International Journal of Science and Research (IJSR)
ISSN: 2319-7064
ResearchGate Impact Factor (2018): 0.28 | SJIF (2019): 7.583

Deposit Modelling of Credit Agricole Morocco (CAM)

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Abstract: ***Modeling of deposits using the Box and Jenkins method.***

Keywords: *Deposit, econometric model, ARMA, Credit Agricole Morocco, Forcasting*

1. Introduction

The modeling of deposits has become a major issue in ALM management, whether for the valuation of future deposits or for the sound management of these outstanding.

So, to better understand the modeling of sight deposits incurring, we decided to restrict to checking accounts and current accounts which constitute a large part of CAM's sight deposits, this will make it possible to leave aside the modeling of other accounts. Which constitute only a small part of the deposits. Most of the studies have focused on estimating their demand deposit model from past data. It is therefore fundamental to build a predictive model and bring out the forecasts of these deposits for future dates.

In the following we will present in the 1st section the data and the econometric technique used to model the evolution of deposits, then the second section will be devoted to the presentation of the results.

2. Data and Methodology

2.1 Data and Sources

Remember that our objective is to model the sight deposits of the CAM using the Box and Jenkins method. To do this, we used data on sight deposits from an Excel file set up by the CAM

We used series of checking accounts and current accounts going from January 2006 to April 2011. In total, we have 64 observations, each of which provides the monthly value of checking accounts and current accounts. of CAM.

2.1.1. Checking accounts

The checking account is one that has the option of issuing checks for its holder. This account is debited during a payment and credited during a collection.

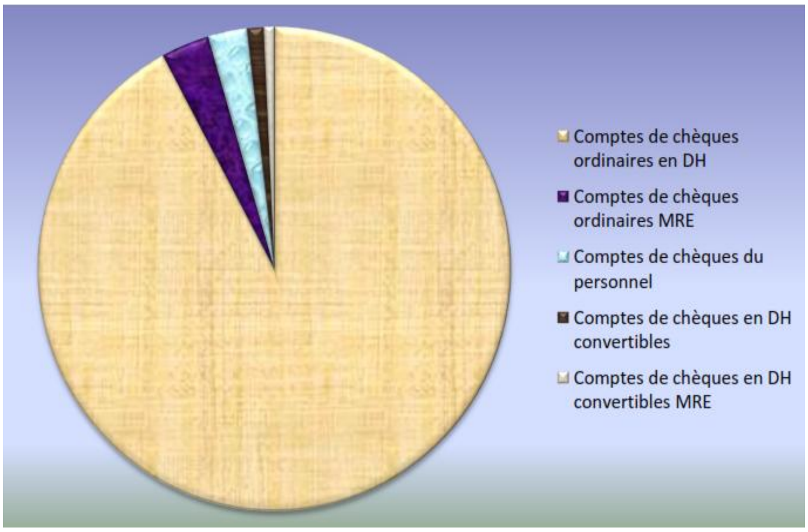

Figure 1: Distribution of CAM chequing accounts: CAM sources

It can be seen that checking accounts are essentially regular checking accounts which make up about 90% of the bank's total checking accounts, while staff accounts and MRE checking accounts share the remaining 10% leaving a very small share for convertible DH checking accounts and MRE convertible DH checking accounts.

The series of checking accounts:

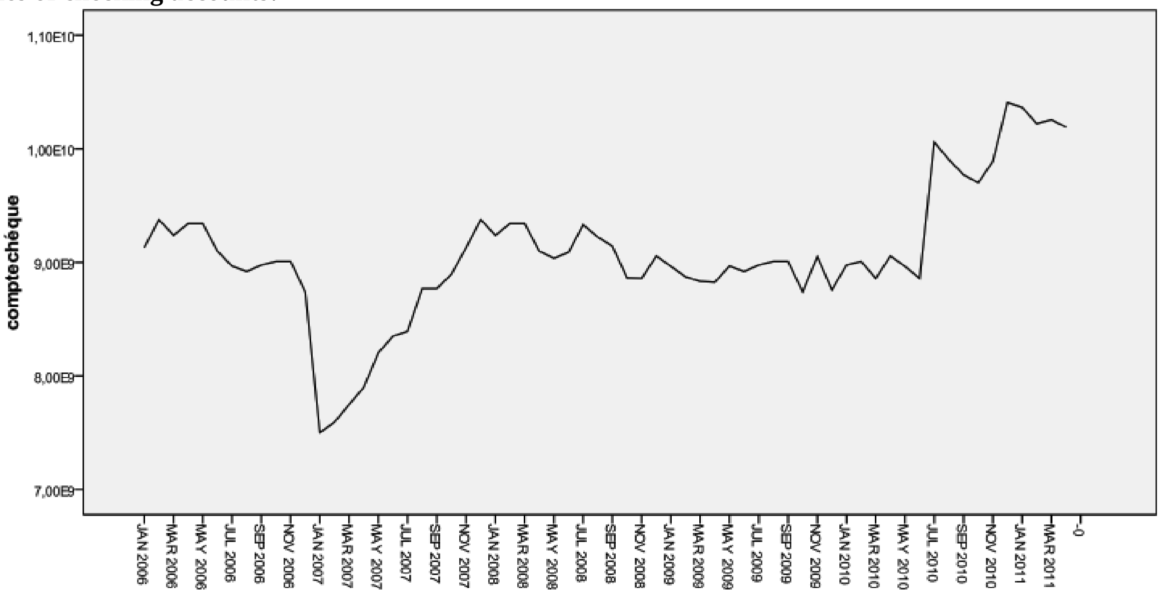

Figure 2: Checking account series from January 2006 to April 2011: Source CAM and produced bythe author

The total balance of CAM's checking accounts varies between 7.5 billion Dirhams and 11 billion Dirhams, there is a constant evolution accompanied by a drop in deposits around January 2007, this constant evolution continued until July 2010 when there is another increase up to around 11 billion dirhams, then a stabilization until today.

2.1.2. Current accounts

CAM current accounts are mainly current accounts in Ordinary Dirhams with a percentage of over 99% of total current accounts, and MRE current accounts and current accounts in convertible Dirhams represent only 1% of these deposits. In this work, we will try to model the evolution of the outstanding balances of the most important category of current accounts, which is that of ordinary current accounts.

So, we are going to make a graphical representation of the deposits of current accounts in order to have an overview of the variations in these outstanding amounts.

