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Uncertainty, Oil Price, and Volatility Regimes: A New Non-Recursive Identification Approach

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Abstract. *During the last few decades, several studies have focused on examining the co-movements between oil prices and uncertainty. In this paper, we apply a new non-recursive identification approach to test whether macroeconomic and financial uncertainty precedes or follows changes in oil prices. Primarily, we explore the interaction between uncertainty and oil price changes across different volatility regimes. Our results indicate that macroeconomic and financial uncertainties are exogenous factors that influence the dynamics of oil prices. Furthermore, our findings reveal that during periods of macroeconomic or financial stability, the effects of uncertainty shocks on the oil market become more pronounced, indicating that such shocks can significantly contribute to macroeconomic fluctuations within the oil market. These findings could aid participants in the oil market by enhancing their understanding of how macroeconomic and financial uncertainties impact oil markets, providing them with a foundation for making decisions regarding risk management and portfolio optimization.*

Keywords: *Oil prices, Identification, Non-recursive SVAR, Uncertainty shocks, Volatility regime.*

JEL Classifications: *C32, C51, E44, G01.*

Introduction

The occurrence of global financial crises during the past three decades has heightened researchers' interest in examining the causes of oil price shocks. Most research in this area has focused on analyzing two main issues related to the effects of macroeconomic and financial uncertainty on oil price dynamics. First, certain works have concentrated on the causal relationship between uncertainty and oil prices. In the literature, uncertainty has been shown to influence oil prices (Bakas & Triantafyllou, 2018; Cheng et al., 2019; Lyu et al., 2021). While these studies have produced supportable findings, particularly in terms of forecasting, they have faced several criticisms concerning the simultaneity of the relationships and the exogeneity of the variables. Another strand of literature has focused on the time variation of the effect of uncertainty on the dynamics of oil prices. Many of these studies have found evidence of a time-varying effect of uncertainty shocks on oil prices (Joëts et al., 2016; Kumar et al., 2021; Lyu et al., 2021).

The dynamics of oil prices are influenced by various factors, among role. Previous research has primarily focused on establishing causal relationships between these uncertainties and oil price fluctuations, yet significant gaps remain in understanding the temporal nature and directionality of these interactions. Existing studies often fail to account for the simultaneity of relationships and the endogeneity of variables, leading to potential misinterpretations of the underlying mechanisms. This paper seeks to fill these gaps by investigating whether macroeconomic and financial uncertainties precede or follow changes in oil prices, particularly across different volatility regimes.

In this paper, we aim to enhance the understanding of the interactions between uncertainty and oil prices by developing a non-recursive structural VAR (SVAR) model that addresses two key objectives. First, we investigate the direction of causality among macroeconomic uncertainty, financial uncertainty, and oil prices, determining whether uncertainty influences oil prices, oil prices affect uncertainty, or if both dynamics occur simultaneously. Second, we apply a non-linear approach to effectively capture the time-varying effects of uncertainty on oil prices, recognizing that previous studies often relied on linear SVAR models (Caggiano et al., 2017; Alessandri et al., 2019; Huang et al., 2022; Dutta et al., 2024) that inadequately account for the varying impacts of uncertainty shocks across different volatility regimes. By addressing these objectives, our study seeks to provide a more nuanced understanding of how uncertainty impacts oil price dynamics.

The occurrence of global financial crises over the past three decades has intensified researchers' interest in examining the causes of oil price shocks. Most research in this area has focused on analyzing two main issues related to the effects of macroeconomic and financial uncertainty on oil price dynamics. First, concentrated some studies have focused on the causal relationship between uncertainty and oil prices, demonstrating that uncertainty can influence oil prices (Bakas & Triantafyllou, 2018; Cheng et al., 2019; Lyu et al., 2021). However, these studies have faced criticisms concerning the simultaneity of the relationships and the exogeneity of the variables. Another strand of literature has focused on the time variation of the effect of uncertainty on oil prices, with many studies finding evidence of time-varying effects of uncertainty shocks (Joëts et al., 2016; Kumar et al., 2021; Lyu et al., 2021). Given these findings, our paper aims to fill significant gaps in the literature by addressing the following research questions: (1) What is the direction of causality between macroeconomic uncertainty, financial uncertainty, and oil prices? (2) How do uncertainty shocks impact oil prices across different volatility regimes? To explore these questions, we propose the following hypotheses: (1) Macroeconomic and financial uncertainty have a significant causal influence on oil prices, leading to fluctuations; (2) The relationship between uncertainty and oil prices is bi-directional, where fluctuations in oil prices also affect levels of uncertainty; (3) The effects of uncertainty shocks on oil prices vary significantly across different volatility regimes; and (4) The variables exhibit endogeneity, indicating that macroeconomic and financial uncertainties and oil prices are interconnected over time. By developing a non-recursive structural VAR (SVAR) model, we aim to enhance the understanding of these interactions and provide a more nuanced perspective on how uncertainty impacts oil price dynamics.

Several concerns are crucial to addressing the bidirectional relationship between uncertainty and oil prices. We propose testing the causal effect using a non-recursive model, as recursive systems are inconsistent with bi-directional causal relationships (Ludvigson et al., 2021). Second, the evidence that uncertainty exhibits a time-varying effect has been supported by the literature (Alessandri & Mumtaz, 2019). Since linear models do not capture regime-dependent effects characterizing uncertainty shocks, we propose a threshold model rather than linear SVAR models. The direction of causality and the temporary effects of uncertainty shocks have been separately tested in the literature. A time-varying model could be more appropriate for capturing variation in model parameters and is further consistent with economic policy that adapts to shocks in the macroeconomic environment and financial markets (Balli et al., 2021; Anand, 2023).

