# Are their collar still white? White-collar crime: Evidence from Paraguay 2000-2016

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# ARE THEIR COLLARS STILL WHITE?

# WHITE-COLLAR CRIME: EVIDENDENCE FROM PARAGUAY 2000–2016

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**Abstract**
This research paper contributes to the literature of white-collar crime by using a unique data set of aggregated monthly white-collar crime incidents for Paraguay. The time series includes data from 2000–2016. Furthermore, a seasonal ARIMA model is presented to model the data. Findings show that white-collar crime has increased more than 800 percent and crime rate more than 640 percent respectively, with a peak in 2015. Fraud and violation of trust contribute to over 91 percent of aggregated white-collar crime. A prediction for 2017 indicates a slight decrease of 5.7 percent compared to 2016.

**Keywords**: White-collar crime, Paraguay, ARIMA models, Time series, Model selection, Akaike weights

## Introduction

While preparing this paper the Brazilian construction company Odebrecht has caused a kind of corruption earthquake in eleven Latin American countries. Corruption in Latin America is not a surprise. Local habitants of these countries already know since quite a while who is who of their local representatives who's white collar is turning grey or black. Even the social and economic magnitude is not a big surprise. It is widely known that corruption involves public servants – often high ranking officials – and that corruption moves millions of US dollars each year. What is kind of surprising is the public attitude against corruption in most of the affected countries, represented by public enforcement agencies and sentences of the justice system. They simply apply current existing law, regardless of the offender's social or economic status, and do not hesitate to accuse or sentence to prison high public officials, senators, vice presidents or even presidents. It might be a kind of political re-contribution to society before elections, avoiding public anger and social unrest or protecting local economy by avoiding loss of reputation preserving foreign direct investments. While the sudden change of heart is unclear, they are sending out a signal of hope for the region.

The term White-collar crime was first coined by Edwin H. Sutherland in 1939, with the objective to draw criminologists' attention to the "upper class" which also commit crime, but has been overlooked so far. This upper or white collar class is mostly composed by respected, socially accepted and approved business or professional men (Sutherland, 1940) – in other words: trusted persons of the society. White-collar crime is not a legal category with a list of specific offenses. The term is more like a social concept rather than a definition. For instance, it is unclear if the term describes the offender, its social status, types of offenses or the *modus*

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*operandi* of the behavior (Shapiro, 1980). The US Federal Bureau of Investigation (FBI) defines white-collar crime in terms of the offense as

> […] those illegal acts which are characterized by deceit, concealment or violation of trust and which are not dependent upon the application of threat of physical force or violence. Individuals and organizations commit these acts to obtain money, property or services; to avoid the loss of money or services; or to secure personal or business advantage (USDOJ, 1989: 3).

The personal or business advantage mentioned above is, furthermore, mostly intended to be obtained in a short time period, a characteristic mostly overlooked. This definition has a more practical approach due to the FBI's Uniform Crime Report (UCR) data base, because there are no indicators of the socioeconomic status or occupation of the offender (Barnett, n. d.). While Sutherland's contributions to white-collar crime and criminology have been acknowledged by criminologists around the world, some scholars also found that he created more confusion, because of his ambiguous definition (Friedrich, 2010; Shapiro, 1980).

On the other hand, at one end of the white-collar crime equation will always be the offender. So, it makes sense to analyze why they do what they do. They do not belong to a "repressed minority", they are generally from respected families, well-educated and not poor. But they are 'leaders' in high-ranking positions which are able to find or even create opportunities and convince some 'followers' for private gains (Bucy et al., 2008; Shapiro, 1990). Until today, as it seems, there is no universal definition of the term white-collar crime. White-collar crime examples are public corruption, tax evasion, environmental law violations, bankruptcy fraud, bribery, money laundering and embezzlement to name a few.

Crime can be observed in societies of all types, but any kind of crime that reaches excessively high levels is pathological in nature. It offends and hurts collective feelings (Durkheim, 1982). Paraguay has been historically less transparent than other countries. Hence, there is no research or literature about white-collar crime, except of some international organizations like World Bank or Transparency International who report about public corruption on a continuously basis. This lack of research is mostly due to a lack of primary data. One of the aims of this research paper is to fill this gap with an analysis of a first-hand data set on white-collar crime incidents. The second objective is to model white-collar crime data with the intention to serve as a basis for public policymakers.

After this introduction a literature review analysis different aspects of white-collar crime, followed by the empirical part of this paper. Next, results will be presented, before concluding with a discussion and recommendations for further research.

**Literature Review**

White-collar crime has been studied for a while from different perspectives and a variety of subfields in numerous countries around the globe. For example, Agnew (1992, 2001) examined the effect of selected types of strain on crime and which types of strains are most likely to lead to crime, for example, such that are seen as unjust which is more likely to create strong emotions like anger. Unjust can be defined as "the voluntary and intentional violation of a relevant justice norm" (Agnew 2001: 329).

Three characteristics of white-collar crime are particularly important: (1) The offender has legitimate access to the target or victim of the crime on the basis of an occupational position, which constitutes his or her primary activity; (2) the offender must involve the power of his position to obtain an increase in economic, political or social standing of himself or the organization to harm one or more victims and (3) the offender's actions have a superficial appearance of legality (Henry and McGurrin, 2013).

