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Dynamic Assessment of Agriculture and Economic Growth Nexus in Morocco: Evidence from Structural VAR and Directed Acyclic Graphs

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Abstract: The recurrence of international crises and their negative impact on the economy and household food security has stimulated a strong revival of interest in the role of the agricultural sector and its relationship with the national economy. Recently, a macro-econometric model has shown a well-established bidirectional causality nexus between the agricultural sector and the Moroccan economy. However, the assessment of the magnitude of effects in both directions and their historical evolution are crucial topics that have not yet been explored. The current study empirically examines the dynamic interrelationships between Moroccan agriculture and GDP using the structural VAR model. The data set consists of the annual macroeconomic time series covering the period 1980-2019, namely: GDP per capita, agricultural GDP, investment rate, money supply and trade openness. This paper exploits recent advances in artificial intelligence to determine the over-identifying restrictions, through Directed Acyclic Graphs. Impulse response functions reveal that the Moroccan economy is very sensitive to agricultural shocks compared to shocks due to other endogenous variables, meanwhile the agricultural sector is very reactive to its shocks. The results from the variance decomposition show that the agricultural shocks are the most important driver of economic growth fluctuations and account for almost 69% of the forecast error variance for the first year. The share of GDP shocks in the variance of the forecast error of agricultural GDP does not exceed 7% for a ten-year horizon, while agricultural shocks dominate the decomposition variance profile and never fall below the 74% threshold. These results highlight the predominance of the Agriculture-Led Growth hypothesis in comparison with the Growth-Led Agriculture hypothesis. The findings resulting from the historical decomposition reconfirm the historical dependence between the national economy and agriculture. This sector sometimes acts as a shock absorber, counteracting the poor performance of other sectors of the economy. Under the Structural VAR model, the historical analysis illustrates that the national economy is increasingly resilient to agricultural shocks because of the improved resilience of Moroccan agriculture to climate shocks. Although the impact of agriculture is historically prominent, the magnitude of its impact has significantly reduced by 22% between 1982-1999 and 2000-2019. Given the strong potential of the agricultural sector to promote economic growth, policymakers should continue to create favorable conditions to support the development of the sector.

Keywords: Agriculture, GDP, Structural VAR, Directed Acyclic Graphs

1. Introduction

Although the role of agriculture in promoting economic growth has been historically debated among economists, the subject is still of renewed interest, especially with the recurrence of international crises and the negative repercussions resulting from them. Internationally, the relationship between agriculture and economic growth has been investigated extensively using theoretical as well as empirical frameworks. Tsakok and Gardner (2007) mentioned the reasons for the lack of resolution of the debate, among others, the econometric methods used which are not rigorous and suffer from several shortcomings and weaknesses [1]. The perception of the role of the agricultural sector in promoting economic growth has evolved considerably over time. Early theorists attributed a passive role to the agricultural sector, which is limited to the reallocation of factors of production from an archaic and unproductive agricultural sector to a modern industrial sector with higher productivity [2, 3]. They emphasized the inability of the agricultural sector to generate sufficiently powerful upstream and downstream effects to drive economic development. However, the green revolution in Asia challenged this view and demonstrated the active role of the agricultural sector in initiating broader economic development by transforming traditional agriculture into a modern sector [4, 5].

However, Diao et al. (2010) point out that while the Agriculture-Led Growth (ALG) strategy has played a crucial role in reducing poverty and transforming the economies of several Asian countries, this path has not yet been successful in Africa [6]. Almost all African countries have not yet met the requirements of a successful agricultural revolution, and the productivity of African agriculture lags behind the rest of the world. This situation cast doubt on the ability of agriculture to promote economic development in Africa, leading to a decline in public policy interest and investment in this sector in some countries. Nevertheless, proponents of the ALG hypothesis point out that agriculture's poor performance reflects inadequate investment and historically biased policies against agriculture [7-9].

While there are multiple channels through which agriculture could stimulate economic growth, a range of arguments presented in the literature indicates that causality could run in the opposite direction, that is, from non-agricultural growth to agricultural growth [10]. This opposing viewpoint supports the Growth-Led Agriculture (GLA) hypothesis indicating that agriculture could benefit from non-agricultural Growth. Agricultural skeptics doubt that the sector can promote sufficient economic growth and are more optimistic about the development of the non-agricultural sector, particularly the industrial sector. This line of thought gains importance in the presence of a number of countries that have developed through the development of the industrial sector without a strong agricultural base. These successful experiences have demonstrated that agriculture has benefited from the industrial and export boom rather than the other way around [1].

In Morocco, while policymakers place the agricultural sector at the center of the Moroccan economy as an engine of growth [11], some economists emphasize the role of the industrial sector as a privileged source of economic growth [12, 13]. However, despite the intense discourse on the relationship between agriculture and the economy in Morocco, the debate is based on empirical intuitions rather than econometric studies. This imbalance did not allow for a clear answer to the debate and left several questions unanswered despite the importance of the topic for the government that could improve resource allocation. Moreover, a clear understanding of the relationship between the agricultural sector and the national economy provides some visibility on the potential impact of investments in agriculture on the GDP.

The agricultural sector in Morocco plays multiple roles at different levels. It contributes significantly to environmental amenities, poverty alleviation, social viability and national culture [14]. Currently, the sector accounts for 13% of GDP and also provides 38% of the employment of the active working population nationwide [15]. The agricultural sector has attracted the attention of policymakers through the launch of various sector strategies, including the Green Morocco Plan (2008-2020) and, most recently, Generation Green (2020-2030). In this context, a range of public incentives and private investments has been oriented towards this sector with a perspective to develop modern, productive and competitive agriculture. With the mobilization of 104 billion dirhams between 2008 and 2020 [16], the dynamics of agricultural GDP have followed an upward growth path, marked by a growth rate of about 5.2% during the period 2008-2017 (HCP [1], 2020). Nevertheless, despite its fundamental importance, Moroccan agriculture faces many structural challenges, particularly the increasingly recurring drought. The predominance of rainfed agriculture, including cereals, exposes the sector and even the economy as a whole to climatic shocks. Despite the significant reduction in the share of agriculture in Morocco's sectoral composition, from 23.44% in 1965 to 11.38% in 2019 (FAOSTAT [2], 2020), the sector continues to weigh heavily on the country's economic performance, particularly because of the spillover effects on other sectors of the economy [15].

The empirical evidence of the bidirectional causality relationship between the agricultural sector and the economy is well established. Using the Granger causality approach in a VAR model framework, Elalaoui et al. (2021) econometrically demonstrated the dynamic two-way interdependence between agriculture and GDP in Morocco [17]. Nonetheless, the assessing of the magnitude of effects in both directions and their historical evolution are topics that deserve to be explored to investigate the predominance of the Agriculture-Led Growth (ALG) or Growth-Led agriculture (GLA) hypotheses. This research investigates the dynamic interrelationships between the agricultural sector and GDP using the Structural VAR (SVAR) model, by using recent tools based on artificial intelligence, particularly the Directed Acyclic Graphs (DAG) approach. The pioneering work on the SVAR model initiated by Blanchard and Watson (1986), Bernanke (1986) and Sims (1986) raised a strong debate in the economic literature [18-20], in particular in the interpretation of business cycle fluctuations [21, 22] and the identification of the effects of different policies [23-25].

Although the reduced VAR model, initially proposed by Sims (1980) has replaced the traditional simultaneous systems of equations [26], the main criticism of this model lies in the

1 Authors' calculation based on statistics from Morocco's High Commission for Planning;
2 Statistics of Food and Agriculture Organization of the United Nations.

interpretation of the instantaneous relationships because they are disguised behind the residuals from the VAR [27]. The original proposal of Sims (1980) was to use an orthogonalized vector moving average (VMA) representation via the Cholesky factorization [26]. This technique is considered arbitrary and therefore unsatisfactory [28], since it imposes a contemporary structure that is not necessarily supported by economic theory. Nevertheless, it should be noted that a VAR model, in its reduced form, could be used satisfactorily for a wide range of purposes, including dynamic simulation, unconditional and conditional forecasting and Granger causality [29]. The structural VAR model has recently updated the reduced VAR model in different research areas, using theoretical identifying restrictions. Given the presence of controversial theories and the difficulty of identifying the model based on short-term restrictions in comparison with long-term restrictions, for which a panoply of theories have been developed, several alternatives have been proposed to properly identify the model, among others, the Directed Acyclic Graphs (DAG) approach. This technique, which has received much attention, involves discovering contemporaneous causal relationships by analyzing the statistical properties of the data.

