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Kamel Jlassi
Central Bank of Tunisia

Rue de Lausanne 132
P.O. Box 136
CH - 1211 Geneva 21
Geneva, Switzerland

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Kamel JLASSI

Central Bank of Tunisia

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Abstract

While there is considerable literature attempting to model current account, there are not many studies to forecast current account balance. This study gives a comprehensive way to model and predict current account deficit (CAD) by evaluating the forecasting performance of direct and indirect approach. At the disaggregated level, I use two variants to model current account components; in the first alternative I apply different ARIMA models with exogenous variables (ARIMA-X) to account for the pattern of the data and exogenous factors. In the second alternative, I integrate the cointegration relationship between exports and imports with ARIMA-X models. With respect to the direct approach, I use error correction model to allow for dynamics in current account. The data used spans from January 2000 to December 2014 and comes from the Central Bank of Tunisia, the Tunisian National Institute of Statistics, and the OECD database. I find that for one-step ahead forecast, both ARIMA-X and reduced form model produce accurate forecast. However, with respect to dynamic forecasts, direct method is more accurate when compared to ARIMA-X. When cointegrating relationship between exports and imports is combined with ARIMA-X models, the indirect approach outperforms the direct approach. I also show that, as volatility of underlying components increase disaggregate approach using time series models become less reliable. In addition, I found that current account is mainly affected by domestic GDP, trade openness, fiscal deficit, exchange rate, credit to the private sector and partner GDP. Estimation of ECM indicates that persistent effect is high and can take more than three quarters to die out. In addition I assess the performance of direct and indirect approach over time using naïve approach as benchmark. It appears that the MSE of naïve approach lies between direct and indirect approach in average up to horizon 12, but then worsen.

Keywords: Aggregate and Disaggregate Approach, Cointegration, Error Correction Model, Time Series Models, Current Account Forecast, One-step ahead and Dynamic Forecast.

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*** Corresponding author email: kamel.jlassi@bct.gov.tn

Introduction

The Tunisian Republic is a developing country primarily depending on trade of goods and services. Its current account deficit (CAD) represents more than 8% of domestic output and is considered the ailing side of the economy. The elusive goal of a lower CAD requires a reduction in imports and a boom in exports. In this context, current account (CA) analysis is an important concept which is often scrutinized due to fact that it's reflect a country's net borrowing needs. So to pay for its deficit the country must increase (decrease) its international liability (assets) position. Consequently, the country must dispose of reliable forecasting figure of CA balance. Therefore predicting the CAD is of high relevance to policy-makers. This area of research has been very fruitful and had helped policymakers to understand and to prevent crises.

In the context of forecasting, they are mainly two groups of models that are widely used. On the one hand, autoregressive integrated moving average models (ARIMA) are more often used in short-term forecasting. These models constitute a convenient way to model a time series with both deterministic and stochastic effects (Lutero and Marini, 2010). The drawback of this approach is that, it takes only the past movement of the individual series, and any more information is considered on the period to be predicted. On the other hand, structural models, which rely on theory-based specifications, provide insights for the functional form between dependent and independent variables. However, they overlook the dynamic structure of the variable itself, that is the parameter value on lagged variables.

In literature, there is a mixed view on whether or not disaggregation improves forecasts. The proponents of the disaggregation approach say that it enables to take into account information heterogeneity and reduce lag order of the underlying model comparatively to aggregating process. As Lütkepohl (1984) said, forecasting with the disaggregate models will theoretically be more efficient than aggregating models. However, opponents say that a disaggregated forecast doesn't lead to a forecasting performance, due particularly to the uncertainty and consistency between individuals forecasts of variables. This is due in part to the fact that macroeconomic variables are linked in the reality, and as a consequence there will be an effect or causality of each variable on another (Dangerfield & Morris, 1992). Moreover as noted by Allen and Fildes (2001) disaggregated series appear to be noisier than aggregates constructed from them.

Empirical evidence tends to be mixed. Lindquist (1999) had demonstrated that when forecasting Norwegian foreign exports disaggregated equation clearly out performs the aggregate ones in periods when commodities evolve differently over time. Lutero and Marini (2010) find that disaggregated data of imports and exports for Italy are less predictable than when using aggregate time series, in the sense that their movement is smoother than when each item is taken apart.

The purpose of this paper is to determine whether CA forecast is a direct forecast (anticipated directly using factor model) or one in which all CA components are forecasted separately and then add up. I have not found any previous studies that have used disaggregate approach to estimate or forecast current account. So I contribute to the existent literature on the CA in several ways. Firstly, I demonstrate that the indirect approach can be more accurate if I use mixed modelling approaches (time series and cointegration approaches) and that ARIMA model would perform poorly when volatility is higher. Second, I demonstrate that the gap between times series models and structural model can be bridged by adding fundamental determinants of CA items to the times series model, and demonstrate that it leads to more robust forecast. Third, I show that the naïve approach lie on average between structural and disaggregated approach, and the forecasting accuracy increase if these methods are combined.

The results show that, indirect approach underperforms direct approach when the volatility of CA components is higher during the forecasting period. This finding gives explanation to way empirical studies report mixed results about the performance of aggregate vs disaggregate approach. I have in addition demonstrated that, the performance prediction of disaggregate approach can be improved by combining different forecasting models.

One implication of this study is to enable policy-makers to make more informed decisions on CA by forecasting CA items. In addition this finding show that authority in developing countries have to control fiscal deficit, trade openness and control over the money supply if they want to lessen external deficit.

The rest of the paper is organized as follows. Section II presents a review of the literature on CA modelling. Section III presents a short review of the Tunisian current account. In section IV, I present the data used and I lay out the methodology that I used to answer the questions posed in this research. Before concluding I present the results in section five.

2 Literature Review

2.1 Theoretical Models of CA Determination

The pattern of CAD has received considerable attention in many years. In fact, several models have been developed in order to explain the behavior of CA and to determine the appropriate economic and monetary response to lessen external or internal shocks. Each model offers a set of variables that considered the main derivers of CA dynamics. These models can be classified into three groups, elasticity approach, absorption approach (saving-investment approach) and intertemporal approach.

Elasticity approach is a partial equilibrium model which focuses exclusively on the analysis of trade balance response to change in foreign exchange rate. The trade balance is determined by domestic and foreign output and real exchange rate. This approach is particularly used to calculate the depreciation need for foreign exchange rate to improve the trade balance (for example IFM calculate the adjustment of exchange rate needed to reduce the CAD based on the trade elasticity's of export and import). The main drawback of this approach is that it considers only the market of goods and services and overlook others markets. The forecast performance of elasticity approach depends on the ability to forecast others items of CA, where elasticity is considered play no forecast role for income or transfer (Hung and Gamber, 2010).

Under the absorption approach or saving-investment approach, CA is equal to total income minus total expenditure (consumption plus investment plus government expenses), or alternatively equal to the difference between domestic saving and investment. This approach is derived based on total equilibrium, and used to emphasize the role of total spending in CA adjustment. Comparatively to elasticity approach, absorption approach includes determinants of saving and investment in CA (Hung and Gamber, 2010).

The intertemporal approach is based on the saving investment approach or equivalently from the change in net foreign asset position (NIIP), but considers the microeconomic level of analysis. More precisely it is a forward-looking approach and assumes that CA is substantively the sum of economic agent optimization behavior constrained by their inter-temporal budget. Those agents maximize their utility over time in order to smooth their consumption using investment-saving decisions. This approach achieves a synthesis between the trade and financial flow perspectives by recognizing how macroeconomic factors influence future relative prices and how relative prices affect saving and investment decisions (Obstfeld and Rogoff, 1994). This approach is used either to determine the optimal size of CA or even to predict it. Despite, the different ameliorated versions of intertemporal approach by introducing for example variable interest rate, non-traded goods, monetary policy (Ca'Zorzi and Rubaszek, 2012) empirical finding delivered mixed result for the case of small open economy. Some authors said that the model performed well and capture important dynamics in the data (Saksonovs, 2006). However others like Nason and Rogers (2003), Gourinchas and Rey (2007a) argue that the use of intertemporal approach to predict the present value of CA fails to provide reliable forecasts. They argue that this approach doesn't take into account unrealized gains or losses of capital due to changes in assets prices and exchange rates.

2.2 Empirical Literature Review and Hypothesis

Exploring the determinants and dynamics of the CA balance is one of the priorities of academic literature and policy-makers. However, in reviewing some literature on the CA modeling it appears that authors use the same variables to study the short and the long run determinants of CA, and even when they draw forward-looking of imbalances. Moreover, CA is often modelled with reduced form equation. The underlying issue behind these research approaches that use factor models for studying CA is to determine if CA imbalances are in line with macroeconomic fundamentals, that is, imbalances are sustainable in long run or not, and to examine how they can be adjusted.

In this wake, Gossé and Serranito (2014) have studied long-run determinants of CA in 21 OECD countries, to determine whether actual CA balance are consistent with equilibrium value or not, using linear and asymmetric panel VECM models with data spanning from 1974 to 2009 at annual frequency. They use 19 variables identified in empirical literature as determinant of CA (fiscal balance, real exchange rate, terms of trade, GDP per capita...).

Cheung et al. (2010) have studied the structural and cyclical determinants of the CA, in order to project the future evolution of CA balances for 94 countries using data from 1973 to 2008 and panel technique. To explain medium-term dynamics of CA they use the same set of structural variables employed in determining the long run behavior of CA, including among others, cross countries difference in fiscal balance, trade openness, oil balance, real exchange rate. Chen and Ito (2005) had investigated medium term determinants of CA using the same set of macroeconomic variables.

Aristovnik (2007) had explored the sort-term empirical link between CA of 17 MENA countries and a set of economic variables drawn from theoretical and empirical literature during the period spanning from 1971 to 2005. These variables include the three groups of structural variables relating to the internal economic condition, external sector and world economy. More recently, Aristovnik (2015) have studied the short-term determinants of CAD using the broad set of economic variable identified in the literature for Eastern Europe and former Soviet Union from 1992 to 2003.

In this paper, I will use time series models for each CA component augmented with exogenous information. In this manner I re-establish a relationship between structural and time series models. This procedure will ensure that the behavior of CA items will be driven also by macroeconomic variables besides their proper structure which I expect that will improve the accuracy and the reliability of the forecast if the underlying times series volatility doesn't increase. Thus the following hypothesis will be tested:

H. 1*: The forecasting performance of structural model is better than disaggregate times series approach when volatility is high.*

In addition authors, use the same set of variables to explain the dynamics of CA either for developed or developing countries. But with regards to the many institutional, financial and macroeconomic differences, it follows that macroeconomic response to domestic or external shocks can be quite different. Moreover, with regard to their foreign trade structures, developing countries are more likely to export raw materials, primary or outsourcing products, which are labor-intensive goods. Thus, foreign GDP play an important role in pushing the demand for local product. Moreover the structure of Tunisian exports is mostly dependent on imports from European countries which are reprocessed and exported after that. In others words, most developing countries are not leading an export-led growth strategy and subsequently the export is affect primarily by imports. For the case of Tunisian exports, they consist mostly of processed imported products, which represent more than 80%. Thus, I expect exports to be driven by the GDP of partner economies.

H. 2*: Partner's trade GDP, play an important role in the explanation of current account deficit*

Moreover, under capital restrictions, or limited access to international financial markets, developing countries cannot afford to borrow limitlessly in foreign currencies to finance their fiscal deficit. These rigidities put a cap to the amount that can be raised from aboard either to finance domestic or external deficit. So, the income from export, tourism and workers remittance constitutes the major share of liquidity of foreign currencies available to fund foreign exchange market. The shortage will be, to certain level bring by central bank. This fundamental issue, can restrain the evolution of CA and even the choice of the policy related to the liberalization of capital account (fear of floating is one of these motivation, particularly when economy is not competitive or do not have enough foreign reserves). Indeed, developing countries, may try to keep a constant percentage of imports by exports. Consequently, exports and imports are more likely to move together. Thus I expect an equilibrium relationship between exports and imports. Therefore I will test the following hypothesis.

