroeconomic studies about the effects of regulation. Furthermore, the study of regulation must not consider basic laws that could hinder research studies, that is the reason why Goff defined regulation as the more quarrelsome rules in a society (1996). His main paper, focused on cross-section and panels of countries, found that, "regulatory fluctuation was the primary determinant of the slow economic growth of the 1970s and the return of growth during the 1980s [in the United States]" (Goff, 1996).

Regulation studies have been focused in microeconomic literature where causes and effects have been founded and they built the path to the macroeconomic analysis of regulation. Therefore, to study regulatory theory, one must review the main contributions and the history in micro and macroeconomic terms. Moreover, most of the studies conducted in macroeconomic terms do not consider the time series characteristics of aggregate variables; therefore, the stationarity properties of the data are not considered (Coffey, Mclaughlin, & Peretto, 2016). For this reason, a review of the main statistical analyses must be conducted before relating regulation with any macroeconomic variable. Finally, time series econometric techniques help us to characterized aggregate variables, that will set the ground for future macroeconomic studies.

Before beginning with the analysis, it must be said that "the central tasks of the theory of economic regulation are to explain who will receive the benefits or burdens of regulation…and the effects of regulation upon the allocation of resources" (Stigler, 1971). Taking a microeconomic perspective, as mentioned by Dawson & Seater the effects of regulation on economic activity are often not straightforward (2013) because there are specific regulations that could correct market failures in one part of the economy, but the aggregate effect is ambiguous. Furthermore, in terms of our interests, "microeconomic analysis will probably not be able to estimate the cumulative effects of regulatory complexity, but macroeconomists may have more success" (Broughel, 2017).

The origins of regulation are studied in the field of public choice, "Pigou's (1938) public interest theory of regulation holds that unregulated markets exhibit frequent failures, ranging from monopoly power to externalities" (Djankov, LaPorta, Lopez-De-Silanes, & Shleifer, 2002). Hence, regulation is required to correct those undesirable effects and the role of the government is to protect their citizens from those market failures. Public choice theory, however, sees the government as less benign and regulation as a potentially socially inefficient mechanism (Djankov, LaPorta, Lopez-De-Silanes, & Shleifer, 2002). As mentioned by Stigler (1971) "[usually] regulated firms gain control of the regulatory agency and use it to their advantage". Besides, neither Pigou's nor Stigler's theories suggest any clear connection between aggregate variables and the amount of regulation (Dawson & Seater, 2013).

Macroeconomic theory is usually centered on four fields-namely, spending, taxation, deficits, and monetary policy. Moreover, empirical studies suggest that regulation changes macroeconomic variables, but there is no theory that directly addresses the effects that regulation has on macroeconomic activity (Peretto, 2007). In order to clarify the link between microeconomic regulations into the macro economic environment, Goff detailed three main arguments:

> "First…if supply/demand shifting or price/quantity manipulating regulations are imposed across many or most of the markets in an

economy, that would provide a seemingly straightforward basis for understanding the micro to macro link. Second, if the direct regulation of one market creates sizable spillovers on the supply and demand in other markets, regulation's effects have another avenue to move from the individual market level to the aggregate level. Third, if a current regulation in one market today creates future adjustments in that or other markets, regulation gains one more pathway toward economy-wide influence" (Goff, 1996).

Furthermore, it is essential to consider that "new regulations interact with existing ones, resulting in effects larger than the new regulations would create on their own" (Broughel, 2017). Additionally, and following a cross-section study, Alesina et.al concludes that "deregulation leads to greater investment in the long-run" (2003). As is evident, this results contrast with the public interest theories of regulation but supports the public choice approach (Djankov et al., 2002) because the greatest benefits of regulations would be directed to the group in power, bringing rent extraction by self-interested politicians. Likewise, as mentioned by Jalialian, Kirkpatric & Parker, the impact of regulatory institutions on economic growth will depend on both: the efficiency of the regulatory policies and instruments that are used, and the quality of the governance processes that are practiced by the regulatory authorities (2007). In this sense, the debate about the effect of regulation is guided to the origin that is an institutional one.

To understand how individual or groups of regulations affect economic growth, a model is needed. Solow's model (1956) has been the main framework for macroeconomic studies; based on the Cobb-Douglas production function, this model captures: Y_t= Real Output D_t= total factor productivity (TFP), K_t^{ζ}= capital services, and $\mathrm{N}_{\mathrm{t}}^{1-\zeta}$ = labor services. Solow's model is applied since regulation has effects on real aggregate output and presumably affects the economy in complex ways (Dawson & Seater, 2013), i.e., affects the main determinants of the output. To study the macroeconomic effects of regulations, a Second-Generation endogenous growth model taken from Peretto (2007) is adapted by Dawson & Seater (2013).

Also, macroeconomists have faced several problems while trying to establish a solid framework to study regulation. First, data obtained from government institutions faces four main complications: short time periods, comprehensiveness, the relation of the opinions of the creators of the index; and as mention by Coffey, McLaughlin & Peretto, “while informative… [these indexes] necessitate tradeoffs” (2016). The restriction to small subsets of regulations and the short-time dimension make our aggregate analysis almost impossible, because economic growth is always measured in the long-term. Second, in the Ecuadorian case, the main issue relies on the construction of the macroeconomic variables. Nevertheless, Córdova “quantifies the stock of capital (gross and net) for Ecuador, for the series 1965-2005, expressed in current and constant terms, by applying the methodology proposed by the OECD” (2005).

Besides, the flow of regulation and how is it obtained represents a major issue for macroeconomic analysis. Dawson & Seater (2013) describe the difficult of this process because there is no theory that tells us what and how we can measure the “marginal regulation rate” as in the theory of taxation. The number of pages in the Code of Federal Regulations of the United States is the measure that Dawson & Seater (2013) use to quantify regulation. In Ecuador, Alcívar (2017) collected legal data between 2008 and 2017 in order to construct a measure of regulation. The Ecuadorian Official Records were stored, and by applying the QuantGov methodology, the regulatory words were counted on a monthly basis from October 20th, 2008 to May 24th ,2017, giving us the basis of the regulation measure used in Ecuador (Alcívar, 2017).

Now that the macroeconomic theory has been studied, statistical time series concepts are described, in order to set the ground for the characterization that is conducted in the next section. Time series analysis are meant to be done "to understand the past and to predict the future, enabling managers or policy makers to make properly informed decisions" (Cowpertwail & Mercalfe, 2009). In the field of macroeconomic data, statistical corrections and cross-sectional econometric studies have been conducted in order to correct auto-correlation problems, simplifying the construction of any time series econometric model. For instance, in (Jalialian, Kirkpatrick, & Parker, 2007) a logging process helped to solve problems of serial correlation and heteroscedasticity. In this way, what a statistical transformation or an econometric model necessity, depends on the observed data and the study that the researcher wants to conduct.

On one hand, statistical transformations emerge as filters that seek the stabilization of the data to get stationary environments. Hodrick & Prescott (1997) developed a widely adopted method that decomposes the observed variables into trends and cycles; the trend being the optimal output of the variable. Therefore, the business cycle of the economy could be "simulated", i.e., the optimal amount of regulation could be obtained. Moreover, this method "introduces spurious dynamic relations that have no basis in the underlying data-generating process" (Hamilton, 2017). On the other hand, econometricians have developed a well-structured framework in which time series variables could be adapted. For forecasting purposes, researches may either describe the behavior of a variable (Univariate time series) or build a more or less structural model describing the relationship between the variable of interest with other economic quantities (Multivariate time series) (Schafgans, 2017). In both cases, it is important to determine whether the time series are stationary and present ergodicity, i.e., the inherent time dependence is not too strong.

As mentioned by Johnston & Dinardo, univariate time series models provide a priori information about the possible relationships between series, and an approximation of theoretical speculations (1997). Also, and following econometric concepts, the observations of macro-economic variables are "considered as realizations of random variables that can be described by some stochastic process" (Verbeek, 2017). In order to describe this stochastic process, stationarity and autocorrelation must be considered. Many economic variables do exhibit strong trends and are clearly not stationary, i.e., the process generating the output does not change. Stationarity is checked by applying the Augmented Dickey-Fuller test (Schafgans, 2017); in the presence of non-stationarity, univariate models transform the time series into a stationary one. Furthermore, autocorrelations of the time series are referred as the autocorrelation function (ACF) or the correlogram. From this function we can infer the correlation of one time among the past and hence, the length and strength of the memory of the process (Verbeek, 2017).

Two models derive from the univariate time series method: Autoregressive (AR) and Moving Average (MA) models. "The series $\{Y_t\}$ is an autoregressive process of order p, abbreviated to AR(p) if

$$Y_t = \delta + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_p Y_{t-p} + \epsilon_t \quad (1)$$

where ϵ_t is white noise" (Cowpertwail & Mercalfe, 2009). Johnston & Dinardo defined the pure MA (q) process as a variable that is expressed solely in terms of the current and previous white noise disturbances (q),

$$x_t = \in_t + \alpha \in_{t-1} + \alpha^2 \in_{t-2} + \cdots \quad (2)$$

therefore, the order of a moving average model can be determined from an inspection of the sample ACF (1997).

Multivariate time series models emerge as a response to the problem that univariate models present that is that they do not allow us to determine what the effects of macroeconomic variables are, for example, in a change in policy or aggregate variable (Verbeek, 2017). By adding more variables, first, one must study the stationarity of the series; when there is a non-stationary process, covariances are ill-defined and a spurious regression can be found

(Verbeek, 2017). There is a common agreement that “the appropriate way to manipulate [non-stationarity] series is to use differencing and other transformations to reduce them to stationarity” (Greene, 2012). Nevertheless, when the non-stationarity series have the same stochastic trend in common, i.e., both are drifting together at roughly the same rate, a cointegration process is the appropriate way to analyze those trending variables (Greene, 2012).

To sum up, the principal studies regarding government regulation have been made in the micro economic field and little attention has been paid to the macro economic environment. Through the use of econometric and macro economy models, it is possible to measure the real effects of regulations on the private sector. Even though the application of any updated filter could improve the decomposition of variables (Hamilton, 2017), and by applying complex econometric models, we could have improved insights about the behavior of the variable, the question relies on what is sought in the data.

Considering that there has not been any study regarding regulation and its effect on macroeconomic variables in Ecuador, it is useful to conduct a characterization of the time series of regulation by applying statistical and univariate time series econometric models. The purpose of this research is to set the ground for future economic studies that use regulation and to provide the statistical framework in which time series analysis that use regulation should be conducted. Stationarity and Autocorrelation examinations provide the main tools to search for a suitable model of the macroeconomic effect of regulation. Finally, in Ecuador and countries that have faced an increase in their regulatory flow, this study hopes to contribute to the debate regarding the question of who is receiving the benefits from regulation that is maybe negatively affecting the aggregate economy.