The contribution of this article to the literature is multiple. First, although the effect of the agricultural sector is widely debated in Moroccan policy discourse, the evaluation of this impact is generally neglected in the empirical literature. This work aims to fill this knowledge gap in this area of research using the SVAR model. Second, existing agricultural economics literature provides various empirical studies investigating the dynamic relationship between the agricultural sector and economic growth in other countries, sometimes including other sectors [30-33]. However, the restrictions imposed for identification are often difficult to justify economically and do not find consensus among economists [34]. The contribution of this work consists of using the theory of Directed Acyclic Graphs, which represent a nonparametric framework for causal inference, in providing relaxed restrictions on the innovations. These techniques emanate from the field of artificial intelligence and computer science. Their strength lies in the ability to infer causal relationships from observational data. Although these tools have been used in several research areas, ranging from ecology, epidemiology, space physics, clinical medicine, neuroscience to many other fields, its application in the context of assessing the impact of the agricultural sector on economic growth is rare and would constitute a significant contribution to future research in the same context. These methods deserve to be expanded for application in the discipline of agricultural economics. To the best of our knowledge, in line with this study, Awokuse and Xie (2014) used Directed Acyclic Graphs and the error correction modeling approach to investigate the causal linkages between agriculture and Gross Domestic Product growth in a selection of nine developing countries [35]. Results from the empirical analysis indicate that the direction of causal relationship between agriculture and GDP depends on the country. It could either support the Agriculture-Led Growth (ALG) or Growth-Led Agriculture (GLA) hypotheses.

The remainder of this paper is organized as follows. Section 2 presents the research methodology, including the dataset, the empirical model and the identification strategy. The main finding of impulse response functions, variance decomposition and historical decomposition analysis are discussed in Section 3. Section 4 reports some concluding remarks, recommendations and policy implications of this research.

2. Research Methodology

2.1. Analysis Strategy

Figure 1 summarizes the econometric approach adopted in this work. The analytical approach consists mainly of defining macroeconomic variables, the application of the Hodrick-Prescott filter, the verification of stationarity, the specification and estimation of reduced-form VAR, the validation of the model using diagnostic tools, the identification of the structural VAR model using the PC algorithm. The three techniques derived from the above econometric approach are impulse response functions, forecast error variance decomposition and historical decomposition. These analyses will make it possible to answer several questions and raise issues about the interdependencies between the agricultural sector and the Moroccan economy.

It should be noted that the structural VAR model building is defined by the underlying equations from (3) to (12) illustrated in Section 2.3.

2.2. Data

The dynamic relationship between GDP and the agricultural sector is explored with annual data series over a sample period from 1980 to 2019. The time series used in this study were collected from the directorate of statistics of Morocco's High Commission for Planning (HCP). The dataset contains five variables, two variables of interest and three control variables to capture the drivers of economic activity and avoid the autocorrelation of errors by omitting important variables. The variables of interest are GDP per capita (GDP), expressed at chain-linked volume in dirhams MAD (base year: 2007) and agricultural GDP (AGR), expressed at chain-linked volume in millions of dirhams (base year: 2007). The three control variables are the investment rate (INV), measured as a ratio of gross fixed capital formation and GDP (%), the money supply (M3), expressed as a percentage of GDP (%) and trade openness (OPN), proxied by the sum of exports and imports in GDP (%). It should be noted that all variables are expressed in the natural logarithmic form to reduce the data variance and constitute the system in this study.

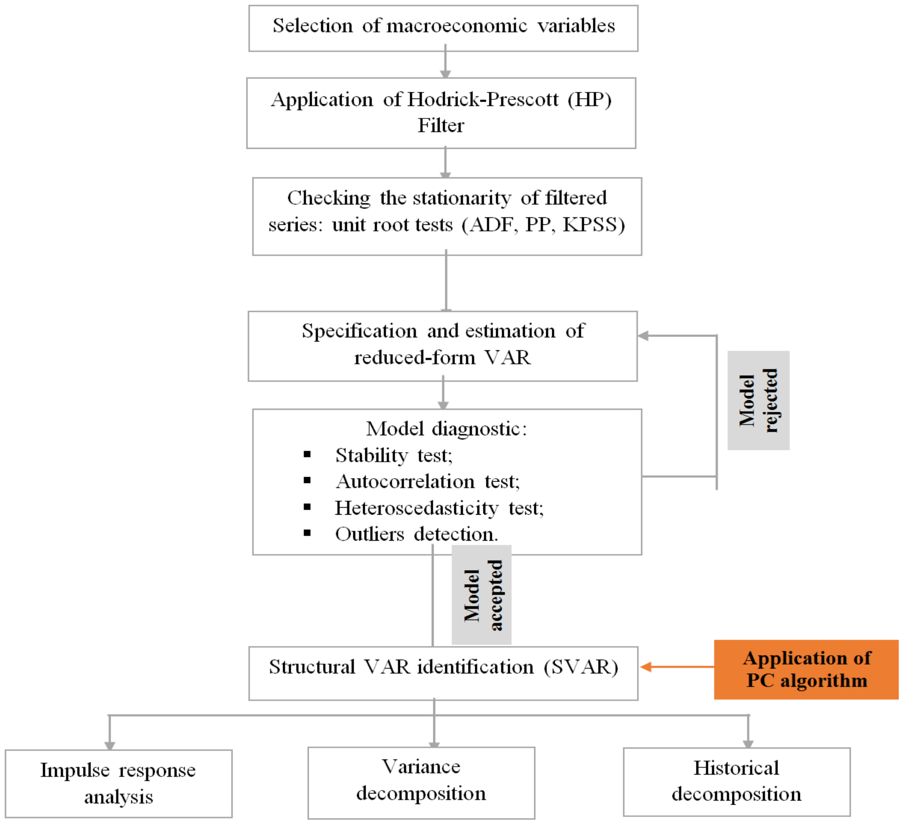


Figure 1. *Analysis procedure of the empirical modeling.*

2.3. Econometric Analysis

2.3.1. Hodrick-Prescott (HP) Filter

The Hodrick-Prescott (HP) filter is one of the most common methods presented by Hodrick and Prescott (1997) [36]. The Hodrick –Prescott filter is a detrending method frequently used to separate cyclical components from the nonlinear trend [37].

The HP filter breaks down a time series (y_t) into two elements: a long-term trend (T_t) and short-term fluctuations (cyclical component (C_t)):

$$y_t = T_t + C_t \; (t = 1,2, \dots \dots \dots, T) \quad (1)$$

It should also be noted that y_t is the natural logarithm of an observed time series used in this analysis.

The HP filter computes the smoothed series T_t of y_t by minimizing the variance of y_t around T_t. In other words, the deviations of the series from the attributed trend should be minimal.

$$\sum_{t=1}^{T}(y_t - T_t)^2 + \lambda \sum_{t=2}^{T-1}\left((T_{t+1} - T_t) - (T_t - T_{t-1})\right)^2 \quad (2)$$

The first term of expression (2) represents the sum of the squared deviations ($\sum_{t=1}^{T}(y_t - T_t)^2$) and thus reflects the adjustment of the deviations to the trend path over time. The second term involves the multiple penalty parameter λ, which controls the smoothness of the series, of the sum of the squares of the trend component's second differences. The higher the value of λ, the smoother the long-term trend T_t will be. The standard practice in the econometric analysis is to set λ as 100 for annual data as the frequency used in this empirical study.

2.3.2. Stationarity Analysis

The verification of stationarity remains a prerequisite of the VAR estimation and a common practice in econometric analysis. Otherwise, a spurious regression will occur [38]. After filtering the examined series for the long-term structural trend, their stationarity is required to ensure valid results. The common tests used for this purpose are the ADF test by Dickey and Fuller (1979) [39], the PP test by Phillips and Perron (1988) [40] and the KPSS test by Kwiatkowski et al. (1992) [41]. The Schwarz criterion (SC) is selected to detect the number of the lag length in the ADF test, while in the PP and KPSS tests, the Newey-West Bartlett kernel criterion was chosen to select the bandwidth.