In general, white-collar crime is a non-violent crime, but not a victimless crime. It is different than street crime, it is more difficult to understand and even sometimes difficult to recognize, with much more victims and more harmful than its counterpart. These acts and sometimes omissions are not only wrongs against the victims, there are also against the state or government who is responsible for maintaining public morals, health, safety and order (Cassel and Bernstein, 2015). Therefore, every criminal judgment is also a social judgment because laws are considered 'the will of the people' and should serve us as a guide for all our practical reasoning (Cassel and Bernstein, 2015: 4; Durkheim, 1982). White-collar crime seems to be a highly significant social problem in the first place, regardless if it should be considered crime or not (Newman, 1958).

Offenders, as a group, who participate in illegitimate activities respond to incentives in much the same way as non-offenders who are engaged in legitimate activities (Ehrlich, 1973). This led Ehrlich (1996, also Becker, 1968) to his 'market model' of offenses, where all participants act to optimize the relations of costs/benefits. Money, financial gain and greed are the most common motives for white-collar offenders according to Bucy et al. (2008) who interviewed prosecutors, defense counsels and white-collar offenders. They argue that the group of offenders can be divided into 'leaders' and 'followers', each with different personality traits. According to the authors the key deterring and detecting is "an informed, active Board of Directors with an adequate number of outside qualified directors […]" (p. 436). Wrong or even perverse incentives, like low penalties for abuse, poor accounting and lax regulations will help to create environments for white-collar crime (Akerlof and Romer, 1993; Black, 2010). Ehrlich (1996) and Black (2010) go even further and argue that only prison sentences or sentencing guidelines shift the tax for crime and can deter the willful violations. It even seems that white-collar crime has resulted in a kind of Pavlov's conditional stimulus-response learning effect. Despite the argument of Banerjee (1992) that socially inefficient herding will bring up mechanisms that reduces herding by modifying the payoff structure, social and economic costs of white-collar offenders are by far higher than ordinary street crime. The Association of Certified Fraud Examiners (2016) reported in his latest report that occupational fraud caused an estimated total loss of US$6.3 Billion, the median loss for Latin America is about US$174.000 per case, financial statement fraud is the category which causes by far the greatest median loss while Owners and Executives causes 10-times more damage.

There is a broad consensus in academic literature that corruption has a negative impact on economic growth. For example, corruption can impact negatively Foreign Direct Investment (FDI), because it increases cost of doing business, creates mistrust and with a corrupt justice system investments do not seem to be save (Barassi and Zhou, 2012; Javorcik and Wei, 2009; Mauro, 1995). Transparency International (2017a) ranked Paraguay 123 in his latest corruption perceptions index (out of 176 countries) and second most corrupt in South America. Paraguayans are most likely to say that their elected representatives are highly corrupt (69 percent), but they also say (82 percent) that citizens could play a major role in fighting corruption (TI, 2017b). Detotto and Otranto (2010) analyzed the impact of crime and economic growth in Italy. They summarized that crime discourages domestic and foreign direct investment, creating uncertainty and reduces competiveness of firms by obscuring and distorting market reality. Méndez and Sepúlveda (2006) argue that corruption and economic growth depends in great part of the political regime and quality of institutions. While corruption in free countries can be beneficial for economic growth on a low level of incidence, mostly due to high bureaucracy, it is harmful on a high level of incidence. This can be confirmed by Auriol, Straub and Flochel (2016). They found out in a more recent research that corruption in the allocation of public contracts has damaging consequences for the economy in Paraguay. First, it destroys entrepreneurs' development potential and second, this kind of rent-seeking directs towards unproductive activities, which results in one of the least industrialized economy in the region.

But the consequences are not only of economic nature. Despite of the individual economic losses, directly caused by the fraud itself and indirectly caused by contracting a law firm and opportunity costs, there are also social consequences. Distrust or cynicism against the justice system or public institutions in general, or emotional consequences like anxiety disorder, major depressive episodes or even suicidal tendencies are mentioned in literature. White-collar crime can sometimes even involve physical harm from polluting the environment with toxic waste, unsafe working conditions or from marketing unsafe products (Brody and Kiehl, 2010; Friedrichs, 2010; Ganzini et al., 1990; Malone, 2010; Payne, 2016; Pridmore and Reddy, 2012; Seligson, 2006). Sutherland (1940: 5) argues that "white-collar crimes violate trust and therefore create distrust, which produces social disorganization on a large scale."

Other research focused on psychological characteristics of white-collar offenders. Low integrity, high hedonism and high narcissism are psychological variables which may predict business white-collar crime (Blickle et al., 2006; O'Brien, 2017). Age, however, always correlated with crime, is almost always reported and therefore easily available. However, the causes of deviations are likely to be the same at any age. (Hirschi and Gottfredson, 1983). Shared religious beliefs and the importance of god in one's life are negatively related to white-collar crime (Corcoran, Robbins and Pettinicchio, 2012).

Other types of white-collar crime like fraud, violation of trust, extortion and others show a lack of research and especially in the case of Paraguay. In general, white-collar crime is underrepresented in literature relative to street crime (McGurrin et al., 2013). This is mostly due to the lack of data. The primary objective of this paper is to fill the lack of research with an analysis of a primary data set, which spans the period from the years 2000-2016.