The current accounts series:

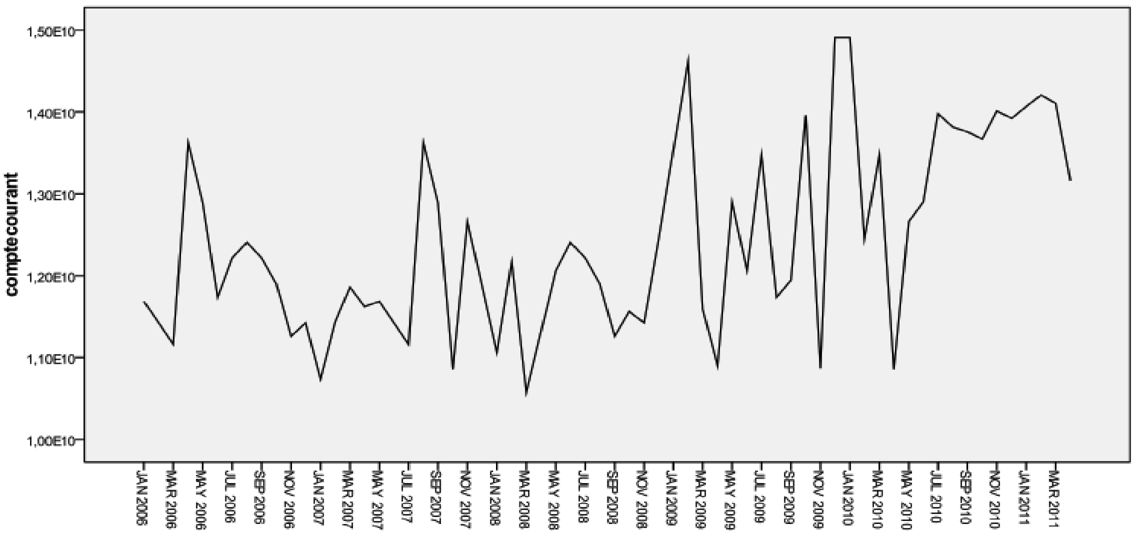

Figure 3: Current account series from January 2006 to April 2011: Source CAM and prepared by the author

For the current accounts of the CAM, we note that these outstandings experience fluctuations, once upwards and once decreases in outstanding amounts and at the same time accompanied by an upward trend on average, in general these outstanding amounts vary between 10 billion Dirhams and 14.5 billion Dirhams.

2.2 Methodology of deposits modeling

As we have specified previously, our objective is to describe the future evolution of sight deposits; for this, we will present the chronological series methods which allow this kind of forecast to be made.

2.2.1. Time series definition:

A time series (or chronological series) is a series of real numbers, indexed by the relative integers in time. Indeed, the variable is calculated for each instant of time and represents the value of the studied quantity of symbol Xt and usually named as a random variable. The set {Xt, t ∈Z} is called a "random process" and represents the different values of Xt as t varies. A time series thus constitutes the realization of a random process.

The random process is characterized by a broad classification, hence the need to specify the class corresponding to each type of time series. Thus, the analysis of time series was therefore initially focused on a particular class of processes: stationary random processes which are characterized by the stationarity of their statistical properties.

Time series are used in practice to choose a practical and suitable model to be able to realize a possible approach of a theoretical process thus making it possible to make forecasts. Although there are many types of models that can meet our need, our choice fell on modeling using an ARIMA model.

2.2.2. *Autoregressive Integrated Moving Average* (ARIMA) Model:

The class of Autoregressive Integrated Moving Average models, which we denote by ARIMA, consists of the reconstruction of the behavior of a process following its submission to random shocks over time, also called a "perturbation event" which occurs between two successive observations of 'a series of measures of this process and which affects the temporal behavior thus modifying the values of the time series of observations.This model uses the data relating to the past of the series to produce a model of the current value and to establish forecasts of future values taking into account the stationarity of the series.

ARIMA models allow three kinds of temporal processes to be combined: autoregressive processes, integrated processes and moving averages.

2.2.2.1 Autoregressive processes:

The autoregressive process is characterized by the fact that each value in the series is a linear combination of the previous values. This process is frequently used in the case of unforeseeable events which only have instantaneous influence. If the current value of the series depends on the previous p terms we can see the autoregressive model as a multiple regression of xt as a function of x (t-1),…., X (t-p).

Le processus Autorégressif d'ordre p, AR (p), s'écrit sous la forme suivante :

$$x_t = \emptyset_0 + \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots + \emptyset_p x_{t-p} + \varepsilon_t$$

Où ε_t est un bruit blanc de variance σ^2et $\emptyset_1, \emptyset_2, \ldots, \emptyset_p$ des paramètres réels.

Un processus autorégressif d'ordre p, AR (p), pourra être noté comme un modèle ARIMA (p,0,0).

2.2.2.2 Moving average processes

The current value of a moving average process is defined as a linear combination of the current disturbance with one or more previous disturbances. The order of the moving average indicates the number of previous periods incorporated into the current value. Thus, a moving average of order 1, MA (1), is defined by the following equation:

$$x_t = \theta_0 + \varepsilon_t$$

There is a difference between "moving average" and "autoregressive" processes. Indeed, for a moving average, each value is a weighted average of the most recent disturbances while for an autoregressive process it is a weighted average of the previous values.

Thus an MA (q) process is written:

$$x_t = \theta_0 + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$$

I.2.2.3. Moving Average Autoregressive Process:

We call the moving average autoregressive process of order (p, q), where p is the autoregressive order and q the moving average order, a satisfying stationary process (Xt; t∈Z):

$$x_t - \sum_{i=1}^{p} \emptyset_i x_{t-i} = \theta_0 + \varepsilon_t - \sum_{i=1}^{p} \theta_i \varepsilon_{t-i}$$

Where:

ϕ_i and θ_i real and ε_t white noise of variance δ^2

This process designated by ARMA (p, q) is a combination between the Autoregressive process of order p and the moving average process of order q.

- ✓ $E(x_t) = \mu$
- ✓ $Var(x_t) = \sigma^2 = \gamma(0)$
- ✓ $Cov\ (x_t, x_{t+k}) = \gamma(k), k \in Z, t \in Z., où\ \gamma(k)$

Is called the auto covariance of delay k.

If the series is not stationary due to the variation of the series mean over the short term or to the variability of the series which is higher over certain periods than in others, it is then appropriate to transform the series to obtain a stationary series.

Before proceeding with the estimation of the model, it is thus advisable to ensure the stationarity of the observed series, because when the variables are not stationary, the estimation of the coefficients by the method of ordinary least squares (OLS) and the Usual t- Students and f-Fisher tests are not valid. That said, the estimated coefficients will not converge to their true value. We will say that the regressions are fallacious.

As the graphic methods of detecting the stationarity or not of the series are not reliable, we use more rigorous tests: unit root tests.