2.3.3. VAR Model: Reduced Form and Structural Form

In this study, the empirical model is based on the SVAR framework to assess the dynamic interrelations between the agricultural sector and the GDP. The general modeling strategy for structural VAR and structural VECM is to specify and estimate a reduced form model first and then focus on the structural parameters and the resulting structural impulse responses [28]. The reduced-form VAR is a dynamic system of equations that captures dynamic interactions among economic variables. Following the terminology from the simultaneous equations literature, equation 3 represents the VAR model in reduced form because all right-hand side variables are lagged or predetermined.

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \mu_t \quad (3)$$

Where y_t is a $(K \times 1)$ vector stationary of endogenous variables at time t ($K = 5$). The vector of endogenous variables y_t consists of GDP per capita (GDP_t), the agricultural GDP (AGR_t), the investment rate (INV_t), the money supply $(M3_t)$ and the trade openness (OPN_t); p denotes the order of the VAR model; y_{t-j} for $j = 1, \ldots, p$ is a vector of lagged variables; A_0 is a $(K \times 1)$ vectors of constants; the $A_j (j = 1, \ldots, p)$ are $(K \times K)$ coefficients matrices associated with the corresponding lagged vector of variables for lag j and μ_t is a five-dimensional white noise with $\mu_t \sim (0, \Sigma_\mu)$. The components of μ_t maybe instantaneously correlated, that is, Σ_μ is not necessarily a diagonal matrix.

Using the delay operator D, equation 3 can be expressed as follows (Equations 4 and 5)

$$\left(I - A_1 D - A_2 D^2 - \cdots - A_p D^p\right) y_t = A_0 + \mu_t \quad (4)$$

$$A(D) y_t = A_0 + \mu_t \quad (5)$$

It should be mentioned that the reduced form VAR model does not give any instantaneous relationship between endogenous variables. These contemporaneous relationships are summarized in the variance-covariance matrix of the residuals [29]. In this sense, the residuals of the reduced form VAR model are not economically interpretable because they are not independent. The proposal of Sims (1980) consists of using the Cholesky decomposition of the variance-covariance matrix, based on the order of the endogenous variables [26]. Since different patterns of the orders of variables could give different shocks and generate different results, Sims (1980) proposed using different triangular orthogonalisations and then check the result's robustness [26]. This technique is considered arbitrary and unsatisfactory, unless there are special reasons for a recursive structure [28].

Within this framework, structural VAR analysis has been proposed as an alternative to the previous techniques, in order to isolate independent shocks through the imposition of a set of theoretical identifying restrictions. In a structural form, instantaneous variables may appear as explanatory variables in some equations. Following the AB Model proposed by Amisano and Giannini (1997) [29], the SVAR model is represented as follows:

$$A y_t = A_0^* + A_1^* y_{t-1} + A_2^* y_{t-2} + \cdots + A_p^* y_{t-p} + B \upsilon_t \quad (6)$$

In this form, a simultaneous equations system is formulated for the errors of the reduced form model rather than the observable variables directly. The invertible $(\mathrm{K} \times \mathrm{K})$ matrix A allows for instantaneous relations among the endogenous variables. The matrix B contains the structural form parameters of the model; $A_j^* = A A_j$ $(j = 1, \ldots, p)$ and υ_t is a $\mathrm{K} \times 1$ structural disturbances vector, which is assumed serially uncorrelated.

The innovations of the reduced form model from equation 3, μ_t, can be expressed as a linear combination of the structural shocks from equation 6, υ_t, as follows:

$$\mu_t = A^{-1} B \nu_t \quad (7)$$

In this case, the reduced form variance-covariance matrix is $\Sigma_\mu = A^{-1} B B' A^{-1'}$. The structural shocks, υ_t, are the central components in an SVAR analysis. Since these shocks are not directly observable, it is necessary to impose certain restrictions on the matrices A and B to isolate them. According to Lütkepohl (2006), with $2K^2$ elements in the structural form matrices, the maximum identifiable parameters is $\frac{K(K+1)}{2}$ and the number required, therefore, for exact identification is $2K^2 - \frac{K(K+1)}{2}$ [28].

2.3.4. Directed Acyclic Graphs: PC Algorithm

The identification of economically meaningful shocks is the focus of SVAR analysis. Often, the economic theory does not always provide enough theoretical restrictions to achieve identification, especially in the short-term. In this regard, other techniques have been used in several studies as alternatives to classical identification methods, among others, the Directed Acyclic Graphs [42-46]. A DAG is a causal map linking variables by removing statistically uncorrelated links and applying logical arguments to identify the direction of the remaining links [47]. This technique represents a significant advance in the analysis of causality, especially in contemporary time.

Causal relationships derived from graph theory are determined by several computer algorithms available in the literature. In this work, identification is achieved by modeling contemporary innovations from the reduced VAR model with Directed Acyclic Graphs, especially by the PC algorithm[3], as presented by Spirtes et al. (2000), since the data set is fully continuous and the distribution of the variables (residuals from the VAR model) is normal [48]. This algorithm has been used in different economic works for different purposes [49-56].

The causal discovery was performed using TETRAD software version 6.9.0, an open source JAVA code that has been developed at Carnegie Mellon University for casual discovery[4]. The input to TETRAD software is a sample size, a covariance or correlation matrix among the variables, and a graph which specifies the known causal connections among the variables [57]. TETRAD offers the possibility to search through a vast number of possible alternatives of results, given that it uses a fast graph theoretic algorithm to determine the over-identifying constraints implied by a model. The strength of this approach used in this study consists of allowing the dataset to provide the over-identifying restrictions for estimating the SVAR model.

A graph is a mathematical structure consisting of a set of nodes, which represent random variables, and a set of edges that connect the pairs of nodes, indicating the relationships between the pair of the variables in the graph. The edges that

3 see, e.g., Spirtes et al., 2000, pp. 84–85; Pearl, 2000, pp. 49–51

4 Tetrad software is freely available from https://www.ccd.pitt.edu/tools/

connect two nodes can be directed (by an arrow) or undirected. A graph is said to be directed if it contains only arrows (directed edges). Observed correlations and partial correlations determine the graph structure. Five types of connection can exist between two variables X and Y: i) a directed edge from X to Y ($X \rightarrow Y$) represents one-way causality from X to Y in contemporaneous time; and ii) $X \leftarrow Y$ indicates one-way causality from Y to X iii) $X \leftrightarrow Y$ signifies the presence of two-way causality between X and Y; iv) $X - Y$ signifies the existence of causality of unknown direction between X and Y; v) XY indicates that the two variables X and Y are (conditionally) independent.

Let X, Y, and Z denote three economic variables and assume that, in the first scenario, X is the cause of the occurrence of Y and Z ($Y \leftarrow X \rightarrow Z$). Since X is the common reason for the occurrence of both Y and Z, the unconditional correlation coefficient between Y and Z is non-zero, but the conditional correlation between the two variables, when X is a conditional variable (given the prior knowledge of the common cause X), is zero. In this case, common causes screen off associations between their joint effects. By contrast, in the second scenario ($Y \rightarrow X \leftarrow Z$) where the two variables Y and Z are the cause of variable X, the unconditional correlation between Y and Z is zero. Nevertheless, when X is a conditional variable (given the common effect X), the conditional correlation between Y and Z is non-zero. In this case, common effects do not screen off association between their joint causes.

Mathematically, following Pearl (2009) [58], a DAG is represented as the conditional independence by the recursive product decomposition:

$$\Pr(v_1, v_2, v_3, \dots, v_p) = \prod_{i=1}^{p} \Pr(v_i | pa_i) \tag{8}$$

Where Pr represents the probability of vertices $v_1, v_2, v_3, \dots, v_p$ and pa_i denotes the realization of some subset of the variables that precede (come before in a causal sense) v_i in order $(v_1, v_2, v_3, \dots, v_p)$. According to Spirtes (2005), any probability distribution that satisfies the property in equation 8 is said to satisfy the Causal Markov Condition for the graph [59]. The concept of d-separation (directional separation) was first introduced by Pearl (1995) as a graphical representation of conditional independence, in order to identify the conditional independence relations which satisfy the Causal Markov Condition [47].