3 METHODOLOGY & DATA

3.1 Methodology

The characterization of quarterly and monthly regulation data begins with statistical description of moments and the decomposition of the observed variable. These processes provide the basis for the econometric model construction that is required. The first statistical moment consists of the average and the second moment encompasses the variances of the time series, both are defined as: $\mu = \sum \frac{x_t}{n}$, and $var = \sum (x_t - \mu)^2$. Following the Cowpertwail & Mercalfe time series approach, plotting the time series provides intuitive insights about frequency and distribution of data (2009). Furthermore, as economic theory is specified in terms of a stationary environment, and in order to transform observed nonstationary data without modeling the previous mentioned process; two decomposition methods are going to be applied. First, the moving average procedure and second the Hodrick-Prescott filter. Both methods rely on the assumption that there is a trend m_t and/or seasonal effect s_t inside the data, in an additive or multiplicative way:

$$x_t = m_t + s_t + z_t \quad (3)$$

$$x_t = m_t * s_t + z_t \quad (4)$$

The moving average procedure does not assume any specific form for the time series, and dive it into its trend and seasonal effect with "an average of a specified number of time series values around each value in the time series, with exception of the first few and las few terms" (Cowpertwail & Mercalfe, 2009), equal weight is given to all data (equation 5). The estimate of the monthly additive effect is obtained by subtracting $\widehat{m_t}$, giving us equation 6. In this way, trend, seasonal effect, and the random variation are obtained. The literature suggests that after this transformation, if the average random variation is equal to 0 and there is no autocorrelation, the model captures all the elements of variability of the time series, and no other transformation is needed (Cowpertwail & Mercalfe, 2009).

$$\widehat{m_t} = \frac{\frac{1}{2}x_{t-6} + x_{t-5} + \ldots + x_{t-1} + x_t + x_{t+1} + \ldots + x_{t+5} + \frac{1}{2}x_{t+6}}{12} \quad (5)$$

$$\hat{s}_t = x_t - \widehat{m}_t \quad (6)$$

Moreover, as the moving average filter does not encompass the cycle term that is present in real aggregate data, Hodrick & Prescott proposed a conceptual framework where the time series y_t is represented by the sum of a growth component g_t and a cyclical component c_t (1997):

$$\min_{\{g_t\}_{t=-1}^{T}} \left\{ \sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=1}^{T} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2 \right\} \quad (7)$$

Their proposed method relies on the assumption that "λ [the smoothness parameter] is a positive number which penalizes variability in the growth component series" (Hodrick & Prescott, 1997). This implies that, when $\lambda \to 0$, the algorithm does not penalize deviations from the trend (no change materializes) and when $\lambda \to \infty$, the penalty over the trend is infinite, therefore, the estimation is the linear approximation obtained by Ordinary Least Squares (OLS). This is the main limitation of the process, due to the sensibility of the model to the λ value; moreover, the common practice is to use a value of $\lambda = 100$ for yearly data, $\lambda = 1600$ for quarterly time series, $\lambda = 14400$ for monthly data (Hamilton, 2017).

On the other hand, modeling the process is another way to adapt non-stationary data into stationary one, but the process that is required is based on econometric theory. As previously mentioned, there are two branches in which econometrics interpret time series: univariate and multivariate time series process. In order to model monthly and quarterly data, the univariate models will be developed first; hence, Autoregressive (AR), Moving Average (MA), and combinations of both are going to be discussed. Recalling Equations (1) and (2), the next step is to identify stationarity and autocorrelation properties of those processes.

$$Y_t = \delta + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_p Y_{t-p} + \epsilon_t \quad (8)$$

$$x_t = \in_t + \alpha \in_{t-1} + \alpha^2 \in_{t-2} + \cdots \quad (9)$$

First, when talking about stationarity and autocorrelation of economic variables, econometric tests can confirm the presence of these properties. Stationarity represents "a stochastic process [where] its probability distribution remains unchanged when time progresses" (Verbeek, 2017). This is to say that realizations over different time intervals would be similar, due to the presence of a stochastic equilibrium. In time series data, it is required that just the means, variances and covariances of the series be independent of time, rather than the entire distribution; this is the definition of a weakly stationary process:

$$E\{Y_t\} = \mu < \infty, \quad (10)$$

$$V\{Y_t\} = E\{(Y_t - \mu)^2\} = \gamma_0 < \infty, \quad (11)$$

$$\text{cov}\{\mathrm{Y_t}, Y_{t-k}\} = E\{(Y_t - \mu)(Y_{t-k} - \mu)\} = \gamma_k, \qquad k = 1,2,3, \ldots \quad (12)$$

"Conditions (10) to (12) require the process to have constant finite mean and variance, while states that the autocovariances of $\mathrm{Y_t}$ depend only upon the distance in time between the two observations" (Verbeek, 2017). As mentioned by Verbeek (2017), "MA processes are stationary by construction and because they correspond to a weighted sum of a fixed number of stationary white noise processes" (2017). However, for AR processes, it is more complicated to determine whether the presence of stationarity, due to the occurrence of unit roots, i.e., stochastic trends. The problem with unit roots is that "shocks (which may be due to policy intervention) have effects that last forever; whereas in stationary models, shocks can only have a temporary effect" (Schafgans, 2017). As shown in the seminal paper of Dickey & Fuller (1979) and bearing in mind equation (8), under the null that $\theta_k = 1$ the standard t-ratio does not have a t distribution, not even asymptotically, due to the presence of non-stationarity that invalidate inference. Instead, Dickey & Fuller (1979) proposed an standardize t-statistic and critical values in order to test stationarity (see Appendix 1):

$$\text{DF} = \frac{\hat{\theta} - 1}{se(\hat{\theta})} \quad (13)$$

Moreover, since the autocovariances of the time series are not standardized in time, the autocorrelations are defined as ρ_k:

$$\rho_k = \frac{cov\{Y_t, Y_{t-k}\}}{V\{Y_t\}} = \frac{\gamma_k}{\gamma_0} \quad (14)$$

Note that $\rho_0 = 1$, while $-1 \leq \rho_k \leq 1$.

The set of autocorrelations as a function of k is referred as the autocorrelation function (ACF) or correlogram. “From the ACF we can infer the extent to which one value of the process is correlated with previous values and thus the length and strength of the memory of the process” (Verbeek, 2017). Additionally, “if $\rho_k = 0$, the sampling distribution of r_k is approximately normal, with a mean of $-1/n$ and a variance of $1/n$…. If r_k [the sample ACF] falls outside these [values], we have evidence against the null hypothesis that $\rho_k = 0$ at the 5% level” (Cowpertwail & Mercalfe, 2009) Therefore, the 5% critical values are calculated as:

$$-\frac{1}{n} \pm \frac{2}{\sqrt{n}}$$

After the description of the stationary and autoregressive characteristics, the question riles on which model and order must be selected, i.e., the number of lags for both (p) and (q). Verbeek (2017) describes two characteristics in which the selection of models is based: the ACF and the Partial ACF (PACF). In the case of an AR(p) process, the ACF must be infinite in extent, in such way that it tails off; and the PACF must be close to zero, for lags larger than (p). In the case of a MA(q) process, the ACF must be close to zero for lags larger than (q), and the PACF must be infinite in extent (it tails off) (Verbeek, 2017). In the absence of these two situations in both models, a combined ARMA may provide a parsimonious representation of the data. In the case of the MA(q) process, as could be notice, the ACF provides the lag that must be imposed. For an AR(p) process, it is better to “fit” it with a Maximum Likelihood

Estimator (MLE), i.e., the number of lags depending on an index that penalizes models with too many parameters: the Akaike's Information Criterion (AIC).

$$AIC = log\sigma^2 + 2\frac{p+q+1}{N-k-1} \qquad (15)$$

The MLE method used in the fitting procedure above is based on maximizing the likelihood function (the probability of obtaining the data given the model) with respect to the unknown parameters. Then, the lowest AIC value of a model is chosen as the one that better fits the AR process. As mentioned before, there are cases in which a simple process is not enough to capture all the structure of the model. Therefore, a combination of processes is needed, giving us as a result the ARMA (p, q) process:

$$\mathrm{y_t} = \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} + \varepsilon_t + \alpha_1 \varepsilon_{t-1} + \cdots + \alpha_q \varepsilon_{t-q} \qquad (16)$$

Or expressed in the form of a backward operator

$$\Theta_p(B) y_t = \phi_q(B) \varepsilon_t \qquad (17)$$

When talking about more complex econometric time series models, the fundamentals of statistics arise once again. Trend and seasonal effects influence the observed data and therefore they change the model that must be applied. Even though, univariate models capture the effects of past values, there could also be the presence of some seasonal effects that always produces a rise in the value in some periods. The ARIMA(p, d, q) (autoregressive integrated moving average) model tries to transform it into a stationary series by first-order differencing the variable (Cowpertwail & Mercalfe, 2009). In this line, the seasonal ARIMA model, along with the AIC criteria are going to be used as the main framework in which the flow of regulation is going to be studied. In this way, monthly and quarterly seasonality is considered:

ARIMA $(p, d, q)(P, D, Q)$

$$\Theta_P(B^s)\theta_p(B)(1 - B^s)^D(1 - B)^d x_t = \phi_Q(B^s)\phi_q(B) w_t \qquad (18)$$

Where:

$$p = 1 \Rightarrow y_t = \phi y_{t-1} + \epsilon_t$$
$$P = 1 \Rightarrow y_t = \phi_s y_{t-s} \Rightarrow y_t = \phi_{12} y_{t-12} + \epsilon_t \quad s = 12\ (monthly\ data) \tag{19}$$

p refers to the autoregressive order

P refers to the seasonal autoregressive order

$$d = 1 \Rightarrow \Delta y_t = (y_t - y_{t-1})$$
$$D = 1 \Rightarrow \Delta^s y_t = (y_t - y_{t-s}) \Rightarrow \Delta^{12} y_t = (y_t - y_{t-12}) \quad s = 12\ (monthly\ data) \tag{20}$$

d refers to the simple difference of the series

P refers to the seasonal difference

$$q = 1 \Rightarrow y_t = \epsilon_t - \theta \epsilon_{t-1}$$
$$Q = 1 \Rightarrow y_t = \epsilon_t - \theta_s \epsilon_{t-s} \Rightarrow y_t = \epsilon_t - \theta_{12} \epsilon_{t-12} \quad s = 12\ (monthly\ data) \tag{21}$$

q refers to the simple moving average order

Q refers to the seasonal moving average order

3.2 Data

The data of the monthly flow of regulation is obtained from Alcívar (2017) and aggregated on a quarterly basis. The methodology applied by Alcívar (2017) is a version of the QuantGov technique that tries to quantify state and federal regulation in the United States. In this sense, the Ecuadorian Official Records and supplements that are daily posted were collected from October 20th, 2008, to May 24th, 2017. It is important to notice that this version of collecting regulation data does not capture the stock of regulation (due to the length of the data) but the flow of regulation. Furthermore, another limitation to this process is that there is no classification among regulations; this is to say that the variety of regulations is broad and covers all number of regulations, from economic regulations to environmental regulations.

Moreover, as mentioned by Alcívar (2017), the flow of regulations has a behavior that is related with presidential terms. In Ecuador, during the period analyzed, three terms are captured and in all of them one president remained in power. Furthermore, three phases are present, from October 2008 to February 2011, where there is not a definite tendency; until August 2015 where there is a lineal increase; and lastly, until 2017 when volatility and shocks are present. Finally, in order to characterize the flow of regulation the aggregate counter variable of Alcívar (2017) is going to be used as our monthly basis. and doing a cumulative process it is going to be changed into quarterly data.

4 RESULTS

4.1 Statistical description and filters

Before structuring the seasonal ARIMA model for the flow of regulation in Ecuador, statistical description is required to obtain basic insights about the distribution of the data in both, monthly and quarterly basis. From Figures (1) and (2), we conclude that there is a tendency, but it is not a linear one in both series; therefore, a deeper study is needed. Furthermore, seasonal effects do influence this process and corrections must be done. As mentioned before, the three phases of regulations in Ecuador are present and visually noticeable in monthly and quarterly basis. When discussing the moments of those time series; for monthly data, the average is 12,428 words with a standard deviation of 4,178; while for quarterly data, the mean is 37,598 with a standard deviation of 10,074 words. Also, in monthly data the maximum and minimum values are: 4,794 and 26,669; for quarterly data, the maximum value is 55,806 and the minimum value is 15,263.