## Data and Methods

### Data set

White-collar crime primary data were obtained from the office of the Public Prosecutor as the only public institution to prosecute offenders and hence, the sole source of data.[2] For the purpose of this paper an offense-based definition of white-collar crime was defined and categorized corresponding to the national law No. 1.160/97 (Penal Code, General part, Title II, Chapter III, 'Punishable offenses against patrimony').[3] The chapter consists of nine offenses (Articles), namely extortion (Art. 185), aggravated extortion (Art. 186), fraud, (Art. 187), fraudulent computer operations (Art. 188), clandestine exploitation of a benefit (Art. 189), sinister with intent to cheat (Art. 190), fraudulent investment promotions (Art. 191), violation of trust (Art. 192) and usury (Art. 193).

The month of January and February 2000 had no reported incidents at all and therefore were excluded from the series. Monthly aggregated data of all nine punishable offenses from March 2000 to December 2016 are available and were included in the time series. Then all nine Articles were aggregated to a univariate series named white-collar crime with the aim to explore for long term and seasonal patterns. No further distinctions were made regarding geography, age, gender or race. For the time period observed, the office of the Public Prosecutor counted, on average, of 13 expert/forensic accountant to cover the entire country.[4]

The office of the Public Prosecutor created a special unit for financial crime and anticorruption (UDEA)[5] which is operative since 2007. Data are available since 2011 and are included in the

[2] Data were queried from the software SiGeFi (Sistema de Gestión Fiscal).

[3]. The Paraguayan Penal code is heavily based on the German "Strafgesetzbuch" (StGB) without taking into account cultural and social differences.

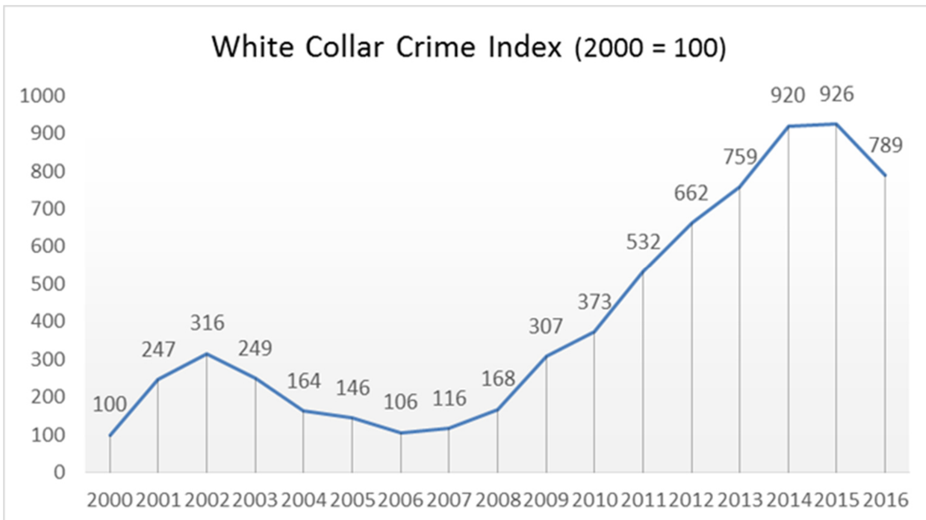
[4] Office of the Public Prosecutor, Department of Public Information, March 20, 2017.

[5] UDEA = Unidad especializada en Delitos Económicos y Anticorrupción. The Unit has limitations and is just able to act in the city of Asuncion (capital), passing a certain amount and if a public institution is a victim. In special cases the attorney general can advise the special unit to investigate.

data set. The average participation of the special unit is 0.90 percent of the total cases reported during the period 2011-2016.

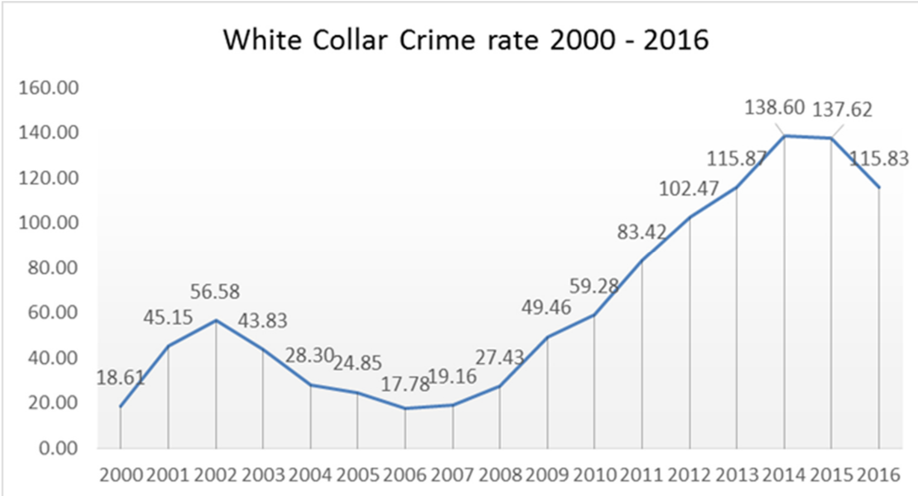
Corruption itself, as a punishable offense, is not included in the above mentioned chapter and therefore not included in the series.[6] In practice, corruption is generally complained along with violation of trust and hence, violation of trust can be seen as a proxy for corruption. In fact, violation of trust, investigated by the special unit increased from 2011 until 2014 by 267 percent and dropped then 47 percent until the end of 2016. Violation of trust counts for 58.91 percent and fraud for 30 percent (n=404) of all cases investigated by UDEA. These numbers show the focus of the special unit**. Figure 1a** shows the index and evolution of white-collar crime in Paraguay, with a peak of 9,137 cases in 2015, while **figure 1b** shows the white-collar crime rate.