H. 3*: Exports and imports are co-integrated, so the dynamic of exports can be predicted using imports trend.*

It is usually reported that combining different forecasting models will improve the forecasting performance. In this wake, I expect that integrating error correction model with times series models will account for more information and consequently improve the forecasting accuracy. In this respect, I expect that the combined models will improve the forecasting performance of CA balance to extent which can be more accurate than the direct approach. Therefore I test the following hypothesis.

H. 4*: The prediction of the CA balance is improved by forecasting the disaggregated items and combining different models.*

3. Overview of the Tunisian Current Account

As a characteristic of open developing countries with little natural resources, Tunisian current account was consistently in deficit in the last decade, with a clear worsening after revolution due to political and social instability. The CAD was around -8% in the last five years. The budget balance was also in deficit for the last five years with an average of -6%, with also important widening after revolution as the government had pursued an expansionary fiscal to support employment and to fight economic slowdown. The examination of exports structure shows that it's dominated by the off-shore branch which account for more than 75% of total export and agriculture (10.5%) and chemical industry (12%). As the offshore branch is tied to European economy (externalized manufactures), the resumption of this sector depend on demand in these countries. Consequently the effect on the CAD will be limited as exports from this branch are consisting mainly of imported items, so exports and imports will decline or increase proportionally. So to reduce CAD, government must focus the recovering of trade sector on goods which depends little on imports. For example chemical and agriculture products can be the major antidotes in this context.

The examination of the component of current account shows that trade balance account for the major part of the deficit and moreover it is the major driver of the CAD. During 2014 the trade balance had registered a pic of minus 2534 Millions of TND.

Figure 1 plots the trade deficit against the current account deficit. The clear pattern is the declining trend of these deficits, which is the major source responsible for the widening of external deficit.

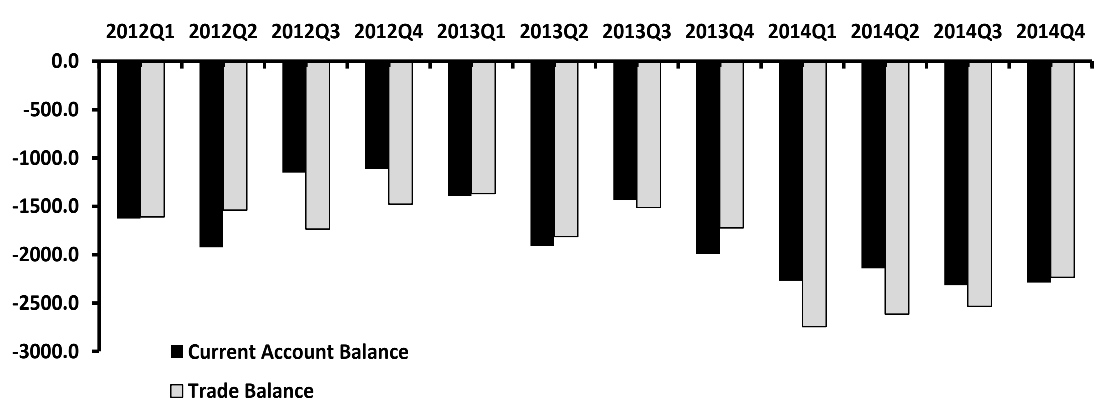

Figure 1: Trade balance and current account balance

Table 1 presents the value of each component and its respective contribution in the total deficit for the year 2013 (which is the latest official figures published by the CBT to now). The first remarkable thing is the higher import and export inside the current account. Consequently, trade balance constitutes the more important part of CAD, and even exceeds the CAD with a value of more than 150%. Regarding balance of service, its represent about 42% and receipts from tourism consist the major part of the total balance. The deficit in transport is mainly due to the shrinkage of the license fee of gas transportation between Algeria and Italy through Tunisia by about 300 million of TND. In normal course, the deficit from transport is lower than 300 million of TND. With respect to net transfers, it represents less than 10% of CAD. These fund are received from others countries as donation. The last component is primary income and it consists mainly of interest payments on external debts, and workers' remittances. The payment of debt service are managed by the ministry of finance and are known in advance, as each new loan predict the mode of payment of interest and principal at precise date. Others transfer is related to the dividend of the two important societies operating in Tunisian local market. Qatar telecom had transferred 439 MDT as dividend of three year exercises, and British gas with 1840 MDT. Information about these items is available in advance and consequently the outflow can be easily predicted with no error. So trade balance, tourism receipts and workers' remittances are the main items to predict.

Table 1: Tunisian Current Account

Current Account Deficit			**-6302**		**Modelling**
Trade Balance	**Export**	**Import**	**Balance**	**In % of CAD**	
	27701	37336	-9635	152.9%	Models for Exports and Imports
Balance of Services	**7425.6**	**4859.5**	**2566.1**	**-40.7%**	
of which Tourism	3221.4	682.8	2538.6	-40.3%	Model for Tourisms
of which Transport	2058.8	2720.5	-661.7	10.5%	
of which Others Service	2145.4	1456.2	689.2	-10.9%	
Net Primary Income	**3971**	**3845.8**	**125.2**	**-2.0%**	
of which Workers' remittances	3721.3	31.8	3689.5	58.5%	Model for Workers' Remittances
of which Investment Income	249.7	3814	-3564.3	56.6%	
Net Current Transfers	615.1	41	**574.1**	**-9.1%**	
Invetsment income outflows comprise mainly, Foreign debt interests: -820 MDT & IDE: -2800 MDT					

Figure 2 plots the main components of current account over time. As discussed earlier the overwhelming part is the trade balance, followed by tourism and by workers' remittances. The graph show that the worsening of deficit had begun in 2008 with the financial crisis of sub-prime, but the worsening was more material after the revolution. In effect a persistent widening of current account coupled with little capital inflows, had constraint the government to borrow from abroad, increasing consequently the interest paid in foreign currency and thus aggravating the situation.

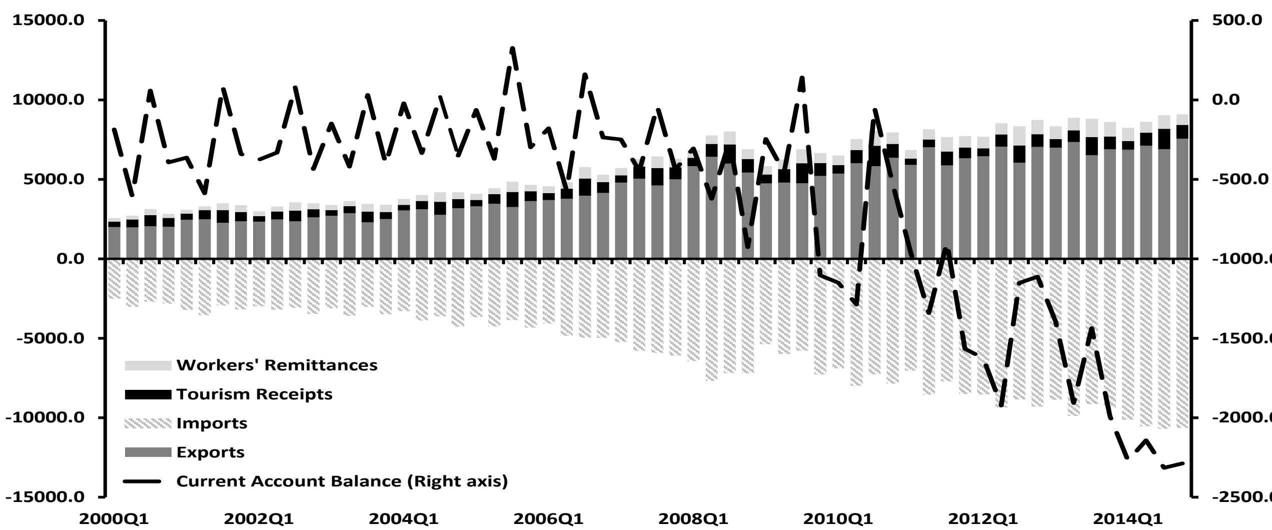

Figure 2: Evolution of main current account items

4 Data and Methodology

4.1 Data

This study uses quarterly time series data for the analysis of CA determinants. As my concern is to predict the money value of current account deficit all the data used are in nominal values. It covers the period spanning from January 2000 to December 2014. Data used comes from the Central Bank of Tunisia, the Tunisian National Institute of Statistics and the OECD database.

4.2 Methodology

In this section, I use three types of models to forecast CA balance. The first one is a reduced form model, similar to those presented in Cheung et al. (2010) and Aristovnik (2015). But unlike the previous literature I use the ECM methodology to account for short-term and long-term adjustments in order to introduce some dynamics in the model for more accurate prediction.

In the second model, I use the ARIMA model with exogenous variables to catch the pattern of the data generating process and to account for external shocks. In this second approach, I use two variants. In the first alternative I use different ARMA-X models. In the second ones, I integrate the cointegrating relationship between exports and imports. The integration of these two methodologies is innovative and permits to measure the improvement of the predictability of indirect approach when different models are used. It also demonstrates the appropriateness of using ARMA models when volatility is relatively high. Finally, I analyze the forecasting performance of these approaches using mean square error.

4.2.1 Structural CA Model

The literature about the determinants of the CA is very broad. Drawing on this strand of research, CA balance will be regressed on the robust determinants identified in the literature and taking into account the specificity of developing countries with regard to restriction on capital account. The variables that will be included in the empirical analysis of the CA model are as follows:

- Domestic GDP: The relation between domestic GDP and CA can be in the two directions. On the one hand, one can expect that an increase GDP growth may widen the CAD. This idea is based on the fact that net capital flows are pro-cyclical. That is, an inflow of net capital increases investment and consequently GDP (Kaminsky et al., 2004). Another line of reasoning is that developing countries are credit constraint (limited national saving), so when GDP is poor, they will run a fiscal deficit, and consequently go to external markets to finance investment which increase the debt servicing and provoke widening of CAD as saving stay constant. On the other hand, an increase of the growth of GDP can be associated with a reduction of CAD (Calvo, 2008). This is often the case for export oriented economies like Asian countries. A sustainable increase in exports leads to increase of GDP growth. In case of developing countries I expect that an increase in GDP lead to an increase of the CAD due to the increase of imports volume.

- Foreign GDP: the effect of foreign output on CA acts opposite to the domestic output. However, it can also influence the CA balance positively or negatively. Following the elasticity approach, exports are positively affected by the foreign level of output, which lead to positive relationship between foreign output and current account. Another sign is expected under the absorption approach, which suggests that if foreign output increases, demand from foreign economy may slowdown in the case when foreign output rise faster than absorption. In the case of developing countries I expect that, an increase in foreign output will reduce CAD due to the increase in exports and capitals inflows.
- Domestic credit: Domestic credit is an important factor to consider because an excessive credit creation (increase domestic credit) results into reserves outflows and worsens CA balance, suggesting a negative relationship between credit and CA. This is variable is measured as the total credit to private sector.
- Fiscal balance: Fiscal balance can affect the current account in different ways depending on the source of financing (internal, external or mixed) the level of debt to GDP and its effect on the private saving. For example, an expansionary fiscal policy is expected to have a positive relationship with CA deficit based on twin-deficit hypothesis (base on positive impact of fiscal deficit and private consumption). In effect, as the private sector doesn't balance the change in public saving, fiscal balance will affect national saving (IMF, 2013). This relationship can turn to be negative based on the perceived sustainability of public debt and in line with Ricardian behavior (consumers will save more as they expect an increase in tax).
- Trade openness: This variable can capture trade and industrial policies that could affect the CA balance. An increase in trade openness can be associated with an increase in current account balance (according to Ohlin, economy with lower income will purchase less of tradable goods as relative price of the tradable goods increase which in turn reduces the CAD). The responsiveness of the current account balance to change in trade openness can also be negative. That is, an increase in trade openness widens the CAD. Country with limited exports is more likely to run a current account deficit, through the increase of imports as the trade openness become larger. This variable is measured as the ratio of total import and export to GDP.