In application, as in Awokuse and Bessler (2003) [42] and Bessler and Yang (2003) [60], Fisher's z-statistic was used to test whether the estimated sample correlations and conditional correlations were significantly different from zero. Fisher's z is expressed as follows:

$$z(p(i,j|k,n) = \left[\frac{1}{2}\sqrt{(n-|k|-3}\right] ln\left\{\frac{1+p(i,j|k|)}{1-p(i,j|k|)}\right\} \tag{9}$$

Where n is the number of observations used to estimate the correlations, $p(i,j|k|)$ represents the population correlation between series i and j conditional on series k (by eliminating the influence of series k on each i and j). $|k|$ denotes the number of variables in k. If i, j and k are normally distributed and $r(i,j|k)$ represents the sample conditional correlation of i and j given k, then the distribution of $z(p(i,j|k)n) - z(r(i,j|k)n)$ is standard normal.

2.3.5. Structural Analysis

Estimating structural VAR is not an end in itself. The main objective of the SVAR model estimation is to examine the dynamic interrelationships rather than to estimate the related coefficients. The properties of the model are derived from several techniques, namely impulse response functions, variance decomposition as well as historical decomposition.

In order to generate the impulse response functions, variance decomposition and historical decomposition, the SVAR must be inverted in its vector moving average (VMA), by applying the Wold representation theorem.

Impulse response functions

Originally proposed by Sims (1980) in the context of VAR modeling [26], the analysis of impulse response functions (IRF) is sometimes called multiplier analysis [28]. It traces the reaction of one variable to a shock in another variable in a system and provides an adequate framework for examining the persistence and the nature of the dynamic effect of a shock on any of the variables included in the model. Deterministic terms are ignored because they are not important for impulse response functions. Under the stability assumption, the process 3 has a Wold Moving Average representation and is expressed by equation 10:

$$\mathrm{y_t} = \Phi_1 \mu_{t-1} + \Phi_2 \mu_{t-2} + \cdots \tag{10}$$

In this representation, the vector y_t is expressed in terms of the mean term and past and present error or innovation vectors μ_t. The coefficient matrices of the moving average representation are the forecast error impulse responses.

In the compact form, equation 10 can be written as follows:

$$y_t = A(D)^{-1}\mu_t = \Phi(D)\mu_t = \sum_{j=0}^{\infty} \Phi_j \mu_{t-j} \tag{11}$$

Where D denotes the lag operator. $\Phi(D) = \sum_{j=0}^{\infty} \Phi_j D^j = A(D)^{-1}$. Φ_j are the $(K \times K)$ coefficient matrices of the infinite order polynomial in the lag operator $A(D)^{-1} = \sum_{j=1}^{\infty} \Phi_j D^j$. The elements of Φ_j represent responses to μ_t innovations. In other words, the marginal response of $y_{n,t+j}$ to a unit impulse μ_{mt} is given by the $(n,m)^{th}$ elements of the matrices Φ_j.

Since the residual covariance matrix Σ_μ is generally not diagonal, the components of the vector μ_t maybe instantaneously correlated. The presence of correlation between the error terms can indicate that a shock on one variable in the system is contaminated by shocks on other variables. Accordingly, impulse responses functions should be based on structural analysis in order to identify purely exogenous shocks, which allow to trace out its dynamic effects. If an identified structural form is available, the corresponding innovations are the structural shocks.

Under the stability assumption, the process 6 has also a Wold Moving Average representation:

$$y_t = \left(A - A_1^* D - \cdots - A_p^* D^p\right)^{-1} B\upsilon_t = \sum_{j=1}^{\infty} \Phi_j A^{-1} B\upsilon_{t-j} = \sum_{j=1}^{\infty} \Psi_j \upsilon_{t-j} \quad (12)$$

Where $\Psi_j = \Phi_j A^{-1} B$ contain the responses to structural shocks υ_t. Equation 12 represents the vector of endogenous variables as a weighted average of current and past structural shocks. It should be noted that the impulse response functions are usually depicted graphically in order to get a panoramic representation of the dynamic interrelationships within the system. For each combination of the n and m variables, the impulse response function is a plot over j periods ahead, which traces the path of the response of the n^{th} variable over time to a shock to m^{th} variable:

$$\frac{\partial y_{t+j,n}}{\partial \upsilon_{t,m}} = \Psi_{j,n,m}$$

Variance decomposition

The variance decomposition is another instrument for the interpretation of the SVAR model. It decomposes the total forecast error variance of a variable into the variances of the structural shocks. In other words, it provides a measurement of the relative proportion of variation in a variable caused due to random innovations in each of the variables in the system. This technique is again based on Wold Moving Average representation. It should be specified that Eviews 12 software reports the relative contribution of variance for various variables and forecast horizons.

Historical decomposition

The historical decomposition illustrates when the shocks occurred and whether such shocks increased or decreased the series because each variable is decomposed into its sub-components concerning the structural shocks, as proposed by Burbidge and Harrison (1985) [61]. It examines the historical time-varying effects of shocks and is based also on the structural Moving Average (MA) representation (equation 12).

3. Results and Discussion

3.1. Data Description

Before fitting a macro-econometrical model to data, it is crucial to highlight some preliminary data set analysis based on descriptive statistics and distributional analysis of time series during 1980-2019 period. The main descriptive statistics for the five variables, GDP per capita (GDP), agricultural GDP (AGR), the investment rate (INV), the money supply (M3) and trade openness (OPN), are shown in Table 1. The relative comparison of the coefficient of variation reveals that M3 and AGR exhibit a significant dispersion around the average in comparison to other series, recording values of 40.91% and 36.80% respectively. Also, all series exhibit a skewness coefficient close to zero indicating that the data distribution is approximately symmetric. Additionally, all variable have a relatively low kurtosis compared to the normal value equal to three, implying that the series distribution potentially exhibits a degree of peakedness and is roughly platykurtic relative to the normal. Finally, the Jarque-Bera test confirms the null hypothesis of normality (p-value > 0.05) for all the variables, which strongly suggest that the data fit the normal distribution and exhibits a proper form to be further analyzed.

Table 1. *Descriptive statistics of the time series for the period 1980-2019.*

Statistical parameter	GDP	AGR	INV	M3	OPN
Mean	18076.89	74824.76	27.30	76.72	63.31
Median	16073.86	72454.51	26.91	69.35	59.24
Maximum	28290.90	126348.00	34.42	119.38	87.97
Minimum	10724.14	28806.61	21.81	36.04	47.09
Std. Dev.	5410.45	27537.96	3.18	31.39	13.87
Coef. of variation	29.93%	36.80%	11,66%	40.91%	21.91%
Skewness	0.48	0.24	0.23	0.18	0.53
Kurtosis	1.91	1.98	2.21	1.42	1.73
Jarque-Bera	3.51	2.14	1.38	4.35	4.53
Probability	0.17	0.34	0.50	0.11	0.10

Note: the data is in its raw form without any transformation. Jarque-Bera is a test statistic for testing whether the series is normally distributed. The null hypothesis of the test is a series is normally distributed.

3.2. Hodrick-Prescott (HP) Filter

All five time series variables were transformed in naturel logarithmic forms before de-trending them through Hodrick-Prescott (HP) filter with a smoothing factor of 100, as suggested in the econometric literature for annual data. Figure 2 shows the components resulted from the HP filter decomposition. The curve in blue shows the plots of the time series from 1980 to 2019. The curve in orange shows the trend, which captures the long-term growth of the series while the curve in green shows the cyclical component, which captures the deviation of the series from this trend.

As reported by graphs (a), (b) and (d) in Figure 2, there is a clear upward trend for GDP per capita (LGDP), agricultural GDP (LAGR) and the money supply (LM3) respectively. In contrast, there is a polynomial structure in the historical trend of the time series corresponding to the investment rate (LINV) and trade openness (LOPN) as reported by graphs (c) and (e) respectively. The polynomial structure of the investment rate in Morocco was marked by a downward trend from 1980 until the mid-eighties, a period from which the dynamics of this variable was characterized by an upward trend. However, from 2011 onwards, the variable again returned to its declining path. Similarly, the dynamics of the variable inherent to trade openness was also characterized by a slight downward trend from 1980 until the mid-eighties to subsequently join a notorious growth path, marked by a deceleration in growth rates during the end of the analysis period.