**Figure 1a**. White-collar crime index Paraguay 2000 - 2016.




[6] Public corruption is regulated in Title VIII, Chapter III, Art. 300-304 of the Paraguayan Penal Code.

**Figure 1b.** White-collar crime rate Paraguay 2000 - 2016.




**Statistical analysis**

During the observed period of 202 month, there were a total of 67,907 offenses counted. The most frequent offense was fraud with 48,879 counts (71.98 percent), followed by violation of trust (n=13,167; 19.39 percent) and extortion (n=4,349; 6.40 percent). The remaining six offenses in this chapter count for a total of 1,512 cases (2.23 percent). The average count of offenses during the time period observed is 3,995 per year with a standard deviation of 2,927, a minimum of 987 (2000) and a maximum of 9,137 cases in 2015. **Table 1** shows a resume of the descriptive statistics of all offenses.

**Table 1.** Descriptive statistics and distribution of white-collar crime offenses.

| Article | Offense | Total counts | % of total |
|---|---|---|---|
| 185 | Extortion | 4,349 | 6.40% |
| 186 | Aggravated Extortion | 217 | 0.32% |
| 187 | Fraud | 48,879 | 71.98% |
| 188 | Fraudulent computer operations | 2 | 0.00% |
| 189 | Clandestine exploitation of a benefit | 738 | 1.09% |
| 190 | Sinister with intent to cheat | 3 | 0.00% |
| 191 | Fraudulent investment promotions | 45 | 0.07% |
| 192 | Violation of trust | 13,167 | 19.39% |
| 193 | Usury | 507 | 0.75% |
| | | 67,907 | 100.00% |

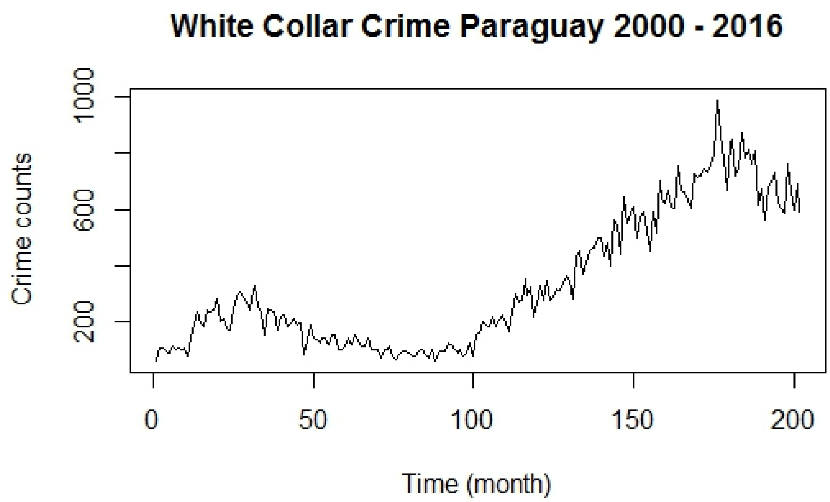
mean = 3,995; Stdv. = 2,927; min = 987; max = 9,137

Note: Offenses are ordered by their respective articles as per Chapter III of the corresponding law, Total counts = total counts per offence from 2000 - 2016.

While white-collar crime rate is mostly presented in literature and official statistics, the original raw data is preferred in this study to avoid an artificial bias. Including the population of

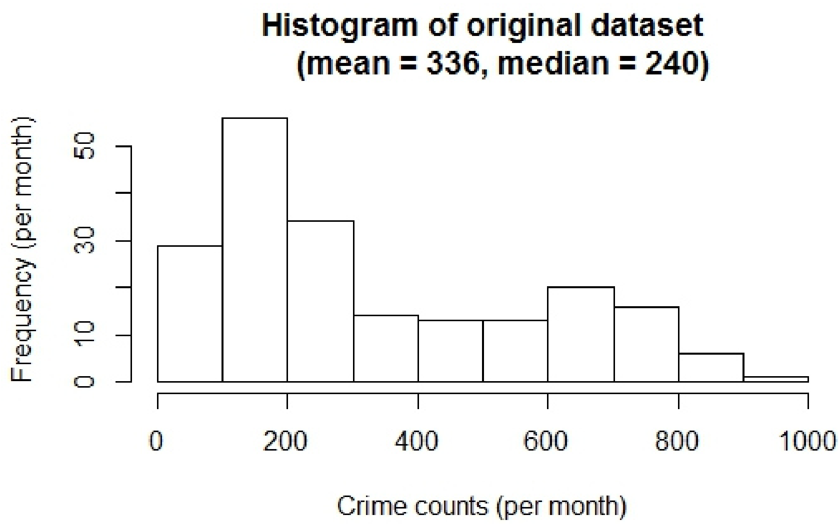
Paraguay to compute a crime rate would convert the data set to a non-time-continuous process (Bramness et al., 2015). Time series variables are related and ordered according to time, which is an important characteristic of time series (Shumway and Stoffer, 2011). Furthermore, both graphs have the same structural shape characterized mainly by fraud and violation of trust incidents.
One of the two purposes of this study is to create a model by fitting the time series and be able to forecast white-collar crime. A first step involves a careful scrutiny of the time plotted data as shown in **Figure 2**.

