INTERNATIONAL JOURNAL OF RESEARCH IN ECONOMICS AND FINANCE, 2026, Vol. 3, No. 9-1, 1-18. http://doi.org/10.71420/ijref.v3i9-1.371

Digital Transformation and Economic Growth in Morocco: Identifying a Structural Shock Using a SVAR Model

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Abstract. This paper analyzes the impact of a structural shock of digital transformation on economic growth in Morocco for the period 2002-2023. A macroeconomic view is required to evaluate the extent to which digitalization is an autonomous driver of growth in addition to traditional drivers such as inflation, investment and trade openness. Methodologically, the study employs a Structural Vector Autoregressive (SVAR) model estimated on annual data. Digital transformation is measured through a composite index built from three normalized indicators drawn from the World Development Indicators: Internet usage, fixed-line telephony, and fixed broadband subscriptions. Following an assessment of the stationarity properties of the series, the index enters the system in first differences. Diagnostic testing supports a first-order specification, and structural shocks are identified through an AB-type factorization with a lower triangular matrix A and a diagonal matrix B, yielding a just-identified model. The results do not support the hypothesis that digital transformation constitutes a measurable driver of Moroccan growth over the period. The structural impulse response of GDP growth to a digital transformation shock is statistically indistinguishable from zero at every horizon considered, with 95 per cent confidence bands containing zero throughout; the point estimates are negative in the first year following the shock before oscillating around zero. The structural forecast error variance decomposition attributes approximately three per cent of the variance of growth to the digital shock. Symmetrically, no individual response linking digital transformation to the other variables of the system attains statistical significance, in either direction. These results indicate that the diffusion of the digital in Morocco over the period 2002–2023 has been mainly in parallel with the real economy, and not in interaction with it. This is consistent with the perspective that digital dividends are not automatic and evenly distributed and that measurable macroeconomic returns depend on absorptive capacity in terms of infrastructure quality, human capital, and institutional conditions that may not yet be in place. The results suggest the need for digital policies for productive integration, not only connectivity.

Keywords : *Digital transformation; Economic growth; SVAR; structural identification; impulse response analysis; Morocco.*

1. Introduction

The digitalization has taken a more and more important place in the analysis of contemporary growth dynamics. It has become a major feature of the current economic transformation characterized by the reorganization of production processes, information flows and resource allocation mechanisms. The evolution of digital technologies is no longer just a matter of technological modernization. They also alter the functioning of markets and contribute to the emergence of new forms of value creation. This development poses questions of particular importance in emerging economies, where digitalization is often viewed as a lever to accelerate the modernization of productive and institutional structures while simultaneously strengthening long-term growth capacity.

In Morocco this has occurred within the framework of economic reform and the gradual modernization of the information and communication infrastructure. The successive national strategies, from Maroc Numeric 2013 to Maroc Digital 2020, have helped to increase access to internet, develop digital services and disseminate technological use. Over 20 years, Internet usage has rocketed from a low base to near saturation. However, beyond this progressive dissemination, the real macroeconomic impact of digital transformation in Morocco is not well known.

In general, literature confirms a positive relationship between ICT diffusion and economic growth (Röller & Waverman, (2001; Czernich et al., 2011; Vu, 2011). However, three gaps remain. The first is that the bulk of empirical evidence comes from cross-country panels, not from country-specific dynamic analysis, so that the Moroccan case is largely unexplored. Second, existing studies on Morocco tend to focus on single connectivity indicators or reduced-form tests of correlation and causality rather than a composite multidimensional measure. Third, and most importantly, none of these studies formally deals with digital transformation as a structural shock in a dynamic macroeconomy, a shock that is purged from contemporaneous feedback from growth, inflation, investment and trade openness.

Therefore, the main research problem can be formulated as follows: to what extent is the digital transformation an independent determinant of the economic growth of Morocco beyond the effects of the traditional macroeconomic variables such as inflation, investment and trade openness? To answer this question, we need to disentangle the specific role of digitalization among a set of interdependent determinants, and to study the channels through which a digital shock may be transmitted to the economy.

This paper tackles the three-part divide stated above by elaborating on an amalgamated digital transformation index for Morocco and determining its structural, dynamic influence on economic growth. Its contributions are both methodological and substantial. On a methodological level, it presents the first instance of a digital transformation shock for Morocco in a structural macroeconomic system where the original component of digitalization is recognized as distinct from its simultaneous interactions with other macroeconomic factors. On a substantive level, it investigates whether the spread of digital technology documented over two decades has resulted in measurable economic returns and places the Moroccan case in a broader debate about the contexts in which digital dividends emerge.

The analysis utilized a Structural Vector Autoregressive model for annual data from 2002 to 2023 with respect to digital transformation evaluated through the development of a composite index. The rest of the paper is structured as follows: the theoretical framework and the literature review on the impact of digital transformation on growth is presented in section 2. Section 3 presents methodology, data collection and index construction as well as empirical findings. Then section 4 discusses the obtained results and finally section 5 draws conclusions.

2. Literature Review

The analysis of the connection between digitalization and economic development is based on theories that see technical advancement as a key factor behind the long-term evolution of the economy. In this context, the emergence of information and communication technologies is treated as an element that increases productivity, reduces coordination costs, and improves the functioning of markets in general.

In essence, according to Robert Solow (1956), it is the idea of technical progress that creates the foundation for long-term economic growth. Building on that foundation, endogenous growth theories by Paul Romer (1986, 1990), Robert Lucas (1988), and Robert Barro (1991) further demonstrate that innovation, human capital, and government policy have a large role in the economy. Additionally, Joseph Schumpeter (1942) approach highlights the significance of innovation and creative destruction in the whole economic process.

Recent research highlights the increasing importance of digitalization as an engine of economic growth. According to Brynjolfsson and McAfee (2014), digital technologies are fundamentally altering economic behavior and enabling productivity improvement. Likewise, empirical research by Parviainen et al (2017), Mićić (2017), and Beier et al. (2017) showcases a positive link between digitalization and economic development manifested in economic performance, job creation, and GDP growth. Along similar lines, studies conducted by Youssef and M'henni (2004), Choi and Yi (2009), and Dedrick et al. (2013) establish that ICTs have a positive and significant impact on economic growth.

As one of the pioneering studies, Röller and Waverman (2001) use data from OECD nations to show that there is a positive causative link between telecommunication development and a nation's economic growth. They also note that this effect becomes significant only once a certain level of telecommunication development is achieved. The above findings were further developed by research that focused on broadband services. Qiang, Rossotto, and Kimura (2009) demonstrate the relation between broadband accessibility and economic improvements, especially in developing countries. Like them, Koutroumpis (2009) states that the impact created by broadband services was both significant and measurable, while also taking notice of the significance of network effects. Furthermore, Czernich et al. (2011) corroborate the previous findings regarding the impacts of broadband dissemination on GDP per capita growth in OECD countries.