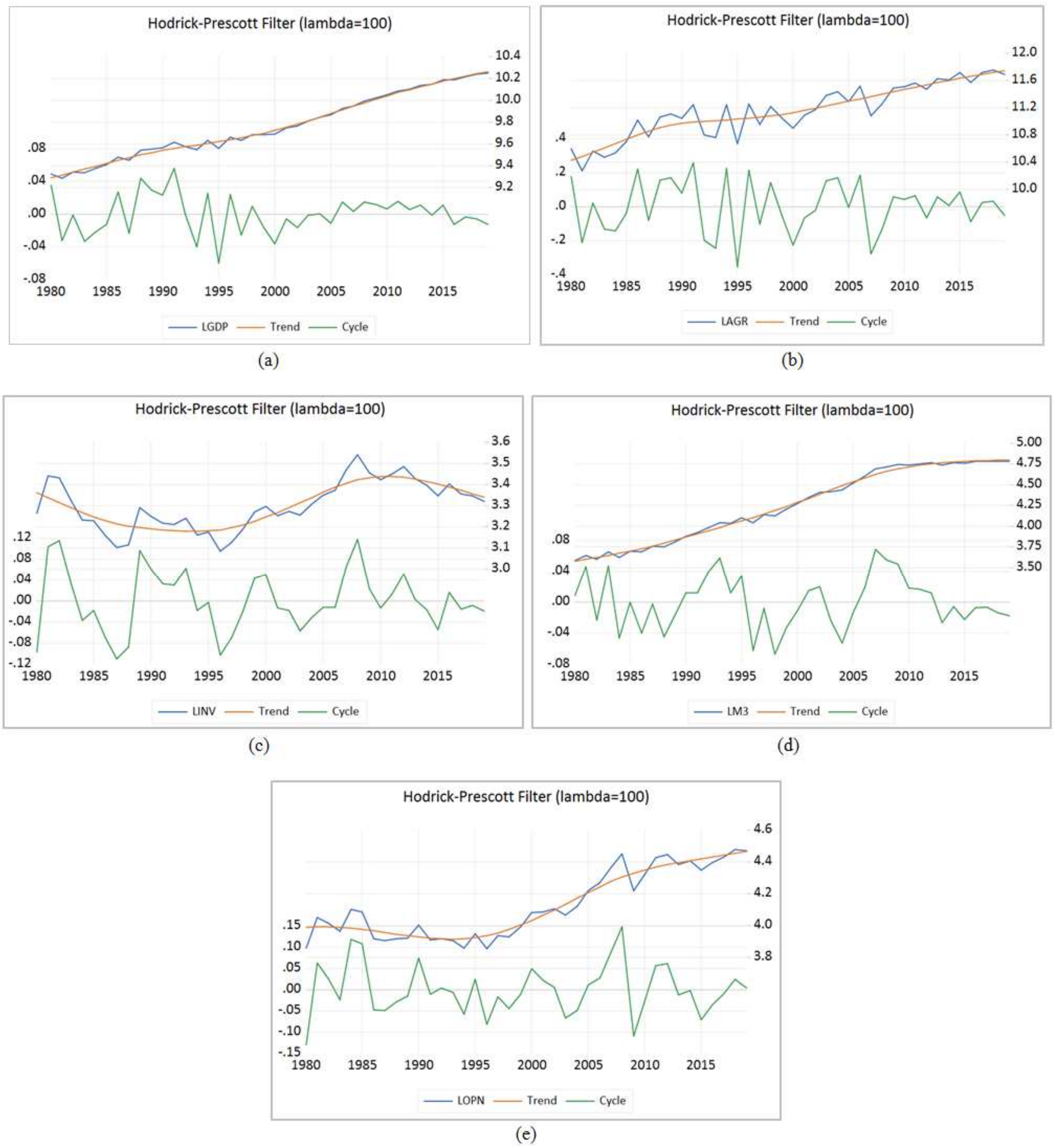


Figure 2. *Data detrending using Hodrick-Prescott (HP) Filter. LGDP (a), LAGR (b), LINV (c), LM3 (d) and LOPN (e) refer respectively to the variables in the natural logarithm form.*

3.3. Stationarity Checking

In order for the methodology described in Section 2 to be valid, all variables included in the SVAR model should be stationary. After HP filtering, the ADF, PP and KPSS unit root tests were used to check the stationarity of the filtered series in order to fulfill SVAR perquisites modeling. The results are illustrated in Table 2. It can be clearly seen that the null hypothesis of the existence of unit root was rejected at the 1% significance level, as evidenced by the p-values relating to the ADF and PP tests for all five variables. According to KPSS test, the null hypothesis of stationarity is accepted at the 1% significance level, which confirms the results obtained by the ADF and PP tests. Consequently, the results suggest that all series are stationary in their level, hence validating the use of the structural autoregressive model (SVAR) rather than the structural vector error correction model (SVECM).

Il should be noted that the comparison of the statistical properties of the de-trending series using HP filter with those obtained by the classical differentiation and regression on the trend filters, reported by Nelson and Plosser (1982) [62], revealed that the HP filter did not over-differentiated the series. Therefore, no perturbation noise is created in the data. So, all series have good statistical properties for further analysis.

Table 2. *Results of testing for unit roots.*

Variable	Level						Remark
	ADF		PP		KPSS		
	t-Stat	*p*-value	Adj. t-Stat	*p*-value	LM-Stat	Critical value (1%)	
FGDP	-3.20^{c***}	0.002	-7.04^{c***}	0.000	0.06^{b}	0.739	I(0), Stationary
FAGR	-8.18^{c***}	0.000	-8.12^{c***}	0.000	0.04^{b}	0.739	I(0), Stationary
FINV	-4.37^{c***}	0.000	-4.21^{c***}	0.000	0.05^{b}	0.739	I(0), Stationary
FM3	-3.90^{c***}	0.000	-4.62^{c***}	0.000	0.05^{b}	0.739	I(0), Stationary
FOPN	-6.14^{c***}	0.000	-6.28^{c***}	0.000	0.08^{b}	0.739	I(0), Stationary

FGDP, FAGR, FINV, FM3 and FOPN refer respectively to the five variables after natural logarithm and Hodrick-Prescott (HP) Filter transformations;
a,b and c represent models with constant and trend, with only constant and without constant and trend, respectively;
***Indicates significance at 1% level.

3.4. Lag Selection

The choice of the optimal order of the model was selected using the information criteria, such as: Akaike information criterion (AIC), Schwarz information criterion (SC), Hannan-Quinn criterion (HQ) combined with other statistics including: the Log Likelihood (LogL), sequential modified LR test statistic (LR) and final prediction error (FPE). Additional tests based on residuals diagnostics of the model such as autocorrelation, stability and heteroscedasticity tests permitted to valid the best model. The numerical outputs from Eviews 12 software are summarized in Table 3. The combination of the information criteria and the residual diagnostic tests reveals that p = 2 is the optimal lag length to estimate a model that generates residuals with statistically acceptable properties. The validation tests of the unrestricted VAR model are presented in appendix. It should also be noted that the diagnostic of the residuals of the reduced-form VAR model dictated adding a dummy variable related to the year 1993 to the model. The introduction of this variable, which corresponds to a year of a very severe drought, significantly improved the goodness of fit of the estimated final model.

Table 3. *Lag length selection criteria.*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	340.0454	NA	1.23e-14	-17.84029	-17.40491*	-17.68680
1	371.6823	51.30306	8.79e-15	-18.19904	-16.67520	-17.66182
2	410.3296	52.22608*	4.64e-15*	-18.93673	-16.32443	-18.01577*
3	437.4337	29.30174	5.32e-15	-19.05047*	-15.34971	-17.74578

3.5. Directed Acyclic Graphs (DAG) Results

Figure 3 presents the contemporaneous causal structure of residuals[5] derived from reduced VAR at different significant levels in order to check the stability of the results and avoid ambiguous graphs at different levels of significance. As suggested by Spirtes et al. (2000), the use of a higher level of significance for smaller samples may increase the performance of the algorithm [48]. This procedure has been applied in several economic researches, reaching a significance level of 20% or even 30% [42, 43, 52, 55, 56]. By setting low significance levels (1%, 5% and 10%), the edges are not directed and therefore the graph is not directed (Figure 3(a) and (b)). The graph is partially directed at the relatively higher level of significance (20%) because there are directed and undirected edges (Figure 3(c)). However, at a significance level of 30%, the graph is completely directed. The PC algorithm retained five contemporary causal relationships (Figure 3(d)). At this significance level, the graph shows no instantaneous causalities between RM3 and ROPN, RM3 and RGDP and between RM3 and RINV. The graph also indicates that there are no contemporaneous causalities between RINV and RAGR as well as between RINV and RGDP. Furthermore, RGDP has significant directed edges with ROPN, running from RGDP to ROPN. The latter exhibits a contemporary causal relationship with RINV, moving from ROPN to RINV. In addition, RM3 and RAGR show an instantaneous causality from RM3 to RAGR and there is a directed path from RAGR to ROPN.