**Figure 2.** White-collar crime Paraguay 2000 - 2016.



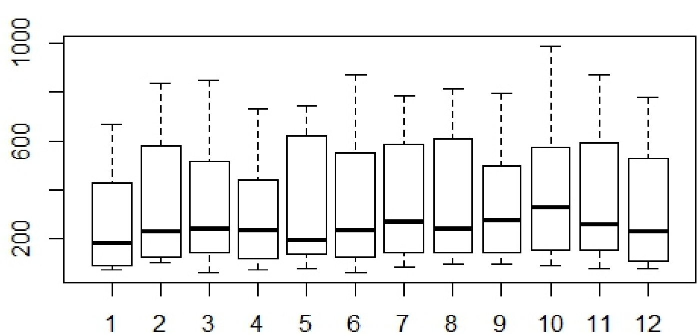

The data shows a clear non-linearity series with no consistent trend. After a decline from 2002 to 2006, the series shows a strong increasing trend from 2007 to 2015 with a systematic change in the mean level. A histogram of the original data reveals a skewed right data set (skewness=0.72) due to the (naturally truncated) lower bound (zero), with a mean of approximately 336 and a median of 240 counts per month (**Figure 3**).
After a first inspection of the data, some issues occurred like non-linearity, seasonality, serial autocorrelation and overdispersion, nevertheless a classical ARIMA model was chosen to model the data and make predictions, due to its widely acceptance and robustness.

**Figure 3.** Histogram of original dataset.




Seasonality that is, an observable, repeated shape around the trend in a one year time period, and can be of different nature like weather, timing of decisions, which have transformed into traditions, calendar and expectation (Granger, 1979). Monthly data is almost equally distributed and does not reveal large amplitudes in variance on a yearly basis, but a seasonal pattern in this particular research can be observed in a box-whisker plot with a clear peak in October and a valley in January, as shown in **Figure 4**.

**Figure 4.** Box – whisker plot of original dataset.




This is probably caused by a calendar event (initiating criminal complaints before the jurisdictional summer break during the hottest months in January to mid of February) and by expectation based on claims on additional income in December.

The original raw data was then splitted into a training set and testing set by means of a Pareto ratio. Non-stationary data, as a rule, are unpredictable and therefore most techniques require a stationary series to perform forecasts. The random nature of the additive error process guarantees that forecasts will not be close to true values. As already mentioned above, the original raw data is a unit root process, for that reason shocks have a permanent effect and do not revert to the mean. Therefore, the next step was to transform the training set into stationary data. Stationarity in a time series means, that mean and variance are roughly the same over time. Different techniques were applied to transform the data and to smooth the series, such as first and second order differences, as well as log normal function. Subsequently, an Augmented Dickey Fuller Test (ADF, Dickey and Fuller, 1979, 1981) and a KPSS Test (Kwiatkowski et al., 1992), as well as a Canova Hansen Test (Canova and Hansen, 1995) for seasonal stability were performed with the aim to observe a more stationary data set. Before implementing the ADF test, an important issue is to select the lag length p. If p is to small then the remaining correlation of the residuals will bias the test, and if p is too large then the power of the test will suffer. Monte Carlo simulations suggest it is better to error on the side of too many lags. For an approximation the following equation was used (Schwert, 1989):

$$p_{\max} = \left[ 12 \cdot \left( \frac{T}{100} \right)^{1/4} \right] \tag{1}$$

After resolving the equation, the approximate lag length is about 13, where T denotes the observations (161 observations in the training set). A standard error of p=0.05 was established to reject or accept the null hypothesis for the ADF and KPSS test. The first order difference of the raw data shows a stationary series on a 10 percent level for the ADF test and supports the null hypothesis of Stationarity on a 1 percent level for the KPSS test. For a second order differenced series the null of a unit root process can be rejected at all levels for the ADF test, while the null of Stationarity for the KPSS test cannot be rejected at all levels, assuming a stationary series. The Canova-Hansen test shows a stable seasonal pattern for all transformed data sets, even for the original raw data (**Table 2**).