- Oil trade balance: Oil trade balance captures the effect of changes in oil price and volume on the current account. For non-oil exporting country an increase in oil price and volume will widen the CAD.
- Nominal Exchange rate: According to IMF (2006), the nominal exchange rates can affect the trade balance through various channels. It argues that a nominal depreciation will have an immediate impact on the prices of exports and imports. The effect of nominal depreciation on trade balance can be indirect and pass through wealth or absorption. In the case when a country has trade deficit, a nominal depreciation will have a negative effect on its foreign asset position, and lead to an increase in external debt and thus trade deficit. If a country has a net trade surplus, nominal depreciation will have a positive effect. As Tunisian trade balance is negative, the expected sign of nominal appreciation (for increase in direct quotation) is to be positive.

Following the methodology proposed by Chinn and Prasad (2003) and Ca'Zorzi et al. (2012) the CA equation can take in general the following form:

$$CA_t = \alpha + \beta X_t + \lambda F_t + \delta P_t + \varepsilon_t \qquad (1)$$

Where CA is the current account, *X* is a vector of macroeconomic variables, *F* is a vector of financial factors, and *P* is a set of institutional determinants.

The set of the variables to be included in forecasting current account can capture macroeconomic (GDP, trade openness, exchange rate, fiscal balance) institutional factor (trade openness, which can be a proxy to account for the trade liberalization) and financial factor (credit to private sector). I also include a dummy variable to capture the effect of the revolution.

If cointegration hypothesis is accepted, I estimate an error correction model for Tunisian current account using maximum likelihood approach. The error correction model for current account balance can take the following form:

$$\Delta CAB_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \, \Delta CAB_{t-i} + \sum_{i=1}^{p} \gamma_i \, \Delta X_{t-i} + \pi(CAB_{t-i} - \phi X_{t-i} - \mu) + \varepsilon_t \qquad (2)$$

Where CAB and X are respectively the current account balance and the set of independent variables.

This approach will allow integrating long term and short term adjustment in a single equation. This methodology will also help in determining the importance of short term and long term drivers of CAD, that account most in widening the deficit.

4.2.2 Disaggregated Approach using ARMA-X Model

The autoregressive moving average model including exogenous covariates extends the ARMA (p, q) by including one or more exogenous series on the linear time series. This dynamic regression model, include exogenous variable with lagged value of dependent variable and disturbances terms. This model is called ARMA-X or transfer function model. These extensions are made to improve forecast and to reduce the forecast error. If data are non-stationary the dependent variable will be modelled in differences, and that will yield an ARIMAX model. In this case, data contain seasonal effect, so the ARMAX model is specified as follow;

$$\Delta y_t = \delta_o + \alpha_p \Delta x_t + \sum_{s=1}^{4} \beta_s D_s + \sum_{i=1}^{p} \gamma_{Vi} \Delta y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (3)$$

where Δ represents first differences, y_t is the value of time series variable in period t, x_t is the exogenous variable included in the linear equation, D_s are seasonal monthly dummies, $\sum_{i=1}^{p} \gamma_{Vi} \Delta y_{t-i}$ represents the autoregressive (AR) component (dynamic shocks), $\sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$ represents the moving average (MA) component (stochastic shocks) and ε_t is an *iid* random error term. Estimation of equation (3) is accomplished using maximum likelihood procedures.

To capture the influence of the revolution, I also include a dummy variable in the model (D =1 from 2011 to 2014, and zero otherwise).

4.2.2.1 Exogenous Variables to include in Tourism ARIMA-X Model

Tourism demand modelling differs corresponding to the approach used; supply or demand approach. Based on the demand approach, tourism demand is mainly measured using tourism arrival or tourism expenditures (Tang, 2011). While the supply approach, which is less used, focus on others variables like marketing expenditure, numbers of beds, or air craft capacity (Dupont, 2006). But for economic assessments or forecasting needs of government or central bank, tourism receipts are often used.

Tourism forecasting methodology can be divided to qualitative or quantitative methods. Qualitative method employ expectations of professional of tourism (probabilistic), however quantitative approach is based on statistical models (univariate or multivariate model, dynamic or static model, artificial neuros network).

With regard to tourism demand modelling, two variables are mainly reported in literature to explain the demand patterns related to economic situation. Relative prices and income constitute the most important factors. Other potential factors include the lagged dependent variables to capture persistence effect of various influencing factors on tourism. Others suggest including time trends to account for changes in tourists' tastes. For example, Song (2010) have estimated tourism receipts (expenditure) as demand function depending on real effective exchange rate and real GDP per capita for the origin countries.

The price variable can be either defined as relative price of tourism between destination country and origin countries (Durbarry and Sinclair, 2005) or as real exchange rate of the destination country. Tourism and relative price are expected to have negative relationship as an increase in relative price, make local goods and service more expensive relative to foreign countries. Income variable is measured either by the real GDP of origin country or by household disposable income.

Quantitative methodology is primarily used to forecast tourism. Under this approach time series method is the most used for short-term and medium-term forecasting. For example, Balogh et al. (2014) have used X-12 ARIMA model to forecast tourist arrival to India and Thailand during the period 2006 to 2010. Data used spans from 1997 to 2005. Claveria and Torra (2014) have used three models to forecast tourist arrival for Catalonia during the period of 2001-2009. Their result demonstrates that ARIMA model has superior forecasting performance comparatively to artificial neuros network (ANN) or self-exciting threshold auto-regression models (SETAR). For example Akal (2004), have integrated the number of tourism as explanatory variable in the ARIMA-X model to forecast the tourism revenue in Turkey. Considering the availability and accuracy of the exogenous variable to include in ARIMA model, I choose to include nominal GDP in ARIMA model because it describes the overall economic situation of origin country. The expected sign is to be positive as an increase in the output of origin countries will increase tourism activity and consequently receipts. In addition as I am interested by the total value of tourism receipts, I use the total GDP and not the per capita GDP and I restrict my focus on European region as the mammoth part of receipts come from these countries. Moreover, the interest is to predict tourism receipts I must consider the availability and the cost of producing forecasted variables (reliable GDP forecast for European countries are available), and the most parsimonious models. For these reasons I don't include any supply variable (as tourism supply exceeds largely the demand in Tunisian market) and the exchange rate as it is not available.

4.2.2.2 Exogenous variable to include in Worker remittances ARIMA-X Model

Most studies of remittances by immigrant workers investigate the impact these inflows on economic growth, financial development (credits and investments), exchange rate appreciation and poverty reduction. However, quantitative modelling of this variable has not received considerable attentions. In fact, worker remittances can be modelled in microeconomic or macroeconomic level. In individual level data, Lucas and Stark (1985) were the first to explain the motivations to remit money by factors such as altruism, self-interest and family and ties. Others factors include education, household composition and gender. These microeconomic determinants are used typically to determine the size of remittances. At the macroeconomic level, the main determinants of worker remittance flow include interest rate differential between home and host countries, wages, exchange rate levels, income, inflation, relative rates of returns (Higgins, Hysenbegasi & Pozo, 2004). From these broad factors, Ratha & Mohapatr (2010) assert that, there are three main factors; migrants stocks (1), income in different destinations countries (2) and incomes in the migrant-sending country (3).

Empirical studies to forecast worker remittances use mainly time series models. For example, to predict the level of workers remittances for Nigeria, Adedokun (2013) have used an ARIMA model to forecast the remitter flows during the next decade (2010-2019). The authors employed annual data form 1977 to 2009. Adams (2008), have combined microeconomic and macroeconomic variables, using panel regression to model the worker remittance for developing countries. Ratha & Mohapatra (2010) have forecasted remitter's flows, using two approaches. In the first assumption, the authors consider the worker's remittances will grow at the same rate of hosting countries GDP. In the second approach, they consider remitters' flows will grow faster than destination countries.

From a forecasting point of view, modelling worker remittances with broad factors is fraught with lack of reliable forecasts for these variables. Moreover empirically, parsimonious model is better than extended model. In this wake, including migrant stock (numbers of people born in a country other than that in which they live), can be biased (for example it includes refugees). So as I use the times series models, last remittance observations is included in the forecasting model which is easily get and updated. Moreover, rather than using two variables relating to nominal GDP, I assume that worker remittances is mainly affected by foreign output to be more conservative and parsimonious. Consequently, ARIMA-X model will include foreign output as explanatory variable.

4.2.2.3 Exogenous variables to include in Exports ARIMA-X Model

In literature, export demand function has taken several forms. But the majority of export models are derived from the imperfect substitute's model of Goldstein and Khan (1985). For developing countries price and income elasticity are the major determinants of trade flows. More precisely, export volume is often estimated as a function of foreign and domestic export price, income variable and effective exchange rate. Nevertheless, specification that uses separate prices (exported good's own price with respect to the price of domestic substitutes) suffers from collinearity between different price indices (Wong, 2008). Moreover, using relative prices is more statistically consistent and takes into account the assumption of imperfect substitutes between domestic and foreign goods. According to demand theory the sign of real exchange rate must be negative, as an increase in import price relative to domestic price will reduces demand for imported goods. With regard to the sign of the income coefficient it could be indeterminate.

From an econometric point of view, empirical studies use various approach to model the export demand function. For example Wang (2008) investigate the determinant of demand for Malaysia's top five electronics exports using cointegration and error correction framework for the period spans from 1990 to 2001. Keck et al. (2009) have used ARIMA model with explanatory variable to forecast import demand. The time series model includes GDP and relative import prices.

The main focus here is to include the variable that helps in improving forecasting performance of the exports value. Consequently, in ARIMA-X model I include nominal foreign trade partner output as exogenous variable only. As the time series models include the lagged terms of dependent variable, I think that including import prices and GDP yield redundancy, because import is considered in GDP, so when I use forecasted GDP, I account for the effect of others explanatory factor affecting imports.

4.2.2.4 Exogenous variable to include in Imports ARIMA-X Model

Theoretical models of import demand function can be grouped in three different approaches. The first approach relates the volume of imports to domestic real income and the ratio of import prices over the domestic prices based on equilibrium or disequilibrium model. The second specification emphasizes that demand import is determined by foreign exchange obtainability. It assumes that all type of imports is positively related to the attainability of foreign exchange. So, this approach relates imports to foreign exchange receipts. But, this approach clearly overlooks the adjustment of exchange rate to excess demand for foreign money in one hand and the effect of relative's prices.

The third approach is the monetarist approach of import demand. This approach use money supply as explanatory variable of imports volume.

Others models include different variables as; trade openness, terms of trade, real foreign reserves, exchange rate volatility , debts, import duties, and export receipts.

In fact, developing countries have limited access to foreign reserves, but have also non-curtailed volume of import which is mainly driven by local activity. Empirical studies used to forecast imports volume include different model. For example, Narayan et al. (2008) have used ARIMA model with exogenous variables to forecast Fiji's exports and imports until 2020. The authors have included the domestic output and relative prices in the ARIMA-X model. Others like, Abd, et al., (2013) have used ARIMA and neural network model. Wang, et al. (2012) used ARDL model.

Considering the availability of forecasted value of the exogenous variable to include in ARIMA-X model, I use local output as explanatory variable. According to supply theory the sign of the income coefficient could be positive, as increase in the domestic activity will raise demand for external product used in the production.