This paper contributes to the literature by proposing a non-recursive SVAR model to analyze the relationship between uncertainty and oil price returns. This approach offers two key advantages: (1) it captures the bi-directional relationship between uncertainty and oil price returns, and (2) it accounts for the effect of uncertainty on oil price changes over time. Previous studies, such as Cologni et al. (2011) and Aizenman et al. (2023), have demonstrated that structural shocks stemming from unexpected changes in macroeconomic policies or the onset of financial crises can trigger exogenous shocks in oil markets. To incorporate the dynamic effect of uncertainty shocks on oil prices, we extend the heteroscedasticity identification approach used by Rigobon (2003) and Lanne and Lütkepohl (2008). Our extension allows the impact coefficients to change over time, enabling the impulse response functions (IRFs) to vary across different volatility regimes (Bacchiocchi et al., 2020; Lu et al., 2021).

In our specification, the dynamics of the structural parameters induce changes in the VAR model's covariance matrix. Identification is achieved through the restrictions imposed on the parameter variations across volatility regimes. This approach results in a more flexible model that offers substantial advantages over standard SVAR models. Specifically, we impose additional moment conditions that, based on theory-driven restrictions, facilitate the identification of macroeconomic shocks. Furthermore, our approach is sufficiently flexible to accommodate both recursive and non-recursive volatility regimes.

We employ this model to address specific limitations found in traditional linear SVAR frameworks, which often fail to account for the dynamic relationships and time-varying effects of uncertainties on oil prices. The non-recursive structure allows for a more nuanced exploration of causal relationships, accommodating the simultaneity and endogeneity inherent in our data. This model also enables us to effectively analyze interactions across different volatility regimes, providing a comprehensive understanding of how macroeconomic and financial uncertainties influence oil prices. By adopting this methodology, we aim to make a significant contribution to the existing literature by uncovering insights that previous models may have overlooked.

This flexibility is particularly important when addressing the issue of uncertainty's exogeneity or endogeneity. Our model provides a formal test of exogeneity while also accounting for the potential effects of uncertainty across different volatility regimes. By doing so, we ensure a more robust and nuanced analysis of the dynamic interplay between uncertainty and oil prices, ultimately leading to more accurate and insightful conclusions. In this paper, we follow the approach of Sheng et al. (2020) and Ludvigson et al. (2021) by employing a three-variable model: oil price (Oil), macroeconomic uncertainty index (UM), and financial uncertainty index (UF). The two uncertainty indices used in this study were developed by Ludvigson et al. (2021). Including macroeconomic and financial uncertainty indices simultaneously in our model is motivated by the fact that these indices may have notably different properties (Ludvigson et al., 2021). They can thus exhibit different effects on oil prices across volatility regimes.

In this study, we use data covering the period 1990–2023. Using recursive estimates of the VAR covariance matrix, we find that volatility breaks are consistent with our empirical design and cover two important episodes in the history of oil markets: the first is the date of the financial crisis (2007–2008), and the second is related to the beginning of the COVID-19 pandemic. The analysis of uncertainty effects on oil prices over the period 1990–2022 is well-motivated by the identification of three volatility regimes in our sample: the “Great Moderation” period (1990M1–2007M12), the “Slow Recovery” period (2009M1–2020M1), and the post-COVID period (2021M1–2023M12).

The three volatility regimes can be easily illustrated through the evolution of prices over the period 1990–2023. As highlighted by Barsky and Kilian (2004), the period 1990–2007 was marked by economic stability accompanied by a rapid increase in oil prices until 2008. At that time, economic growth fueled the demand for oil, but available production capacity was low. In the second quarter of 2008, inflation-adjusted oil prices peaked at $125 a barrel. Oil prices collapsed by 66% soon after due to the global financial crisis. Then, prices almost stabilized until the COVID-19 pandemic triggered a price decline. The pandemic-related global recession and confinement measures caused oil prices to collapse in the spring of 2020 and increased oil market volatility during the period 2021–2023 (Sheng, 2023).

Our empirical results lead to three original findings. First, we find that macroeconomic uncertainty is an exogenous factor affecting oil prices. Macroeconomic shocks cause an increase in oil prices, and their effect is particularly significant and persists during the recovery period (2008–2020). The endogenous effect of macroeconomic uncertainty is not supported by our results. This result holds in the three volatility regimes. Second, during the post-COVID period, we find that financial uncertainty affects oil prices indirectly through macroeconomic uncertainty. The effect intensified after the financial crisis (2007–2008). Financial uncertainty is found not to be affected exogenously by macroeconomic uncertainty or oil price shocks. Third, the impulse responses are shown to be time-varying across volatility regimes. This result contradicts the findings of the heteroskedastic SVAR models used previously (Van Robays, 2012; Kristjanpoller & Concha, 2016; Kilian & Vigfusson, 2017; Esmaeili et al., 2021; Carriero et al., 2021; Liu et al., 2023; Dutta et al., 2023; Uddin et al., 2023; Lucey et al., 2024) and demonstrates that the structural parameters are not constant across the different volatility regimes.

The rest of the paper is organized as follows. Section 2 presents the literature review. Section 3 describes our non-recursive identification approach. Section 4 introduces the data used to run the model and the empirical results obtained from the non-recursive SVAR. Section 5 concludes and shows main implications.

2. Literature review

Most previous studies have shown that only financial uncertainty has an exogenous effect on oil prices (Soojin, 2014; Apostolakis et al., 2021; Guo et al., 2022; Igeland et al., 2024), while macroeconomic uncertainty was found to have an endogenous effect on oil prices. A distinct result arising from this study is the exogeneity of macroeconomic uncertainty. For this purpose, we develop two non-recursive SVAR models. The first is an unrestricted model that includes macroeconomic uncertainty as an endogenous variable across the three volatility regimes. The second model is a restricted model where macroeconomic uncertainty is not affected by oil price shocks on endogenous markets in the three volatility regimes. We find that the restricted model is supported by our data. Both models are built on the assumption that financial uncertainty is not driven by oil shocks and macroeconomic uncertainty. This assumption is supported by the reduced form evidence associated with the SVAR model, suggesting that financial uncertainty is poorly correlated with oil prices and macroeconomic uncertainty, mainly in the post-financial crisis period (2009-2020) (Wei et al., 2019; Degiannakis et al., 2023).