**Table 2.** Stationarity tests for different data transformation.

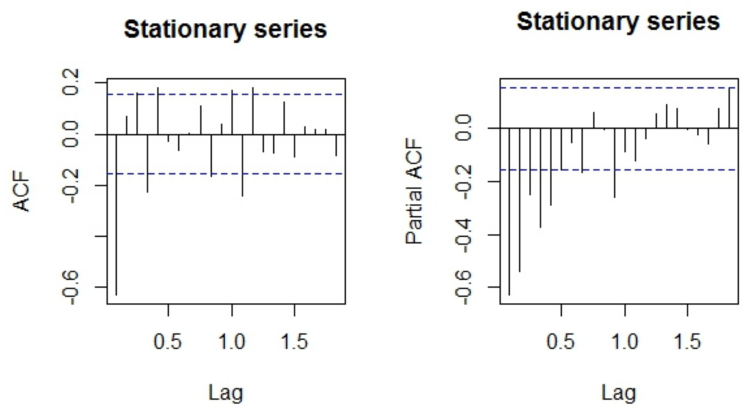
| | **Stationariety Tests for different data transformations on Training set** | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Test** | | **Original variable** | | | **logOrig** | | | **DifflogOrig** | | | **DiffOrig** | | | **Diff2Orig** | |
| ADF Test (L=13) "none" | | | | | | | | | | | | | | | |
| p.-Value | | 1.4745 | | | 0.5856 | | | -2.4757 | | | -1.9212 | | | -8.1115 | |
| Critical values | 1% | 5% | 10% | 1% | 5% | 10% | 1% | 5% | 10% | 1% | 5% | 10% | 1% | 5% | 10% |
| | -2.58 | -1.95 | -1.62 | -2.58 | -1.95 | -1.62 | -2.58 | -1.95 | -1.62 | -2.58 | -1.95 | -1.62 | -2.58 | -1.95 | -1.62 |
| KPSS Test (L=13) | | | | | | | | | | | | | | | |
| p.-Value | | 0.2826 | | | 0.245 | | | 0.1455 | | | 0.147 | | | 0.054 | |
| Critical values | 10% | 5% | 1% | 10% | 5% | 1% | 10% | 5% | 1% | 10% | 5% | 1% | 10% | 5% | 1% |
| | 0.119 | 0.146 | 0.216 | 0.119 | 0.146 | 0.216 | 0.119 | 0.146 | 0.216 | 0.119 | 0.146 | 0.216 | 0.119 | 0.146 | 0.216 |
| Canova Hansen Test | | | | | | | | | | | | | | | |
| p.-Value | | 1.557 | | | 1.593 | | | 1.546 | | | 1.526 | | | 1.497 | |
| Critical values | 2.49 | 2.75 | 3.27 | 2.49 | 2.75 | 3.27 | 2.49 | 2.75 | 3.27 | 2.49 | 2.75 | 3.27 | 2.49 | 2.75 | 3.27 |
| nsdiffs (Test="ch") | | 0 | | | 0 | | | 0 | | | 0 | | | 0 | |

Notes: Original variable=Original crime counts without any transformation; logOrig=natural logarithm of original variable; DifflogOrig=first difference of natural logarithm of original variable; DiffOrig=first difference of original variable; Diff2Orig=difference of second order of original variable.

### Model selection

For a first seasonal autoregressive integrated moving average model (ARIMA) estimation with the general form (p,d,q) (P,D,Q)m, the stationary series of second order differenced data (Diff2Orig) was used. The correlogram of the stationary series indicates an ARMA (5,0,2) process as a starting point (**Figure 5**). The seasonal component (0,2,2) was also included. Six different model candidates were tested on the training set.

**Figure 5.** Correlogram of the stationary series.




The widely used Akaike Information Criterion (AIC; Akaike, 1973), as an objective measure of the "goodness of fit", was used as a model selection criterion for this multiple model set. The lowest AIC value should indicate the best model fit with the lowest information loss and with the best predictions when applied to new data. However, the AIC column in **Table 3** shows a very small difference between model M5 (1,310.02) and M6 (1,310.59) in the training set. This makes it difficult to decide if the difference between M5, with the lowest AIC, to model M6 is statistically important. Furthermore, the log likelihood measure shows almost the same value for the two models, which indicates model redundancy.

Therefore, a weighted AIC ratio was used, as proposed by Wagenmakers and Farrell (2004), to address this uncertainty in model selection. Akaike weights should give more evidence for one model over another model. As a first step, the differences between the model with the best AIC value and the competing models are calculated. That is,

$$\Delta_i \text{ (AIC)} = \text{AIC}_i - \text{minAIC} \tag{2}$$

Models with $\Delta_i \leq 2$ have strong support, whereas, on the other extreme, models with $\Delta_i \geq 10$ have no substantial evidence (Burnham and Anderson 2004). Next, the Akaike weights, $\omega_i$ AIC, should sum up to 1 and are obtained by

$$\omega i = \frac{\exp\left(-0.5\Delta_i(\text{AIC})\right)}{\sum_{K=1}^{K}\exp\left(-0.5\Delta_i(\text{AIC})\right)} \tag{3}$$

In the training set the Akaike weights for M6 (0.32) and M5 (0.43) show almost equal values, with slightly more evidence for M5, while all other models reveal $4 \leq \Delta_i \leq 7$ and therefore considerable less support. It is good practice to study the residuals of the sample. A first choice is the residuals' autocorrelation plot. In addition, a statistical Ljung Box test was applied. Low p-values indicate a lack of evidence for independency of the deviants (Box and Pierce, 1970; Ljung and Box, 1978). The same model set was then tested on new data (test set) for a prediction. The weighted AIC ratio shows now a stronger support for M6 (0.61) over M5 (0.34), while $\Delta_i$ (AIC) shows almost no support for any other model. Recall that for the training set M5 was the preferred model. In other words, M6 is now 1.8 times more likely to be the best model and with a (normalized) probability of about 65 percent M6 would predict better results than M5. The Ljung-Box test supports evidence that the residuals can be assumed as independent. **Table 3** provides a statistical summary of the multiple model set tested on an in-sample and out-of-sample data set.