Figure 1: Monthly Flow of Regulation from 2008 to 2017

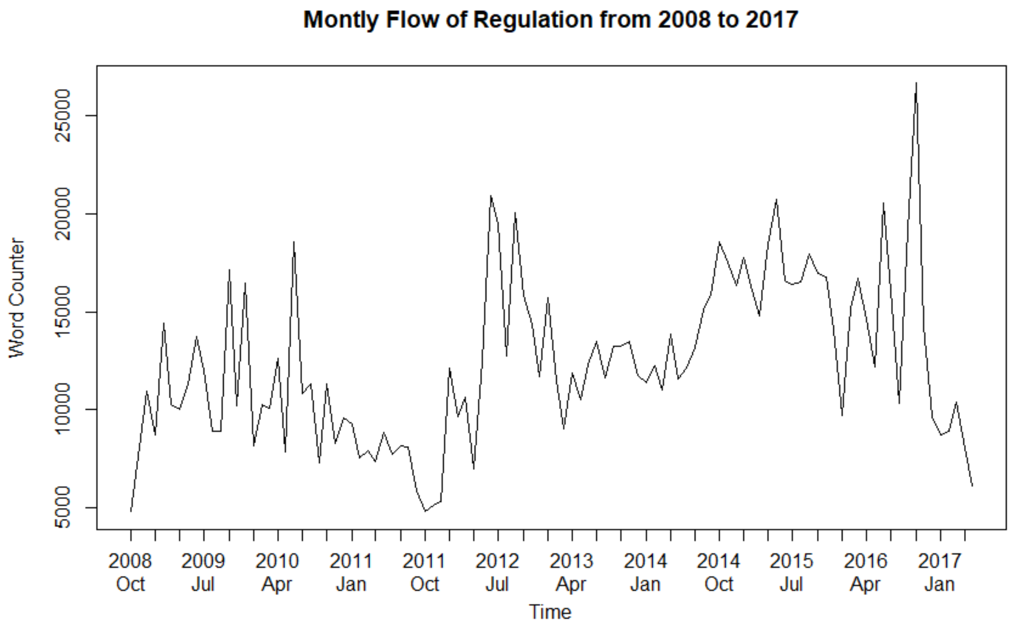
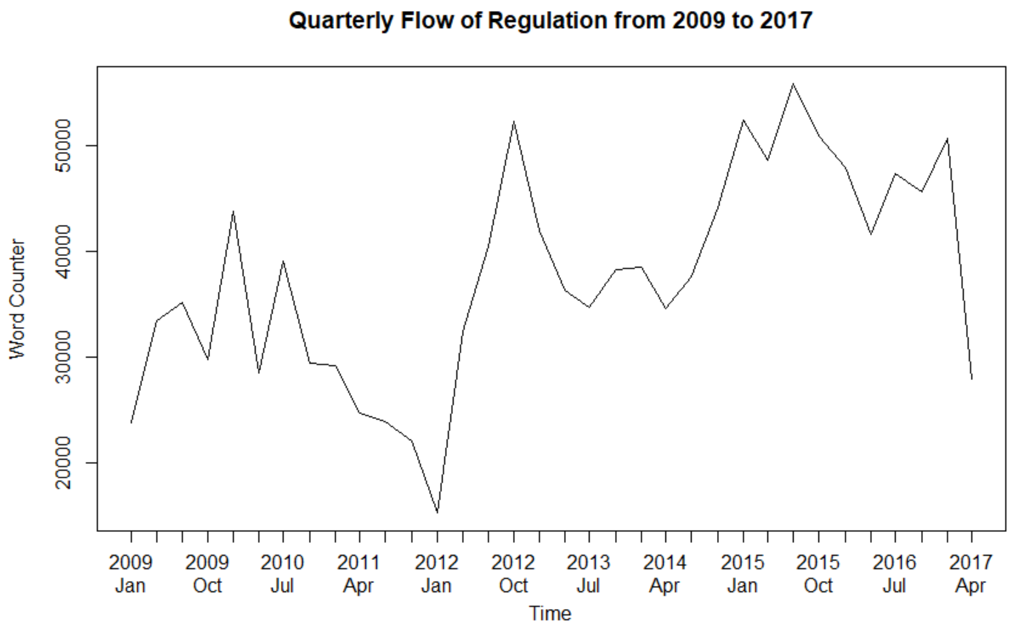


Figure 2: Quarterly Flow of Regulation from 2009 to 2017



The months with higher regulatory words are: June, October, July, September, and August; all the averages over the sample mean are reported in Table 1. The quarterly data has the same pattern, giving us the second and third quarters as the ones with greater regulatory flow (Table 2). After the statistical description, the common filters will be applied: moving averages and the Hodrick-Prescott Filter. The fitted results will be plotted and compared with the unfiltered time series. The Moving averages process will follow equations (5) and (6) from which the trend, seasonal components, and random variation are obtained from both series and plotted in Figures (3) and (4). As noticeable in the results, the seasonal component is present in both series and there is a pattern along all the period. Furthermore, the trends in both processes are not linear (as expected) and have been fitted into the process with the Moving Averages method. About the random variation, the results show us that after removing trend and seasonality, the mean is around 1 and the standard deviation is 0.192 and 0.116 for monthly and quarterly basis; that in fact is a correction that reduces the normal standard deviations that were 4,178 and 10,074 respectively.

Table 1: Monthly Distribution of Regulation

Monthly Distribution of Regulation

January	February	March	April	May	June
0,91	0,95	0,9	0,93	0,91	1,23
July	**August**	**September**	**October**	**November**	**December**
1,10	0,95	1,09	1,16	0,97	0,95

(1) > 1 represents regulation above the monthly mean
(2) < 1 represents regulation below the monthly mean

Table 2: Quarterly Distribution of Regulation

Quarterly Distribution of Regulation

I Quarter	II Quarter	III Quarter	IV Quarter
0,91	1,04	1,04	1,02

(1) > 1 represents regulation above the monthly mean
(2) < 1 represents regulation below the monthly mean

Figure 3: Moving Average Decomposition of Monthly Regulation

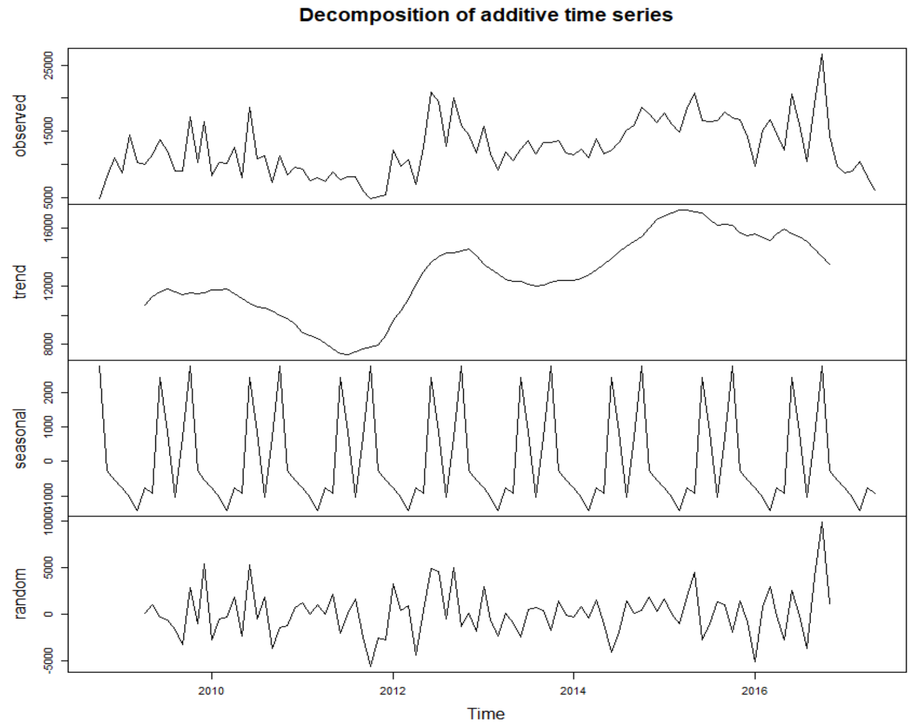
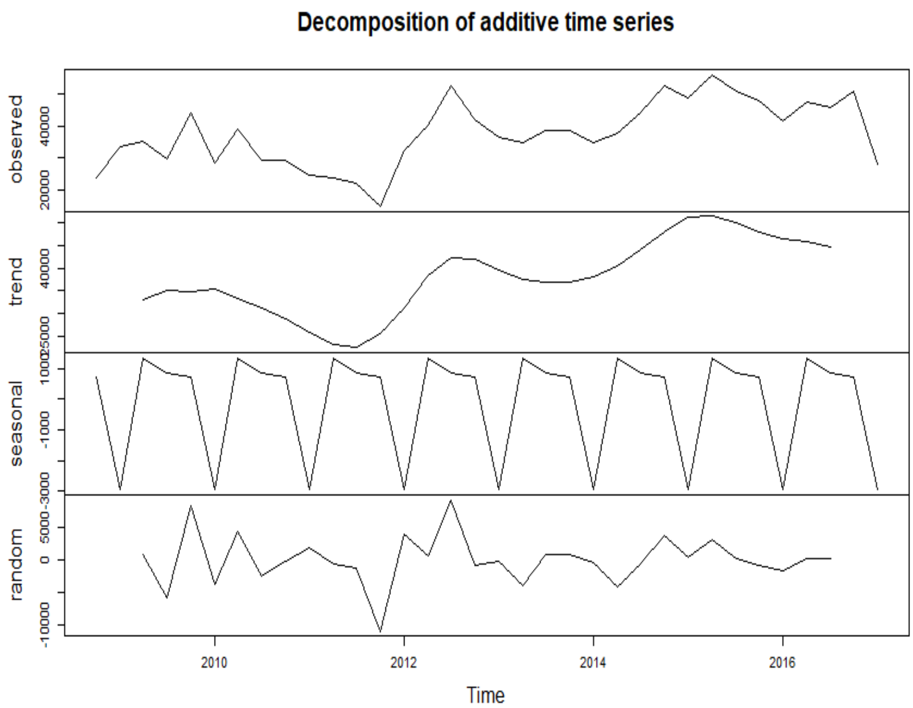


Figure 4: Moving Average Decomposition of Quarterly Regulation



Even though, the Moving Average method suggests a precise correction for the data; it does not encompass the theory of stationarity; therefore, an autocorrelation test must be applied to the random variation, that will be done in the next section. Moreover, the combined trend and seasonality are plotted in Figures (5) and (6) in order to have a better understanding of both time series. As reviewed in the methodology section, the Hodrick-Prescott (HP) filter is the most common filter applied to economic variables in order to obtain stationarity and to elaborate business cycles with the data.