Among the existing unit root tests we use the augmented Dickey-Fuller test, developed in 1979 and 1981 by Dickey and Fuller.

The simple Dickey-Fuller model is written in the following form:

$$y_t = \rho y_{t-1} + \varepsilon_t$$

Where:
yt: is the variable of interest,
t : is the time index,
ρ :is a coefficient,
ε_t :is the error term.

A unit root exists if ρ = 1 and will imply the non-stationarity of this model.

The regression model can thus be written in the following final form.

$$\nabla y_t = (\rho - 1)y_{t-1} + \varepsilon_t = \delta y_{t-1} + \varepsilon_t$$

Where y_t represents the operator of the first difference.

This model can be estimated and tested with a unit root for d = 0 (where d = ρ - 1). There are three types of test in the Dickey-Fuller test that we will briefly present below:

- Test for a unit root:

$$\nabla y_t = \delta y_{t-1} + \varepsilon_t$$

- Test for a unit root with constant:

$$\nabla y_t = a_0 + \delta y_{t-1} + \varepsilon_t$$

- Test for a unit root with constant and deterministic time trend:

$$\nabla y_t = a_0 + a_1 t + \delta y_{t-1} + \varepsilon_t$$

- The autoregressive processes of order p, AR (p), exhibit an autocorrelation function whose values decrease exponentially with possible alternations of positive and negative values; their partial autocorrelation function exhibits exactly p peaks at the first p values of the partial autocorrelation correlogram.
- The autoregressive processes of order p, AR (p), exhibit an autocorrelation function whose values decrease exponentially with possible alternations of positive and negative values; their partial autocorrelation function exhibits exactly p peaks at the first p values of the partial autocorrelation correlogram.
- To ensure that the residues are white noise, statistics are used on the residues, the main ones of which are:
  - Normality test.
  - Independence test.
  - Homoscedasticity test.

3. Application

The sight deposit series are our main data, it is necessary to study their nature whether in terms of seasonality or trend, because typical modeling uses seasonally adjusted series.

3.1 Study of the nature of the series

3.1.1 Current accounts

As part of the study of seasonality, we will avoid a direct application of software to seasonally adjust the series; we will proceed instead to a trend analysis and a step-by-step deseasonalisation.

In what follows, we will explain the methods used by presenting their application for the sight deposit series.

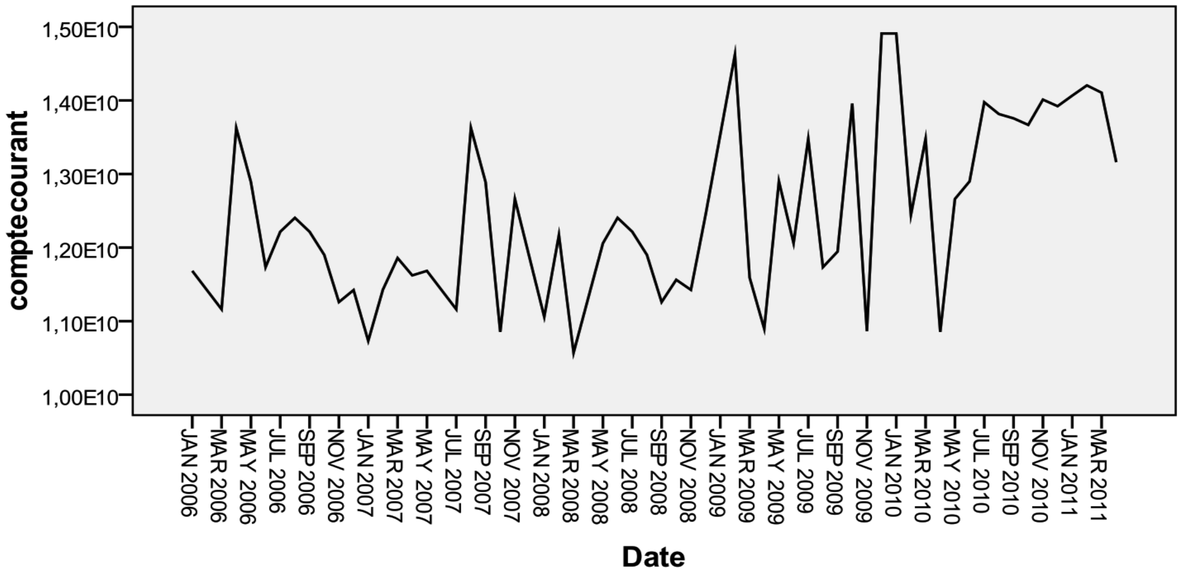

Figure 4: Current account series from January 2006 to April 2011: Source CAM and prepared by the author

On the graphical representation of the series we can see a general upward trend movement, however we do not observe seasonal movements which are difficult to spot.

3.1.2 Trend estimate

In order to cushion cyclical, seasonal and accidental movements, the method of moving averages is used. This method is intended to smooth a time series and which makes it possible to highlight the trend of the series by removing the seasonal component and attenuating the amplitude of irregular fluctuations.

The centered moving average of order K consists in calculating for each instant t the empirical average of the K observations close to that corresponding to the date t.

Our data being monthly, so we will calculate the centered moving averages of order 12, we lose information since these are twelve observations that disappear from our original data: the first six months and the last six.

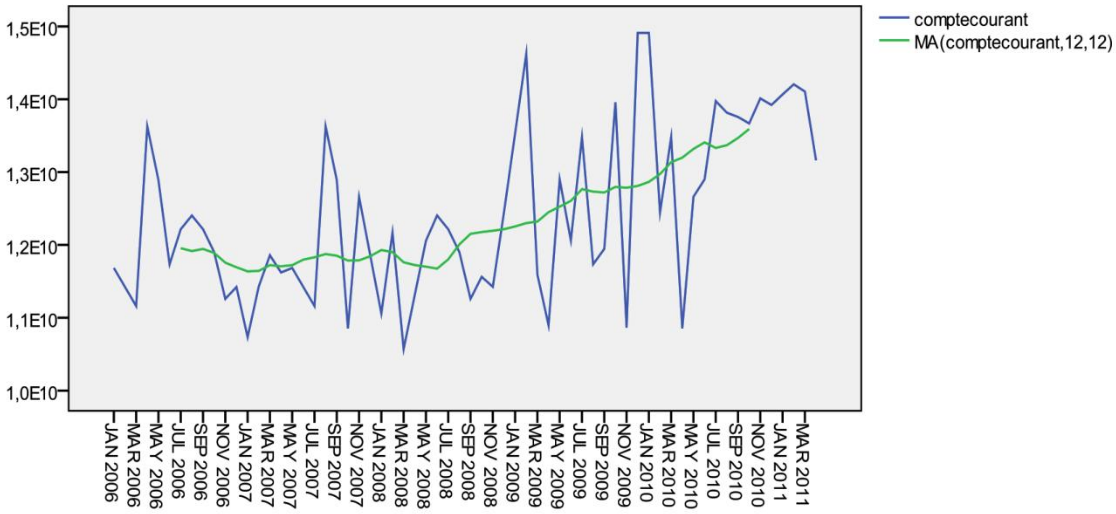

Figure 5: Smoothing of the checking accounts series by moving averages.
Source: CAM data and developed by the author

3.1.3 Estimation of seasonal movements:
To carry out the analysis of seasonal movements, we must first see if we are in the presence of a series in which for a given observation O:

- The seasonal variation S is simply added to the resultant of the other components R, it is the additive model O=R+S.
- The seasonal variation S is proportional to the result of the other components R, O = C × R, then this is the multiplicative model.