4.2.3 Disaggregated Approach using ARMA-X Model

Combining information from different models can improve the accuracy and the robustness of forecasting, as the errors from different models can cancels each other's and may be more stable. According to Yang et al., (2015) mixing different models enable to gather information more effectively which in turn improve the forecasting performance.

In this wake I will test first for the existence of cointegrating relationship between exports and imports. The existence of such equilibrium relationship enables to take into account useful information when deriving the forecast of the current account using disaggregates approach. In effect, as the developing countries have restricted access to foreign financial markets and restricted stock of foreign reserves, it will try to preserve his external budget constraint by keeping the trade deficit at certain level.

It is worth to say that empirical research have found, mixed result with respect of the existence of cointegration relationship between export and import. Some have reported the existence of long run relationship (Uddin, 2009; Babatunde, 2014; Hussein, 2014) and others have rejected the existence of such a relationship (Cheong, 2005; Saaed & Hussain 2015).

As the exports have greater proportion of imports, so the imports cause exports to increase and not the opposite. So that, The model estimated between exports and imports is described as follows:

$$\Delta EX_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \, \Delta EX_{t-i} + \sum_{i=1}^{p} \gamma_i \, \Delta IM_{t-i} + \pi(EX_{t-1} - \phi IM_{t-1} - \mu) + \varepsilon_t \quad (4)$$

Where EX, IM, α_0 and π are exports, imports, constant and speed adjustment respectively.

4.3 Evaluation of the forecasting performance

Commonly used measure for comparison of forecasting performance is based on the root mean of squared error (RMSE). The consequence of squaring the error is to put more weight on the outlier. The RMSE can be expressed as following:

$$RMSE = \left(\frac{\sum_{i=1}^{k} \left(ca_i - f_i \right)^2}{k} \right)^{1/2}$$

Where, ca_i is actual observation of the current account balance at point i, f_i is the corresponding predicted value at point i, and k is the number of points being compared.

This measure of the goodness of fit depends on the scale of forecasted variable, and must be interpreted as relative measure. The best forecasting model is the one that have small error.

5. Results and Discussion

I will present the outcomes of estimating the reduced form model and then, the disaggregated model. After that I will compare the goodness of the forecast for one-step ahead and dynamic forecast.

5.1 Reduced Form Model

Before estimating the reduced form model, I will present some statistical properties of the determinants of current account balance and I will test for the stationarity as statistical inference will be not the same when times series are not stationary.

5.1.1 Stationarity Test

The unit root test is conducted using two tests. The first test is the DF-GLS[1] modified Dickey-Fuller test of Elliott, Rothenberg, and Stock (1996) that has greater power than the augmented Dickey-Fuller test (trend and mean of the series are first removed via GLS regression, and then an augmented Dickey-Fuller regression is performed on the transformed data). The second test is the Phillips-Perron test which is similar to the ADF but it includes a correction for serially correlated residuals and does not require normally distributed errors.

The results of different unit roots test are reported in table 2. The null hypothesis of unit root is not rejected whatever the test or the model (constant or constant and trend) used for data in level. However in first difference the null of unit root is rejected at 5% level.

[1] - The optimal lag order is calculated by the Ng and Perron (1995) sequential t test on the highest order lag coefficient, stopping when that coefficient's p-value is less than 0.10.

Table 2: Unit root results

Variables	FD-GLS tests statistics				PP tests statistics				Decisions
	I(0)		I(1)		I(0)		I(1)		
	C	C&T	C	C&T	C	C&T	C	C&T	
gdptn	-1.638	-1.638	-4.838	-4.838	-0.534	-1.711	-8.097	-8.062	I(1)
gdpez	-1.536	-1.536	-3.562	-3.562	-1.867	-1.648	-0.354	-4.37	I(1)
fb	-3.646	-3.646	-7.793	-7.793	-6.07	-6.852	-20.023	-20.595	I(1)
credit	-1.159	-1.159	-3.799	-2.399	1.285	-2.266	-3.622	-5.702	I(1)
ob	-1.539	-1.539	-7.026	-7.026	-2.358	-4.291	-17.71	-18.737	I(1)
reer	-1.343	-1.343	-6.163	-6.163	-0.988	-1.715	-7.113	-7.063	I(1)
to	-3.065	-3.065	-4.354	-4.354	-7.754	-7.946	-21.25	-21.039	I(1)
cab	-1.882	-1.882	-5.264	-5.264	-1.449	-4.334	-19.21	-21.594	I(1)
critical value are at 5%: DF-GLS are -3.17 (with or without trend); Phillips-Perron are -2.92 (without trend) and -4.13 (with trend)									

As all variables are integrated of order one, it may exhibit a long run relationship. In this situation testing for co-integration is a more suitable technique. In this case the first step is to determine the optimal lag length of the VAR model.

5.1.2 Lag order selection for VAR

The most common strategy to select the right lag order is based on Akaike Information Criterion (AIC), the Schwarz Information Criterion (SIC), the Hannan-Quinn Criterion (HQC), Final prediction error (FPE) and the general-to-specific sequential Likelihood Ratio test (LR). However, as Ivanov and Kilian (2005) point out, the most accurate criteria for data with quarter frequency data is HQC when sample size contains more than 120 observations. In the case when the sample size is less than 120 observations, SIC is more accurate. Results are reported in Table 3.

Table 3: Lag order selection based on VAR model

Lag order	LR	FPE	AIC	SC	HQ
0	NA	91683.69	14.2619	14.55387	14.37481
1	1.057065	93001.85	14.27528	14.60376	14.40231
2	0.002794	96548.01	14.31158	14.67655	14.45272
3	1.447797	97016.03	14.31504	14.71651	14.47029
4	9.792268	80252.38	14.12368	14.56164	14.29304
5	5.222515*	73639.12*	14.03570*	14.51016*	14.21918*

* indicates lag order selected by the criterion

The maximum lag length is chosen automatically by the system. The VAR estimation shows that the optimal lag length for all criteria is five periods. This result suggests that the shock from each variables takes 5 quarters to die out, which is a plausible amount of time for an economic shock to be absorbed.

The next step after choosing the right lag, consist to test for the existence of long run relationship between current account and explanatory variables, since are all integrated of order 1.

5.1.3 Testing for cointegration

In the presence of more than two variables Johansen-Juselius (1990) cointegration test is more superior to Engle-Granger (1987) cointegration test, because it allows for multivariate cointegration equation. To determine the number of cointegration equation, this approach focuses on the rank of matrix π, which is equal to the number of independent cointegrating vectors (the sum of its non-zero eigenvalues). There two statistics that can be used to determine the number of cointegrating vectors; the eigenvalue (λ_{Max}) and trace statistic (λ_{Trace}). The decision rule is to reject the null hypothesis that there are r cointegrating vectors if the calculated statistic is larger than the critical values tabulated by Johansen, and I accept the alternative hypothesis of the existence of r+1 vectors. Table 4 reports the results for trace and eigenvalues statistics.

Table 4: Cointegration test results

Hypothesized No. of CE(s)	Max-Eigen Statistic	5% Critical Value	p-value	Trace Statistic	5% Critical Value	p-value
None *	70.38576	58.43354	0.0023	263.6288	197.3709	0
At most 1 *	52.37413	52.36261	0.0499	193.2431	159.5297	0.0002
At most 2 *	50.20064	46.23142	0.0179	140.869	125.6154	0.0042
At most 3	32.31832	40.07757	0.2859	90.66831	95.75366	0.1064
At most 4	22.24876	33.87687	0.5884	58.34999	69.81889	0.2895

As shown in Table 4, trace statistic indicate the presence of three cointegrating vectors. The null hypothesis of two cointegrating vector is rejected in favor of the alternative hypothesis of three cointegrating vectors. Calculated statistic is lower than the tabulated value at third rank (90.66<95.75). Regarding eigenvalue statistic, it indicates also the presence of 3 long term relationships. Indeed two statistics support the existence of long term relationship, it remain to decide in the choice of number of vectors to estimate as recommend Hendry and Juselius (2000). In effect, as these authors have stated, when the t-values of corresponding speed adjustment coefficient is lower, including this vector will not lead to any gain. Following this rules of thumb, when I estimate more than one cointegrating vector, it appears that the additional vector have no statistical significance. So, I estimate one cointegrating vector between Cad and others independents variables.

5.1.4 Estimation of Cointegration Vector an Error Correction Model: Dependent Variable: CAB

After testing for the existing of cointegrating vectors, I turn now to estimate the long term relationships between current account balance as dependent variable and independent variables. Table 5 report the result of cointegrating equation.

Table 5: Long run determinant of the current account balance with dummy variable

Variables	**CREDIT**	**Fisc_bal**	**GDP_EZ**	**GDP_TU**	**NEER**	**Oil_bal**	**Trade_Op**	**Constant**
Coefficients	-0.073011	-0.122071	-0.003879	1.149500	54.95690	-0.913282	27.85837	-10245.84
std. errors	(0.00971)	(0.04095)	(0.00028)	(0.07733)	(5.37252)	(0.12557)	(5.07289)	(264.878)
t-stat.	[-7.52109]	[-2.98103]	[-13.6395]	[14.8653]	[10.2293]	[-7.27282]	[5.49161]	[-38.68135]

In line with the a priori expectations all coefficients appears to have the expected sign (except for the oil balance). The coefficients associated with these variables are significant at 1%. The domestic output have a positive effect suggesting that an increase of national output by 1%, will cause an increase in the CAD by more than 1.14%. With regard to the foreign GDP, 100 basis point of growth contribute to reduce the CAD by more than 38 basis points. The fiscal balance turns to have a negative effect, supporting the Ricardian behavior. Trade openness coefficient is positive and significant at 1%, suggesting that more openness improve the current account balance as expected by Ohlin. This means that trade liberalization and technology transfer have a positive impact on exports. The nominal exchange rate has significant and positive effect. So a depreciation of exchange rate doesn't improve the current account balance in the long term as suggested by the elasticity's approach. The negative relationship can be established based on the effect of depreciation on foreign asset position, which in turn leads to an increase in external debt and thus trade deficit. In effect, Tunisian exports consist mainly of primary commodities, while imports are necessity goods. In that sense exports and imports are inelastic toward exchange rate depreciation and lead mostly to worsening of trade balance. Not surprisingly, the total credit to private sector is also significant. An increase in credit to private sector worsens the current account in long term as liquidity become more abundant.

The Euro Zone GDP affects the current account as whole. This finding supports the second hypothesis. In effect, Tunisian exports are driven by imports from foreign countries, so as foreign GDP increase the imports of non-finished goods will increase and boost in turns the local exports.

Other important result is the opposite sign of the oil balance in long term. One explanation is that oil current account balance may react with lag to the current account balance.

I now turn to estimate the error correction model which integrates short-run adjustment with long run dynamics of the current account. I include two dummies, one to capture the effect of the revolution and the second is to account for the seasonality. The results of the estimation are reported in table 6. I will present only the significant variables.

Table 6: Error Correction Models results

Variables	coefficients	std. Errors	t-stat
D(CAB(-3))	0.332	0.2	1.700
D(GDPEZ(-2))	-0.0185	0.006	-2.687
D(GDPTN(-3))	0.72	0.417	1.724
D(NEER(-3))	-144.36	50.77	-2.843
D(CREDIT(-3))	-0.414	0.176	-2.348
D(CREDIT(-2))	-0.416	0.19	-2.123
D(TO(-1))	48.38	16.88	2.865
D_revolution	-667.9	302.02	-2.210
ECT_{-1}	-0.853	0.448	-1.901
R-squared	**0.92**		

The first thing to check in the ECM is the sign and significance of the adjustment speed. The error correction term is negative and significant suggesting that deviation from long term equilibrium is corrected by more than 85%. The revolution appears to have a significant and negative impact on the current account. After the revolution, the CAD deficit shifts down by more than TND667 million. The seasonality turns to be not significant. One explanation is that the ECM is lagged enough to capture the seasonality effect. Regarding the fiscal balance which plays a role in the long run, appears to not play a significant role in the short term. The oil balance is not significant in the long run and in the short term. This finding can be explained by the fact that the change in oil balance is not important as the export of oil cover an important portion of oil imports, leaving the change constant in value. The lagged current account has a negative and significant effect. The coefficient shows that the persistent effect is not transitory. The local GDP and the exchange rate, continue to play a significant effect on the short term adjustment. Finding show also high adjusted R squared. This result is in line with Elhendawy (2014) who find a higher adjusted R squared (0.98) when estimating an ECM for Egyptian current account deficit using annual data covering the period 1980 to 2011. Chinn and Prasad (2003) have reported also an adjusted R squared equal 0.94 for industrial countries using cross-sectional and panel regression.