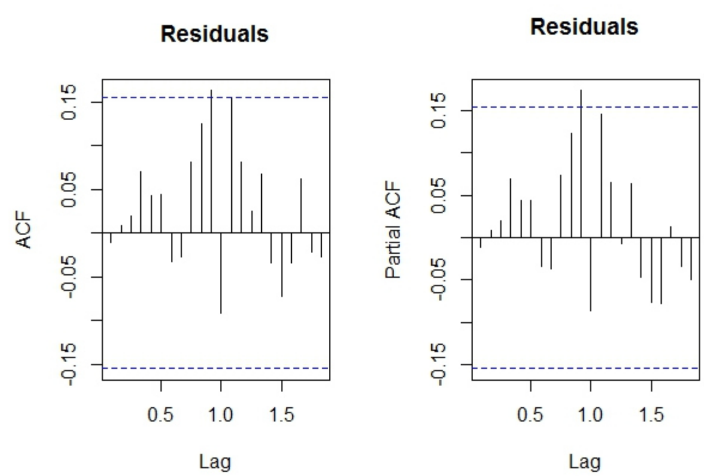
**Table 3.** Statistical summary of accuracy measurements of different models.

| | Accuracy measures for different ARIMA models on training and test set | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **M** | **ARIMA model** | **RMSE** | **MAE** | **MAPE** | **MASE** | **AIC** | **Ljung Box** | **logL** | **$\Delta_i$ (AIC)** | **$\omega_i$ (AIC)** |
| **Training Set** | **1** | (2,0,3)(0,2,2)[12] | 37.66139 | 27.0051 | 14.971 | 0.387240 | 1313.36 | 0.071 | -655.678 | 3.34 | 0.0808 |
| | **2** | (3,0,3)(0,2,2)[12] | 35.13080 | 24.4824 | 13.726 | 0.351066 | 1313.63 | 0.439 | -655.815 | 3.61 | 0.0706 |
| | **3** | (4,0,3)(0,2,2)[12] | 35.13705 | 24.6389 | 13.826 | 0.353311 | 1314.00 | 0.296 | -656.002 | 3.98 | 0.0587 |
| | **4** | (5,0,1)(0,2,2)[12] | 37.78036 | 26.6443 | 14.732 | 0.382067 | 1314.90 | 0.086 | -656.449 | 4.88 | 0.0374 |
| | **5** | (5,0,2)(0,2,2)[12] | 35.63795 | 25.9354 | 14.326 | 0.371902 | 1310.02 | 0.488 | -654.012 | 0.00 | 0.4294 |
| | **6** | (5,0,3)(0,2,2)[12] | 35.82379 | 26.0546 | 14.350 | 0.373611 | 1310.59 | 0.275 | -654.296 | 0.57 | 0.3229 |
| **Test Set** | **1** | (2,0,3)(0,2,2)[12] | 43.22982 | 29.6880 | 14.649 | 0.420206 | 1472.45 | 0.964 | -735.227 | 14.54 | 0.0004 |
| | **2** | (3,0,3)(0,2,2)[12] | 39.25022 | 26.4828 | 13.357 | 0.374540 | 1464.74 | 0.590 | -731.372 | 6.83 | 0.0202 |
| | **3** | (4,0,3)(0,2,2)[12] | 39.12505 | 26.5692 | 13.439 | 0.376063 | 1464.21 | 0.899 | -731.104 | 6.30 | 0.0263 |
| | **4** | (5,0,1)(0,2,2)[12] | 42.71612 | 29.2689 | 14.418 | 0.414127 | 1469.96 | 0.992 | -733.982 | 12.05 | 0.0015 |
| | **5** | (5,0,2)(0,2,2)[12] | 39.59277 | 28.2375 | 13.974 | 0.399676 | 1459.11 | 0.602 | -728.554 | 1.20 | 0.3372 |
| | **6** | (5,0,3)(0,2,2)[12] | 39.52104 | 28.3303 | 13.999 | 0.400990 | 1457.91 | 0.889 | -727.954 | 0.00 | 0.6144 |

Note: RMSE = Root mean square error of model $_i$ ; MAE = Mean average error; MAPE = Mean average percentage error; MASE = Mean absulte scaled error; AIC = Akaike Information Criterion; Ljung Box = test for independence of residuals; logL = natural logarithm of the maximum likelihood of model $_i$ ; $\Delta_i$ (AIC) = (AIC$_i$ - minAIC); $\omega_i$ (AIC) = Akaike weigths.