This study is related to several previous studies that focused on the exogeneity and endogeneity of uncertainty in relation to oil markets (Ludvigson et al., 2021; Carriero et al., 2021). Much research has attempted to explain the dynamics of oil prices in the case of demand or supply shocks (Kilian, 2009; Fueki et al., 2016). Although many studies exist on the macroeconomic effects of oil and commodity shocks, the literature is silent on the impact of macroeconomic uncertainty on oil and commodity price fluctuations. Stock and Watson (2003) and Nakov and Pescatori (2010) examine to what extent changes in oil prices explain macroeconomic uncertainty in the United States since the middle of the 1980s. Blanchard and Gali (2010) compare the response of macroeconomic uncertainty to oil shocks in a group of industrialized economies since 1970 and find that oil shocks significantly affect macroeconomic uncertainty. According to Kilian (2014) and Alsalman (2016), the different sources of oil shocks can explain uncertainty in financial markets. Particularly, these authors find an endogenous effect of financial uncertainty on oil price changes. Nevertheless, the most recent empirical studies, such as Balke et al. (2010) and Baumeister and Hamilton (2019), found that oil prices increase with macroeconomic uncertainty.

Changes in macroeconomic and financial uncertainty can reflect shifts in global economic activity, which, in turn, can impact oil demand and supply dynamics (Hamilton, 2009; Basher et al., 2012). For example, during periods of heightened uncertainty, businesses may delay investment decisions, leading to lower oil demand, while geopolitical tensions or supply disruptions can increase oil price volatility. By employing a non-recursive VAR model, we assess whether changes in macroeconomic and financial uncertainty precede or follow changes in oil prices, providing insights into the underlying drivers of oil price movements. Furthermore, economic agents' expectations play a crucial role in shaping economic outcomes. Rational expectations theory, introduced by Lucas (1972), suggests that agents form expectations based on all available information and update them as new information arrives. However, in the presence of uncertainty, agents may rely on heuristics or adaptive expectations, leading to potentially suboptimal decision-making. By using a non-recursive identification approach, we analyze how different forms of expectations formation interact with uncertainty and oil price changes, providing insights into agents' behavior and its implications for economic dynamics.

Gkillas et al. (2020) suggest that volatility is inherent to the functioning of oil markets, and that mechanical persistent volatility stems from the fact that it is the main concern of financial market investors. Unpredictable volatility is harmful to both exporting and importing countries and can be a major driver of increased financial and macroeconomic uncertainty. Using a threshold vector autoregressive (TVAR) model, Van Robays (2012) examines the impact of fundamental oil price changes in periods of high macroeconomic uncertainty. They measure macroeconomic uncertainty by the volatility of industrial production growth. They endogenously identify high- and low-uncertainty regimes across the whole sample period, 1990-2020. In line with the works of Peersman and Van Robays (2012) and Baumeister and Peersman (2013), they identify three types of oil shocks using sign restrictions: oil supply shocks, oil demand shocks driven by economic activity, and oil-specific demand shocks, and they find evidence of an endogenous role for macroeconomic uncertainty on oil shocks.

Sheng et al. (2020) examine the across 45 economies. Their results support the endogeneity of uncertainty, as oil shocks drive economic uncertainty mainly during the Global Financial Crisis (GFC). Park and Ratti (2008) and Aye et al. (2014) analyze channels through which oil shocks affect macroeconomic uncertainty. Unexpected oil price changes are found to exert significant impacts on the volatility of macroeconomic and financial variables. In particular, Aye et al. (2014) find that changes in oil prices may increase fluctuations in the firm's expected cash flows, thereby increasing uncertainty about future stock returns. Kang and Ratti (2013) analyze the causal effects of oil price shocks and economic uncertainty. They find that oil price shocks and economic policy uncertainty are interconnected and jointly influence stock markets. However, they do not separately identify the effects of macroeconomic and financial sources of uncertainty on economic fluctuations. Antonakakis et al. (2014) explore the spillover effect of oil price shocks and economic uncertainty. They find evidence that economic uncertainty and oil price shocks are negatively correlated, confirming the endogeneity of macroeconomic uncertainty. Kang and Ratti (2015) use a structural VAR model to analyze the interdependencies among China’s policy uncertainty, the global oil market, and China's stock market returns. Their results support that a positive shock to economic policy uncertainty in China has a delayed (lagged) negative effect on global oil production, real oil prices, and real stock market returns.

3. Empirical Approach

In our study, we employ a non-recursive structural vector autoregression (SVAR) model to explore the interactions between macroeconomic uncertainty, financial uncertainty, and oil prices. This approach allows us to examine the direction of causality and the time-varying effects of uncertainty on oil prices without the limitations of traditional linear models. Specifically, we incorporate a non-linear framework that captures the varying impacts of uncertainty shocks across different volatility regimes, providing a more comprehensive analysis of the dynamic relationships at play. By clearly defining this methodology, we aim to enhance the rigor and transparency of our research findings.

This section outlines the threshold structural VAR model approach employed in this study to investigate regime dependence and to jointly identify uncertainty and oil price shocks.

3.1. Identifying oil price shocks under homoskedasticity

The VAR model, as introduced by Sims (1980), has become a prevalent tool in Macroeconomics for specifying the dynamics of oil prices. Impulse Response Functions and variance decomposition are commonly employed to illustrate the dynamic nature of these empirical models. However, the bi-directional relationships between the variables are often obtained through mechanical techniques that some authors consider unrelated to economic theory. Cooley and Le Roy (1985) argue that this method, often described as atheoretical, rests on an economic structure that is difficult to reconcile with economic theory.