Figure 3 plot the estimated short term adjustment of the Current account versus the observed difference. The model appears to capture well the turning points of the current account. The errors are higher after starting from 2010.

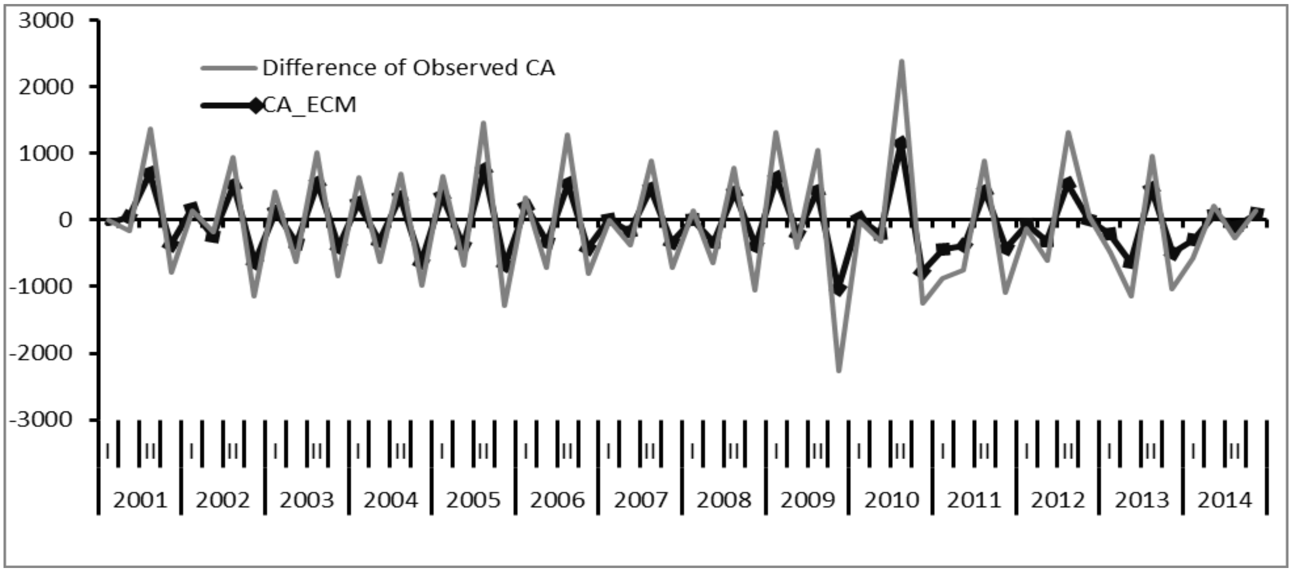

Figure 3: Short term adjustment of the Current Account

In the following figure, I decompose the expected dynamic of current account balance to its short term and long term components to see which part account for the most part of widening of current account deficit.

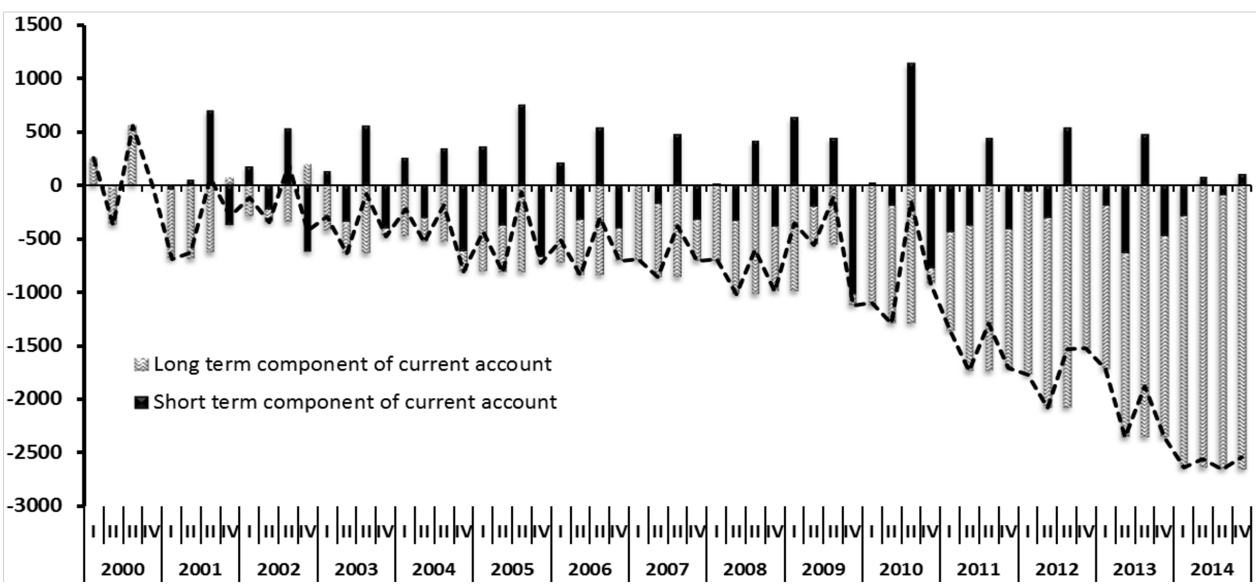

Figure 4: Short term and Long term Component of Current Account Balance

The examination of figure 4, show that the long term component of current account balance dominates the short term component, which is largely negative. The resulting current account balance appear to be driven more by fundamental factors as fiscal balance, trade openness and local GDP. For this reason, it is considered to persist in foreseeable future if the government doesn't act to reduce budget deficit, increase GDP, or tighten trade liberalization.

To test the robustness of the model, I test the normality of the residual of the error correction model, because forecast will be inefficient in presence of serial correlation. One method is to use Lagrange-multiplier test, because it can test high order of autocorrelation. The null hypothesis is that there is no autocorrelation at specified lag order. Table 7 shows results for autocorrelation test.

Table 7: Lagrange-multiplier Test

Lag	**Chi2**	**df**	**Prob > chi2**
1	82.8802	81	0.42117
2	63.1472	81	0.92894
3	86.7227	81	0.31152
4	71.2995	81	0.77094
H0: no autocorrelation at lag order			

The results demonstrate the absence of autocorrelation among residuals through lag 1 to lag 4. The null hypothesis cannot be rejected at 1%. In absence of residuals autocorrelation, prediction is more accurate, because error in given forecast period is independent from the previous ones.

Once I have estimated the error correction model for current account balance, I can use the empirical results to perform one-step ahead and dynamic forecast. Figure 5 plot the one step ahead and dynamic forecast (starting in 2010 Q4) of the current account versus the observed values.

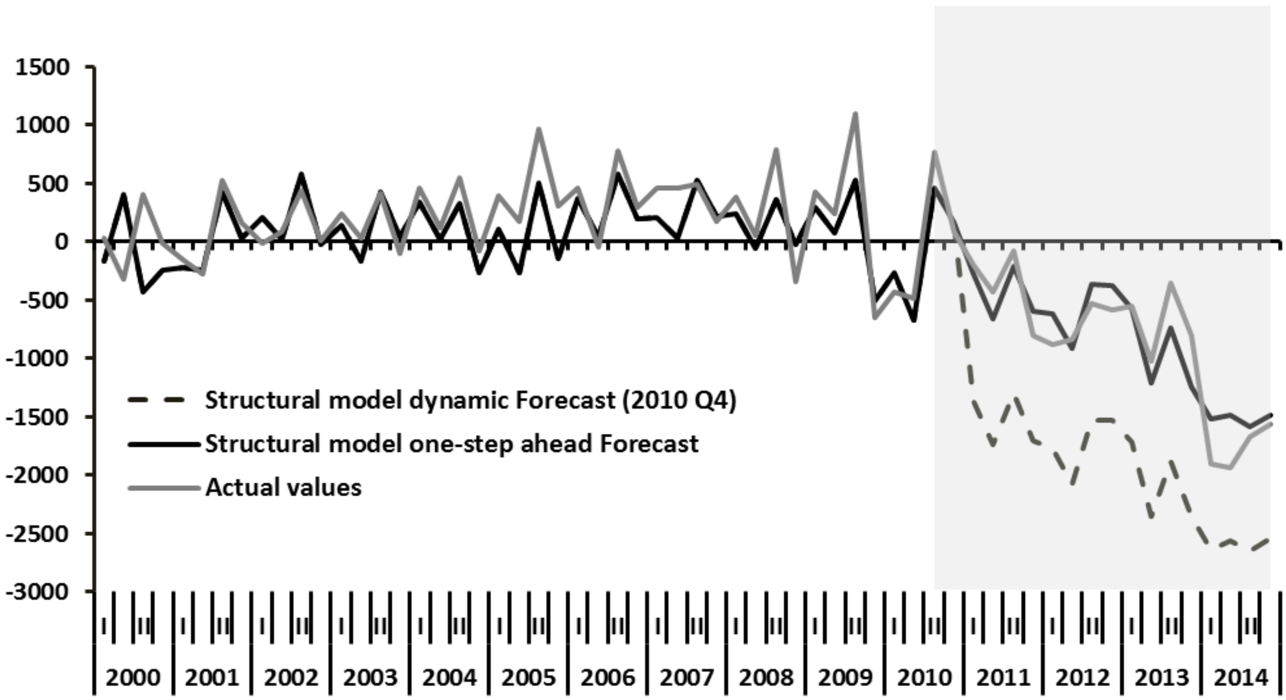

Figure 5: Aggregate approach; Dynamic vs one step ahead forecast of CA balance

One step ahead forecast predicts the dependent variable for one coming period based on the last fitted value estimate until the last observation of actual data. As the explanatory power of the reduced model is high, one can expect that in-sample one-step ahead forecast would be good. Figure 5 show that the reduced model makes good prediction of the current account balance at one-step ahead. The model closely tracks the pattern of current account balance. The RMSE forecast for one-step ahead of structural model is expected to be lower, as it is theoretically equal to the residuals of the model in corresponding period.

Dynamic forecast can be view as a multi-step ahead forecast, starting from the data that just come before the point of forecast origin. In-sample dynamic forecasts for reduced form model also provide good predictions. Moreover, in comparing one step-ahead forecast to dynamic RMSE forecast, it appears that the later have large forecast errors than one step-ahead forecast. Since the horizons forecast is not so longer and all data are used to fit the reduced model, the forecast values doesn't move much from the actual values.

5.2 Disaggregated forecasting model

5.2.1 Descriptive statistics

To assess the distributional properties of the variables, I report in table 8 various descriptive statistics.