In the literature, the subject matters have been developed from a narrow understanding of digital infrastructure to a wider interpretation of digitalization as an extensive transformation of the economy. In this context, Vu (2011) stated that the increase in the use of ICT was one of the key contributors to the economic growth in the context of the development of the information economy, especially in case enough technological absorptive capability is present. This line of thought is continued in the work of Katz and Koutroumpis (2013), who made an effort to develop an index of digitalization that would include access to technologies as well as effective use of such technologies in social and economic processes. Such a contribution is of great significance since it moves beyond investigating the connectivity in a separate way and provides a more systemic interpretation of digitalization. In a similar manner, the World Bank (2016) asserts that digital dividends are neither a given nor uniformly distributed. Digital technology can promote economic growth, create opportunities, and enhance the efficiency of public and private services. Nevertheless, these outcomes will be unevenly produced and will depend to a great extent on the institutions, human capital, and regulations in a given country.

While analysing the processes in emerging economies, most researchers come to the conclusion that digital transformation itself is a potential driver of economic growth, but this impact will largely depend on national economic structure. In other words, digitalization is not equivalent to economic growth, since its consequences vary depending on the level of technology penetration, quality of infrastructure, development of the financial sector, and readiness of economic actors to use digital technologies in production and financing.

The influence of digital technology in Morocco is not arbitrary, as it is part of a larger process of modernization of economies and institutions. Recent Moroccan studies emphasize the importance of digital technology as a driver of economic growth and competitiveness. However, the analysis of its macroeconomic impact is still rather limited in national academic literature. Against this background, the current research extends previous studies but introduces an important new perspective by identifying the structural shock of digital transformation and analyzing its impact on the economy of Morocco in macroeconomic terms.

3. Methodology

This paper uses a quantitative empirical approach to assess the impact of a structural shock of digital transformation on the economic growth in Morocco for the period 2002-2023. The analysis is based on a Structural Vector Autoregressive (SVAR) model selected for its ability to identify structural shocks and map their dynamic transmission in a macroeconomic system of economic growth, inflation, investment, trade openness and digital transformation. The methodological strategy consists in the analysis of the statistical properties of the series, the estimation of a reduced form VAR model, the determination of the optimal lag length, the performing of diagnostic tests on the model and the identification of the structural shocks through an AB-type factorisation.

Before proceeding to structural identification, it is necessary to clarify what a structural digital transformation shock represents economically. In the SVAR framework, the structural innovation associated with the differenced index, once orthogonalized from the contemporaneous innovations of the other system variables through the AB-type factorization, captures the component of digital transformation that is unexplained by the current state of growth, inflation, investment, and trade openness. Economically, this innovation is best interpreted not as a single well-defined event but as a composite of two related forces: first, exogenous technological diffusion — the adoption of digital infrastructure and services driven by global technology trends and falling access costs, largely independent of short-run domestic business-cycle conditions; and second, discretionary digital-policy initiatives, such as Morocco's Maroc Numeric 2013 strategy (implemented between 2009 and 2013) and the Maroc Digital 2020 strategy (launched in 2016), which introduced supply-side infrastructure expansion programmes not systematically driven by contemporaneous macroeconomic conditions.

This dual interpretation is consistent with the broader literature treating broadband and ICT infrastructure rollout as quasi-exogenous with respect to short-term output fluctuations (Röller & Waverman, 2001; Czernich et al., 2011). It is also supported by the estimation itself: as reported below, no lagged macroeconomic variable significantly explains the differenced index, whereas its own lag is highly significant, indicating that digital diffusion in Morocco follows a largely autonomous trajectory. Given the annual frequency and the length of the sample, the structural shock identified here should be understood as capturing this broader diffusion-and-policy dynamic rather than any single discrete event.

The general structural form of the SVAR model can be expressed as follows:

$$AYt = \sum_{k=0}^{n} \Gamma i\, Yt - i + B\varepsilon t \qquad (1)$$

Where Y_t represents the vector of endogenous variables, A denotes the matrix capturing the contemporaneous relationships among these variables, B represents the matrix associated with the structural shocks, Γ_i denotes the coefficient matrices of the lagged variables, and ε_t is the vector of structural innovations.

In this study, the vector Y_t is defined as follows:

$$Yt\text{=(}GDP\ Growth\ t\ ;\ \Delta\ DT\ Index\ t\ ;\ INFLt\ ;\ INVESTt\ ;\ OPEN\ t \qquad (2)$$

Where Δ DT Index t denotes the first difference of the composite Digital Transformation Index, $INFL_t$ represents the inflation rate, $INVEST_t$ denotes the level of investment, $OPEN_t$ represents the degree of trade openness, and $GDP\ Growth_t$ refers to economic growth.

The composite Digital Transformation Index is constructed from three indicators drawn from the World Development Indicators, each normalized using the min-max method over the full 2002–2023 sample, according to the expression X_norm,t = (X_t − X_min) / (X_max − X_min), where X_min and X_max denote respectively the minimum and maximum values observed over the period. The three components are: Individuals using the Internet, as a percentage of population (WDI code IT.NET.USER.ZS); Fixed telephone subscriptions per 100 people (WDI code IT.MLT.MAIN.P2); and Fixed broadband subscriptions per 100 people (WDI code IT.NET.BBND.P2). Each normalized series is therefore bounded between 0 and 1 by construction. The composite index is obtained as the simple arithmetic mean of the three normalized series, according to the following expression:

DT Index t = (Internet Xt + Fixed Telephony Xt + Fixed Broadband Xt) / 3

Where X_t denotes the normalized value of each component at time t. Given the statistical properties of the series, the index is subsequently introduced into the model in first-difference form.

a. Data source

Before proceeding to the first estimation of the model, it is essential to point out that the data used in this study are mainly from the World Bank. The variables used in the analysis and the corresponding data sources are presented in the following table.

Table 1 : Data source

Variables	Description	Data Sources
Economic Growth	GDP Growth	World Bank (WDI)
Digital Transformation	Digital Transformation Index (DTI)	World Bank (WDI)
Inflation	INFL	World Bank (WDI)
Investment	INVEST	World Bank (WDI)
Trade Openness	OPEN	World Bank (WDI)

Source : Author

Empirically, we will focus our analysis on Morocco, using data from the period 2002–2023. This period is suitable to study trends in the variables studied over a sufficiently long period, considering recent economic developments.

b. Statistical Properties of the Variables

For this research, a descriptive statistical analysis was carried out on a sample of 22 observations, to show the main characteristics of the variables. The results show that the digital transformation index has a moderate dispersion around its mean, indicating relatively heterogeneous levels of digitisation. GDP growth shows significant variability, including outliers, indicating large economic fluctuations during the study period. However, inflation presents significant dispersion and asymmetric distribution which reveals the existence of some outliers. Investment, meanwhile, seems relatively stable, with little spread around its mean. Finally, the degree of trade openness shows moderate variability and a slightly skewed distribution

In general the results show the heterogeneity of the distribution and volatility of the variables, which justifies their inclusion in the subsequent econometric analysis.