In order to make this distinction, we use a graphic method called the profile method which consists in superimposing the seasons represented by the profile lines on the same graph which follows:

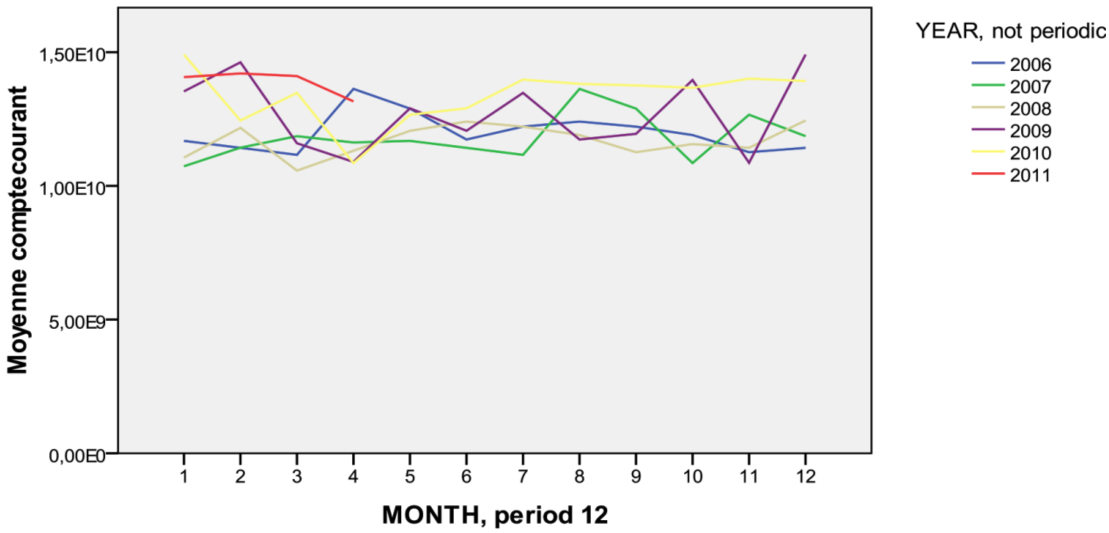

Figure 6: Representation of the profile lines for the current accounts series.
Source: CAM data, developed by the author

The profile lines thus represented are not parallel, so the model is not an additive model. We can therefore still see by another graphic method called the band method that the two trends passing through the minima and the one passing through the maxima of each season are not parallel, so the model is not a multiplicative model.

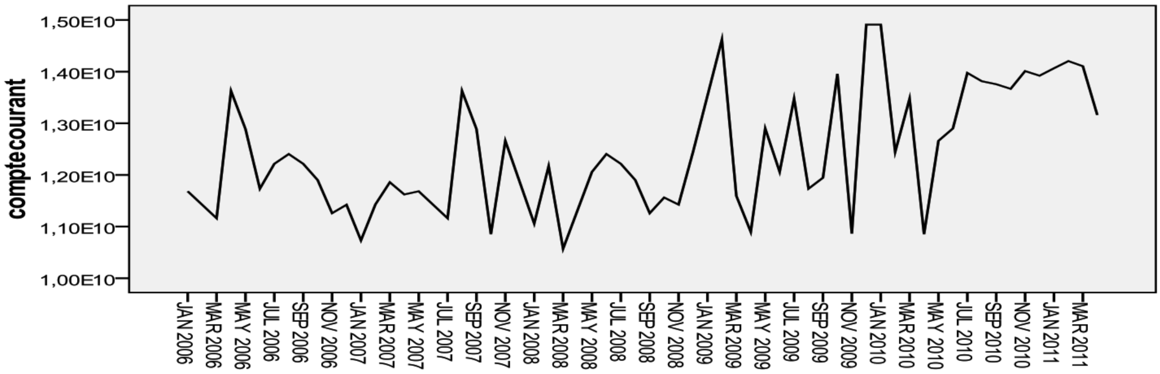

Figure 7: Representation of the two trends passing through the minima and maxima of checking accounts.
Source: CAM data, prepared by the author.

Sources: prepared by the author

3.1.4 Justification by a seasonality test:

Model tested: Model tested: ζ annual = a and annual average =b.

- Hypotheses:
- H0: a = 0: The model is additive: means and standard deviations are independent. In other words, the trend is the seasonality are independent.
- H1: a ≠ 0: The model is multiplicative.
- Student Test :

We import our standard deviations and annual averages under SPSS. We then find the results in the table above:
The critical probability associated with the Student test for the mean is less than 5%

Table 1: Student test for seasonality

Model		Coefficients non standardises		Coefficients standardises		
		A	Erreur Standard	Beta	t	Sig.
1	Constante	7,256E8	2,308E9		,314	,769
	Moyenne annulle	,010	,183	, 026	,053	,960

According to the results of the table, the model is not a multiplicative model, and according to the graph the model therefore has no seasonal movement.

3.1.5 Correction of seasonal variations:

We have seen that current accounts are not affected by seasonal movements, and we will show this by transforming the initial series into seasonally adjusted or seasonally adjusted series.

So to do this, we will proceed by a calculation of the seasonal ratios which are the ratio of the initial balances to the balances minus the values of the moving averages of order 12 which correspond to them.

We then take the averages of the seasonal reports for each period of the season. These averages are called seasonal coefficients.