Structural changes in the economy, such as policy shifts, technological advancements, and major geopolitical events, lead to changes in market volatility. These structural changes can cause shifts in the economic environment, resulting in different regimes with distinct volatility characteristics (Stock & Watson, 1996). Empirical studies (Hamilton, 1989) have also documented breaks in volatility across various financial markets. For example, significant historical events like the 1973 oil crisis, the 1987 stock market crash, and the 2008 financial crisis have been shown to cause structural breaks in financial time series.

Regime-specific factorsfactors can influence the relationship between economic uncertainty and oil prices. For instance, during periods of high uncertainty, such as geopolitical tensions or economic crises, oil prices might react more sensitively due to heightened risk aversion and speculative activities (Kilian, 2009). Baumeister and Peersman (2013) suggest that the impact of uncertainty on oil prices varies over time and can be influenced by different regimes. For example, oil price dynamics during the 1970s oil shocks were different from those during the 2008 financial crisis. A Structural Vector Autoregression (SVAR) model with regime-specific parameters can capture the changing dynamics between uncertainty and oil prices. This approach is justified by the empirical identification of volatility breaks and supports the hypothesis that these relationships change across regimes (Sims & Zha, 2006).

To capture time-varying relationships between variables, various structural VAR specifications have been developed. Primiceri (2005) introduced a time-varying parameter VAR (TVP-VAR), in which variance and covariance terms are time-varying, allowing for interactions among variables (Feng et al., 2021). This approach has been utilized in the literature to analyze the interactions between uncertainty and economic policy uncertainty (Yang et al., 2021). In this paper, we adopt a structural TVP-VAR model to explore the time-varying impact of uncertainty on oil prices and the exogenous effect of macroeconomic and financial uncertainties. The structural VAR relies on a set of restrictions that significantly reduce the number of unidentified variables to be estimated.

We Consider the following SVAR:

$$Y_t = \gamma + \alpha_1 Y_{t-1} + \ldots. + \alpha_p Y_{t-p} + K\varepsilon_t = \Sigma\varphi_t + K\varepsilon_t,\ \varepsilon_t \sim \varphi N(0_{n\times 1}, I_n)\,, t = 1, \ldots, T \qquad (1)$$

With p the lag order used in the estimation, T is the sample length, Y_t is the vector of dependent variables, γ is $n\times 1$ constant vector, α_i , $i = 1, ..., p$ is $n\times n$ matrices of parameters, $\Sigma := (\alpha_1, ..., \alpha_p, \gamma)$,

$\varphi_t := (Y'_{t-1}, ... Y'_{t-p} , 1)'$, K is a $n \times n$ non-singular matrix of structural parameters. ε_t is the of mean zero vector. We suppose that $\alpha(L) := I_n - Y_1 L - ... - Y_p L^P$ is the solutions to $det(Y(z)) = 0$ satisfy $|z| > 1$.

Assume $\mu_t = K\varepsilon_t$ is the $n \times 1$ vector of innovations, and Π_μ *the* unconditional covariance matrix such that: $\Pi_\mu = KK'$.

To model the dynamic effects of the structural shocks in ε_t, let Ω be the VAR companion matrix, $Y_t^c := (Y'_t, Y'_{t-1}, \dots, Y'_{t-p+1})'$ the state vector associated with the VAR companion form and $P := (I_n, 0_{n\times n}, \dots, 0_{n\times n})$ a matrix such that $Y_t = PY_t^c$, $PP' = I_n$.

The IRF illustrates the dynamic response of X_{t+h} to shock ε_{jt} to the variable Y_{jt}:

$$IRFj\,(h) := \mathrm{P}\,(\Omega)^h\ \mathrm{P}' k_j\,, h = 0, 1, 2, \dots, j = 1, \dots, n \qquad (2)$$

with k_j is the *j-th* column of K, i.e. $K := (k_{\bullet j} : k_j : k_{j\bullet})$. $k_{\bullet j}$ and $k_{j\bullet}$ are the sub-matrices that include the columns that precede and follow the column k_j , respectively. the IRF illustrated in eq.(2) requires full identification of k_j as it includes orthogonal information to $k_{\bullet j}$ and/or in $k_{j\bullet}$.

For $h = 0$, the element k_{lj} of the K matrix in eq. (2) captures the immediate effect of the *j-th* structural shock on the *l-the* variable of the model.

In our specification we set $Y_t := (U_{Mt}, Oil_t, U_{Ft})$'. The three variable model are: Oil price (Oil_t), Macroeconomic uncertainty (U_{Mt}) and Financial uncertainty (U_{Ft}). If no restrictions are imposed our model can be written as:

$$\underbrace{\begin{pmatrix} \mu_{Mt} \\ \mu_{Oilt} \\ \mu_{Ft} \end{pmatrix}}_{\mu_t} = \underbrace{\begin{pmatrix} K_{M\_M} & K_{M\_Oil} & K_{M\_F} \\ K_{Oil\_M} & K_{Oil\_Oil} & K_{Oil\_F} \\ K_{F\_M} & K_{F\_Oil} & K_{F\_F} \end{pmatrix}}_{K} \underbrace{\begin{pmatrix} \varepsilon_{Mt} \\ \varepsilon_{Oilt} \\ \varepsilon_{Ft} \end{pmatrix}}_{\varepsilon_t} \qquad (3)$$

where $\varepsilon_{Mt}, \varepsilon_{Ft}\ and\ \varepsilon_{Oilt}$ are the Macroeconomic uncertainty shock, the financial uncertainty shock, and the Oil shock, respectively.

We impose at least three restrictions on eq. (3) to identify the shocks in a Gaussian setup.

To identify the 9 elements of K, the variance-covariance matrix $\Pi_\mu = KK'$presents n (n+ 1)/2 = 6 symmetry restrictions. K is supposed to be a triangular matrix providing three zero restrictions.