The PC algorithm suggests also a contemporary causality between RGDP and RAGR that runs from RGDP to RAGR. However, since the SVAR estimation procedure is not a fixed process, but rather an iterative one, the restrictions suggested by the PC algorithm should not constitute a "black box" that would mask economic assumptions and practical evidence. As suggested by Bruneau and De Bandt (1999), the results obtained at one-step of the estimation procedure for a structural VAR may put into question the choices made at an earlier step [63]. Therefore, given the iterative approach

5 The letter R at the beginning of all variables emphasizes the use of the residuals from the reduced VAR model to run the PC algorithm.

advocated in this work and for practical considerations, the contemporary causality, during the current year t, between the agricultural sector and GDP should go from the agricultural sector to GDP. Furthermore, each year, policymakers provide forecasts of economic growth in Morocco based on the performance of the agricultural sector, among others. The forecasts related to economic growth are adjusted as data on the agricultural sector become available, mainly data inherent to rainfall level for the current agricultural season. Indeed, the agricultural sector is exogenous with respect to GDP at contemporary time t. Hence, the direction of contemporaneous causality between RAGR and RGDP proposed by the PC algorithm is changed in the opposite direction.

Moreover, given the large literature on the importance of monetary shocks on the economy, a restriction on the directed relationship of the money supply to GDP has been added. This restriction is theoretically and empirically justified in the short run, since the data are annual. So, there is enough time for the economy to adjust instantaneously, at time t, to monetary shocks.

Therefore, under all these assumptions, the relationship between VAR residuals and structural shocks, as expressed by equation 7, is defined as follows:

$$\begin{bmatrix} 1 & a_{12} & 0 & a_{14} & 0 \\ 0 & 1 & 0 & a_{24} & 0 \\ 0 & 0 & 1 & 0 & a_{35} \\ 0 & 0 & 0 & 1 & 0 \\ a_{51} & a_{52} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_t^{GDP} \\ \mu_t^{AGR} \\ \mu_t^{INV} \\ \mu_t^{M3} \\ \mu_t^{OPN} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 \\ 0 & 0 & 0 & 0 & b_{55} \end{bmatrix} \begin{bmatrix} \upsilon_t^{GDP} \\ \upsilon_t^{AGR} \\ \upsilon_t^{INV} \\ \upsilon_t^{M3} \\ \upsilon_t^{OPN} \end{bmatrix}$$

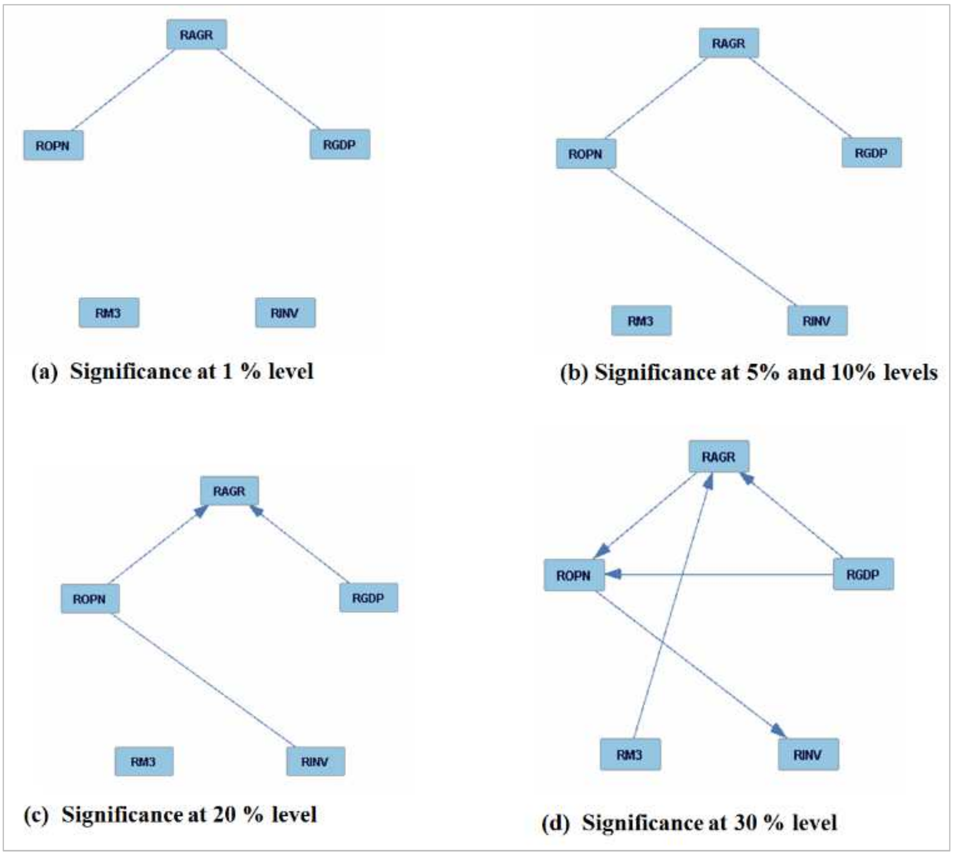


Figure 3. *Directed acyclic graph results.*

The estimation of the parameters of matrices A and B revealed the significance of all parameters at the 1% level, except for the coefficient a_{51}, which is significant at 5% level, and the coefficient a_{24} which is significant at 10% level. In order to generate robust results, only the coefficients that are significant at 1% and 5% levels were retained for further analysis. The coefficient a_{24} was therefore eliminated. The order condition for identification suggests the presence of an over-identified structure with five over- identifying constraints imposed on the parameter. Their validity and legitimacy can be checked by means of a likelihood ratio (LR) test. Under the null hypothesis that the restrictions are valid, the LR statistic is asymptotically distributed as $\chi^2(q)$, where q is the number of over-identifying restrictions.

As a result of this analysis, the null hypothesis of validity of the restrictions is accepted since the probability of significance is well above 0.05 ($\chi^2(5) = 5.30, p - value = 0.38$). In this regard, the validity of the over-identifying restrictions has been found to be supported by the data and the restrictions imposed on the parameters are therefore plausible.

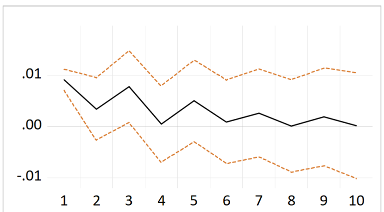
3.6. Impulse Response Functions

In order to respond specifically to the main objective of this study, which consists of evaluating and quantifying the relationship between the agricultural sector and GDP, only the impulse response functions which trace the response of these two variables following a structural shock over ten periods horizon which are reported in Figure 4. Since the estimated VAR model is stationary, the effect of shocks fades out at some point in the future. The middle lines in black represent the impulse response functions. The dashed lines in orange represent the confidence interval bands generated using the Monte Carlo approach and computed as +/–2 Standard Error (SE) confidence bands. The impulse response is significant if the horizontal line is not included in the confidence interval band. The graphs represent the response of the variable of interest to one standard deviation positive shock in each of the variables, assuming the rest remains constant.

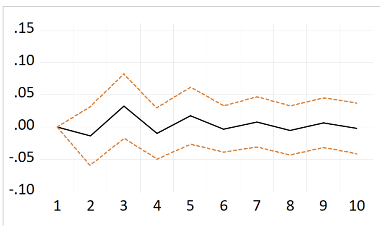
As reported in Figure 4(a), a positive agricultural GDP shock induces a GDP increase immediately and significantly during the first period, reaching the highest level compared to the remaining periods horizon. More precisely, the GDP responds positively to a positive shock in the agricultural sector, thus confirming the crucial role of this strategic sector on the Moroccan economy. After the maximum level reached during the first period, the impact of the shock gradually dampens (although insignificant).