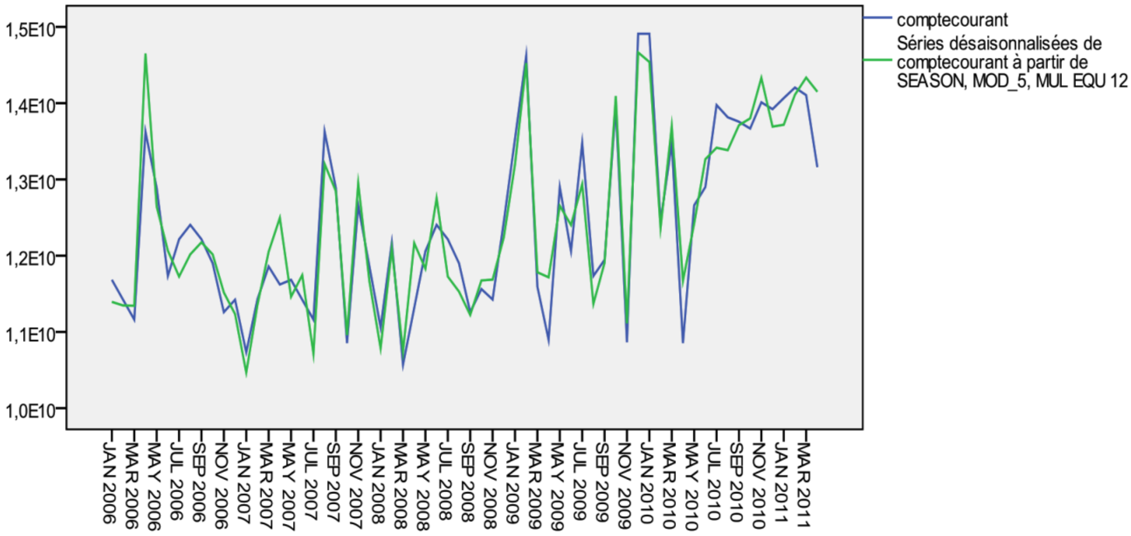

Figure 8: Representation of the seasonally adjusted series of current accounts

From the graph, we can see that the seasonal effect is weak, so in the following we will work with the series of logarithms of the initial current accounts to stabilize the variance.

3.2 Analysis of the chequing accounts series:

3.2.1. Graphic presentation of the log series (current accounts):

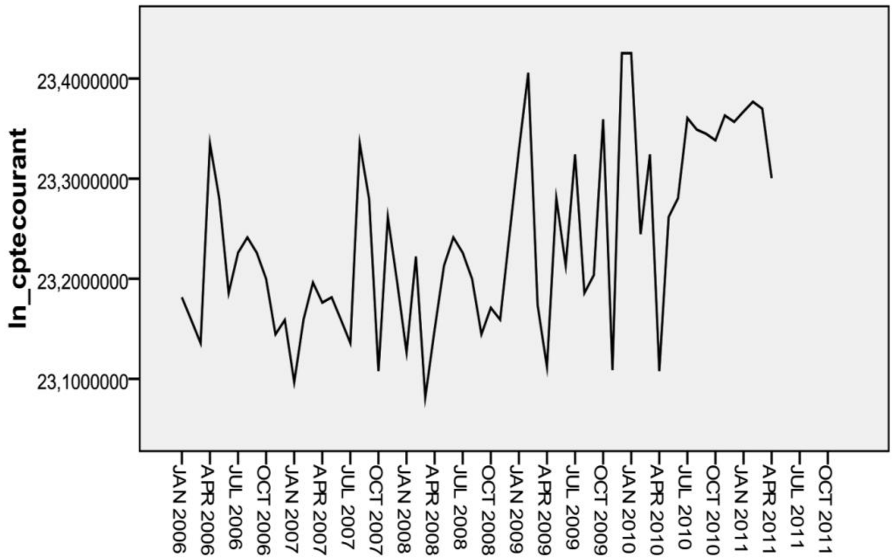

Figure 9: Log series (current accounts).
Sources: CAM data, prepared by the author

3.2.2.Analysis of the stationarity of the transformed series of outstanding checking accounts (log (checking accounts)):

Before starting the stationary series, we will study the presence or not of a unit root in the series used to then perform the appropriate stationary procedure according to the order of integrity of the series concerned.

The first thing to do is to choose the number of lags to include in the equations of the Augmented Dickey-Fuller test strategy. To do this we relied on the information criteria. Indeed, these criteria aim to minimize the variance of errors and the number of lags to be integrated into the model to whiten the residuals while guaranteeing a quality specification for the forecast. The result of this analysis carried out with the Stata software is given in the table below:

Table 2: Selection of the number of delays in the ln_comptechèque series

Selection-order criteria
Sample: 2006m5 - 2011m4 Number of obs = 60

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	58.2331				.008689	-1.90777	-1.89412	-1.87287
1	62.8818	9.2973*	1	0.002	.007695	-2.02939	-2.00209*	-1.95958*
2	63.8834	2.0031	1	0.157	.007695	-2.02945	-1.98848	-1.92473
3	65.296	2.8252	1	0.093	.00759*	-2.0432*	-1.98859	-1.90358
4	65.5753	.55869	1	0.455	.007776	-2.01918	-1.95091	-1.84465

Endogenous: ln_cptcourant
Exogenous: _cons

All the information criteria suggest incorporating one (1) delay in the test equations to bleach the residues. This is what we will do next.

We will proceed with the estimation of the three dickey-fuller models, we will do the Dickey-fuller test increased with the number of shifts determined by the Akaike criterion.

Table 3: ADF of the log series (checking accounts) with trend and constant: developed by the author

Augmented Dickey-Fuller test for unit root Number of obs = 62

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.089	-4.124	-3.488	-3.173

MacKinnon approximate p-value for Z(t) = 0.0001

D.ln_cptco~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_cptcour~t						
L1.	-.8888171	.1746402	-5.09	0.000	-1.238397	-.5392369
LD.	.0053599	.1317612	0.04	0.968	-.2583887	.2691086
_trend	.0023996	.0007366	3.26	0.002	.0009252	.0038741
_cons	20.57848	4.042886	5.09	0.000	12.48576	28.67119

In this model, we tested the null hypothesis of the presence of a unit root in the log series (checking accounts). The result of the test states that there is no single root. Indeed the calculated p-value is equal to 0.0001 which is lower than the theoretical threshold of 5%.

Unfortunately the coefficient of the trend is statistically zero at the 5% threshold, as evidenced by the student test applicable in this particular case. So we carry out the test again with the model without trend.

Now we will perform the test with a smaller model, the one with constant and without trend, we have found a p-value is equal to 0.0053 which is much greater than 5%, so we accept the presence of a unit root.