Table 2 : descriptive statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
DT Index	22	0.00	0.83	0.4527	0.24435	-0.599	-0.538
GDP Growth	22	-7.18	8.15	3.6173	2.9904	-2.139	8.009
Inflation	22	0.30	6.66	1.9489	1.6708	1.881	3.196
Investment	22	24.41	35.51	30.3213	2.4939	-0.513	0.658
Trade Openness	22	24.68	44.71	31.3526	4.8057	1.359	2.729

Source : SPSS

c. SVAR Model Estimation Procedure

The SVAR model was estimated in a sequential manner. We first checked the statistical properties of the time series to identify their order of integration and to guarantee the econometric consistency of the system. Then a reduced VAR was estimated as a preliminary step to structural identification. The number of lags was chosen optimally by using standard information criteria which differ in this application: the LR, FPE and Hannan-Quinn criteria choose one lag, the Akaike criterion chooses two and the Schwarz criterion chooses zero. A VAR(1) specification was chosen as the modal choice across criteria and on grounds of parsimony given the constraints imposed by the sample size.

Having chosen this specification, several diagnostic tests were performed to verify the validity of the estimated model. The stability condition was analysed by roots of the characteristic polynomial, all of them are inside the unit circle, which confirms the dynamic stability of the system. The LM test for autocorrelation of the residuals failed to reject the null hypothesis of no serial autocorrelation at individual lags. This is not the case for the residuals of the growth equation that individually deviate from normality, reflecting the extent of the output contraction in 2020. However, the joint statistics cannot reject the hypothesis of multivariate normality of the residuals.

In a third step structural identification was performed by an AB-type factorisation. Matrix A was defined as a lower triangular matrix and matrix B was supposed to be diagonal. This structure yields a just-identified model so that structural shocks can be uniquely identified. The structural impulse response functions and structural variance decomposition were used to analyse the dynamic effects of these shocks.

d. Presentation of the Results

i. Unit Root Test

Table 3 : ADF Stationarity Test Results

Variable	Model	At level		1st Difference		Result
		P.V*	O.I**	P.V*	O.I**	
GDP Growth	Intercept	0,00	I (0)	0,00	I (1)	**I (1)**
	Trend and Intercept	0,00	I (0)	0,02	I (1)	
	None	0,22	NS	0,00	I (1)	
Δ Digital Transformation Index (ΔDTI)	Intercept	0,11	NS	0,00	I (1)	**I (1)**
	Trend and Intercept	0,51	NS	0,00	I (1)	
	None	0,10	NS	0,00	I (1)	
INFLA	Intercept	0,30	NS	0,00	I (1)	**I (1)**
	Trend and Intercept	0,54	NS	0,00	I (1)	
	None	0,35	NS	0,00	I (1)	
INVEST	Intercept	0,06	NS	0,00	I (1)	**I (1)**
	Trend and Intercept	0,44	NS	0,00	I (1)	
	None	0,77	NS	0,00	I (1)	
OPEN	Intercept	0,71	NS	0,00	I (1)	**I (1)**
	Trend and Intercept	0,07	NS	0,00	I (1)	
	None	0,89	NS	0,00	I (1)	

Source : *EViews*

Notes: **p-value = probability value; NS = Non-Stationary; I(0) = stationary at level; I(1) = stationary after first differencing*.

The results of the Augmented Dickey-Fuller (ADF) unit root test show that the variables included in the model generally exhibit nonstationary behavior in level terms but become stationary after first differentiation. For GDP growth, the results at the level vary depending on the specification chosen: the series is stationary in models with a constant and with a constant plus a trend but is not stationary in the specification without a constant or a trend. For methodological caution and to ensure the homogeneity of the system, this variable is ultimately treated as integrated of order one. Regarding D_INDICE_TD, inflation (INFLA), investment (INVEST), and trade openness (OUV), the p-values observed at the level remain above the 5% significance threshold, which leads to not rejecting the unit root hypothesis. However, after first-order differentiation, all these variables become stationary, with p-values of zero or very low across all specifications considered. These results thus lead to the conclusion that all variables in the model can be considered first-order integrated, I(1), which justifies continuing the analysis within a multivariate dynamic framework.

On this basis, it is then necessary to verify the possible existence of a cointegration relationship among the variables before proceeding with the estimation of the SVAR model

ii. Cointegration Test

Based on the stationarity results, the existence of a long-run relationship between the variables was examined using the Johansen cointegration test. This test was applied to the 2002–2023 period, with 22 observations, a lag range of 1 to 1 in first differences, and under the deterministic Case 3 assumption, which includes a constant in both the cointegration relationship and the short-run dynamics.

Table 4 : Summary of the Johansen Cointegration Test

Test Type	Statistic	p-value	Conclusion
Trace Test	68.047	0.0686	No cointegration
Maximum Eigenvalue Test	37.580	0.0172	One cointegrating relationship

Source : EViews

However, the results appear to be mixed. On the one hand, the trace test does not allow us to reject the null hypothesis of no cointegration at the 5% significance level, since, for the hypothesis $r=0$, the trace statistic is 68.04718, which is less than the critical value of 69.81889, with a p-value of 0.0686. From this perspective, the trace test leads to the conclusion that there is no cointegration relationship between the variables in the model.

On the other hand, the maximum eigenvalue test yields a different conclusion. Under the hypothesis $r = 0$, the Max-Eigenvalue statistic is 37.58010, which is greater than the critical value of 33.87687, with a p-value of 0.0172, leading to the rejection of the null hypothesis of no cointegration. However, the hypothesis $r \leq 1$ is not rejected, suggesting the existence of a single cointegration relationship.

Thus, the results of the Johansen test remain inconsistent between the trace test and the maximum eigenvalue test. In this context, and given the small number of observations, the absence of robust cointegration is adopted as a working hypothesis, which justifies continuing the analysis using a reduced VAR model, followed by an SVAR model.

iii. Choosing the Optimal Number of VAR Delays

The optimal lag order was determined using five information criteria computed over a common sample of 19 observations. The sequential modified likelihood ratio test, the final prediction error criterion, and the Hannan-Quinn criterion all select one lag; the Akaike criterion selects two lags, while the Schwarz criterion selects zero. The criteria therefore diverge, and the majority of them three out of five support a first-order specification.