Figure 5: Monthly Flow of Regulation from 2008 to 2017 - Trend & Seasonality

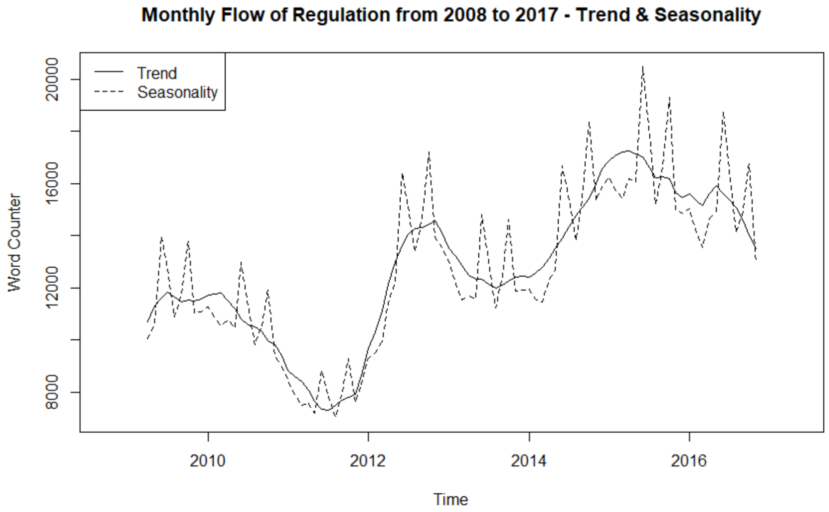
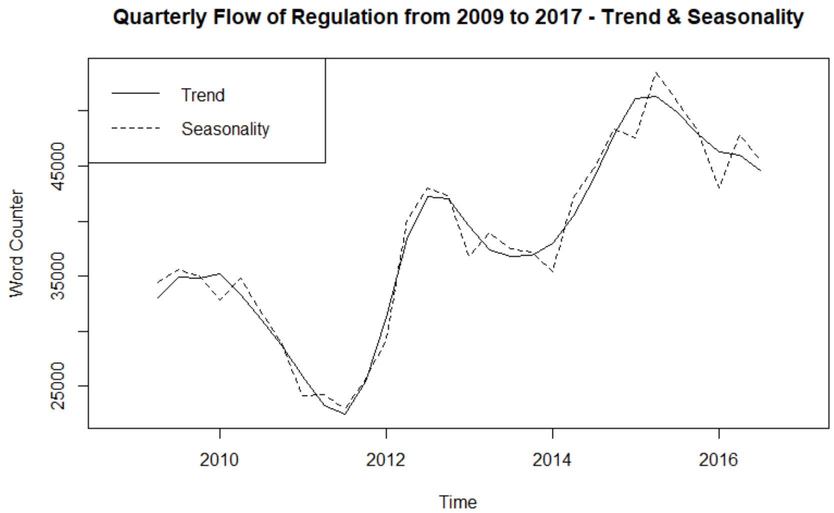


Figure 6: Quarterly Flow of Regulation from 2008 to 2017 - Trend & Seasonality



Recalling equation (7), with $\lambda = 14400$ and $\lambda = 1600$ for monthly and quarterly data, the HP filter was applied to the regulation data and as result Figure (7) and (8) are obtained. What calls our attention to this result is that for both time series the HP filter does not produces a suitable fit. This could be because as both series present high volatility; hence, a different lambda could be applied in order to obtain better results with this filter. Nevertheless, the application of the HP filter or any variation, are not part of this research. Moreover, the application of econometric theory could provide a better modeling process than any sophisticated filter. For this purpose, autocorrelation and stationarity must be considered as the main problems of the next models that are going to be tried on the data.

Figure 7: HP Filter for Monthly Regulation Data

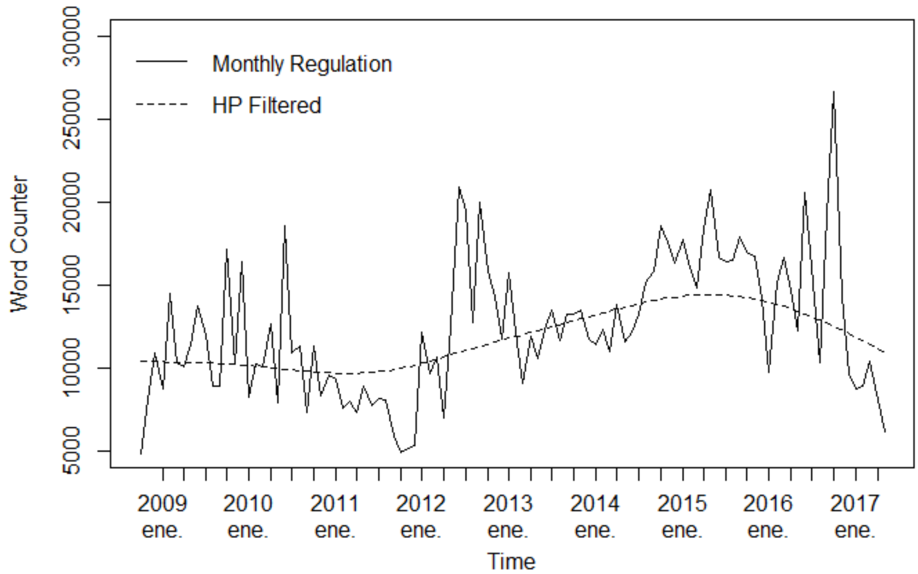
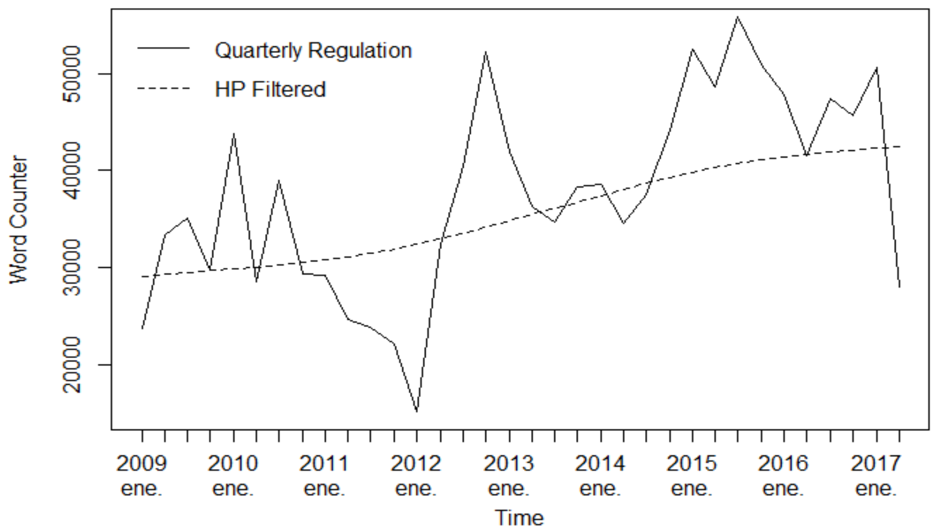


Figure 8: HP Filter for Quarterly Regulation Data



4.2 Autocorrelation and stationarity tests

The first step in econometric time series analysis is to define the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), established in Equation (14). Furthermore, as in Equation (13) the Dickey-Fuller test will help us to determine if there is stationarity in our process and how well models fit our data. The results of both techniques are shown in Figures (9), (10), and Tables (3) and (4), respectively for monthly and quarterly basis. The ACF tests reflect that, in monthly basis the autocorrelation is statistically insignificant after lag 6; and for quarterly data after lag 2. The Dickey-Fuller tests show that in a monthly basis the process is stationary in two lags, in processes with drifts and with/out trends. but after those periods the process is non-stationary. In quarterly data, the process is non-stationary in all lags.

Figure 9: ACF & PACF for Monthly Regulation

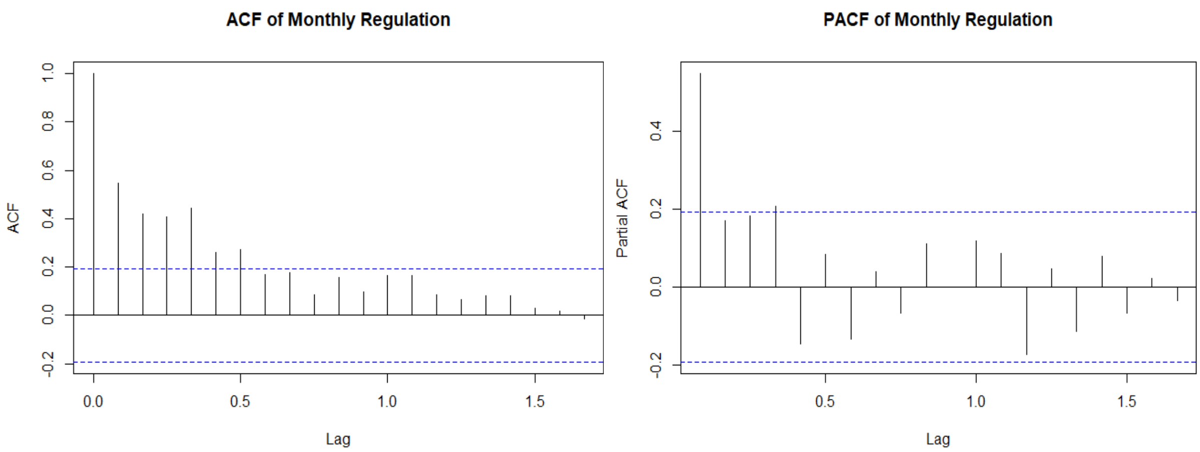


Table 3:Mothly Augmented Dickey-Fuller Test

alternative: stationary

Type 1: no drift no trend				Type 2: with drift no trend				Type 3: with drift and trend			
	lag	ADF	p.value		lag	ADF	p.value		lag	ADF	p.value
[1,]	0	-1.480	0.147	[1,]	0	-5.38	0.0100	[1,]	0	-5.74	0.010
[2,]	1	-1.033	0.308	[2,]	1	-3.88	0.0100	[2,]	1	-4.07	0.010
[3,]	2	-0.808	0.389	[3,]	2	-2.88	0.0534	[3,]	2	-2.94	0.185
[4,]	3	-0.590	0.468	[4,]	3	-2.20	0.2529	[4,]	3	-1.94	0.595
[5,]	4	-0.804	0.391	[5,]	4	-2.28	0.2222	[5,]	4	-2.43	0.396
[6,]	5	-0.656	0.444	[6,]	5	-2.03	0.3184	[6,]	5	-1.95	0.591
[7,]	6	-0.732	0.416	[7,]	6	-2.32	0.2049	[7,]	6	-2.48	0.373
[8,]	7	-0.735	0.415	[8,]	7	-2.29	0.2173	[8,]	7	-2.52	0.358
[9,]	8	-0.814	0.387	[9,]	8	-2.41	0.1708	[9,]	8	-2.76	0.258
[10,]	9	-0.642	0.449	[10,]	9	-2.07	0.3005	[10,]	9	-2.32	0.437