Most of the previous studies have employed recursive models, focusing primarily on the impact of uncertainty on oil prices (Yang et al., 2022; Huang et al., 2022; Li et al., 2023). Financial and macroeconomic uncertainties are observed to respond to oil shocks with delays (Aimer et al., 2022; Nguyen et al., 2022). The constraint that the matrix K be upper triangular with zero restrictions does not enable the identification of simultaneous causal relationships among the model's parameters: Koil-M, KOil_F, KOil_Y, and KF_Oill.

Stock and Watson (2016, 2018) demonstrate that the reverse causality problem and the associated identification issue can, in principle, be resolved by using valid external parameters, thereby increasing the number of useful moment conditions without imposing additional restrictions (Mertens & Ravn, 2013). Ludvigson et al. (2021) have examined derivatives of such approaches within the uncertainty framework and have improved this methodology by asserting that the endogeneity of financial and macroeconomic uncertainty complicates the identification of observable parameters that exogenously affect uncertainty. However, Angelini and Bacchiocchi (2017) suggest that while the use of external parameters and set-identification approaches addresses the reverse causality issue, it does not offer a solution for the problem of regime-dependent effects of uncertainty shocks. In the next section, we examine this issue.

3.2 heteroskedasticity identification of uncertainty and oil market shocks

To address the regime, change effects of uncertainty shocks and simultaneously account for the endogeneity of uncertainty, we propose an approach based on a non-recursive structure for the matrix K, with parameters of K varying according to the macroeconomic regime as dictated by changes in the unconditional matrix Π_μ. This approach generates impulse response functions (IRFs) that depend on the regime of uncertainty shocks. To achieve this, we leverage the heteroscedasticity inferred by the reduced-form errors μ_t in different macroeconomic regimes that have characterized the oil markets over the study period. Our approach acknowledges that the unconditional covariance matrix Π_μ may change across different uncertainty regimes.

Over the study sample we assume two main structural changes in the covariance matrix Π_μ which corresponds to identifying three different volatility regimes.

Let T_{K1} and T_{K2} the two structural breaks, with $1<T_{K1} < T_{K2}<T$. our SVAR model can be expressed as follow:

$$Y_t = \Sigma(t)\varphi_t + \mu_t, \quad \Pi_\mu(t) := E(K_t K_t'), \ t = 1, ..., T$$

$\Sigma(t)$ is the dynamic matrix given by:

$$\Sigma(t) := \Sigma_1 \times \boldsymbol{I}\,(t \le T_{k1}) + \Sigma_2 \times \boldsymbol{I}\,(T_{k1} < t \le T_{k2}) + \Sigma_3 \times \boldsymbol{I}\,(t > T_{k2})$$

The covariance matrix of errors $\Pi_\mu(t)$ is given by

$$\Pi_\mu(t) := \Pi_{\mu,1} \times \boldsymbol{I}\,(t \le T_{k1}) + \Pi_{\mu,2} \times \boldsymbol{I}\,(T_{k1} < t \le T_{k2}) + \Pi_{\mu,3} \times \boldsymbol{I}\,(t > T_{k2})$$

To ensure that the volatility changes according to the three regimes, we set the following restriction: $\Pi_{\mu,1} \neq \Pi_{\mu,2} \neq \Pi_{\mu,3}$.

Under the three volatility regimes, the non-recursive SVAR model is given by:

$$\mu_t = K\varepsilon_t 1 \le t \le T_{k1},$$

$$\begin{cases} \mu_t = K\varepsilon_t, & 1 \le t \le T_{k1} \\ \mu_t = (K+\delta_2)\varepsilon_t, & T_{k1} \le t \le T_{k2} \\ \mu_t = (K+\delta_2+\delta_3)\varepsilon_t, & T_{k2} \le t \le T \end{cases}$$

K is the non-singular matrix setting the relationships between oil prices and uncertainty shocks in volatility regime 1.

With δ_2 and δ_3 are matrices such that $(K+\delta_2)$ and $(K+\delta_2+\delta_3)$ depict the movements in the structural relationship between oil price and uncertainty in the second and the third volatility regimes, respectively.

Angelini and Bacchiocchi (2017) show that the second-order moment conditions are given by:

$$\Pi_{\mu,1} = KK'$$

$$\Pi_{\mu,2} = (K+\delta_2)(K+\delta_2)'$$

$$\Pi_{\mu,3} = (K+\delta_2+\delta_3)(K+\delta_2+\delta_3)'$$

After setting the restrictions the regime dependent, IRFs can be generated from the SVAR specification. Let Ω_i , i = 1, 2, 3 be the reduced form companion matrices associated with the system in eq. (6). The dynamic response of Y_{t+h} to standard deviation shock in variable j at time t is given by the following IRFs:

$$IRF_j(h) := \begin{cases} P'(\Omega_1)^h P\tilde{k}_j & t \le T_{k1} \\ P'(\Omega_2)^h P(\tilde{k}_j + \tilde{\delta}_{2j}), & T_{k1} \le t \le T_{k2} \\ P'(\Omega_3)^h P(\tilde{k}_j + \tilde{\delta}_{2j} + \tilde{\delta}_{3j}), & t > T_{k2} \end{cases}$$

With *j* = *M*, *Oil*, *F*.

$\tilde{k}_j$, $(\tilde{k}_j + \tilde{\delta}_{2j})$ and $(\tilde{k}_j + \tilde{\delta}_{2j} + \tilde{\delta}_{3j})$ are the *j-the* column of the matrix *K*, $(K+\delta_2)$ and $(K+\delta_2+\delta_3)$, respectively.

4. Database and empirical results

In this section, we provide an overview of our oil price database, along with the macroeconomic and financial uncertainty time series. Subsequently, we conduct a thorough examination to identify evidence for three significant regimes of oil price volatility. Next, we present the outcomes from our non-recursive Structural Vector Autoregressive (SVAR) model. Finally, we delve into an analysis of the exogeneity of uncertainty and scrutinize the Impulse Response Functions (IRFs).