Table 5 : VAR Lag Order Selection Criteria

Criterion	Selected Lag	Value at selected lag	Conclusion
LR	1	45.298	Selects one lag
FPE	1	1.2530	Selects one lag
AIC	2	14.113	Selects two lags
SC	0	15.405	Selects zero lags
HQ	1	14.556	Selects one lag

Source : EViews

A VAR(1) specification is retained on two grounds. First, it is the modal choice across the criteria considered. Second, and more importantly given the sample size, the Akaike criterion is known to select overly rich specifications in short samples, whereas the Schwarz and Hannan-Quinn criteria impose heavier penalties on parameter proliferation; between the two admissible non-degenerate options, parsimony is the prudent choice. A second-order specification would require 55 coefficients estimated on 19 observations, leaving only eight degrees of freedom per equation, a configuration under which the adjusted coefficients of determination deteriorate markedly and become negative for the investment equation.

iv. Estimation of Reduced VAR

The reduced-form VAR was estimated for the adjusted period 2004–2023, a total of 20 observations after accounting for one lag. The system consists of five endogenous variables, namely GDP growth, the change in the digital transformation index (D_INDICE_TD), inflation, investment and trade openness. In the output of the estimation we have 30 coefficients in total.

Some equations in the system have more explanatory power than others. The economic growth and investment are comparatively less explained, while all adjusted coefficients of determination are positive. Trade openness, inflation and the differenced digital transformation index are comparatively better explained.

Two coefficients belonging to the growth equation are renowned to be statistically significant at the five percent approval level as follows: the lag of the own growth (−0.4935, t = −2.17) meaning presence of a mean-reverting tendency within a short-run frame as well as the lag of trade openness (−0.5163, t = −2.14). In contrast to previous point, the own lag of the digital transformation index identified in the growth variable is negative and not statistically significant (−4.9184, t = −0.38). In opposite, the digital transformation equation does not include any lagged variable being macroeconomic with such lagged variables contributing in the following rejection of growth variable (t = 1.14) as well as investment (t = -1.26) as well as trade openness (t = 0.09) but making use of its own lag being notable (0.6066, t = 3.19). Thus, it seems that digital variable is more or less separated from the rest of the system with the confirmations pointed out below.

Table 6 : Summary of the Reduced VAR Estimate

Equation	R²	Adjusted R²	F-statistic	Overall Assessment
GDP Growth	0.3580	0.1287	1.5613	Limited explanatory power
Δ Digital Transformation Index (ΔDTI)	0.5321	0.3650	3.1839	Satisfactory fit
Inflation	0.5525	0.3926	3.4564	Satisfactory fit
Investment	0.4337	0.2314	2.1440	Modest but positive fit
Trade Openness	0.5623	0.4060	3.5971	Best-explained equation

Source : EViews

- ***Small-Sample Considerations and Degrees of Freedom***

The yearly frequency of the data element raises a limiting factor with regard to dimensionality in this framework; it is worth explaining in detail. The entire sample comprises 22 annual observations (2002–2023); by first-differencing the digital transformation index and taking one lag into account, VAR is calculated using 20 observations. There are five endogenous variables and first-order specification, which means that five lagged regressors and one constant can be located in all equations, leading to a total of 30 coefficients and 14 degrees of freedom per equation.

The simplicity of the retained specification is not coincidental but necessary. However, the findings that result from the usage of VAR analysis in this context are subject to some limitations arising from the usage of a small sample. First, the conclusions drawn from categorical analysis of VAR-type models are based on the assumption of asymptotic normality, thus it must be diffused that error estimates and confidence bands are only approximate rather than exact results. Second, the least-squares estimates generate autoregressive coefficient estimates that are biased towards zero in finite samples, hence its impact on the estimation of the dynamics may be underestimated. Finally, the limited number of observations causes limitations in tests performed on the parameter constancy or regime shifts performed during 2008 and 2020 crises.

These points have an immediate effect on how the results are interpreted. It is important to note first that the lack of significant effects that will be discussed below should be taken as the lack of significance in the conventional sense, and not as evidence that there are no effects at all: namely, because of the small number of observations (20), the confidence bands are wide and the test has a small power in detecting even moderate effects. This distinction will be preserved through the further discussion.

This indicates that an advanced study in the structural framework is warranted to understand the macroeconomic shocks and the economy's transmission mechanisms more accurately.

After one has computed the VAR model in reduced form, it is then essential to carry out diagnostic checks at this point. One of the things that has to be checked in terms of the adequacy of the model is its stability, as well as the absence of any serial correlation and normality of the residuals. After that it will be possible to carry out the structural identification of the model.

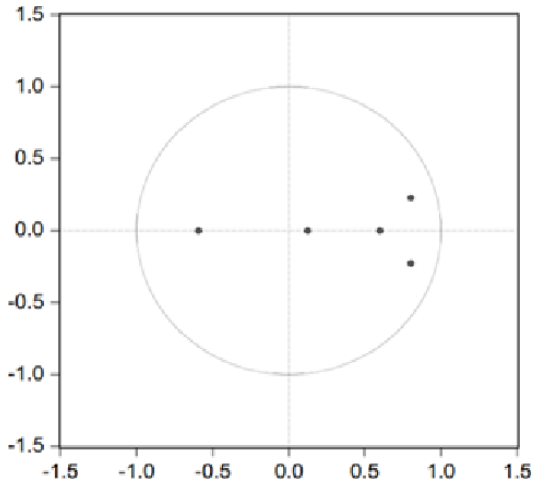
v. Reduced VAR Diagnostic Test

- ***VAR Stability Test***

To determine the stability of the VAR model, the inverse roots of its autoregressive characteristic polynomial were used. The graphical representation of the roots confirms that all the roots lay inside the unit circle. The table of roots backs the graphical presentation with roots having absolute values of 0.831835, 0.831835, 0.596270, 0.595270, and 0.122483, all being less than one. EViews states that “The roots lie within the unit circle thus confirming compliance with the stability condition.”

The estimated VAR model therefore fulfills the stability criterion. This verification is crucial as it permits us to proceed with the dynamic analysis in the SVAR format and allows for meaningful interpretations of impulse response functions and variance decomposition.

Figure 1 : Inverse Roots of AR Characteristic Polynominal



Source : EViews

- ***Autocorrelation Test of Residuals***

The residuals were checked for serial correlation after confirming that the model is stable, employing the Lagrange multiplier test. The test outcomes fail to reject the null hypothesis of no presence of serial correlation at the individual lags, with p-values linked to the Rao F statistic being equal to 0.6497 at lag 1 and 0.5058 at lag 2, which are significantly higher than the 5% level of significance. The cumulative test at lags 1 to 2 on the other hand returns a p-value of below 0.001, however, caution must be exercised in interpreting such results, considering the need for 50 restrictions to have been placed on a system of just 20 observations, thereby leaving only 3.4 of denominator degrees of freedom such that the distribution at play here is not reliable. Therefore, individual-lag tests should be preferred in this case as being more enlightening regarding the condition of the residuals that can be treated as being free of the first- and second-order serial correlation.