Note: in fact, p.value = 0.01 means p.value <= 0.01

Figure 10: ACF of Quarterly Regulation

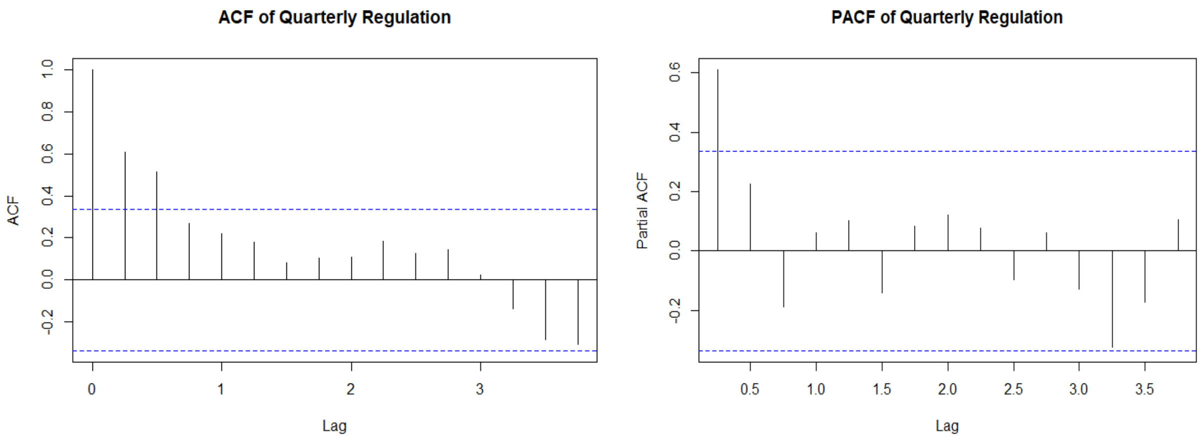


Table 4: Quarterly Augmented Dickey-Fuller Test

Augmented Dickey-Fuller Test

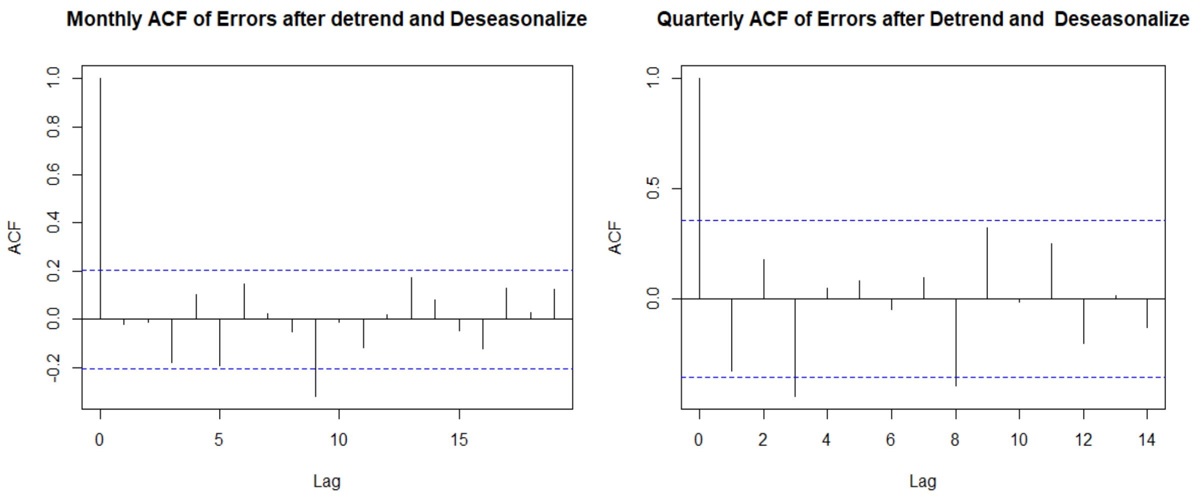
alternative: stationary

Type 1: no drift no trend				Type 2: with drift no trend				Type 3: with drift and trend			
	lag	ADF	p.value		lag	ADF	p.value		lag	ADF	p.value
[1,]	0	-0.553	0.473	[1,]	0	-2.737	0.0841	[1,]	0	-2.89	0.222
[2,]	1	-0.345	0.538	[2,]	1	-1.910	0.3631	[2,]	1	-2.11	0.516
[3,]	2	-0.574	0.465	[3,]	2	-2.175	0.2660	[3,]	2	-2.90	0.220
[4,]	3	-0.224	0.572	[4,]	3	-1.916	0.3608	[4,]	3	-2.22	0.474
[5,]	4	-0.347	0.537	[5,]	4	-1.335	0.5699	[5,]	4	-2.26	0.456
[6,]	5	-0.389	0.525	[6,]	5	-1.891	0.3698	[6,]	5	-2.78	0.263
[7,]	6	-0.118	0.603	[7,]	6	-1.306	0.5800	[7,]	6	-2.36	0.422
[8,]	7	0.105	0.667	[8,]	7	-1.020	0.6790	[8,]	7	-2.53	0.356
[9,]	8	0.373	0.744	[9,]	8	-1.187	0.6211	[9,]	8	-1.85	0.618
[10,]	9	0.524	0.787	[10,]	9	-0.841	0.7413	[10,]	9	-2.13	0.507

Note: in fact, p.value = 0.01 means p.value <= 0.01

Moreover, the ACF observation discards the Moving Average process, due to the presence of significant autocorrelation at lag 9 in monthly data and, lags 3 and 8 in quarterly data (Figure 11).With the data obtained from these analyses, and after rejecting the filters as methods to be used in this time series, it is now possible to set up some basic models as an Autoregressive (AR) or Moving Average (MA) with the adequate orders that were studied in section 3. Furthermore, the analysis will continue to the ARIMA and seasonal ARIMA processes from which the last is the main model to be applied in this paper.

Figure 11: Monthly and Quarterly Detrend and Deseasonalize ACF



4.3 Univariate models: Autoregressive and Moving Average processes

Following the Verbeek (2017) approach to univariate time series models, the MA(q) model is effortless to specify. An observation of the ACF provide us enough information in order to set the lags of the process; hence, for monthly data, after lag 6, the autocorrelation is statistically indistinguishable from 0 at 5 % significance level, and for quarterly data after lag 2, the autocorrelation is statistically 0 at the same significance level. The models in MA process could be written as:

$x_t = \epsilon_t + \alpha\, \epsilon_{t-1} + \alpha^2\, \epsilon_{t-2} + \alpha^3\, \epsilon_{t-3} + \alpha^4\, \epsilon_{t-4} + \alpha^5\, \epsilon_{t-5} + \alpha^6\, \epsilon_{t-6}$ for monthly data, with

$$x_t = \epsilon_t + 0.478\, \epsilon_{t-1} + 0.0832\, \epsilon_{t-2} + 0.345\, \epsilon_{t-3} + 0.433\, \epsilon_{t-4} + 0.183\, \epsilon_{t-5} + 0.452\, \epsilon_{t-6}$$

and

$x_t = \epsilon_t + \alpha\, \epsilon_{t-1} + \alpha^2\, \epsilon_{t-2}$, with

$x_t = \epsilon_t + 0.5596\, \epsilon_{t-1} + 0.7897\, \epsilon_{t-2}$, for quarterly data.

In the case of the Autoregressive models, since it is not easy to interpret the Partial Autocorrelation Function along with the Autocorrelation Function, the MLE procedure with the AIC variable are conducted, as suggested by Cowpertwail & Mercalfe (2009). The results of the model are reported as an AR (5) for monthly data and AR (1) for quarterly data:

$Y_t = \delta + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \theta_3 Y_{t-3} + \theta_4 Y_{t-4} + \theta_5 Y_{t-5} + \epsilon_t$, with

$Y_t = 1 + 0.439\ Y_{t-1} + 0.092\ Y_{t-2} + 0.102\ Y_{t-3} + 0.295\ Y_{t-4} - 0.170\ Y_{t-5} + \epsilon_t$, for monthly data,

$Y_t = \delta + \theta_1 Y_{t-1} + \epsilon_{t,}$, with

$Y_t = \delta + 0.6479\ Y_{t-1} + \epsilon_{t,}$ for quarterly data.

As mentioned by Verbeek (2017) the selection of models is not based on any subjective parameter that could give us the perfect model for our time series. Yet, the models follow the econometric theory of lag selection; hence, a diagnostic of the residuals must be conducted in order to determine whether the modelling process is working in a suitable way. Furthermore, the combination of models (ARMA) improves the estimation of the previous univariate time series methods. Appendixes 2 to 7 summarize the residuals diagnostic for all models, where the ACF, PACF, White Noise Probability and Theoretical Quantiles are displayed. Subsequently, we can conclude that; for monthly models, the AR process does not correct the PACF, the residuals do not follow a White Noise process after lag 7 and the theoretical quantiles do not fit with the model extremes (see Appendix 2). For the MA (6) model, it does not reduce the PACF to 0 when lag $\longrightarrow \infty$, and the White Noise probability could be improved (see Appendix 3). The combination of models as the ARMA (5, 6) provides a better fit, but the White Noise probability, along with the theoretical Quantiles represent major issues for applying this model, due to non-stationary characteristics (see Appendix 4).

On the other hand, for quarterly basis models, the AR (1) does not reduce the PACF to 0 in time, the White Noise probability is not significant enough and the theoretical quantiles go out of the expected values (see Appendix 5). The MA (2) process, does not correct the PACF and the theoretical quantiles do not fit the expectation (see Appendix 6). Finally, both models together provide a satisfactory fit, but the PACF could be improved to reduce its value in time (see Appendix 7). For this reason and because no model has seasonality characteristics, the next section will develop the application of the seasonal ARIMA model as discussed in section 3.

4.4 The ARIMA model

As defined by Cowpertwail & Mercalfe (2009), "a seasonal ARIMA model uses differencing at a lag equal to the number of seasons (s) to remove additive seasonal effects". The specification of a seasonal ARIMA model, could have several combinations depending on the orders and lags that could be included, because of the presence of the AR, MA, and integration parts: ARIMA $(p, d, q)(P, D, Q)$. Hence, it is relevant to try a wide range of models before arriving at the best fitting one. For this purpose, the Akaike's Information Criterion (AIC) must be used in both monthly and quarterly series.

For monthly regulation, the seasonal ARIMA model is specified as follows:

ARIMA $(4,0,4)(1,0,0)_{12}$

$$\Theta_1(B^{12})\theta_4(B)(1-B^{12})^0(1-B)^d x_t = \phi_0(B^{12})\phi_4(B)w_t \qquad (22)$$

Where:

$$p = 4 \Rightarrow y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \phi_4 y_{t-4} + \epsilon_t, \text{ with}$$

$$\mathbf{B}(\mathbf{AR}): 1 + 0.368\mathbf{B^1} + 0.888\mathbf{B^2} - 0.339\mathbf{B^3} - 0.1911\mathbf{B^4}$$

$$P = 1 \Rightarrow y_t = \phi_s y_{t-s} \Rightarrow y_t = \phi_{12} y_{t-12} + \epsilon_t \quad s = 12\ (monthly\ data), \text{ with} \qquad (23)$$

$$\mathbf{B}(\mathbf{S}_{ar}): 1 + 0.131\mathbf{B^{12}}$$

p refers to the autoregressive order

P refers to the seasonal autoregressive order

$$d = 0 \Rightarrow \Delta y_t = 0$$

$$D = 0 \Rightarrow \Delta^s y_t = (y_t - y_{t-s}) \Rightarrow \Delta^{12} y_t = 0 \quad s = 12\ (monthly\ data) \qquad (24)$$

d refers to the simple difference of the series

D refers to the seasonal difference

$$q = 4 \ \Rightarrow y_t = \epsilon_t - \theta\epsilon_{t-1} - \theta\epsilon_{t-2} - \theta\epsilon_{t-3} - \theta\epsilon_{t-4}, \text{ with}$$

$$\boldsymbol{B}(\boldsymbol{MA}) \colon 1 + 0.0894\mathbf{B}^{\mathbf{1}} - 0.781\mathbf{B}^{\mathbf{2}} + 0.1996\mathbf{B}^{\mathbf{3}} + 0.542\mathbf{B}^{\mathbf{4}} \qquad (25)$$

$$Q = 0 \Rightarrow y_t = \epsilon_t - \theta_s\epsilon_{t-s} \ \Rightarrow y_t = 0 \quad s = 12\ (monthly\ data)$$

q refers to the simple moving average order

Q refers to the seasonal moving average order

Residuals tests are reported in Appendixes 8 and 9 for monthly and quarterly basis. On the other hand, in quarterly data, the seasonal ARIMA model is specified as follows:

ARIMA $(7{,}1{,}6)(1{,}1{,}1)_4$

$$\Theta_1(B^4)\theta_7(B)(1 - B^4)^1(1 - B)^1 x_t = \phi_1(B^4)\phi_6(B)w_t \qquad (26)$$