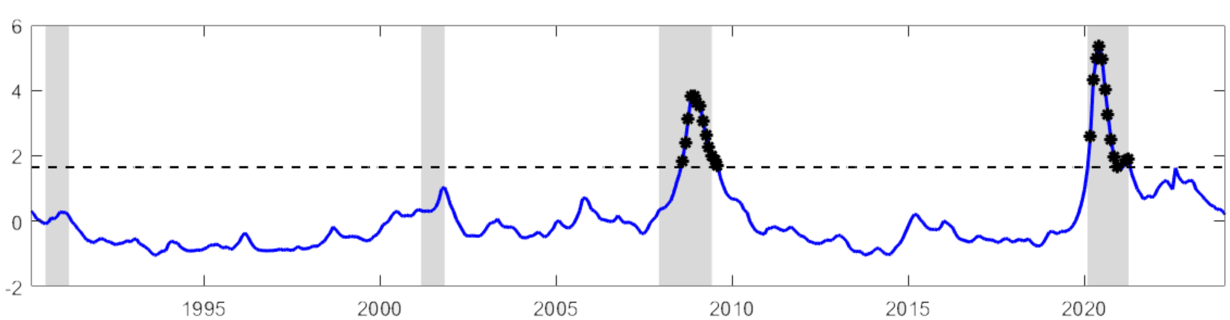
4.1 Data

Our structural VAR model includes three monthly variables: Oil_t, UM_t, and UF_t. Oil_t is the oil price measured by the change in the Log of the WTI price collected from the U.S. Energy Information Administration (EIA) database over the period 1990M1 to 2023M12. UM_t is the macroeconomic uncertainty variable over a horizon of 1 month or over a horizon. UF_t is the financial uncertainty variable over a 1-month horizon. Both uncertainty time series are collected from the Ludvigson home page. Our sample comprises 402 observations. The joint analysis of macroeconomic and financial uncertainty is crucial for understanding the causal relationship between oil priceshocks and uncertainty.

The choice of Ludvigson measures in our study is motivated by several factors that contribute to the robustness and validity of our analysis. Firstly, Ludvigson measures are widely used in the literature to capture macroeconomic and financial uncertainty dynamics effectively. These measures are constructed from comprehensive datasets encompassing more than 20 economic and financial variables, enabling a thorough assessment of uncertainty across different dimensions of the economy. By employing Ludvigson measures, we ensure that our analysis is grounded in established methodologies and can be compared with existing research in the field, such as Angelini et al. (2017) and Jurado et al. (2015). Furthermore, Ludvigson's measures offer certain advantages that make them particularly suitable for our study. Their construction involves aggregating information from a diverse set of indicators, providing a more comprehensive measure of uncertainty compared to single-variable proxies. Additionally, Ludvigson measures are designed to capture both short-term fluctuations and longer-term trends in uncertainty, allowing for a nuanced analysis of uncertainty dynamics over time. However, it is important to acknowledge the drawbacks associated with Ludvigson measures, particularly their reliance on mean squared error (MSE) as a measure of uncertainty. MSE-based measures treat under- and over-predictions of macro variables symmetrically, which may not fully capture the asymmetric effects of uncertainty on economic outcomes. For example, while both an overestimation and an underestimation of GDP growth may contribute to uncertainty, they may have different implications for economic decision-making and market behavior. This limitation underscores the need for careful interpretation and validation of our results, while accounting for the potential biases introduced by the MSE-based construction of Ludvigson measures.

Figure 1 plots the estimated h=1-month-ahead macro and financial uncertainty, along with the NBER recession dates. The dots on the curves indicate the observations on U_{Mt} and U_{Ft} exceeding the 1.65 standard deviation above the unconditional mean of each series. A preliminary examination of this figure shows three distinct volatility phases, separated by the two dates 2007 and 2020.

Aggregate Macro Uncertainty UM 1990–2023



Aggregate Financial Uncertainty UF 1990–2023

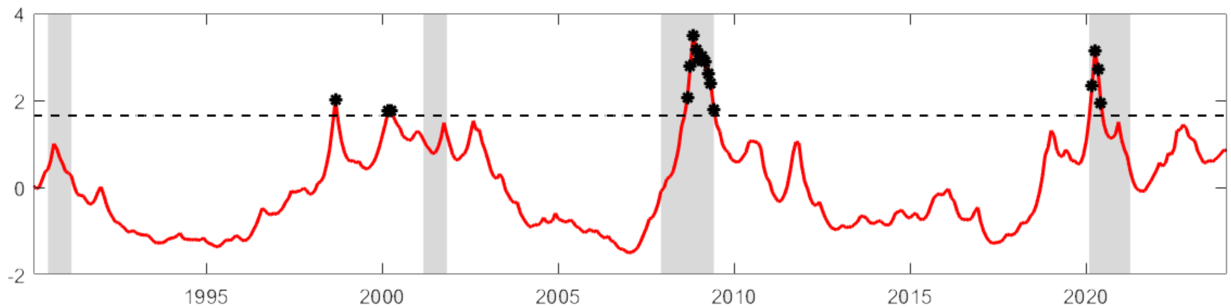


Figure 1. The estimated h=1 month–ahead macro uncertainty and financial uncertainty,

4.2 Identification of Volatility Breaks

Our SVAR specification has the main characteristics that the identification approach involves breaks in the unconditional volatility across regimes. We hypothesize that connectedness between uncertainty and oil prices change across the three regimes as the unconditional variance of Oilt change. We hypothesize that the relationship between uncertainty and oil prices varies across the three regimes as the unconditional variance of oil changes.

To examine the evidence of volatility breaks, we follow three approaches. First, we use recursive estimates of the residual variance of our basic VAR model. Second, we use Bai and Perron (2003) to identify the three volatility regimes. Third, we use Chow-type tests to test for two structural breaks, with possible break dates identified in the first step. Then, we follow the approach of Forni and Gambetti (2014) to examine the informational sufficiency of our VAR specification.