Table 7 : Summary of the autocorrelation test for residuals

Test	p-value	Conclusion
Serial Correlation LM Test (lag 1)	0.6497	No serial correlation
Serial Correlation LM Test (lag 2)	0.5058	No serial correlation
Cumulative LM Test (lags 1 to 2)	0.0000	Not reliable: 3.4 denominator df

Source : EViews

- ***Normality Test for Residuals***

The normality of the VAR residuals was examined using the multivariate normality test. The null hypothesis posits that the residuals follow a multivariate normal distribution. The results show that the joint statistics for skewness, kurtosis, and the Jarque-Bera test are associated with p-values of 0.1366, 0.2414, and 0.1281, respectively. Since these values are all above the conventional 5% threshold, the null hypothesis of multivariate normality cannot be rejected.

Although some individual components appear significant—particularly in the first equation—it is the joint statistics that must be considered for the overall assessment of the system's normality. Consequently, the VAR residuals can be considered generally consistent with the normality assumption, which reinforces the validity of the specification chosen prior to proceeding to the structural identification of the SVAR model.

Table 8 : Summary of the Normality Test for Residuals

Test	p-value	Conclusion
Skewness	0.1366	Normality is not rejected
Kurtosis	0.2414	Normality is not rejected
Jarque–Bera	0.1281	Normality is not rejected

Source : EViews

vi. Structural Identification and Estimation of the SVAR Model

Upon the confirmation of the reduced VAR estimates validity, the next step to undertake is the structural identification of the system by the implementation of the AB-type factorization. In Table 8, it can be observed that maximum likelihood estimation has converged in 29 iterations, producing a just-identified model. The structure chosen consists of a lower triangular matrix A and diagonal matrix B, thus making it possible to determine the structural shocks of the system with precision and accuracy.

The identification via the lower triangular matrix A creates a situation where the variables are ordered in a recursive manner in time, thus necessitating justification for this arrangement. The order is the following: economic growth, digital transformation, inflation, investment, and openness to trade. By putting growth in the first position, we assume that total output stays unaffected by the other changes in the system within the respective accounting year as these changes are not reflected immediately in production due to long time-slots between the digital adoption, price changes, and making decisions concerning investment. Digital transformation appears next because of the slow emergence of infrastructure in time and the long period of diffusion of technologies. Empirical evidence for this assumption is the absence of any substantial contemporaneous and lagged links between the macroeconomic variables and the index.

This ordering has a direct implication for the reading of the impulse responses: the contemporaneous response of growth to the digital shock is constrained to zero by construction, so that the effect of digitalization on output can only manifest from the second period onward. Correspondingly, the dominance of the growth innovation in the variance decomposition at short horizons is partly mechanical and should not be interpreted as a substantive finding.

Table 9 : Results of the SVAR Model Estimation

Indicator	Value
Estimation Method	Maximum Likelihood (Newton–Raphson)
Convergence	Achieved after 29 iterations
Model Status	Just-identified
Structure of Matrix A	Lower triangular
Structure of Matrix B	Diagonal
Log-Likelihood	-127.9579

Source : Author

- ***Analysis of Structural Impulse Response Functions***

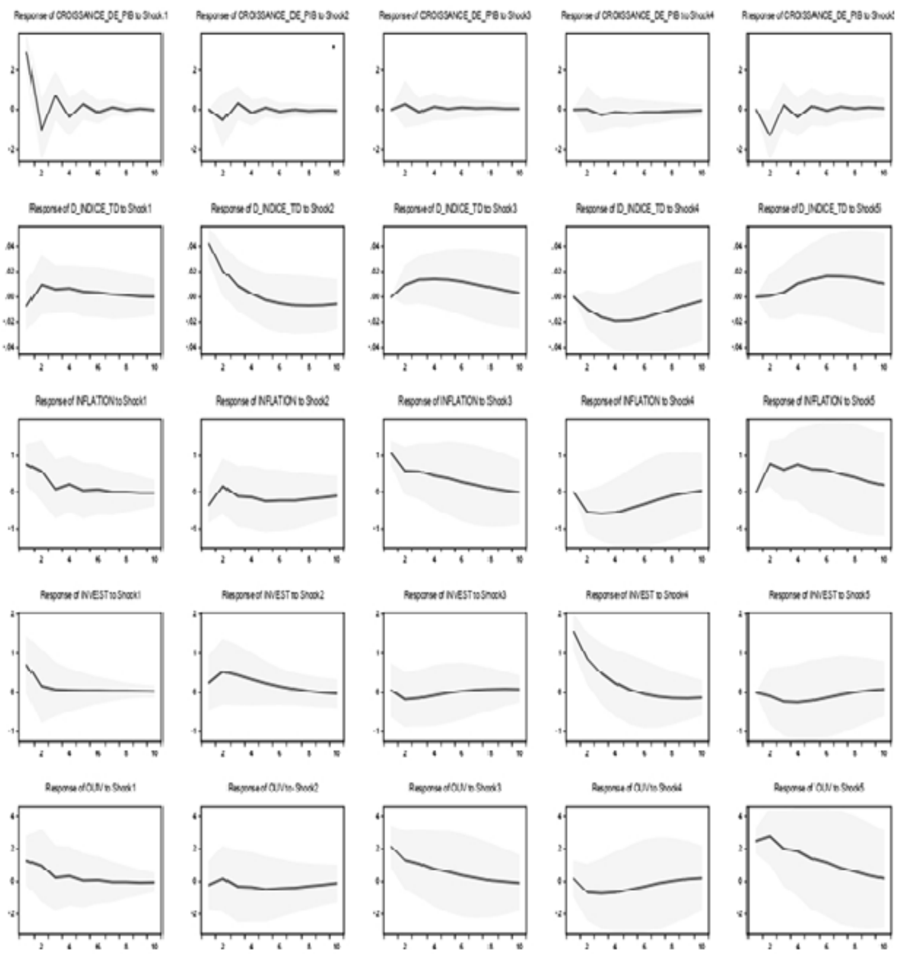
After structurally identifying the SVAR model, the next step is to analyze the structural impulse response functions, which allow us to assess the dynamic response of endogenous variables following a structural shock. The responses were computed over a horizon of ten periods with 95 per cent confidence intervals based on analytic asymptotic standard errors. Attention focuses on the response of economic growth to the digital transformation shock.

The response of growth to the digital shock is constrained to zero on impact by the recursive ordering. In the following period it is negative, at –0.529 percentage points, before turning positive at +0.313 in the third period and subsequently oscillating around zero with a declining amplitude. None of these responses is statistically significant: the ratio of the point estimate to its standard error does not exceed 0.78 in absolute value at any horizon, so that the confidence interval contains zero throughout. The cumulative response over ten periods is −0.538 percentage points. The evidence therefore does not support the existence of a detectable effect of the digital transformation shock on Moroccan economic growth over the period examined.