Table 8: Summary statistics

	Exports	Tourism	Remittances	Imports	Current Account Balance
Mean	4543.922	697.8433	574.865	-5895.678	-675.6033
Median	4737.6	670.1	530.15	-5592.75	-411.35
Maximum	7557.4	1283.7	1204.8	-2524.8	327.1
Minimum	1962.2	339.7	221.8	-10704.4	-2315.2
Std. Dev.	1802.808	249.558	228.4014	2520.868	701.6805
Skewness	0.056172	0.68468	0.583178	-0.364423	-0.937395
Kurtosis	1.537017	2.77031	2.889024	1.784083	2.832914
Jarque-Bera	5.38235	4.819767	3.43176	5.024179	8.856891
Probability	0.067801	0.089826	0.179805	0.081099	0.011933
Observations	60	60	60	60	60

As expected, the standard deviation of different current account items differs largely. Tourism and worker remittances have low standard deviation comparatively to others current account items. The standard deviation of all current account items is larger than for current account balance. But, if these items are negatively correlated, the variance between these items may be lower than the variance of current account taken as whole. There also a difference in terms of distribution. Tourism, worker remittances and exports are right skewed, while current account balance and imports are left skewed. However, only worker remittances appear to be normally distributed according to Jarque-Berra test with p-value lower than 10%.

5.2.2 Test of stationarity

The first step of the Box-Jenkins method is to verify if the time series is stationary and if it presents a seasonality pattern (in this case the series will not have a stable variance). Generally there are three important methods to check stationarity; visual inspection; correlograms and unit root test. Plotting the time series can provide useful information.

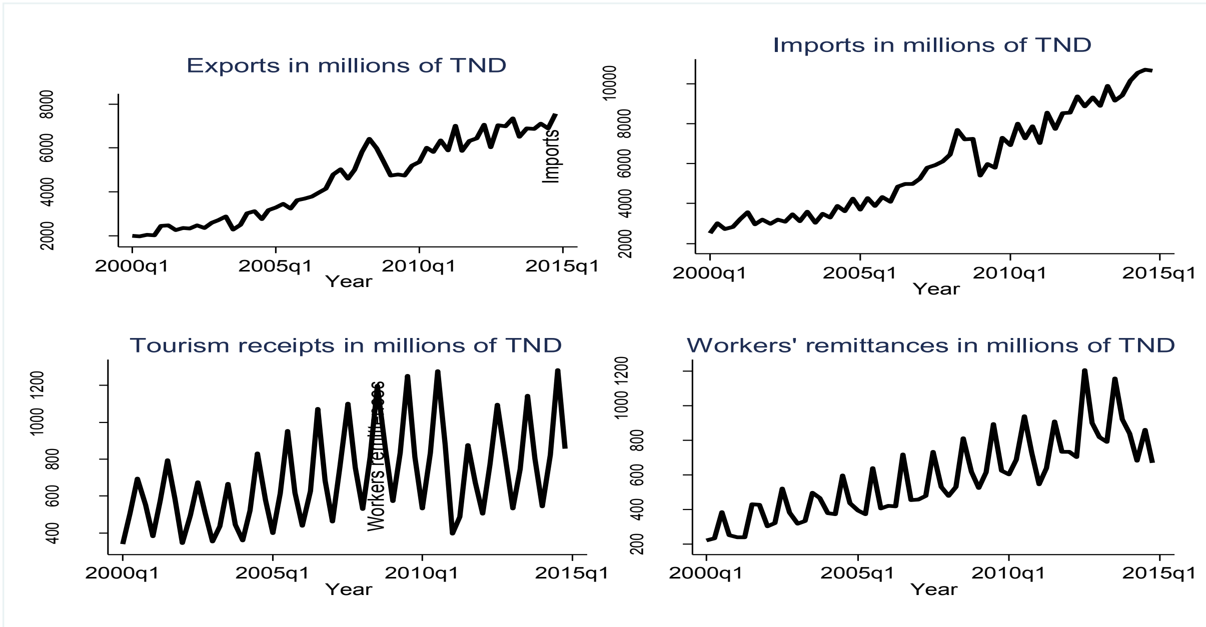

Figure 6: Time series plot of current account items.

In Figure 6 the graphical analysis of current account components allow to identify two patterns in these time series: trend and seasonality. Exports and import are more likely to exhibit time trend, while tourism and workers' remittances show a great seasonality, and to some extent a time trend. Identifying these patterns will help first in extrapolating them in the future and to perform more accurate forecast. The presence of seasonality in tourism is due to the fact that nature of Tunisian tourism which is seaside tourism concentrated in hot season between Jun, July and August. With regard to workers' remittances it can be explained by the departure and return of overseas workers in summer.

After accounting for the presence of seasonality in tourism and worker remittances, I introduce a seasonal factor when testing for the presence of unit root. These tests are performed using ADF and PP tests. Results for stationary test are presented in table 9.

Since the statistic value for both test are greater than their corresponding critical value, neither of these test reject the presence of unit roots in the series at 5% level. However in first difference these tests clearly reject the null hypothesis of the presence of unit root at 5%.

Table 9: Results of unit root tests for stationary (variables in levels and first differences)

Variables	AFD tests statistics				PP tests statistics				Decisions
	I(0)		I(1)		I(0)		I(1)		
	C	C&T	C	C&T	C	C&T	C	C&T	
Exports	-0.373	-2.785	-4.627	**-4.878**	-0.317	-4.037	-11.723	**-11.811**	I(1)
Imports	0.978	-2.649	-4.141	**-5.168**	0.269	-4.113	-14.754	**-15.195**	I(1)
Worker receipts*	-1.699	-1.543	-3.338	**-3.524**	-3.296	-3.379	-10.684	**-10.93**	I(1)
Local GDP	1.908	-2.527	-2.98	**-3.616**	-0.534	-1.711	-8.097	**-8.062**	I(1)
Foreign GDP	-1.435	-1.575	-3.067	**-3.236**	-1.867	-1.648	-0.354	**-4.37**	I(1)
Tourism receipts*	-2.512	-2.484	-4.227	**-4.163**	-3.369	-3.341	-5.191	**-5.13**	I(1)

(*)The unit root test include dummies variable to account for seasonnality
Critical value are at 5%: -3.58 (without trend) and -4.150 (with trend) for ADF; -2.92 (without trend) and -4.13 (with trend) for Phillips-Perron

5.2.3 Forecast using ARIMA-X models

The next step is to determine the lag order for each model. This step is crucial part, because determining the appropriate lag will have a great implication on forecasting exercise. This task can be accomplished based on the inspection of the correlograms of autocorrelation and partial autocorrelation of each series or using information criteria as AIC and SBC. Based on correlogram, the procedure consists to determine whether the series can be modeled as AR(p), MA(q) or a combination of these terms to correct the correlation. In others words when the correlation and partial autocorrelation are white noise there is no need to search out for another ARIMA model.

While using information criteria allow choosing the appropriate lag based on a tradeoff between good fitting the data and the desire of using parsimonious model. Following this approach, the optimal model is one that have the lower AIC or SBC values. Further the picked up model, is tested for the presence of autocorrelation using portmanteau test.

The selected model for each current account items is presented in table 10 with Ljung-Box Portmanteau test whose null hypothesis is that residuals are not auto-correlated.

Table 10: Model selection results for ARIMA with exogenous and seasonal dummy variables

	Exports		
ARIMA-X(1,1,2) + Dummy			
AIC	870.943	**Portmanteau (Q) statistic**	16.4891
SBC	883.4082	**p-value**	0.943
	Imports		
ARIMA-X(1,1,1) + Dummy			
AIC	876.3208	**Portmanteau (Q) statistic**	43.56
SBC	888.786	**p-value**	0.029
	Remittances		
ARIMA-X(2,1,2) + Dummy+ Seasonal Dummy			
AIC	544.4567	**Portmanteau (Q) statistic**	8.7902
SBC	551.311	**p-value**	0.9989
	Tourism		
ARIMA-X(2,1,1)+ Dummy + Seasonal Dummy			
AIC	692.2772	**Portmanteau (Q) statistic**	17.4826
SBC	713.0526	**p-value**	0.9185

The results in table 10 show the absence of the autocorrelation in residuals for models selected based on information criteria. For exports and imports, I only include exogenous independent variables with dummy variable relating to revolution and autoregressive and moving average terms, while for tourism and worker remittances I include also a seasonal dummy variable. I also compare model for tourism and worker remittances based on additive and multiplicative seasonality. Model with multiplicative seasonality have superior value of information statistics.

After identifying the appropriate time series model for each current account items I estimate each model and I perform one-step ahead and dynamic forecast. Figure 7 bellow show the one-step ahead and dynamic forecast for using disaggregate approach based on single current account items.

The one-step ahead forecast graphs demonstrate that the aggregate forecasting fit the data very well and capture the seasonality pattern present in tourism and worker remittances. With respect to dynamic forecast, forecasted values depart clearly from observed values. Comparatively to the one–step ahead forecast, the dynamic forecasting approach yields worse performance. This is due mainly to the fact that errors from exports and imports are opposite; one cannot conceal the other when they are added to reach the whole current account.

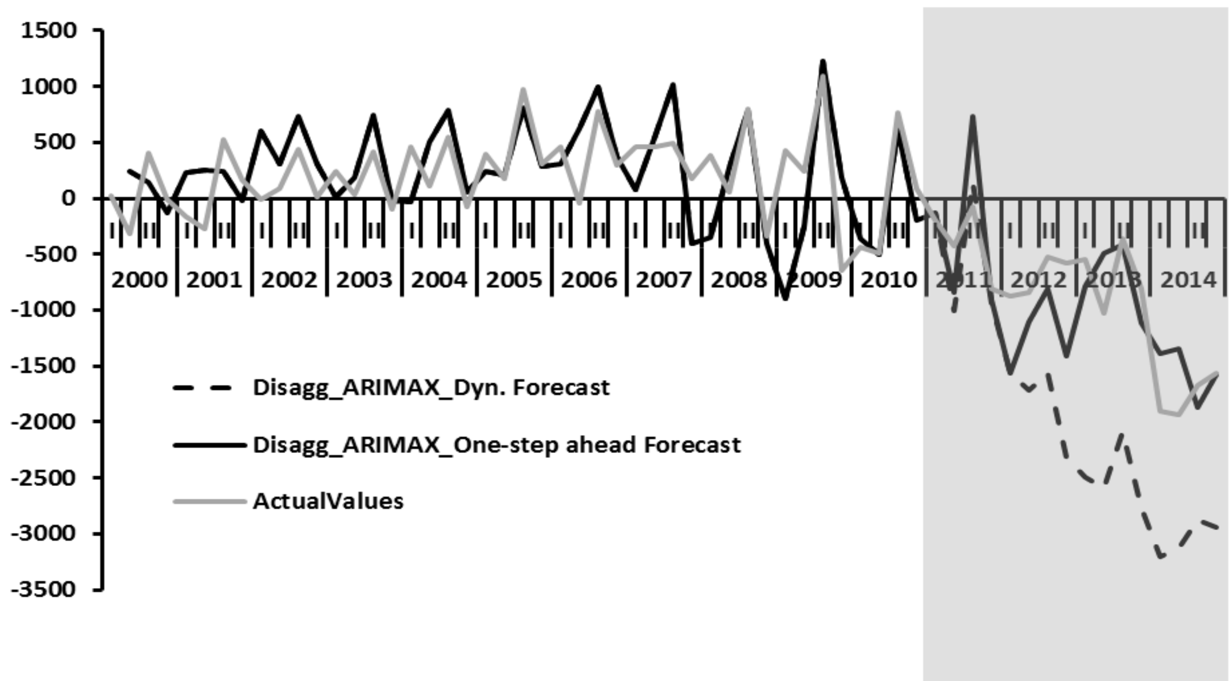

Figure 7: Cumulative disaggregated forecast

One explanation is that as the volatility of current account items have increased after revolution, consequently the time series models forecasting performance decreases, as it is a linear and statistical method. The sum of the error of the current account components becomes larger than the current account balance taken as whole. In effect, the tendency and the level of the current account items become more changing and consequently ARIMA-X models cannot predict the direction of the change, if these parameters are not consistent over times. Here I find support to the first hypothesis, and I provide a plausible explanation to the mixed result reported in literature regarding the accuracy of the indirect approach using time series models.