Table 4: ADF of the log series (current accounts) without trend and with constant: prepared by the author

Augmented Dickey-Fuller test for unit root   Number of obs = 62

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-3.626	-3.563	-2.920	-2.595

MacKinnon approximate p-value for Z(t) = 0.0053

D. ln_cptcour~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_cptcour~t						
L1.	-.528428	.145727	-3.63	0.001	-.820027	-.2368289
LD.	-.1700555	.1296836	-1.31	0.195	-.4295518	.0894408
_cons	12.28233	3.386173	3.63	0.001	5.506612	19.05805

Now we will perform the test with the model without trend or constant, again we accept the hypothesis of the presence of a unit root. So we will have to differentiate the series of logs (current accounts) to test for the presence of a unit root.

Table 5: ADF of the log series (current accounts) without trend or constant: prepared by the author

Augmented Dickey-Fuller test for unit root   Number of obs = 62

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	0.332	-2.615	-1.950	-1.610

D. ln_comptec~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_comptec~e						
L1.	.0000585	.0001762	0.33	0.741	-.0002939	.0004109
LD.	-.0065045	.1285115	-0.05	0.960	-.2635659	.2505568

The differentiated series of log (current accounts) will undergo the same tests to ensure its stationarity. If in this model we accept the unit root hypothesis, then we have to differentiate the series again and repeat the tests until we find a stationary series. The number of times we have differentiated the initial series represents its order of integrity.

Table 6: ADF of the delta.log series (current accounts) with trend and with constant: prepared by the author

Augmented Dickey-Fuller test for unit root   Number of obs = 61

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-9.346	-4.126	-3.489	-3.173

MacKinnon approximate p-value for Z(t) = 0.0000

D.Deltacpt~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Deltacptec~t						
L1.	-1.967573	.2105167	-9.35	0.000	-2.389125	-1.54602
LD.	.3647792	.1239458	2.94	0.005	.1165821	.6129763
_trend	.0000331	.0006597	0.05	0.960	-.0012878	.0013541
_cons	.0048944	.0240773	0.20	0.840	-.0433196	.0531084

In this model, we reject the hypothesis of the presence of a unit root.

Unfortunately the coefficient of the trend is statistically zero at the 5% threshold, as evidenced by the student test applicable in this particular case. So we carry out the test again with the model without trend.

Table 7: ADF of the delta.log series (current accounts) without trend and with constant: prepared by the author

Augmented Dickey-Fuller test for unit root — Number of obs = 61

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-9.432	-3.565	-2.921	-2.596

MacKinnon approximate p-value for Z(t) = 0.0000

D. Deltacptec~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Deltacptec~t L1.	-1.967181	.2085554	-9.43	0.000	-2.38465	-1.549712
LD.	.3645642	.1228021	2.97	0.004	.1187492	.6103793
_cons	.0059534	.0115272	0.52	0.607	-.0171208	.0290277

Likewise in the second model of the augmented Dickey-fuller test strategy, we reject the hypothesis of the presence of a unit root. However, Student's test suggests that the constant is zero, as shown in the table above. Now we will perform the test on the most constrained model.

Table 8: ADF of the delta.log series (current accounts) without trend and without constant: prepared by the author

Augmented Dickey-Fuller test for unit root — Number of obs = 61

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-9.477	-2.616	-1.950	-1.610

D. Deltacptec~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Deltacptec~t L1.	-1.960689	.2068786	-9.48	0.000	-2.374653	-1.546726
LD.	.3613678	.1218815	2.96	0.004	.1174835	.6052521

Finally, in the most contrived model, namely the model without trend or constant, we reject the hypothesis of the presence of a unit root. This proves that the differentiated series of log (current accounts) is integrated of order 0 and has neither constancy nor trend.

In other words, the presence of a unit root in the log series (current accounts) has been correctly corrected and that the differentiated series is stationary.

3.2.3.The interaction between the interest rate and the level of outstanding current accounts:

The purpose of this paragraph is to test a possible relationship between the interest rate and the level of outstanding demand deposits and more exactly the outstanding current accounts, because in the banking sector most of the money flows are more or less controlled by changes in interbank interest rates, so it was found necessary to test the possibility of the existence of such a relationship in order to properly begin the work of the modeling and to have satisfactory results. We have a monthly series of interest rates from January 2006 until April 2011.

We will test this relationship with the series of sight deposits corresponding to the same period, that is to say from January 2006 until April 2011. For this we used the Granger Causality test.

Granger's Causality Test:

Granger (1969) developed the concept of causality which makes it possible to highlight the direction of causality between two variables. Indeed for Granger to say that the variable Xt is the cause of Yt, means that the predictability of Xt is improved when the information relating to Yt is incorporated into the analysis.

We performed this test with the STATA software, this test on the log variables (current accounts) and the log variable (interest rate). We got the following results:

Table 9: Result of the Granger causality test: Prepared by the author

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
ln_cptcourant	ln_TM	1.2738	2	0.529
ln_cptcourant	ALL	1.2738	2	0.529
ln_TM	ln_cptcourant	4.2788	2	0.118
ln_TM	ALL	4.2788	2	0.118

From the previous table, we accept the null hypothesis in the two cases of non-existence of a causal relationship between current accounts and interest rates (both probabilities are greater than 5%).

This result allows us to conclude at the 5% threshold that there is no sense of causality between the two variables according to Granger. The interest rate does not cause a fluctuation in outstanding chequing accounts, and outstanding chequing accounts do not cause changes in the interest rate. So we can predict the level of outstanding checking accounts without knowing the movement of the interest rate because its movement is not significant on the level of stock of checking accounts.

3.2.4. Study of the series according to Box and Jenkins methodology:

The preliminary step of the Box and Jenkins methodology has been done. Namely the estimation of the trend, the seasonal adjustment and the stationary.

3.2.4.1. Identification and estimation of the model parameters of the evolution of the log series (current accounts):

We showed in part II.2.2 that the log series (current accounts) is not stationary and that it is represented by a DS process. We have stationed it by applying a first differentiation to it. We have designated by current difflncpt the first difference of the log series (current accounts).

So to determine the potential model for the log series (current accounts) we will need to have the simple and partial correlogram of the Difflncurrent series.