We started by running our Structural VAR for $Y_t := (UM_t\,, Oil_t, UF_t\,)'$recursively. Figure 2 depicts the unconditional VAR error covariance matrix Π_μ of a four-lag model. The two vertical dashed lines indicate the dates 2007M1 and 2020M1, which clearly point out the separation between three different volatility regimes.

The figure reveals that the average volatility level varies over time, starting with a low level in the 1999s and 2007, spiking from 2007 through the end of 2020, dropping once again following the COVID pandemic, and then stabilizing. The covariance $UM_t\_Oil_t$ and $UF_t\_UM_t$ show totally opposite movements. The variance of oil prices also seems to have the same trend as the volatility of macroeconomic uncertainty. Overall, the two dates 2007 and 2020 appear to separate three different oil market volatility regimes. the $UF_t\_Oil_t$ covariance does not seem to be highly correlated with the other two covariances, but it clearly shows different movements across the three identified regimes.

The entire sample period 1990M1–2023M12 was divided into three separate sub-samples by these two break dates: the pre-crisis period (1990M1–2007M12), the recovery period (2009M1–2019M12), and the post-COVID period (2022M1-2023M12). However, it is important to note that while the unconditional variance associated with the proxy for financial uncertainty roughly follows the same volatility pattern as the unconditional volatility of Oilt, the unconditional variance associated with the proxy for macroeconomic uncertainty shows only moderate changes until the beginning of 2009. Macroeconomic and financial uncertainty, as well as oil prices, show a sharp increase in volatility during the second regime, 2009-2020. The third regime is showing higher macroeconomic volatility and more stable oil and financial volatility.

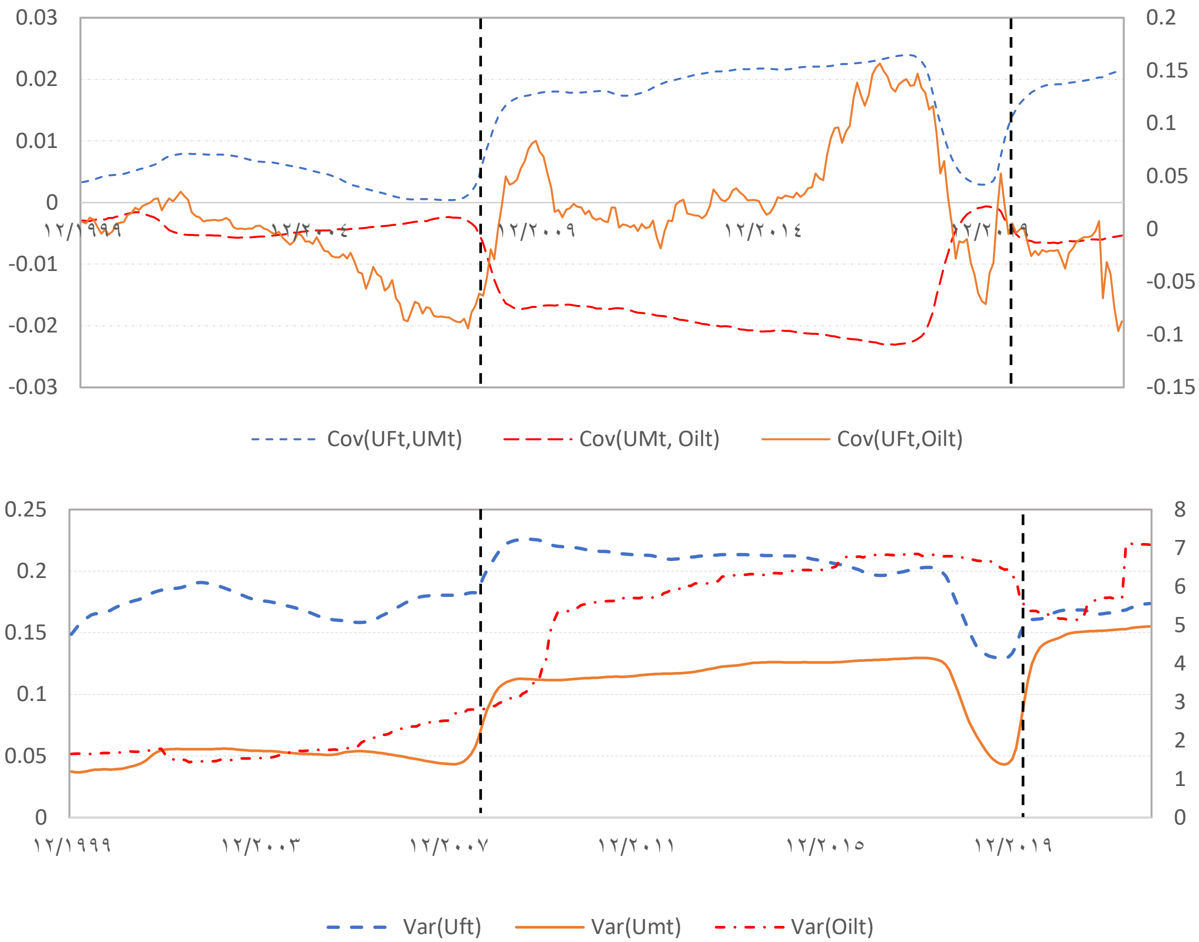


Figure 2. The unconditional VAR error covariance Π_{μ} of a four–lags VAR model presented in Eq. (1).

In this section, we use the structural break test proposed by Bai and Perron (2003) to identify the breakout date of oil markets over the sample period. We begin by estimating separate equation specifications using least squares for the three variables UM, UF, and the oil price, each consisting of the dependent variable and a constant regressor. We perform the Bai-Perron tests of globally optimized breaks against the null of no structural breaks.