5.2.4 Forecast using combined approach

Visual inspection of imports and exports graphs shows that they have tendency to move together, and suggest therefore the existence of long run equilibrium between these variables (see figure 8). Consequently if such relation exist, when variable can be predicted using the other. For example, when I look to ratio of export to import for the Tunisian trade, I can easily observe that remains approximately stable over time (hover around 70%). This finding describes a commitment made by the government to keep the trade deficit at acceptable level (keep holding the international budget constraint).

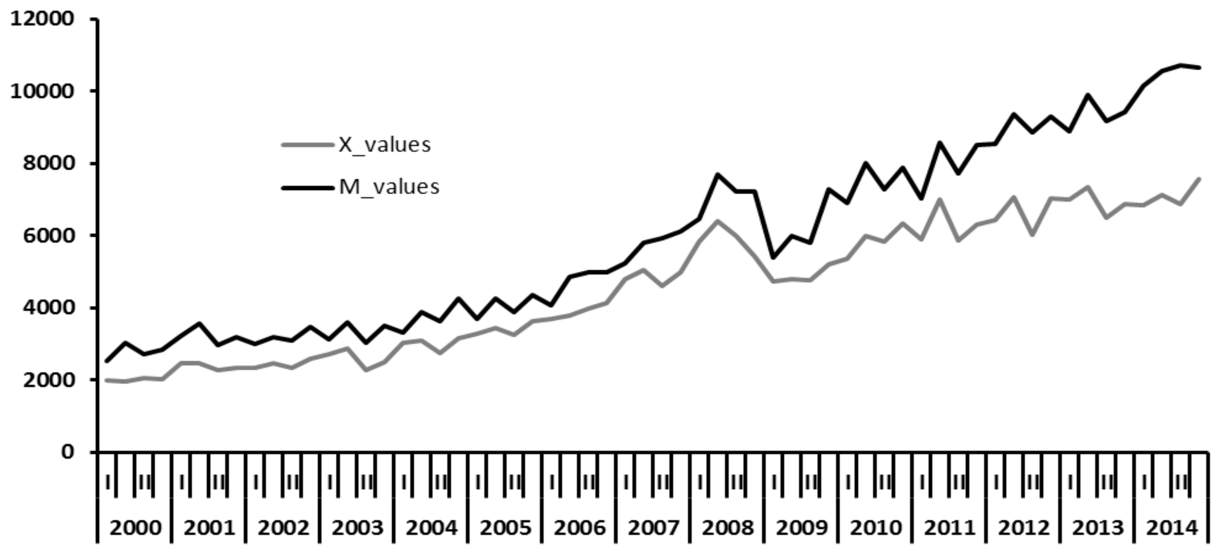

Figure 8: Exports and imports time series plot

To confirm this judgment, I test for existence of cointegration relationship between export and import using Johansen cointegration approach (with linear deterministic trend). These two variable are founded to be integrated of order one. Optimal lag is chosen based on information criteria which suggest an optimal lag of 8 periods. After determining the optimal lag, I turn to test for the existence of long run relationship between exports and imports. This test is done using trace statistic and eigenvalues tests. These two tests confirm the existence of one long run relationship between exports and imports at 5% level. This finding confirm with Saaed & Hussain (2015) who's found a cointegration relationship between exports and imports for Tunisia.

As these two variables are cointegrated, I estimate an error correction model, which enables to account for short term and long term dynamic.

Table 11 reveals the existence of negative and significant error correction term when export is the dependent variable. This confirms the consequence of choosing a dependent variable ex-ante. The result is comfortable because I expect the existence of causality from import to export and not the opposite, as Tunisian exports have great proportion of import components (more than 80%). Consequently, when imports rose, exports also soar. As I expected in the third hypothesis imports and exports appear to have a long run relationship. This equilibrium relationship will help in improving the forecasting performance of time series models. This finding supports the third hypothesis.

Table 11: Cointegrating Vector and Error correction Model between export and imports

Long-run relationship between Exports and Imports

	Constant	Trend	Imports
	-3765.91	-0.223	0.755

Error Correction Model: D(Exports) dependent variable

Variables	coefficients	std. Errors	p-value
D(Exports(-3))	-0.4472	0.159	[0.105]
D(Import(-3))	0.5233	0.263	[0.047]
ECT_{-1}	-0.342	0.111	[0.006]
R-squared	0.669		

I only report the significant lags in the error correction model. The model is significant with an explanatory power of 67%, implying that imports are important factors in determining the behavior of Tunisian exports. These results also show that only three lagged period exports and imports impact the exports level. The error correction term is significant at 1% level. The adjustment speed between exports and imports is important approximating 35%, suggesting that shocks on imports are absorbed in the three following quarters.

Figure 9 bellow shows the one-step ahead and dynamic forecast of indirect approach when exports are predicted from imports using long run relationship. Comparatively to the pure time series models, the forecasting performance has greatly improved.

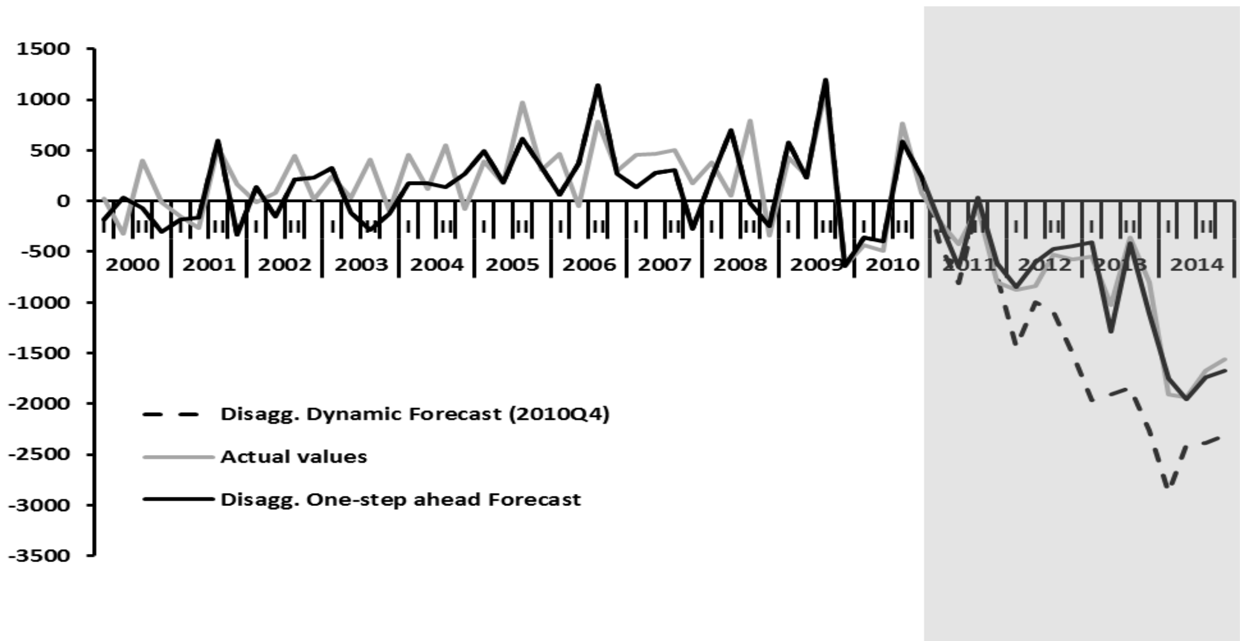

Figure 9: cumulative disaggregate forecast

This proves the capability of combined model improved the accuracy of the dynamic forecast. Probably errors from different model have canceled each other's, and so that the prediction is more close to the actuals values.

6. Comparing Forecasting Performance of Aggregated and Disaggregated Models

Now I compare the forecasting performance of reduced and disaggregated model. Firstly, visual inspection of one-step ahead forecast of direct and disaggregate approach show that aggregate approach produce the best prediction as it doesn't move much from the observed values (see figure 10). But, in general the two models produce a good in sample one step-ahead.

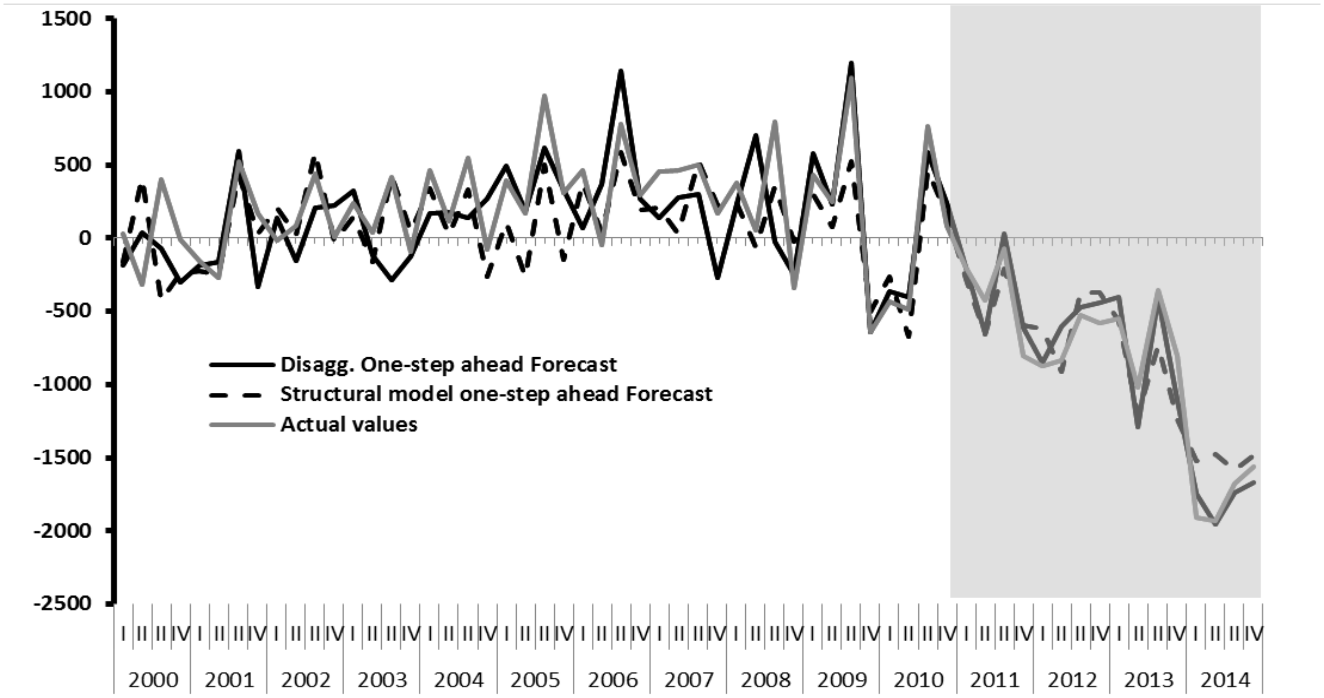

Figure 10: Comparison of one step-ahead forecast of direct and indirect approach

Regarding the dynamic forecasting approach (see figure 11), structural model more often overestimate the value of current account balance, while the aggregate approach underestimate more often time the value of current account balance. This finding is very interesting, and reveals the idiosyncratic functioning of each model. On the one hand, the structural model which is based on macroeconomic variables which are more stable (as aggregated or macroeconomic level doesn't changes as in microeconomic level) have more tendency to move close to central forecast (as they estimated with OLS, the sum of the error will be zero). On the other hand, the times series models are more likely to repeat the last observation stocked in memory. Another thing to cite is the increase of the level of the errors as the volatility of current account component increase after revolution. Without considering the cointegration relationship between export and import, the time series models have produced worse prediction as the volatility have increased. But integrating the long run relationship between export and import has improved notability of the performance of ARIMA-X models.