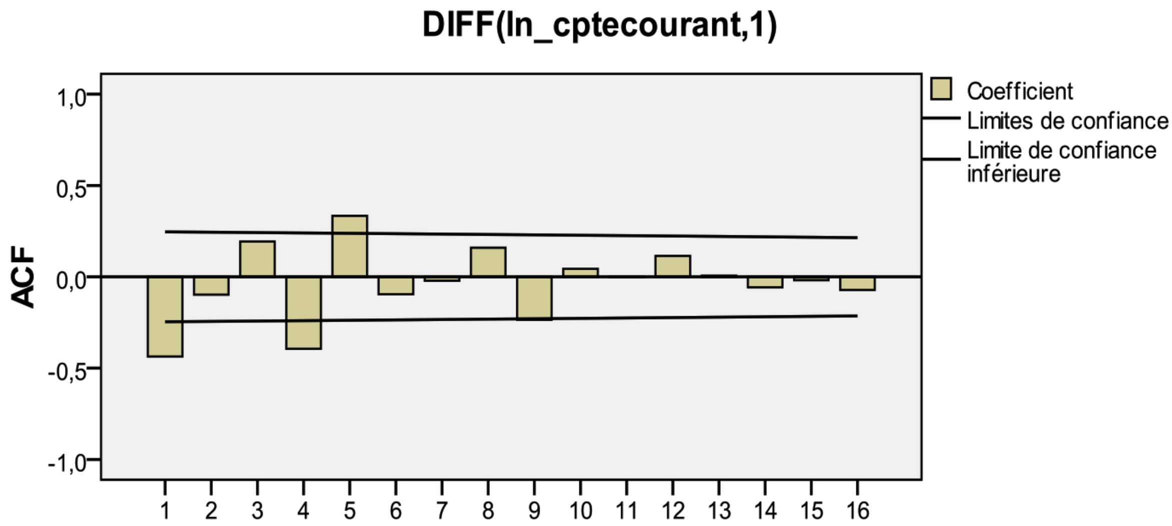

Figure 10: Simple correlogram of the Difflncptechèque series

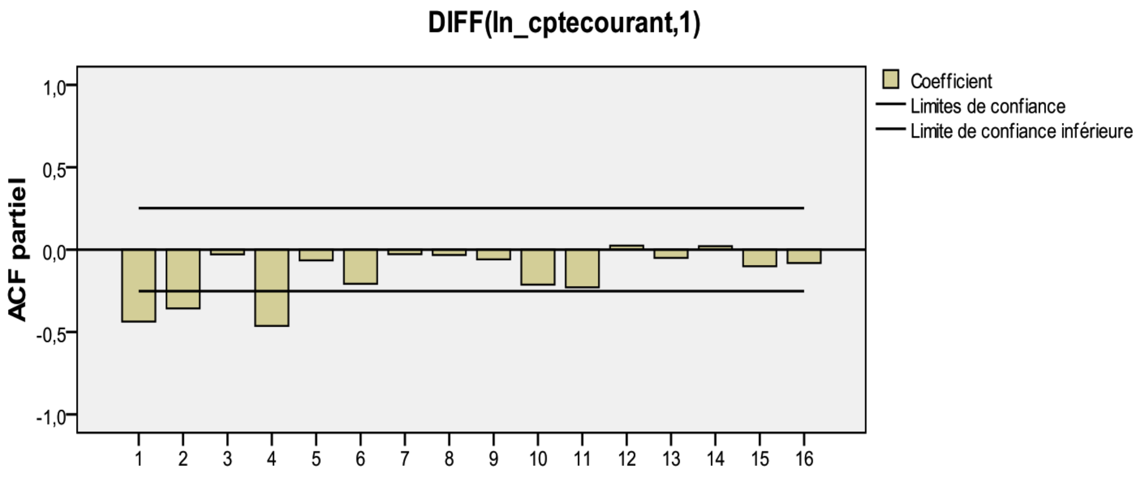

Figure 11: Partial correlogram of the Difflncp techèque series

After reading the correlogram of the Difflncpte current series above, the potential models for the log series (current accounts) are ARIMA (4,1,5), ARIMA (4,1,4) up to ARIMA (0,1,1). When estimating the parameters of all these models, it appears that only the coefficients of the ARIMA (1, 1, 2) and ARIMA (0, 1, 1) models are significant at the 5% level.

Table 10: Estimation and parameters of the ARIMA (0, 1, 1) log model (current accounts).

Estimation des paramètres

Modèle	Nombre de variables indépendantes	Statistiques de qualité d'ajustement du modèle	Ljung-Box Q(18)			Nombre de valeurs éloignées
		R-deux stationnaire	Statistiques	DDL	Sig.	
ln_cptecourant-Modèle_1	0	,408	18,491	17	,358	0

Paramètres du modèle ARIMA

					Estimation	SE	t	Sig.
ln_cptecourant-Modèle_1	ln_cptecourant	Aucune transformation	Constante		,003	,001	2,084	,041
			Différence		1			
			MA	Lag 1	,898	,070	12,827	,000

Source: developed by the author

Table 11: Estimation and parameters of the ARIMA (1, 1, 2) log model (current accounts).

Estimation des paramètres

Modèle	Nombre de variables indépendantes	Statistiques de qualité d'ajustement du modèle	Ljung-Box Q(18)			Nombre de valeurs éloignées
		R-deux stationnaire	Statistiques	DDL	Sig.	
ln_cptecourant-Modèle_1	0	,445	15,110	16	,517	0

Paramètres du modèle ARIMA

					Estimation	SE	t	Sig.
ln_cptecourant-Modèle_1	ln_cptecourant	Aucune transformation	Constante		,003	,001	2,134	,037
			AR	Lag 1	-,729	,111	-6,569	,000
			Différence		1			
			MA	Lag 2	,828	,107	7,737	,000

Source: developed by the author

Now we will in the following study the suitability of these three models before making a judicious and optimal choice.

3.2.4.2.The ARIMA model (0,1,1):

The MA coefficients (1) and the ARIMA model constant (0, 1, 1) are all significantly different from 0 for only one of 5%. Other statistics like stationary R² point to a good fit.

We will now analyze the residuals from its autocorrelation function.

No term of this correlogram is outside the two confidence intervals and the Ljung-box statistic is greater than the 5% threshold. So the residues are independent and we can assimilate them to a white noise process. We also performed an ARCH test to detect heteroskedasticity, we found F-statistic = 1.07 and the probability = 0.30 greater than 5%, so we reject the hypothesis of heteroskedasticity. Residues are a white noise process, not autocorrelated and homoscedastic.

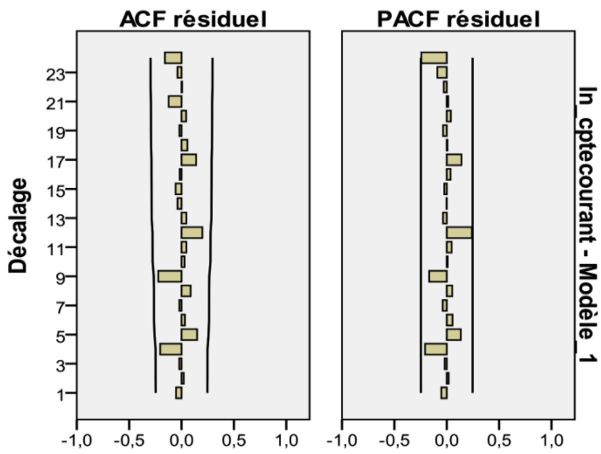

Figure 12: Autocorrelation and partial autocorrelation of the residuals. Source: prepared by the author

The estimate of the ARIMA model (0, 1, 1) is therefore validated. The log series (current accounts) can be represented by a process of the ARIMA type (0, 1, 1) with constant.