The same conclusion holds across the system. The digital shock generates no statistically significant response in inflation, investment, or trade openness at any horizon. Symmetrically, the coefficients of the estimated matrix A linking the digital innovation to the contemporaneous innovations of the other variables are all statistically insignificant, and no lagged macroeconomic variable significantly explains the index. At the level of individual responses, therefore, digital transformation appears neither to drive nor to be driven by the other components of the system, its only significant dynamic relationship being with its own past. The variance decomposition reported below qualifies this reading at longer horizons.

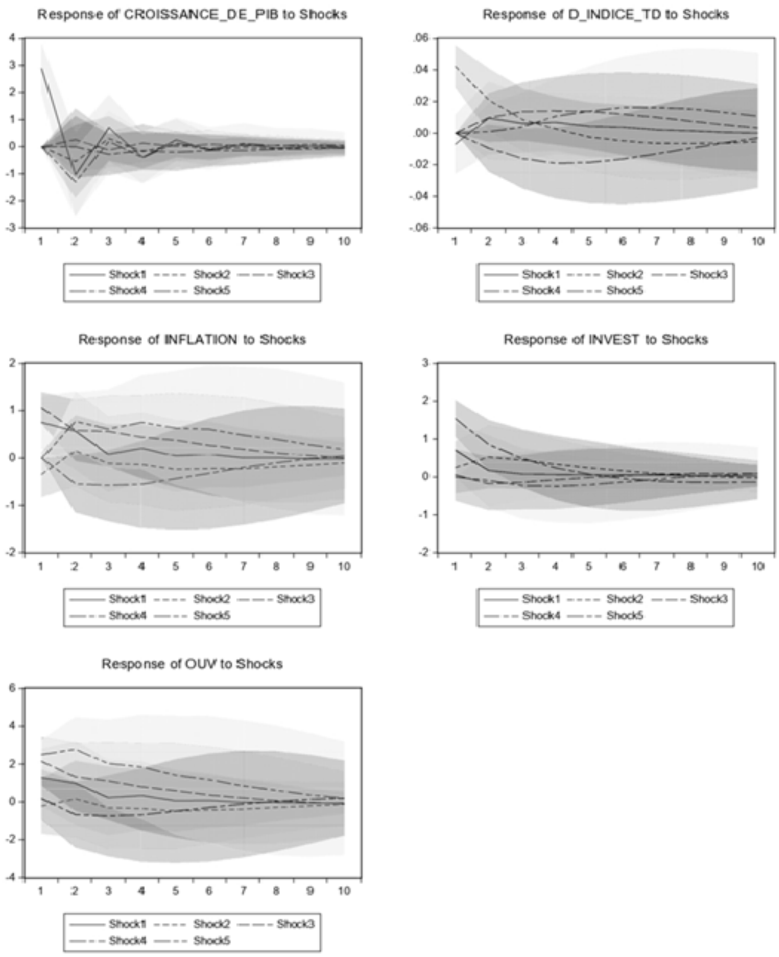
Two other structural relationships within the system do attain significance and are reported for completeness. A trade openness shock exerts a significant negative effect on growth in the year following the shock (−1.296 percentage points, t = −2.03), and the contemporaneous relationship between inflation and trade openness is the strongest link in the system (2.146, t = 3.27). A growth shock also raises inflation contemporaneously (0.762, t = 2.75). Figures 2 and 3 present the full set of structural responses.

Figure 2 : Structural impulse response functions of the SVAR model



Source : EViews

Figure 3 : Combined plot of structural impulse responses



Source :EViews

The next step is to examine the structural decomposition of the variance in forecast errors in order to assess the relative contribution of each structural shock to the variability of economic growth and the other variables in the model.

- ***Structural Decomposition of the Variance in Forecast Errors***

After analyzing the impulse response functions, the next step is to examine the structural decomposition of forecast error variance in order to assess the relative contribution of each structural shock to the dynamics of the model's endogenous variables. The results are presented over a horizon of ten periods.

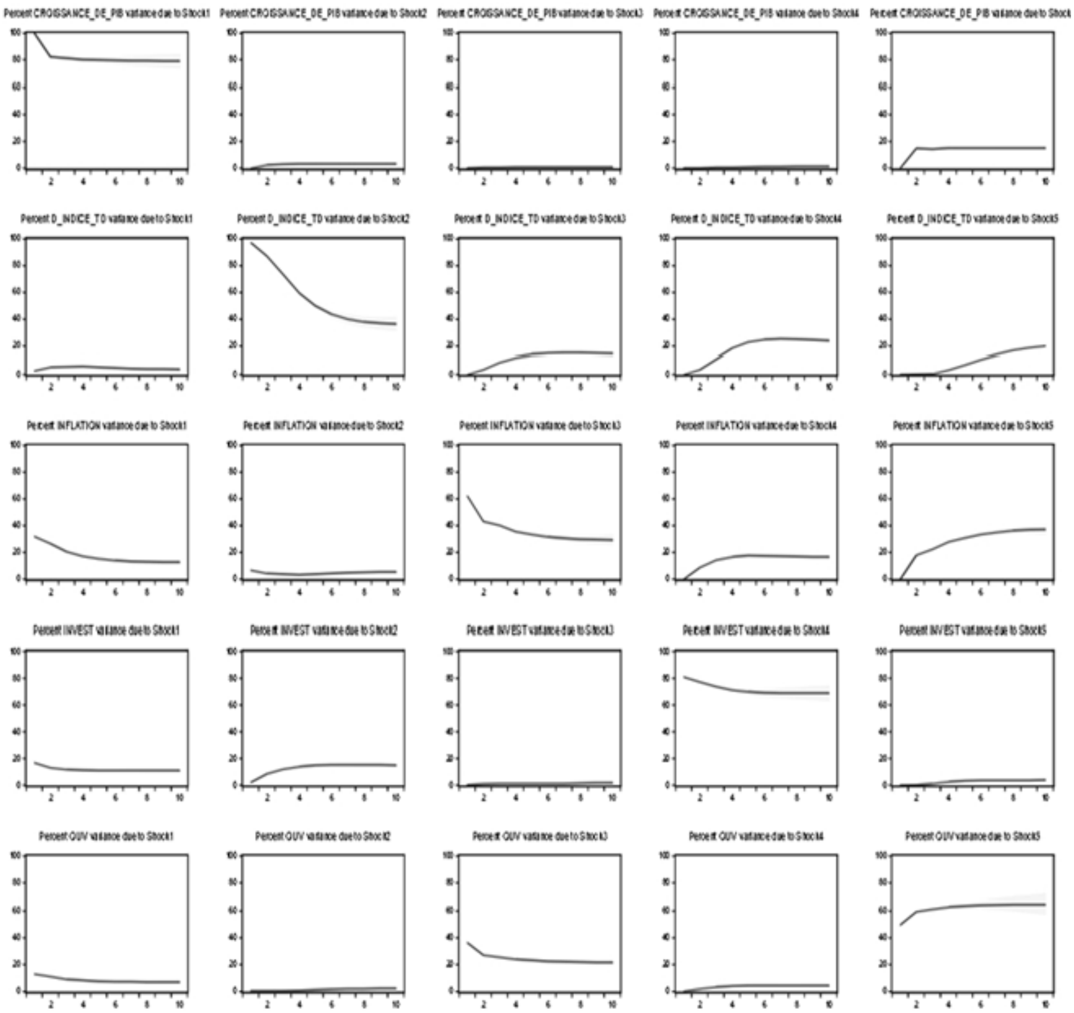
The decomposition confirms the conclusions drawn from the impulse responses as far as economic growth is concerned. The variance of growth is explained predominantly by its own innovations across the entire horizon, falling from 100 % on impact to 79.1% after ten periods ; this dominance is partly mechanical, since the recursive ordering attributes the whole of the first-period variance to the growth innovation by construction. The digital transformation shock accounts for 2.5% of the variance of growth at a two-year horizon and 3.4% at a ten-year horizon. The trade openness shock is the second contributor, at approximately 15% throughout, while the inflation and investment shocks each remain below 1.4%.