Where:

$$p = 7 \ \Rightarrow y_t = \phi y_{t-1} + \phi y_{t-2} + \phi y_{t-3} + \phi y_{t-4} + \phi y_{t-5} + \phi y_{t-6} + \phi y_{t-7} + \epsilon_t$$

$$P = 1 \Rightarrow y_t = \phi_s y_{t-s} \ \Rightarrow y_t = \phi_4 y_{t-4} + \epsilon_t \quad s = 4\ (quarterly\ data) \qquad (27)$$

p refers to the autoregressive order

P refers to the seasonal autoregressive order

$$d = 1 \ \Rightarrow \Delta y_t = (y_t - y_{t-1})$$

$$D = 1 \Rightarrow \Delta^s y_t = (y_t - y_{t-s}) \ \Rightarrow \Delta^4 y_t = (y_t - y_{t-4}) \quad s = 4\ (quarterly\ data) \qquad (28)$$

d refers to the simple difference of the series

P refers to the seasonal difference

$$q = 6 \ \Rightarrow y_t = \epsilon_t - \theta\epsilon_{t-1} - \theta\epsilon_{t-2} - \theta\epsilon_{t-3} - \theta\epsilon_{t-4} - \theta\epsilon_{t-5} - \theta\epsilon_{t-6}$$

$$Q = 1 \Rightarrow y_t = \epsilon_t - \theta_s\epsilon_{t-s} \ \Rightarrow y_t = \epsilon_t - \theta_4\epsilon_{t-4} \quad s = 4\ (quarterly\ data) \qquad (29)$$

q refers to the simple moving average order

Q refers to the seasonal moving average order

5 DISCUSSION

5.1 The ARIMA model & economic analysis

While an econometric model gives us the best fitting process that describes the times series, the interpretation of the results, e.g., the meaning of an AR (1) process, is beyond the scope of the econometric literature. However, for our purposes we could mention the behavior of y in terms of t, such that y_t is defined in terms of an Autoregressive, Integrated, Moving Average and seasonal patterns. Thus, the economic implications of this characterization will be deployed for both time series. Describing monthly data, the AR (4) tells us that regulation in t depends linearly on the regulation level at $t-1$, $t-2$, $t-3$ & $t-4$. An I (0) implies that the time series does not need to be differentiated in order to present a stationary process with no trend. The MA (4) implies that regulation in t depends linearly on the regulation shocks at $t-1$, $t-2$, $t-3$ & $t-4$.The seasonality, in this case is 1 for the AR process, thus, this is a simple transformation over $t-12$ periods.

On the other hand, the quarterly time series the AR (7) tells us that regulation in t depends linearly on the regulation level seven times backwards. An I (1) implies that the first difference converges the series into a stationary process with no trend. The MA (6) implies that regulation in t depends linearly on the regulation shocks at lag number 6. Nevertheless, the structure of this model does not provide an adequate fit for our purposes. This is to say that there are problems of convergence in the data while trying different models. This could be possible because of the length of the data, 34 observations are not enough for a quarterly seasonal ARIMA model that identifies patterns and provides us a relevant estimation; nevertheless, the model is reported in Appendix 9.

6 CONCLUSION

To sum up, this paper studies the different univariate time series models and adapts them to monthly and quarterly flow of regulation with the aim of obtaining first insights about the behavior of both series. As mentioned in the previous section, the analysis and economic interpretations of the models described in section 4 are not straightforward and therefore, further research should focus attention on the economic studies are to be conducted. In our case, the univariate models give us the lag structure in Autoregressive and Moving Average models, along with the seasonal description that the series maintains.

For monthly data, we conclude that regulation in time t depends linearly on regulation and on the regulation shocks at four lags, while controlling for seasonality at 12 periods. Thus, the monthly data after applying the ARIMA (4,0,4) $(1,0,0)_{12}$ is stationary and is controlled for autocorrelation. For quarterly data, due to the small subset of observations, the results are not robust enough to be considered appropriate. Nevertheless, the first difference transforms the model into a stationary one with no autocorrelation. Now that the ground has been set, the analysis about regulation could be applied, here multivariate time series arises, and this paper provides the basis for the different models. Cointegration between the flow of regulation and aggregate economic variables, and the use of Vector Autoregressive models could be the main guidelines for further multivariate characterization of regulation.

Finally, Dawson &Seater (2013) use cointegrated process in order to calculate the effect of regulation over GDP, Total Factor Productivity and Capital in the United States. Therefore, the contribution of this paper is to set the ground over the time series analysis required in order to obtain the correct characterization of the flow of regulation. Multivariate models and the study of cointegration processes over the previously analyzed series are the next step in order to determine the quantitative effect of regulation on the macroeconomy of Ecuador.

7 BIBLIOGRAPHY

Alcívar, J. (2017). *Cuantificación de las restricciones legales en el Ecuador durante el período 2008-2017 [Trabajo de Titulación]*. Quito: Universidad San Francisco de Quito.

Alesina, A., Ardagna, S., Nicoletti, G., & Schiantarelli, F. (2003). *Regulation and Investment. Working Paper #950.* Cambridge, MA: National Bureau of Economic Research.

Broughel, J. (2017). *Regulation and Economic Growth. Applying Economic Theory to Public Policy.* United States of Amerca: Mercatus Center ar George Mason University.

Coffey, B., Mclaughlin, P., & Peretto, P. (2016). *The Cumulative Cost of Regulations.* Duke I&E Research Paper No. 2016-45; Mercatus Research Paper 2016. doi: http://dx.doi.org/10.2139/ssrn.2869145

Córdova, G. (2005). *Estimación del Stock de Capital para la Economía Ecuatoriana en Dolarización. Maestría en Ciencias Económicas con Mención en Macroeconomía y Finanzas.* Quito - Ecuador: FLACSO.

Cowpertwail, P., & Mercalfe, A. (2009). *Introductory Time Series with R.* United States of America: Springer.

Dawson, J., & Seater, J. (2013). Federal Regulation and Aggregate Economic Growth. *Journal of Economic Growth*. Retrieved from https://ssrn.com/abstract=2223315

Djankov, S., LaPorta, R., Lopez-De-Silanes, F., & Shleifer, A. (2002). The Regulation of Entry. *Quarterly Journal of Economics, 117,* 1-37.

Goff, B. (1996). *Regulation and Macroeconomics Performance.* Boston: Kluwer.

Greene, W. (2012). *Econometric Analysis* (7th ed.). United States: Pearson.

Hamilton, J. (2017). Why You Should Never Use the Hodrick-Prescott Filter. *The Review of Economics and Statistics*.

Hodrick, R., & Prescott, E. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking, Vol. 29*(1), 1-16.

Jalialian, H., Kirkpatrick, C., & Parker, D. (2007). The Impact of Regulation on Economic Growth in Developing Countries: A Cross-Country Analysis. *World Development Vol. 35*, 87-103. Retrieved from https://www.sciencedirect.com/science/article/pii/S0305750X06001823

Johnston, J., & Dinardo, J. (1997). *Econometric Methods.* McGraw-Hill.

Peretto, P. (2007). Corporate Taxes, Growth, and Welfare in a Scumpeterian Economy. *Journal of Economic Theory, 137*, 353-382.

Schafgans, M. (2017). Advanced Econometrics. Time Series [PDF Slides]. London School of Economics Summer School.

Stigler, G. (1971). The Theory of Economic Regulation. *Bell Journal of Economics and Management Science*, 3-21.

Verbeek, M. (2017). *A Guide to Modern Econometrics.* United States: Wiley.

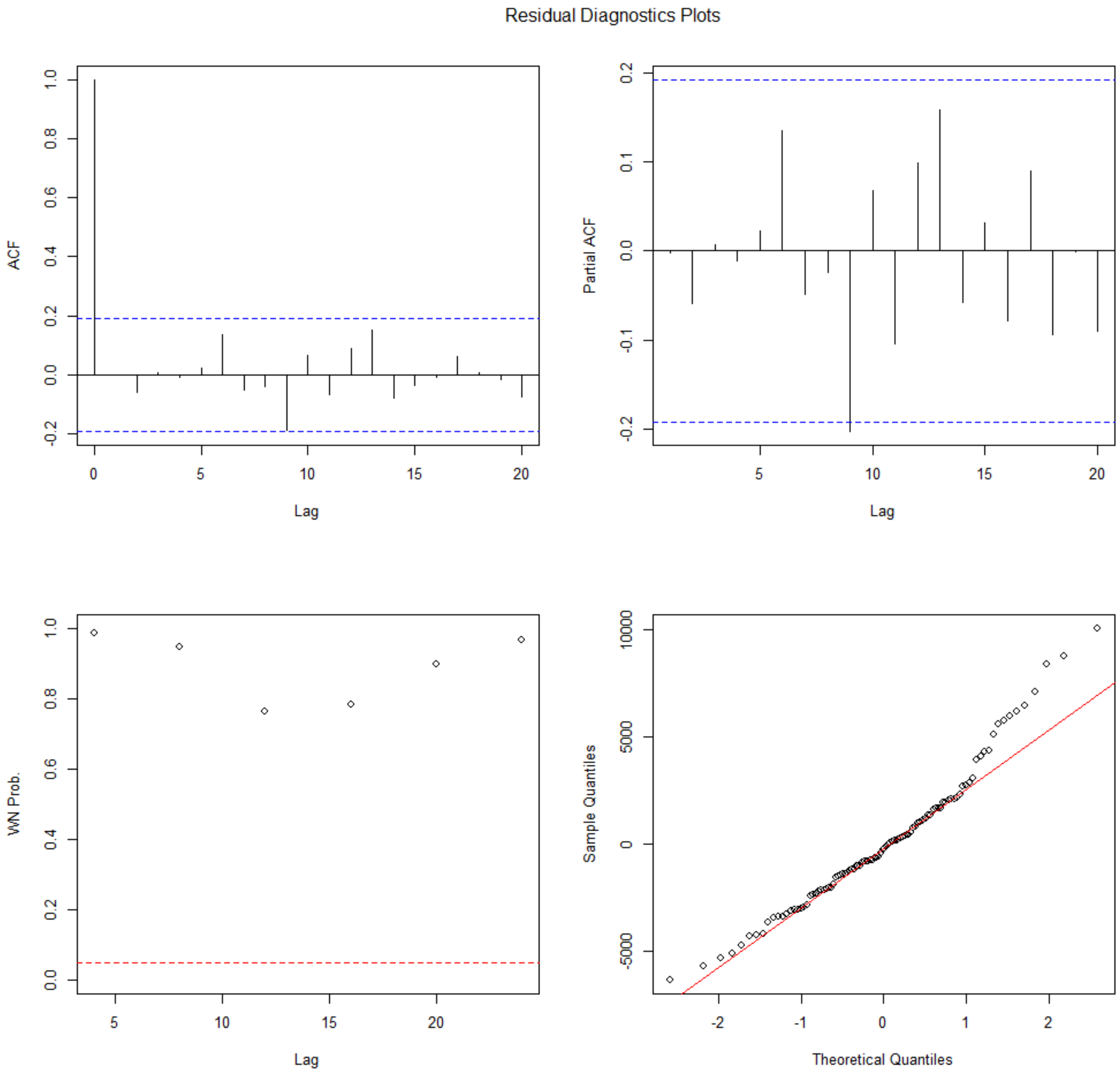
8 APPENDIX 1: DICKEY-FULLER CRITICAL VALUES