It should also be noted that the country's economy is very sensitive to a unit shock from the agricultural sector compared to all the shocks of the other endogenous variables of the system (Figure 4(e)). The high positive sign of the impact of agricultural GDP shock on GDP suggests a strong positive relationship between the two spheres.

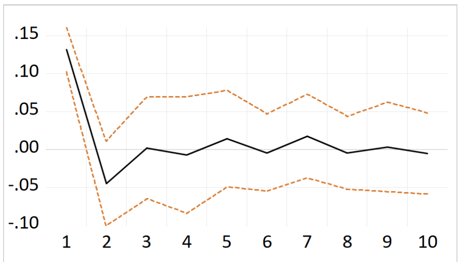
As for the response of the agricultural sector to a positive shock to GDP, reported in Figure 4(b), the response is insignificant and relatively mixed. This result highlights the weakness of the causal link from the economy to the agricultural sector and casts doubt on the Growth-Led Agriculture (GLA) hypothesis.



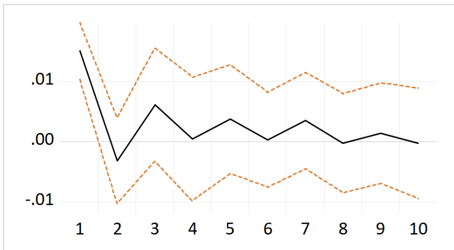
(a): Shock: AGR → Response: GDP



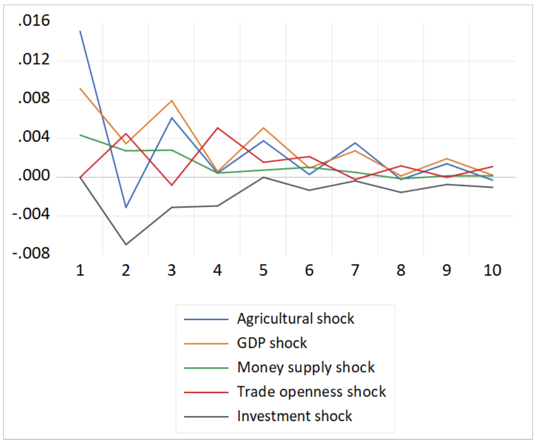
(b): Shock: GDP→ Response: AGR



(c): Shock: AGR → Response: AGR



(d): Shock: GDP → Response: GDP



(e) Response of GDP to structural VAR shocks

***Figure 4.** Impulse response functions results.*

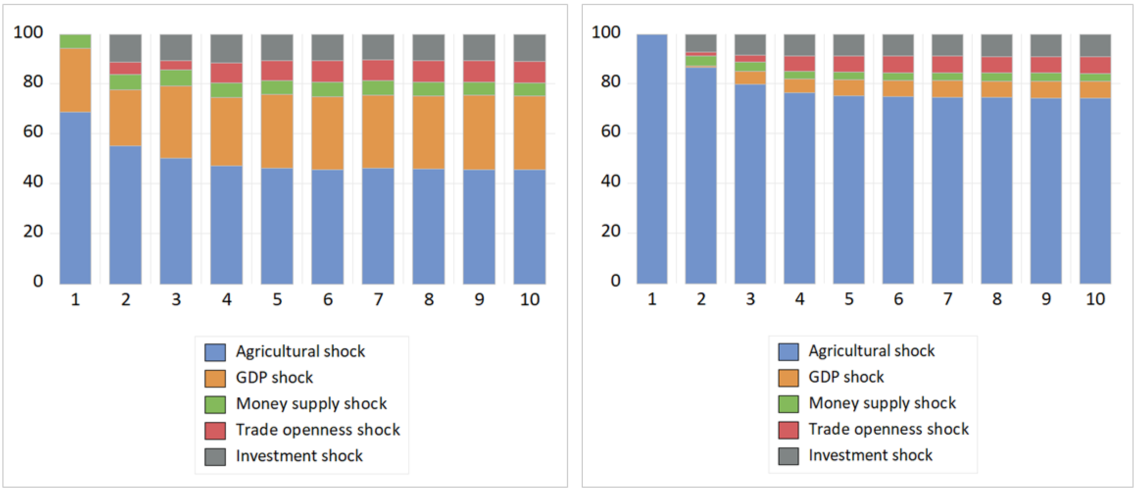
Moreover, another striking result, shown in Figure 4 (c) is that the agricultural sector is very sensitive to its own growth. This result could be explained by the high sensitivity of the agricultural sector to increasing climatic variations. The impact of drought on the performance of the agricultural sector, which is transmitted to the economy as a whole, remains a structural phenomenon in Morocco. Thus, GDP responds significantly and positively to its own shocks (Figure 4 (d)). Consequently, the results derived from the impulse response functions empirically support the Agriculture-Led Growth (ALG) hypothesis, since a positive and significant response is observed for GDP following an agricultural shock.

3.7. Forecast Error Variance Decomposition

The dynamic decomposition of the variance of the forecast error relative to GDP and agricultural GDP is displayed in Figure 5. The variance decomposition technique gives the relative importance of each of the shocks as sources of the variability of the variable of interest. This technique gives an idea of the forecast error variance share explained by different shocks at various horizons, in this case ten periods. The results presented in Figure 5(a) indicate that agricultural shocks explain a large part of the GDP forecast error variance, even at longer horizons. Indeed, the agricultural GDP shocks are the most important driver and account for almost 69% of the forecast error variance for the 1st period, 55% for the 2nd period and 50% for the 3rd period before stabilizing around a value of 45%. These shares explained by agricultural shocks greatly exceed the shares explained under other shocks due to all remaining variables of the system. In particular, only 26% of GDP forecast error variance is explained by its own innovations during the first period and roughly 30% after 10 periods.

As for agricultural GDP, the decomposition of the variance of this variable corroborates the results of the impulse response functions. As reported in Figure 5(b), the agricultural sector is very sensitive to its own innovations, which dominates the variance decomposition profile and does not fall below the 74% threshold for all horizons. Clearly, the contribution of the GDP shock does not exceed the value of 7%. This again proves the dominance of agricultural shocks in explaining the variance of GDP compared to the contribution of GDP shocks in explaining the variance of agricultural GDP. This result confirms the causal strength of agricultural shocks. The substantial contribution of agricultural shocks in explaining GDP fluctuations supports the ALG hypothesis that Agriculture-Led Growth rather than the GLA hypothesis. It corroborates, therefore, the idea stipulated by several economists that the agricultural sector is a prerequisite for economic development and serves as an engine of growth.

Although Granger's causality study between agriculture and the economy, illustrated in the work of Elalaoui et al. (2021), showed a bidirectional causality between the two spheres [17], the results of the impulse response functions and the variance decomposition from the SVAR analysis reveal robust evidence of the dominance and strength of the relationship which runs from the agricultural sector to GDP.



(a): Variance decomposition of GDP (b): Variance decomposition of agricultural GDP

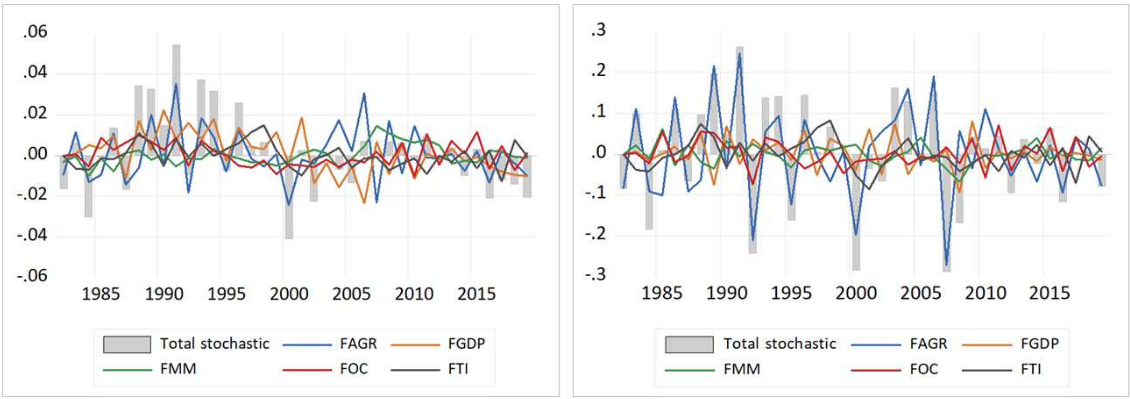
Figure 3. *Variance decomposition results.*

3.8. Historical Decomposition

Unlike the variance decomposition, the historical decomposition makes it possible to analyze the relative importance of shocks across different sub-periods in order to assess the evolution of their effect over time. It focuses on the contribution of each structural shock to the historical path of the variables of interest. Figure 6(a) explores how the five identified shocks, including agricultural shocks, have historically contributed to GDP dynamics at specific times. The impact of the agricultural sector on GDP exhibits time-changing effects between 1982 and 2019. The analysis period shows episodes in which the agricultural sector pushes the Moroccan economy upward and other episodes that were marked by negative downward effects.