3.2.4.3 The ARIMA model (1,1,2):

The coefficients of AR (1), MA (2) and the ARIMA model constant (1, 1, 2) are all significantly different from 0 for a threshold of 5%.%. Other statistics like stationary R² point to a good fit. We are now going to analyze the residuals based on their autocorrelation function. No term of this correlogram is outside the two confidence intervals and the Ljung-box statistic is greater than the 5% threshold. So the residuals are independent and can be compared to a white noise process. An ARCH test was also performed to detect heteroskedasticity. The F-statistic = 1.45 with a probability of 0.37 greater than 5%. So the residuals are white noise, not autocorrelated and homoscedastic. The estimateof the ARIMA model (1,1,2) is then validated

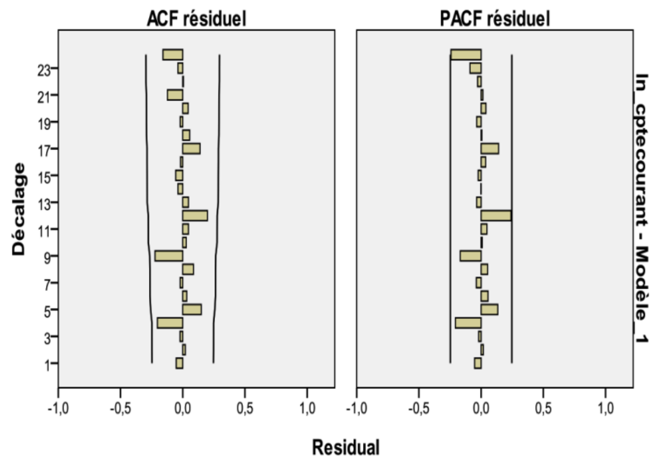

Figure 13: Autocorrelation and partial autocorrelation of the residuals. Source: prepared by the author

3.2.5.Choice of model:

We have found that both models pass the verification phase and that it is appropriate to choose from that set. The choice of the optimal model will be based on the model with the largest adjusted R^2, the model with the largest R^2 is the one which better explains the approximations of the reality of current accounts. Thus, after comparison of the two models, we retained the ARIMA model (1, 1, 2) with constant as generator of the log series (current accounts).

3.2.6.The forecasts:

We will make the forecast for the series of checking accounts outstanding until December 2011. For this, we will first forecast the log series (current account). The curves corresponding to the estimated data and the forecasts from April 2011 are presented in the following graph:

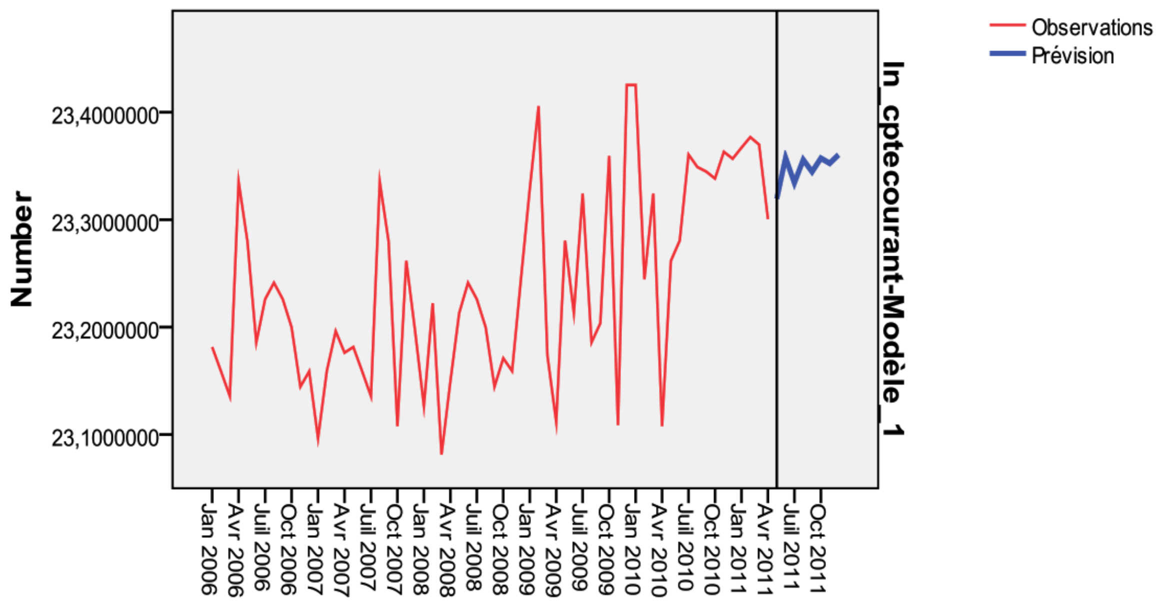

Figure 14: Estimated data and forecasts from April 2011 from log (current accounts): Prepared by the author

From the graph, we can see that current account outstandings will experience an upward trend by December 2011, it also appears that the estimates are satisfactory, which indicates that the model fits well with reality.

We will now establish the table of forecasts of current accounts from the table that we obtained with SPSS which contains the forecasts of log (current accounts).

Table 12: Forecast of current accounts and the confidence intervals of these forecasts until April 2011: Prepared by the author

	Mai 2011	Juin 2011	Juil 2011	Août 2011	Sept 2011	Oct 2011	Nov 2011	Déc 2011
Prévision log (comptes courants)	23,3194013	23,3576999	23,3342645	23,3558048	23,3445785	23,3572241	23,3524780	23,3604024
prévision comptes courants	13411807572	13935423073	13612638503	13909040124	13753766084	13928794238	13862843553	13973135128
intervalle de confiance (UCL)	23,4752201	23,5191577	23,4957719	23,5200258	23,5088805	23,5231364	23,5186924	23,5277590
intervalle de confiance (LCL)	23,1635825	23,1962420	23,1727571	23,1915838	23,1802766	23,1913118	23,1862635	23,1930458

4. Conclusion

We used the box jenking method in order to model the sight deposits of CAM and we validated the ARIMA model (1,1,2) finally we proceeded to the forecasts of future deposits.

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