The decomposition of the remaining variables reveals a more nuanced picture. The variance of the digital transformation index is explained almost entirely by its own innovations on impact (97.4%), but this share declines steadily to 36.7% after ten periods, in favour of the investment shock (24.3%), the trade openness shock (20.2%), and the inflation shock (14.9%). This gradual decline indicates a growing interdependence between digital transformation and the macroeconomic environment as the horizon lengthens, even though none of the corresponding impulse responses attains statistical significance individually.

Digital shock contributes 14.9% to investment variance after ten periods - its maximum value in the entire system, and 5.1% of inflation variance. On the other hand, inflation demonstrates more balanced decomposition, which matches the multilayered character of its dynamics, while on the contrary, investment and trade openness are driven by few structural shocks.

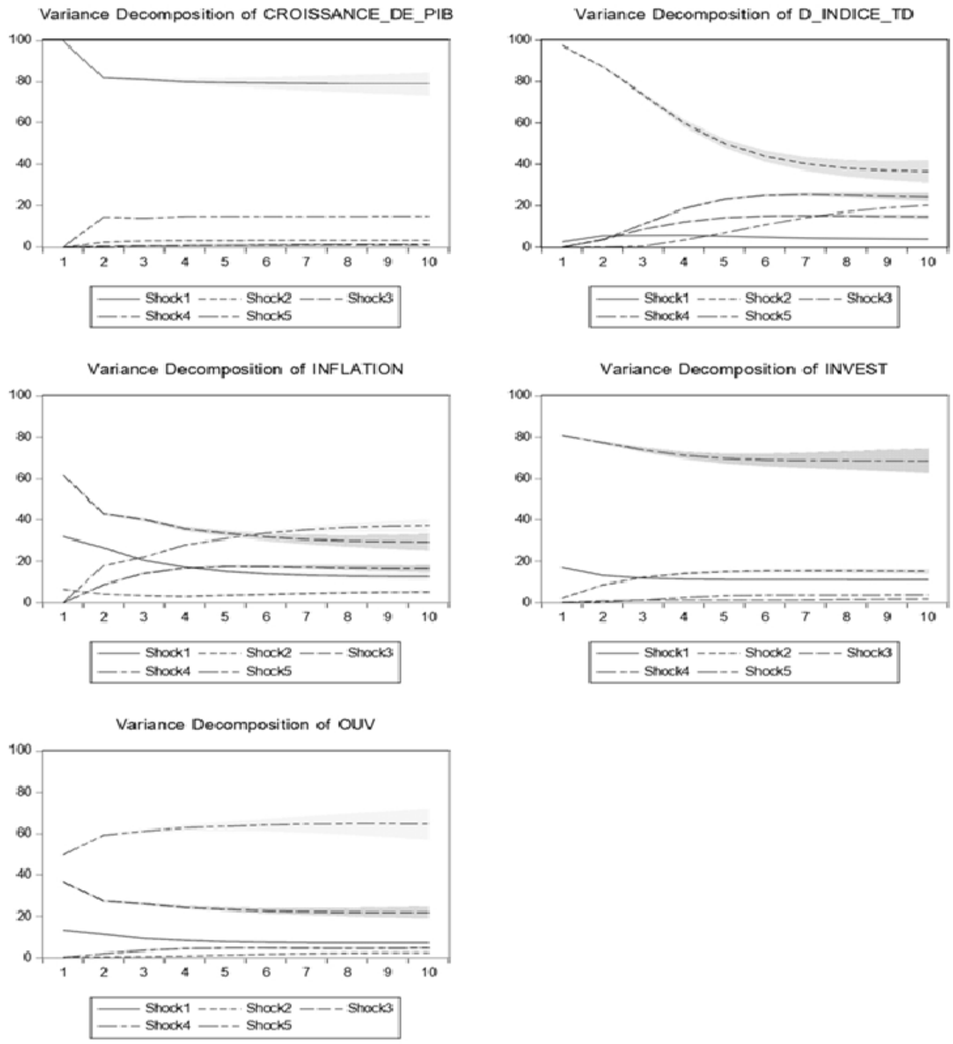
These figures have two important limitations. First, although the analytic standard errors used in the decomposition usually underreport uncertainty—which tends to be especially true when the respective shares are near zero—the presented percentages, therefore, have to be viewed primarily as rough estimates. Second, it is important to note that the share attributed to the digital shock, both in investment and index equations, cannot be verified by impulse responses, none of which appears to be statistically different from zero. In conclusion, based on the results of the decomposition, it seems that the digital transformation shock had little contribution to growth fluctuations in Morocco during the time period analyzed, although this does not exclude the possibility of long-term effects that become apparent only over a longer time horizon.

Figure 4 : Structural Decomposition of the Variance in Forecast Errors



Source : EViews

Figure 5 : Stacked representation of the relative contributions of structural shocks



Source : EViews

Note : Shock1 denotes the structural innovation to GDP growth ; Shock2 the digital transformation shock ; Shock3 the inflation shock ; Shock4 the investment shock ; and Shock5 the trade openness shock. D_INDICE_TD denotes the first difference of the Digital Transformation Index; OUV denotes trade openness; CROISSANCE_DE_PIB denotes GDP growth. Confidence bands are 95% intervals based on analytic asymptotic standard errors.

4. Discussion of the results

The findings of the econometric analysis utilizing the SVAR model are of a contradictory nature in relation to the fundamental backdrop of the research This becomes evident during the period from 2002 to 2023, when the structural digital transformation shock has no influence on economic growth in Morocco that can be detected The estimated values for the first year after the shock are negative and fluctuate around zero afterward. This information is confirmed by variance decomposition, which indicates that the digital shock accounts for about 3% of the variance of growth.