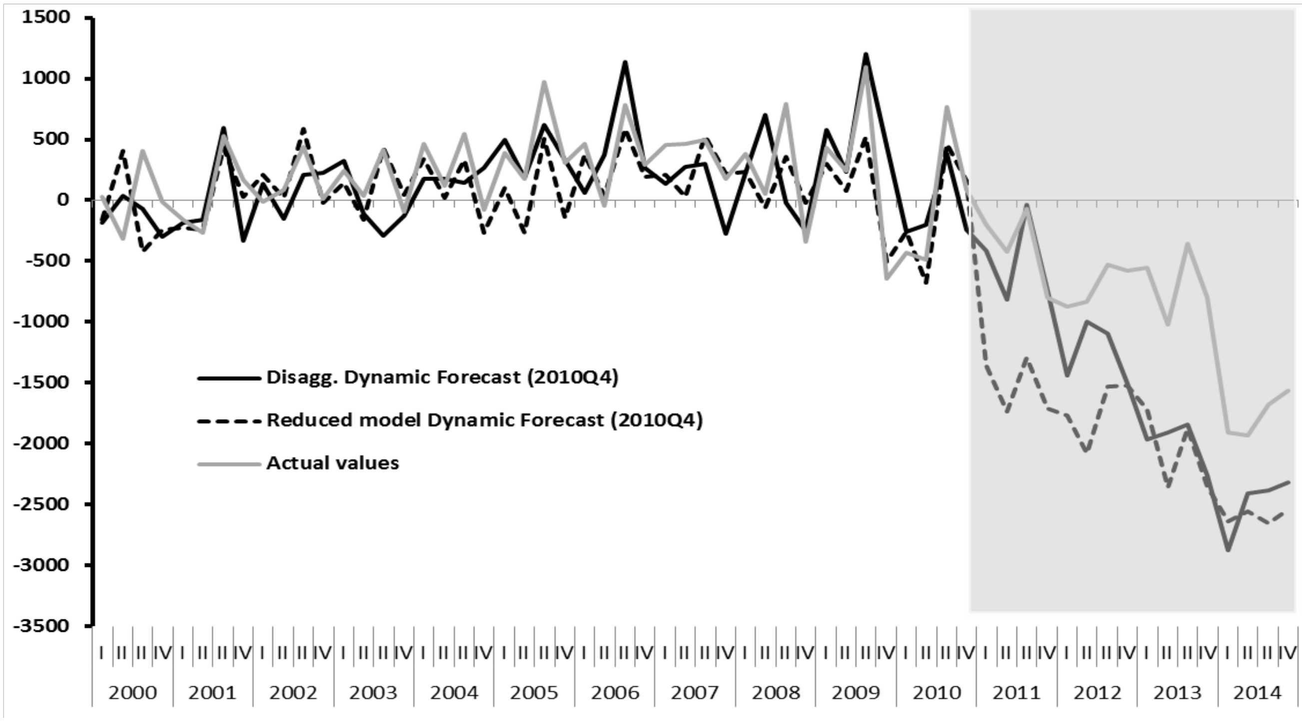

Figure 11: Comparison of dynamic forecast of direct and indirect approach

Table 12 presents statistic measure to assess the performance of disaggregated models and structural model. More conceptually the performance of prediction is investigated through root mean squared error (RMSE).

The results show that for one-step ahead forecast ARIMA with exogenous variables is slightly more accurate than the structural model. This finding proves the superiority of times series model in term of forecast at short-term. In effect, including autoregressive and moving average terms with exogenous independent variables allows for rapid adjustment for changes in pattern of the data and for external shocks. The superiority of times series models at short term is reported in literature as for example with Keck et al. (2009) whose demonstrate that aggregate OECD model at regional level perform better than an overall OCDE model as it account for the divergence in explanatory variables between regions. More recently Lutero and Marini (2010) showed that indirect approach is more accurate at short-term.

Table 12: Dynamic and One-step ahead prediction properties

	Root Mean Square Errors			
	One-step ahead	**Percent. Error of GDP**	**Dynamic Forecast**	**Percent. Error of GDP**
Reduced Form Model	273.01	1.99%	629.24	4.60%
Disagg. Equations				
- Time series Models	271.36	1.98%	1169.66	8.54%
- Cointegration and Time series Models	271.36	1.98%	525.01	3.83%

However, regarding dynamic forecast, reduced model appear to be more accurate, and the benefit from disaggregated forecasting approach using ARIMA-X models, fades out. Also the direct approach appears to be more optimistic, as the current account is foreseen to be improved in the future. This is surprising as ARIMA-X methodology include the data pattern and the external factors. But, this finding reveals an important thing; that is when, the variability of the series increase, the forecasting power of the times series models decrease as the model does not include a second moment terms. In other words, the model is able to track time series level and seasonality well if the underlying variable does not vary importantly. This may explain why the structural model has better performance in dynamic forecast beginning from the fourth quarter of 2010, when current account items are more volatile after revolution. In effect macroeconomic variables are more stable and likely to change with small amplitude. This result have been also highlighted by Khan (2011) who found that VAR model is more accuracy than ARIMA model in forecasting Bangladeshi imports. Also, Kongcharoen and kruangpradit (2013) reported that aggregate approach is more accurate than direct forecast in modelling Thailand export. It is worth to note, that none of these work account for the change in volatility of the component of exports or imports. It is statistically correct to have more volatility at disaggregate level than on aggregate if the component are more volatile than the sum of they move in the same direction (positively correlated).

Integrating the cointegration relationship between export and import with ARIMA-X models has improved the forecast performance of aggregate approach. The RMSE of indirect approach become well below of the direct approach and it falls by about 40%. The better performance of combined models is due to the information gains from the long run relationship between exports and imports. This finding support the fourth hypothesis and demonstrates that the combination of more forecasting tools yield more accurate prediction rather than using one model. When forecasting GDP using aggregate approach, Baffigi et al. (2004), have demonstrated that aggregating national account produce more precise forecast.

In the following graph, I compare the performance of the disaggregated and aggregated approach relative to the naïve approach. It is well established in the literature (Meese-Rogoff puzzle), that naïve approach can perform well than macroeconomic approach at short term. Figure 12 plot the graph of MSE up to horizons 16.

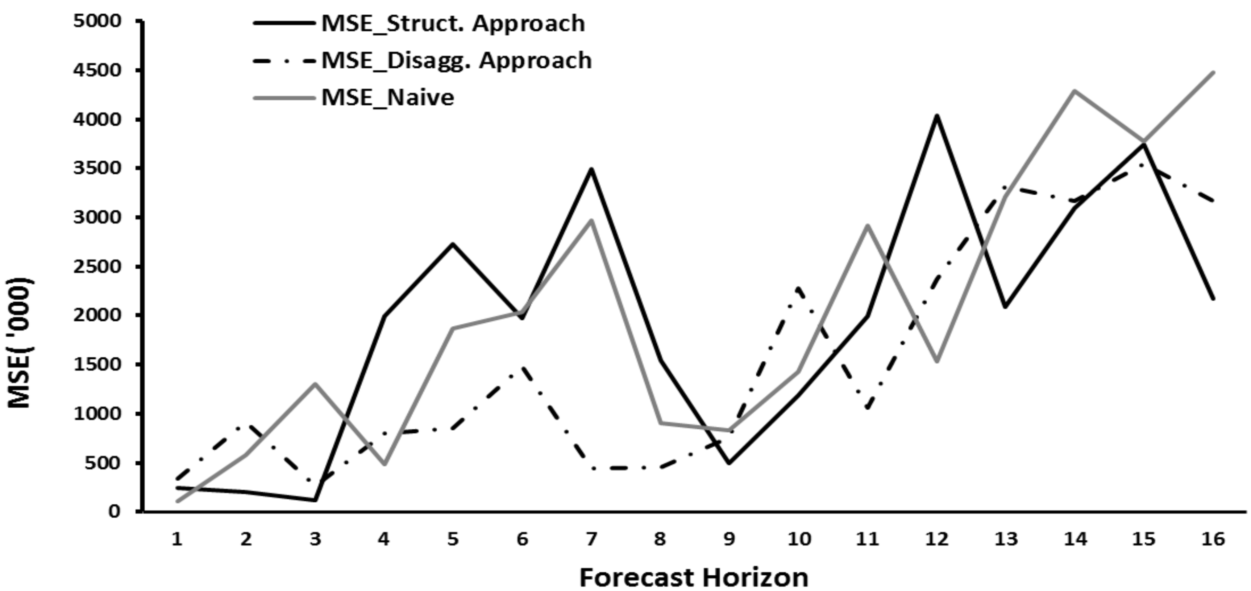

Figure 12: Comparison between Naïve, Structural and Reduced Form approaches Forecast

As shown by the graph, the disaggregate approach performs better than structural or naïve approach on average. For all most horizons the naïve approach lies between direct and indirect approach. This finding confirm at certain extent the random walk puzzle, that is naïve approach can perform better than structural model. But as we move forward in the future, the naïve approach become the most worsen approach. In effect, up to horizon 12 naïve approach is better on average, but after this horizon, the trend is inversed and the naïve approach become clearly the most worsen. This is because the error accumulates and widen as the horizon increase, consequently at long term it is expected that random walk approach cannot outperform regression modelling. Nevertheless at the different horizons, there is no clear winner, and there is times when each approach is better and in others times is the worst as demonstrated by Kuzin, Marcellino et Shumacher (2011) and which confirm the need to combine more than one approach to improve the forecasting exercise.

Conclusion

The aim of this paper is to build a model for current account forecasting purpose using time series methodology at the disaggregated level. First, the one-step ahead and dynamic forecasts are calculated based on current account items at disaggregated level and reduced model at aggregated level. Second, I use the cointegration approach to improve the forecasting performance of time series model.

The data used are quarterly and span from the period January 2000 to December 2014. After testing for stationarity and identifying the best fitting model for each item, forecasts are made at aggregate and disaggregate level. Finally forecast performance is measured using RMSE statistics.

The finding shows that:

- There is evidence in long run relationship between exports and imports, which help in forecasting the level of export, from the imports.
- The partner's foreign output, Fiscal budget, liquidity exchange rate, trade openness and local GDP are founded to play an important role in explaining Tunisian export.
- The direct and indirect approaches produce good forecasting at one-step ahead forecast, with slightly better performance for ARIMA model with exogenous variables.
- Structural model yield more accurate forecast for dynamic forecasting when volatility is higher as macroeconomic variable are less volatile than microeconomic.
- Combining ARIMA-X model with VAR model improve highly the forecasting performance of indirect method and beat easily the direct approach.
- In average the naïve approach is more accurate than structural model. Up to horizon 12, the naïve approach lies between direct and indirect approach, but moving forward the naïve approach provide the worst performance.

One of the implications of this work is to demonstrate that to reduce deficit government should diversify export goods by creating products that contain mainly domestic inputs, reduce budget deficit, enhance local GDP and review trade policy. In effect as the importation cost are rising faster than domestic cost (due to exchange rate pass-through, shipping cost, price increase in international financial markets). Consequently exports will never overcome imports because the greater composition of imported parts. The second implication, deal with the monetary and budgeting policy. The increases in government deficit (which in turn increase the monetary demand for domestic and foreign debt) widen the trade deficit. So tightening, the monetary policy will limit the ability of the government and external sector to contract more debt and purchase from abroad. Moreover, although the government appear effective in respecting her international budget by keeping the ratio of the export to import stable, it will be hard to pursue this policy in the future as long term component of current account balance is most driver of the current account deficit.

The third implication is related to forecasting; government can reach more accurate forecasts by using disaggregated approach and combining more than one model. The indirect approach produces better performance for one-step ahead and dynamic forecast when is combined with error correction model. This method is less costly and time dependent as compared to the structural model approach. In effect, it relay only on the time series itself and one explanatory variable which is local output. The direct approach needs to forecast numerous factors which will more sensitive to the changes of these variables when I exercise an out of sample forecast.

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