Although the impact of agricultural shocks on GDP is historically prominent between 1982-1999 and 2000-2019, the magnitude of its impact has significantly reduced by 22% between the two periods. At the same time, the degree of dependence, as measured by the correlation coefficient between the total stochastic of GDP and agricultural shocks, decreased from 0.83 to 0.54. In other words, the last period shows a smaller proportion of GDP deviations attributable to agricultural shocks compared to the first period. This result shed light on the economic resilience of both the agricultural sector and the economy as a whole, especially after the measures taken by the government as part of the agricultural strategy "Green Morocco Plan" to mitigate the devastating impacts of drought on agriculture. Another finding of the historical decomposition analysis is that the agricultural sector sometimes acts as a shock absorber during periods when other economic sectors are performing poorly, pushing the economy upwards.

As for the decomposition of agricultural GDP, the strong contribution of agricultural shocks to its own historical path is very evident (Figure 6(b)). The impact of agricultural shocks on the sector itself was reduced by 19% between 1982-1999 and 2000-2019. On the basis of the above, it should be highlighted that the revealed resilience of the economy to agricultural shocks is most likely due to the improved resilience of the agricultural sector to its own shocks, consisting mainly of climatic shocks.



(a): Historical decomposition of GDP (b): Historical decomposition of agricultural GDP

Figure 6. *Historical decomposition results.*

4. Conclusion

Given its socio-economic importance, the agricultural sector in Morocco has always represented a debated topic amongst policymakers but is rarely a cause of concern for researchers and academics. This research focused on assessing the dynamic interrelationship between agricultural sector and GDP in Morocco over the period 1980–2019. Using a system of five macroeconomic variables (GDP per capita, agricultural GDP, investment rate, money supply and trade openness), this study applies the structural VAR modeling. Unlike previous studies on the dynamic relationship between the agricultural sector and economic growth in different countries, where the model identification was recursive, this study employs Directed Acyclic Graphs, specifically the PC causal discovery algorithm, in order to uncover the structural shocks. Overall, the importance of the agricultural sector in the Moroccan economy is strongly evident. Agricultural shocks are important driving forces behind output oscillations. Compared to all the shocks inherent to the different variables mobilized, the impulse response functions reveal that the Moroccan economy is very sensitive to an agricultural shock. GDP responds positively and significantly to positive agricultural shocks. However, the results related to the response of agriculture to GDP shocks remain insignificant. By employing variance decomposition technique as a complementary analysis tool, the findings prove that the agricultural shocks are the most important driver and account for almost 69% of the forecast error variance for the first year horizon. However, the contribution of GDP shocks to explaining the forecast error variance of agricultural GDP does not exceed 7%. The agricultural sector has proven to be very sensitive to its own shocks, which does not fall below the 74% threshold for all horizons examined. Moreover, the technique of historical decomposition has provided additional results. First, although the historical dependence between the economy and the agricultural sector is undeniable, the degree of impact of agricultural shocks on GDP has been reduced by 22% between 1982-1999 and 2000-2019, thus implying an increasing resilience of the economy to agricultural shocks. This result is most likely due to the improved resilience of the agricultural sector to climate shocks. Second, the sector sometimes acts as a shock absorber for the Moroccan economy during periods when other economic sectors are performing badly.

Consequently, although an earlier study showed bidirectional causality between the agricultural sector and the economy, the results derived from the SVAR model highlight the strength of the causality from the agricultural sector to GDP compared to the opposite direction. In other words, the results support the ALG hypothesis, which states that Agriculture-Led Growth, rather than the GLA (Growth-Led Agriculture) hypothesis.

Based on these results, agricultural growth in Morocco is causally prior to economic growth and consequently to industrial development. Unlike countries that have been able to develop by building a strong industrial base without developing the agricultural sector, agricultural growth in Morocco is necessary for the country's economic development and it has a strong potential to stimulate economic growth. In this regard, the agricultural sector should be an integral part of the country's overall priorities, especially since the international crises made it necessary for policymakers to pay attention to this strategic sector, which plays a key role in the food security of Moroccan households and agricultural labor, particularly for the rural population. In view of the results of this study, which show the strong potential of the agricultural sector in promoting agricultural development, “agro-pessimism" should be overcome. Thus, the debate should shift from questioning the capacity of the agricultural sector to stimulate growth to finding viable solutions to a number of structural problems inherent to the sector, particularly the drought issue.

From a policy implications point of view, a number of recommendations can emanate from this study. Firstly, policymakers need to ensure that sectoral strategies are synergistic and harmonious in order to strengthen the backward and forward linkages between the agricultural sector and other sectors of the economy. Secondly, given the undeniable importance of the agricultural sector in the economy, especially during crises, the government should continue to create favorable conditions to support the development of Moroccan agriculture. Finally, policymakers should exploit the growing dynamics of the agricultural sector and its strong impact on the socio-economic tissue to achieve several sustainable development goals of the 2030 agenda granted by the international community, several of which have a close relationship with agriculture.

For future investigations, the role of the agricultural sector should be examined within a holistic framework that integrates the economy, the social, and the environment. This overcomes the shortcomings inherent in one-dimensional approaches in comparison with the relatively recent multidimensional approaches.

Appendix: VAR Model Validation

The modulus of all inverse roots is less than 1 and lies inside the unit circle, which is an indication that the VAR satisfies the stability condition.

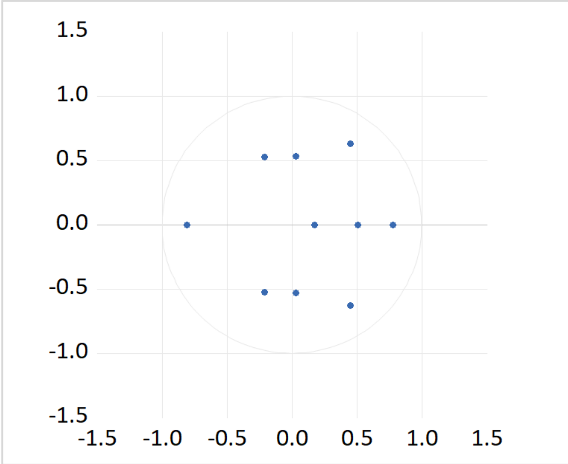


Figure 7. *Inverse roots of AR characteristic polynomial.*

From Table A1, all the probabilities related to LRE stat Rao F-stat are greater than 0.05. Consequently, the estimated VAR (2) residuals show no evidence of serial correlation.

Table A1. *Serial correlation LM test results.*

Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	28.04950	25	0.3056	1.151651	(25, 64.7)	0.3174
2	24.40702	25	0.4960	0.977078	(25, 64.7)	0.5079
3	21.43542	25	0.6681	0.840715	(25, 64.7)	0.6778
Null hypothesis: No serial correlation at lags 1 to h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	28.04950	25	0.3056	1.151651	(25, 64.7)	0.3174
2	50.30250	50	0.4614	0.982352	(50, 58.1)	0.5232
3	69.64523	75	0.6529	0.782563	(75, 37.7)	0.8177
*Edgeworth expansion corrected likelihood ratio statistic.						

From Table A2, the p-value (0.2406) is larger than 0.05 implying the absence of residual heteroscedasticity.

Table A2. *VAR Residual Heteroscedasticity test.*

Joint test:		
Chi-sq	**df**	**Prob.**
332.3242	315	0.2406

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