The lack of a detectable effect needs to be interpreted carefully, and two interpretations should be distinguished. The first one is statistical: 20 observations make the confidence intervals wide, and the test has limited power, so the true effect, most likely, is quite modest and remains undetected. Therefore, the outcome is the failure to detect the effect rather than proof of one being absent altogether. The second interpretation is economic and is confirmed by another interesting feature of the estimates: there is no individual link between the digital transformation index and the other variables of the system which is statistically significant, in either direction. It seems that digitalization in Morocco follows its path, largely disregarding the macroeconomic cycle over the periods during which data permit estimations.

However, this independence ought not to be exaggerated. The variance decomposition assigns the digital shock a sizeable share of investment variance at long horizons, while the variance of the index itself is increasingly explained by macroeconomic innovations as the horizon increases. This behavior indicates the existence of some interactions across longer horizons than those at which the impulse responses provide an accurate resolution of the reality experienced, suggesting that the null result presented here applies to the short- to medium-run transmission to output as opposed to the entire relevance of digitalization for the Moroccan economy.

According to the analysis of absorptive capacity, this trend can be understood. The reference to the growth in connectivity measured by the index Internet adoption growing from zero to almost complete coverage in 20 years does not reflect in any quantifiable economic benefit. The original meaning of the phrase is reflected in the findings of the World Bank (2016) which prove that there are no such things as automatic and equal digital dividends and they depend on a number of factors connected with the quality of institutions, human resources, and regulatory environment. In addition, it is in line with the threshold phenomenon described by Röller and Waverman (2001) who had found out that the effect of telecommunications facilities appears only after reaching a particular level of their spread and additional competency.

Furthermore, the findings that arise call for caution regarding how digitalization is supposed to work. The model examined here consists of a variety of items, including economic growth, digital transformation, inflation, investment, and trade openness. However, it does not include any financial variable, such as domestic credit, interest rates, financial depth, or financial inclusion figures. Therefore, one cannot measure the effects of digitalization on the financial side of the economy through, for instance, the reduction of information asymmetries, enhancement of savings allocations, or expansion of access to financing. All such processes are treated as theoretical assumptions that agree with the research literature, rather than practical findings established by the current analysis.

In the end, the analysis does uncover important structural relationships in the system. An opening of trade results in a decline in growth in the next year, and the correlation between inflation and trade openness is much stronger at the time than any other correlation in the model. This finding reinforces the interpretation of the zero result: the absence can be related to digitalization and not be of a general nature.

5. Conclusion

This study aimed to establish whether a structural shock of a digital transformation had an impact on the economy of Morocco over the period of 2002 to 2023, using a structural VAR. The empirical methodology involved the compilation of a composite digital transformation index based on three normalized indices, running a reduced VAR, assessing its statistical properties, and identifying the model through AB-type factorization. The results of the methodology confirm a first-order specification, confirmed by the majority of the information criteria being satisfied, and a stable model that is free of serial correlation at individual lags and consistent with the joint hypothesis of multivariate normality.

The results based on empirical data show that despite the considerable attention given to the impact of digital transformation, its economic advantages with regard to economic growth are imperceptible, since the impulse response functions contained no statistically significant result for any time horizon used in the analysis. The decomposition of variance has confirmed the finding, since only about three per cent of the variance of economic growth can be attributed to digital shock. Moreover, no relationships between the digital transformation index and the other factors of the model were noticed, since it evolved independently of other variables.

However, one must be aware of the limitations of the analysis performed in this paper. The dataset has only 20 observations, meaning that the power of the analysis is limited. It should be clarified that the study has not been able to show the non-existence of the effect, but rather the fact that it is impossible to detect one. The conclusion, however, is in line with the previous studies suggesting that the results of digitalization in economic terms should not be viewed as an automatic phenomenon.

The policy implications are clear. If twenty years of infrastructure expansion have failed to result in any measurable growth, then the obstacle is unlikely to be found in connectivity itself. It would be better to bring the policy into focus on the conditions for the use of the digital tools for production: digital skills, the use of technology by companies, digitalization of the public services and ways of governing and regulating the digital markets. The next logical step in the research is to include financial variables and use high-frequency data for better specification.

6. References

- Barro, R. (1991). Economic growth in a cross section of countries. *The Quarterly Journal of Economics, 106*(2), 407–443.
- Beier, G., Ullrich, A., Niehoff, S., Reißig, M., & Habich, M. (2017). Industry 4.0: How it is defined from a sociotechnical perspective and how much sustainability it includes – A literature review. *Journal of Cleaner Production, 166*, 1250–1263.
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
- Choi, C., & Yi, M. H. (2009). The effect of the internet on economic growth: Evidence from cross-country panel data. *Economics Letters, 105*(1), 39–41.
- Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal, 121*(552), 505–532. https://doi.org/10.1111/j.1468-0297.2011.02420.x
- Dedrick, J., Kraemer, K. L., & Shih, E. (2013). Information technology and productivity in developed and developing countries. *Journal of Management Information Systems, 30*(1), 97–122.
- Katz, R. L., & Koutroumpis, P. (2013). Measuring digitization: A growth and welfare multiplier. *Technovation, 33*(10–11), 314–319. https://doi.org/10.1016/j.technovation.2013.06.004 (ScienceDirect)
- Koutroumpis, P. (2009). The economic impact of broadband on growth: A simultaneous approach. *Telecommunications Policy, 33*(9), 471–485. https://doi.org/10.1016/j.telpol.2009.07.004 (ScienceDirect)
- Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics, 22*(1), 3–42.
- Mićić, L. (2017). Digital transformation and its influence on GDP. *Economics, 5*(2), 135–147.
- Parviainen, P., Tihinen, M., Kääriäinen, J., & Teppola, S. (2017). Tackling the digitalization challenge: How to benefit from digitalization in practice. *International Journal of Information Systems and Project Management, 5*(1), 63–77.
- Qiang, C. Z., Rossotto, C. M., & Kimura, K. (2009). Economic impacts of broadband. In *Information and Communications for Development 2009: Extending Reach and Increasing Impact* (pp. 35–50). World Bank.

- Röller, L.-H., & Waverman, L. (2001). Telecommunications infrastructure and economic development: A simultaneous approach. *American Economic Review, 91*(4), 909–923. https://doi.org/10.1257/aer.91.4.909 (aeaweb.org)
- Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy, 94*(5), 1002–1037.
- Schumpeter, J. A. (1942). *Capitalism, socialism and democracy*. Harper & Brothers.
- Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics, 70*(1), 65–94.
- Vu, K. M. (2011). ICT as a source of economic growth in the information age: Empirical evidence from the 1996–2005 period. *Telecommunications Policy, 35*(4), 357–372. https://doi.org/10.1016/j.telpol.2011.02.008 (sci-hub.in)
- World Bank. (2016). *World development report 2016: Digital dividends*. World Bank Publications.
- Youssef, A. B., & M'henni, H. (2004). Les effets des TIC sur la croissance économique : Quelques résultats empiriques pour les pays en développement. *Économies et Sociétés, 38*(6), 1067–1092.

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