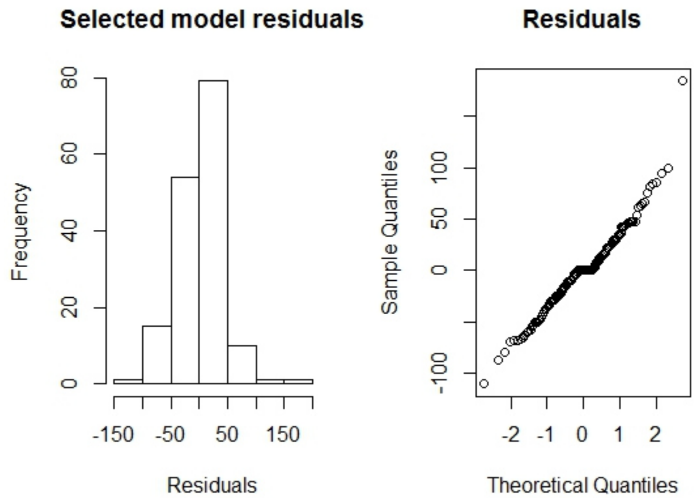
**Figure 6** shows the autocorrelations and partial autocorrelations (acf and pacf) of the residuals of model M6. All lags (with one exception due to chance) are between the upper and lower confidence bounds and statistically not significant.

**Figure 6.** Autocorrelations of selected model M6.




A histogram and a normal probability plot of the residuals support the assumption of a reasonable normal distribution (**Figure 7**).

**Figure 7.** Distribution of the residuals of the selected model.




A prediction for 2017 was made based on model M6. Total white-collar crime counts would therefore be between 5,655 and 9,048 offenses in a lower and upper 95 percent confidence bound and a 5 percent error margin. The average point estimate is about 7,351 offenses at the end of 2017. That would mean a decrease of 5.7 percent compared to 2016.

**Key Findings**

White-collar crime incidence increased 826 percent since 2000 with its peak in 2015. While white-collar crime rate increased 644.76 percent with its peak in 2014 and 139 incidents per 100.000 habitants. In these new created measures fraud with a total of 48,879 incidents (71.98 percent) and violation of trust with a total of 13,167 (19.39 percent) cases are the main offenses responsible for the increasing trend. Fraud alone increased 946 percent from 2000 till 2015. The yearly average during the observed time span is 3,995 offenses. Shocks can be observed in 2001, 2009 and 2011.

The univariate time series seems to a have a seasonal component. A slight peak in the month of October and a valley in January can be observed, different from the mean of 336 offenses per month, probably caused by a calendar event and expectation.

White-collar crime offenses will continue on a high level in 2017, with a mean far above the series mean of 3.995 counts. It is estimated that total offenses for 2017 will be, on average, around 7,351 cases with a variance ($\sigma2$) of 1,697 at a 95 percent confidence interval. This would indicate a decrease of around 5.7 percent compared to the previous year.

**Conclusion and Discussion**

This paper has presented the first descriptive data on white-collar crime for Paraguay for a time span from 2000-2016. Furthermore, an aggregated monthly time series of white-collar crime incidents has been analyzed and modeled, with the intention to predict the following year in the series.

The results indicate a dramatically increase in white-collar crime offenses. It can also be assumed that the true numbers of offenses are much higher than indicated, as many victims do not present official complaints due to (additional) costs or mistrust towards the justice system. While the special unit against financial crime and anti-corruption has just a small impact in prosecution in this research, the vast majority of the victims depend on the expertise or good-will of the local prosecutor of the case. Therefore, the radius of action for the special unit should be less restrictive to make better use of human resources and their technical knowledge to guarantee a better service to society. Similarly, more prosecutors should be instructed (e.g. by the special unit) in white-collar crime and financial crime and be present in every larger city. Some of the law chapter articles have extremely low counts considering the time span and therefore should be revised.

Macroeconomic variables of Paraguay, generally associated as a mitigating factor of crime, are sound with an average GDP growth rate of about 3.64 percent and a GDP per capita average growth rate of 2.1 percent over the same time period of this research. The financial crises during 2007-2008 did not affect Paraguay (Guillén, 2011), but hit the agricultural and other dependent sectors hard (e.g. transport) due to climate change (draught), which caused a 25 percent decline in production and around 4 percent in GDP in 2009. White-collar crime increased about 80 percent in the same year. However, GDP increased in the following years, and so did white-collar crime. It seems that white-collar crime did not affect economic growth in Paraguay. This seems logical taking into consideration the most common motives for white-collar offenders. An increasing economy is a healthy ground for more opportunities. The theory that an economic downturn will increase unemployment and therefore increase crime may hold for 'street crime', but it is not obvious for white-collar crime.

It should be noted that the offenses grouped here as white-collar crimes do not span the scale of offenses that can and should be regarded as white-collar crime. For example, public corruption, embezzlement, tax evasion, money laundering, bankruptcy fraud and bribery are notably absent. Nevertheless, the data indicates clearly an epidemic problem.
Therefore, conducting further empirical studies is recommended and required to better understand white-collar crime in Paraguay. Research could answer the questions if there is a contagion or learning effect in society or how does society behave towards white-collar crime. This paper should be seen as a first step in this direction and also to get more awareness of public policymakers.

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