1% and 5 % critical values for Dickey-Fuller tests

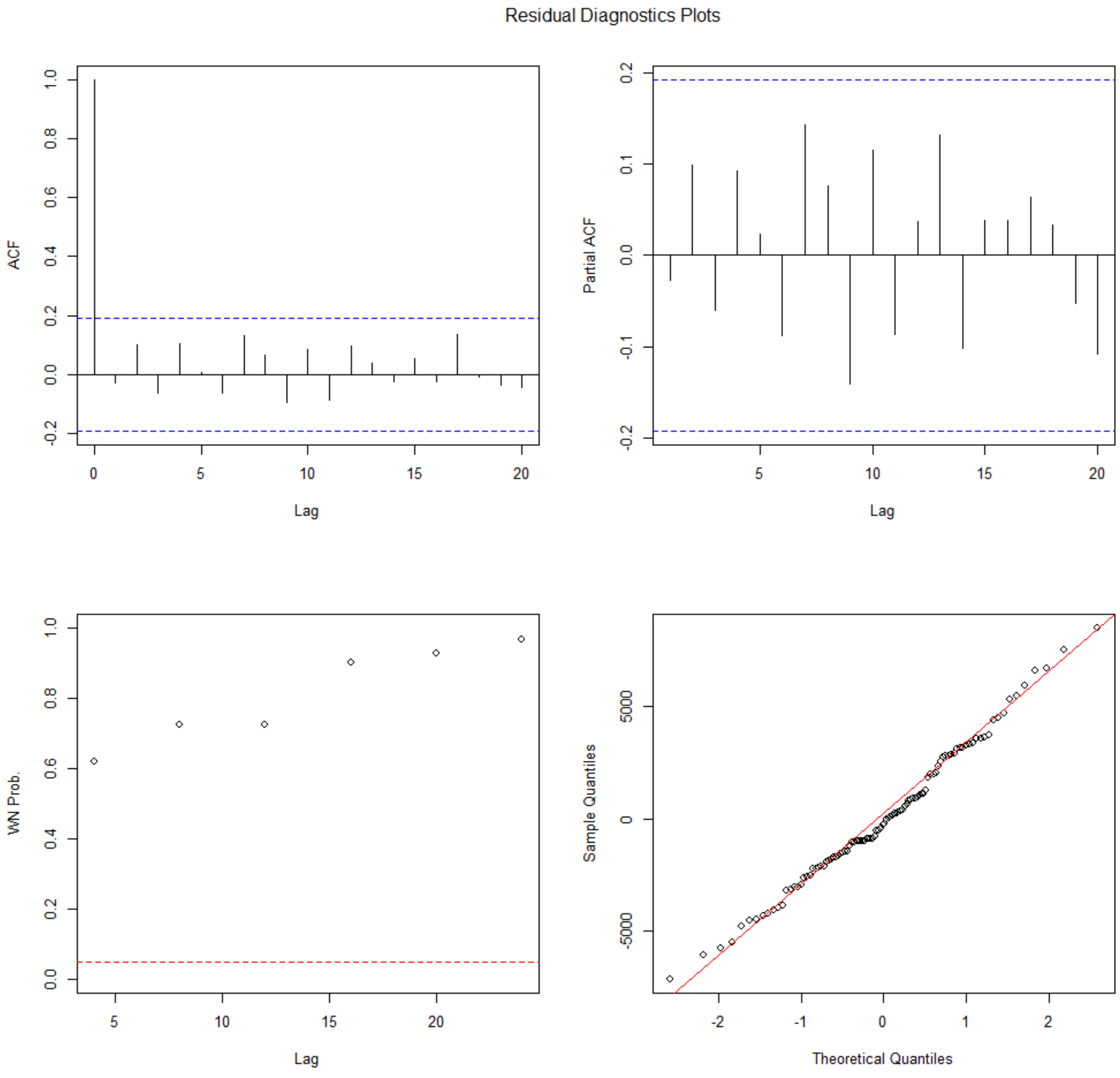
	Without trend		With trend	
Sample size	1%	5%	1%	5%
T = 25	-3,75	-3,00	-4,38	-3,60
T = 50	-3,58	-2,93	-4,15	-3,50
T = 100	-3,51	-2,89	-4,04	-3,45
T = 250	-3,46	-2,88	-3,99	-3,43
T = 500	-3,44	-2,87	-3,98	-3,42
T = ∞	-3,43	-2,86	-3,96	-3,41

Source: Fuller, W. (1976). *Introduction to Statistical Time-Series.* p. 373. John Wiley &Sons Inc: New York.

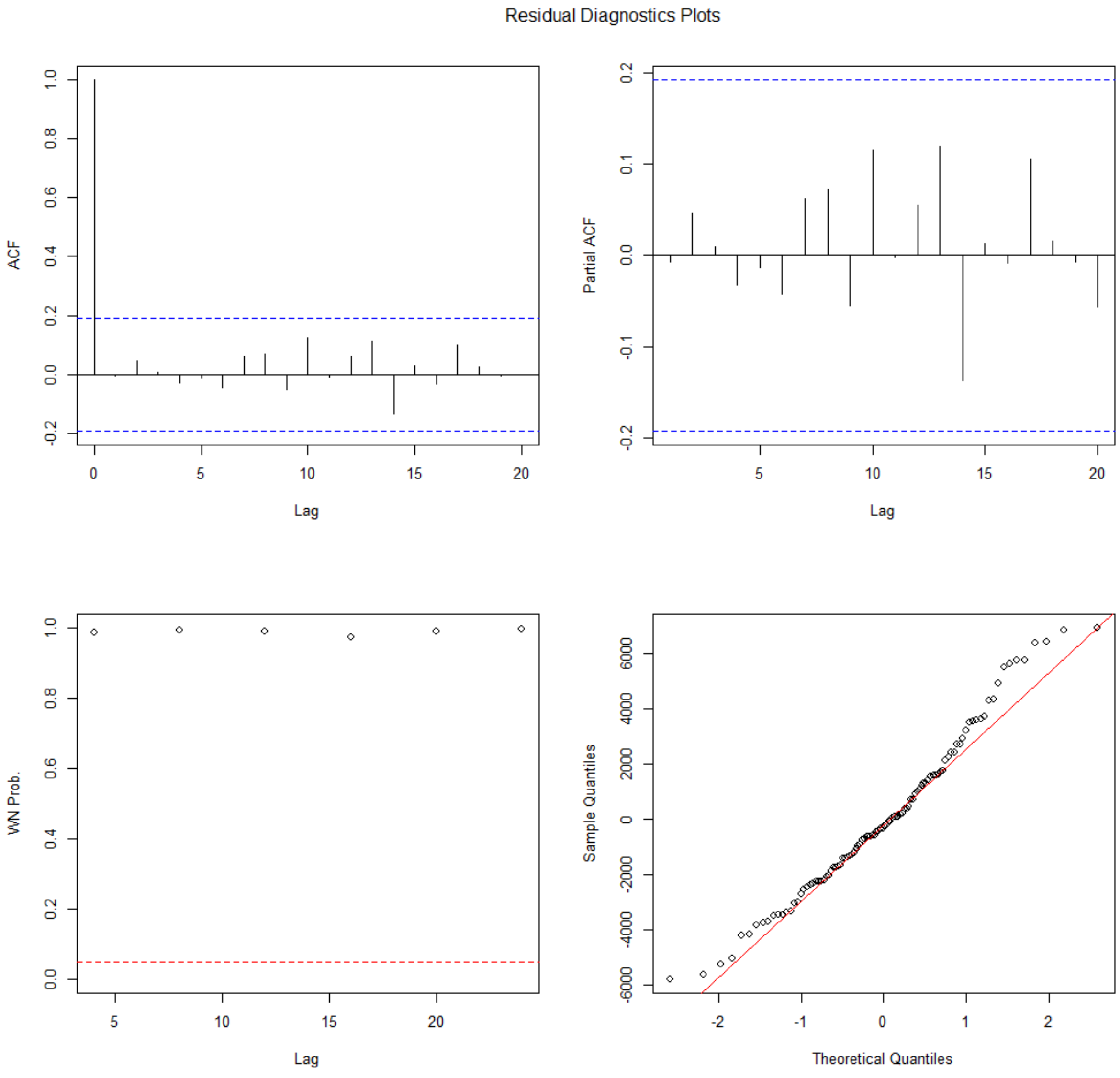
9 APPENDIX 2: MONTHLY AR (5) RESIDUAL DIAGNOSTIC PLOTS



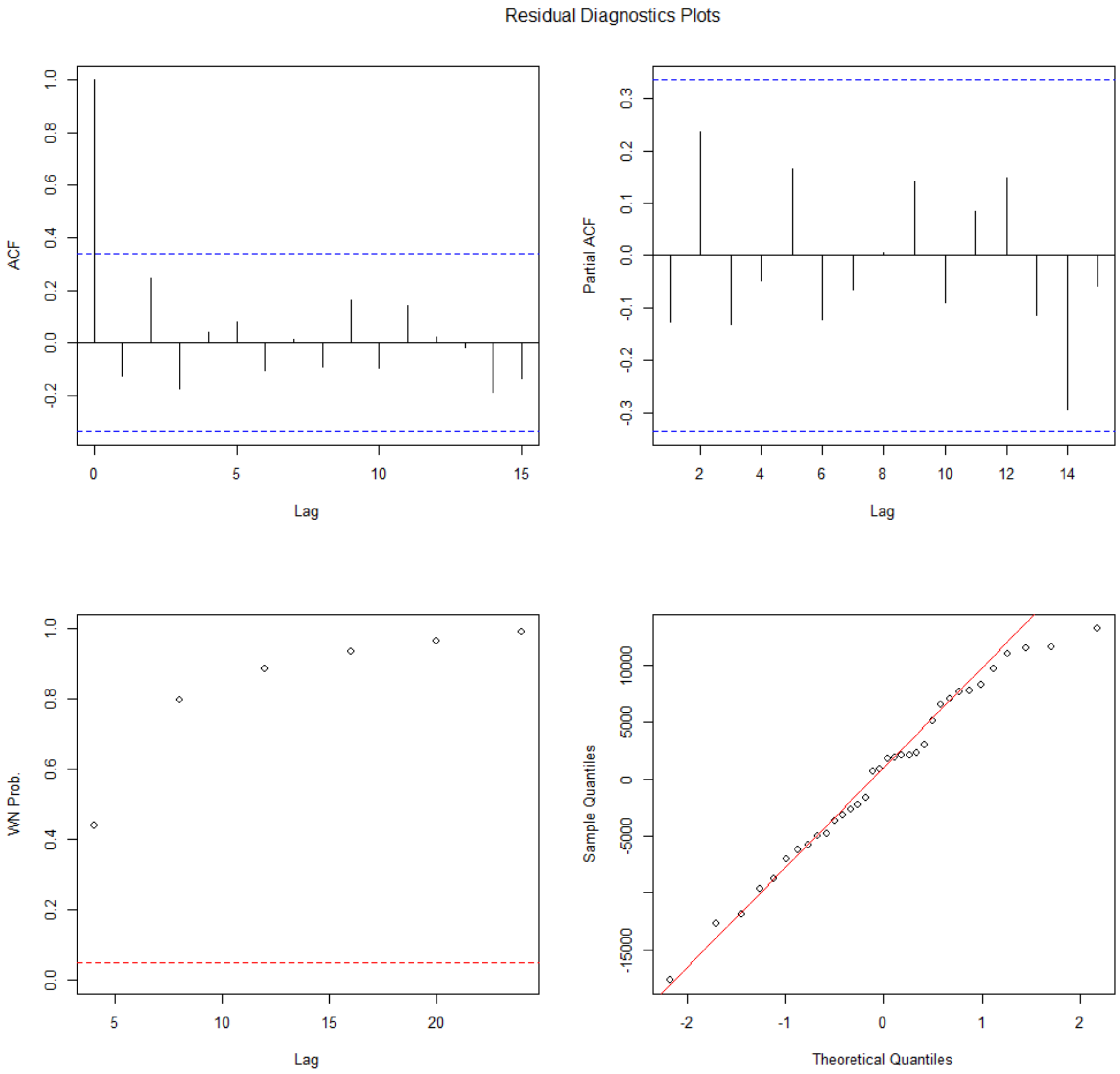
10 APPENDIX 3: MONTHLY MA (6) RESIDUAL DIAGNOSTIC PLOTS



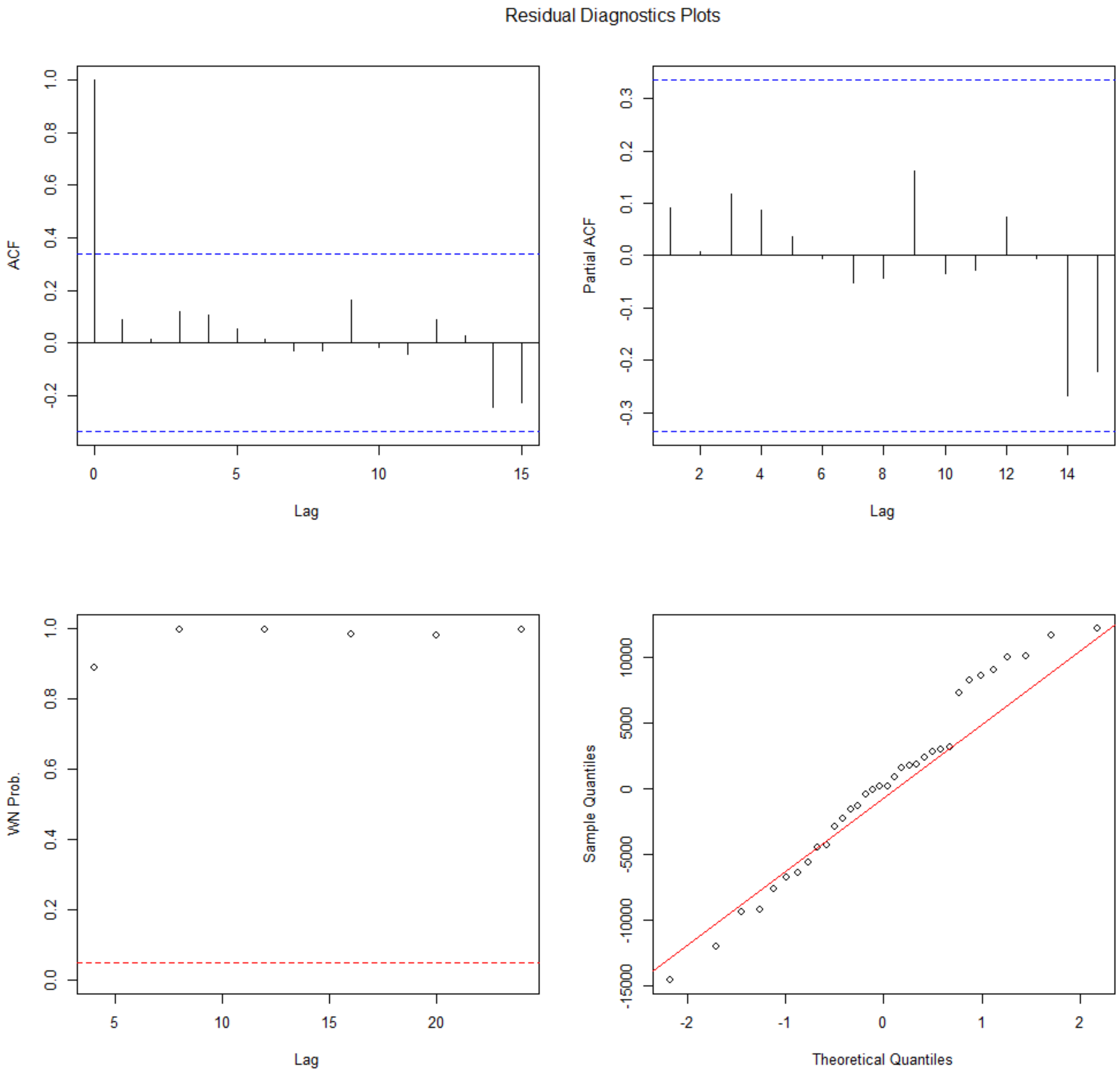
11 APPENDIX 4: MONTHLY ARMA (5,6) RESIDUAL DIAGNOSTIC PLOTS



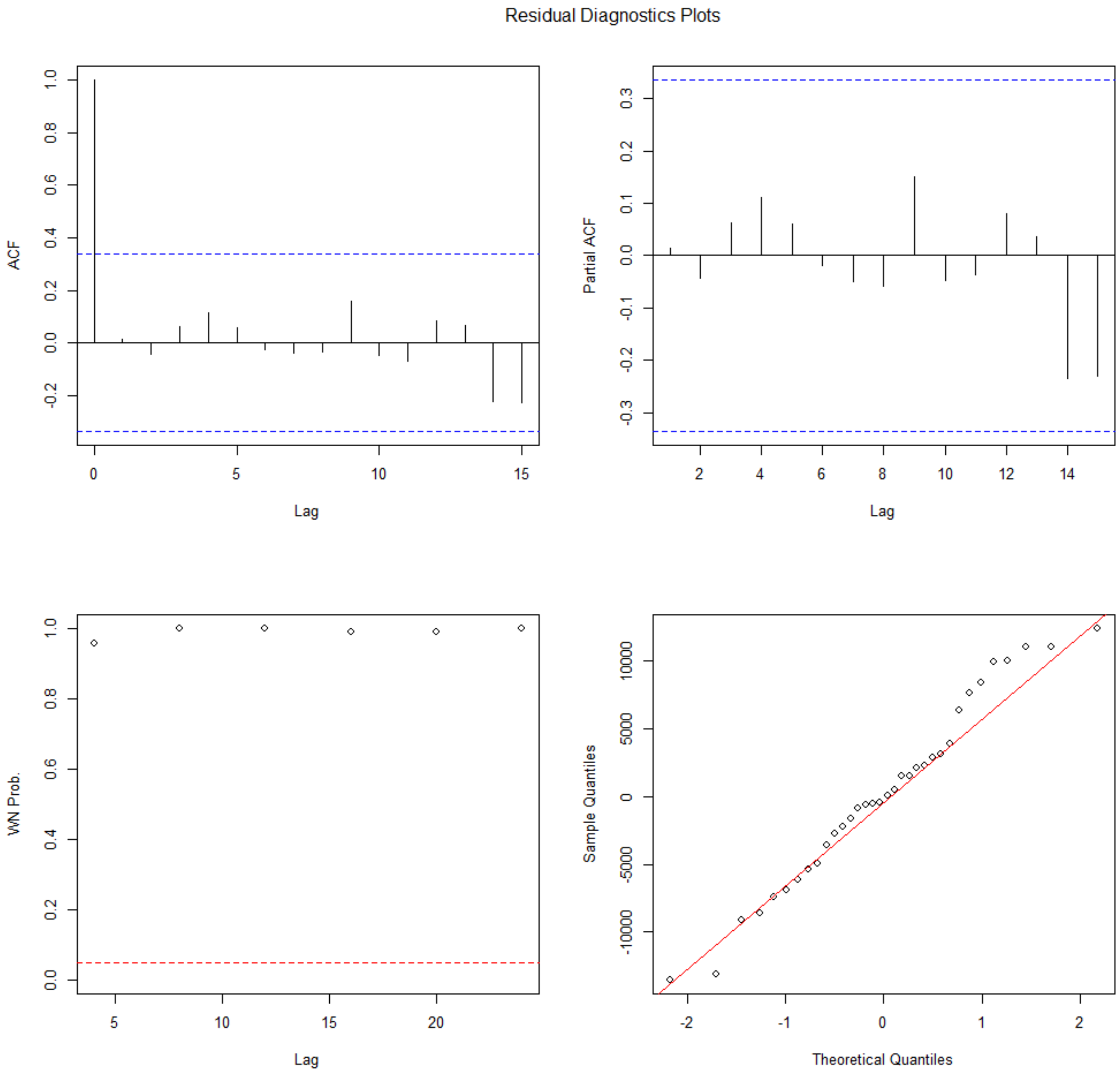
12 APPENDIX 5: QUARTERLY AR (1) RESIDUAL DIAGNOSTIC PLOTS



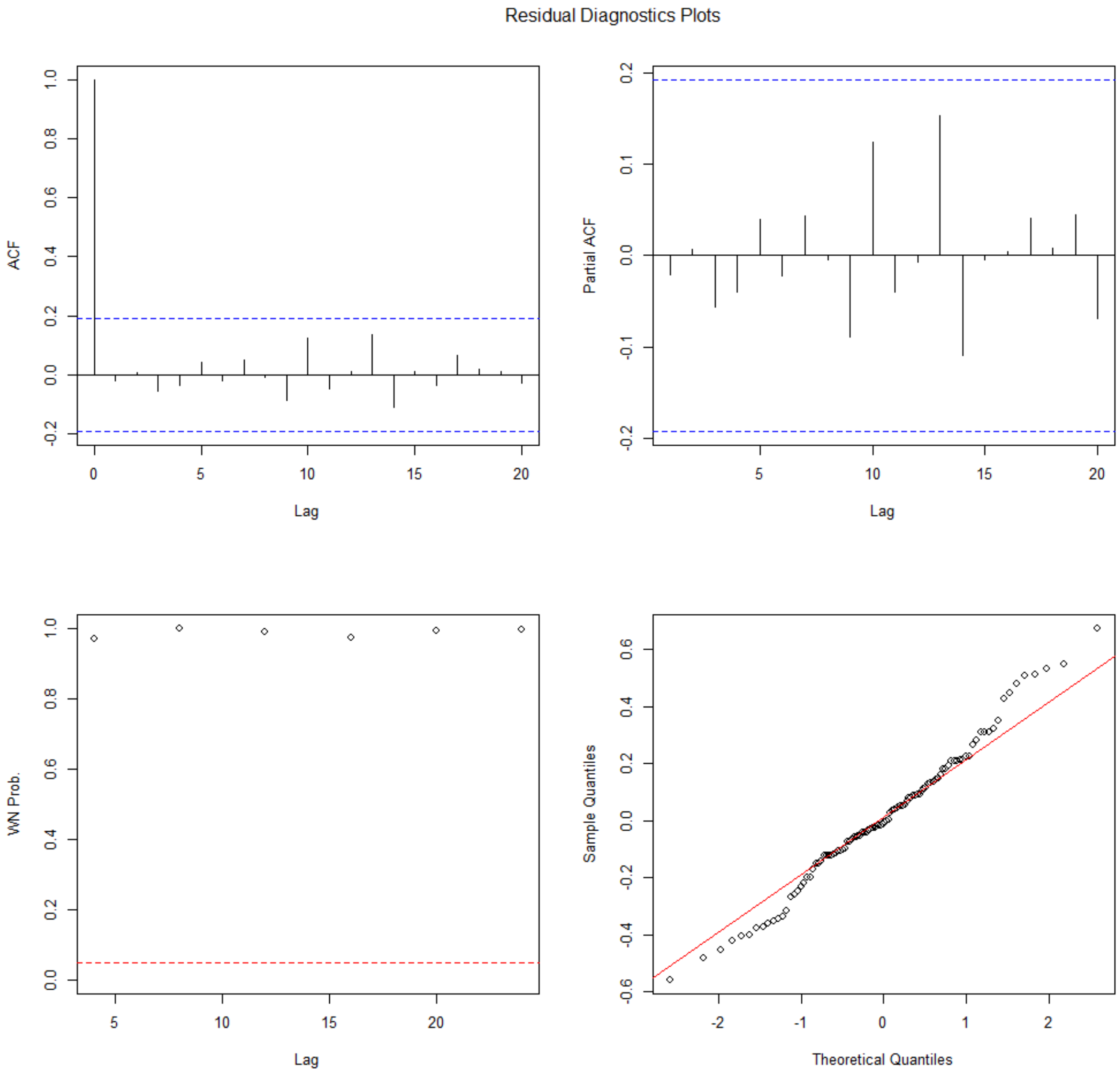
13 APPENDIX 6: QUARTERLY MA (2) RESIDUAL DIAGNOSTIC PLOTS



14 APPENDIX 7: QUARTERLY ARMA (2) RESIDUAL DIAGNOSTIC PLOTS



15 APPENDIX 8: SEASONAL ARIMA MONTHLY MODEL



16 APPENDIX 9: SEASONAL ARIMA QUARTERLY MODEL