The Bai-Perron method allows breakpoint (Reeves et al., 2007). The Bai-Perron tests use an iterative procedure to estimate rigorous break points. Comparative studies often demonstrate that the Bai-Perron method outperforms other techniques in terms of power and accuracy. These studies show that it is more reliable in identifying the correct number of breaks and their locations, especially in complex time series with multiple shifts (Kim et al., 2009).

By default, the tests allow up to 5 breaks, use a 15% trimming percentage, and set the significance level to 0.05 for sequential testing. The results , across the three-time series, the maximized statistics indicate the presence of two breaks. The test shows the global optimizers for the breakpoints for each number of breaks. In Table 1, we present the global optimizers for the breakpoint locations with two breaks. The results show that the first breakout date for all variables is between 2007M08 and 2008M01. These dates are consistent with the last financial crisis, 2007-2008. The table shows that the crisis was reflected in financial uncertainty before macroeconomic uncertainty. Oil markets reacted to the crisis a few months later, which supports the hypothesis that macroeconomic and financial uncertainties had an exogenous effect on oil market shocks. The second break occurred between December 2019 and March 2021. The second break in oil and uncertainty coincides with the start of the COVID-19 pandemic. Macroeconomic uncertainty is shown to be the first variable affected by the pandemic.

Table 1. Break dates over the period 1989M7 to 2023M12

Variable	Break date 1	Break date 2
Oil	2008M01	2020M02
UM	2007M12	2019M12
UF	2007M08	2020M02

In a third step, to empirically check that the dates 2007 and 2020 are consistently two structural breaks in the VAR error covariance matrix, we use a set of Chow-type tests and misspecification-type tests. We start by testing the null hypothesis of no structural breaks in all VAR model parameters:

$$H_0: \begin{pmatrix} \omega_1 \\ \Pi_{\mu,1} \end{pmatrix} = \begin{pmatrix} \omega_2 \\ \Pi_{\mu,2} \end{pmatrix} = \begin{pmatrix} \omega_3 \\ \Pi_{\mu,3} \end{pmatrix} = \begin{pmatrix} \omega \\ \Pi_{\mu} \end{pmatrix}$$

With ω_1, ω_2 *and* ω_3 are the slope coefficients.

Once H_0 is rejected, we test in the following step the null hypothesis of absence of volatility regimes:

$$H_0': \Pi_{\mu,1} = \Pi_{\mu,2} = \Pi_{\mu,3}$$

The upper part of Table 2 reports the estimates of the parameters of the sub mu matrix through OLS regression across the overall sample and across the three sub-samples separately. The results shown in Table 2 and the evidence stated in Figure 1 are consistent. These findings support that unconditional variances and covariances change throughout time. Table 1 also shows that the residuals are not Gaussian and not correlated within the three regimes. As anticipated, and in line with Cúrdia et al. (2014), the non-normality of VAR disturbances is observed throughout the entire sample period as well as within macroeconomic regimes.

The results of the LR tests for the hypotheses H_0 and H_0' are reported in the bottom part of Table 1. The results strongly reject both H_0 and H_0'. As a last check, we test if the reported regime-dependence in the residual covariance matrix is attributed to the change in regime characterizing the autoregressive parameters. To this end, we estimate the structural VAR in equation (6) with covariance matrix constant and allowing the autoregressive parameters to fluctuate across the three regimes as in equation (7). We test the (unconditional) homoskedasticity null hypothesis in the residuals (H''). The results strongly reject the homoskedasticity hypothesis and confirm previous findings. A further preliminary finding that emerges from Table 1 is that the relationship between oil price and macroeconomic and financial uncertainty changes across the three identified regimes. Overall, we find that our SVAR specification system $Y_t := (UM_t, Oil_t, UF_t)'$ offers a good match of the data and is informationally adequate.

Table 2. test of the null hypothesis of no structural breaks

	Overall period	Pre-crisis period 1990M1-2007M12	Recovery Period 2008M1-2020M1	Post crisis period 2020M1-2023M12
Cov $\widehat{\Pi}_\mu$	$\begin{pmatrix} 0.004* & 0.321* & 0. \\ & 0.002* & 0 \\ & & 0. \end{pmatrix}$	$\begin{pmatrix} 0.003* & 0.050* & 0.61* \\ & 0.006* & 0.724 \\ & & 0.083 \end{pmatrix}$	$\begin{pmatrix} 0.001* & 0.271* & 0.510 \\ & 0.001* & 0.00 \\ & & 0.005 \end{pmatrix}$	$\begin{pmatrix} 0.001* & 0.316* & 0.159* \\ & 0.041 & 0.006 \\ & & 0.007* \end{pmatrix}$

	Overall period	Pre-crisis period 1990M1-2007M12	Recovery Period 2008M1-2020M1	Post crisis period 2020M1-2023M12
Correlation $\hat{\rho}_{\mu}$	$\begin{pmatrix} 1 & 0.267* & 0.023* \\ & 1 & 0.742 \\ & & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 0.034* & 0.017* \\ & 1 & 0.163 \\ & & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 0.059* & 0.038* \\ & 1 & -0.142 \\ & & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 0.077* & 0.081* \\ & 1 & 0.276 \\ & & 1 \end{pmatrix}$

4.3 Non-recursive SVAR approach

In this section, we present our Structural VAR model that put emphasize on the dynamics between oil shocks (e_{oil}), macroeconomic uncertainty (e_M) and financial uncertainty (e_F) through the three regimes identified in the previous section. The correlations between chocks residuals shown in table 1, illustrate an increase by more than 30% in the correlations between macroeconomic uncertainty and oil prices between the economic recovery period to the post covid period, from 5.9% to 7.7%. This finding aligns with the structural analyses by Caggiano et al. (2017a) and Plante et al. (2018). The correlation between financial uncertainty and oil price change residuals is negative only in the Recovery period, but is not significant. The table also shows that the correlation between macroeconomic and financial uncertainty residuals increases substantially across the three volatility regimes (1.7%, 3.8% and 8.1%, respectively). These findings strongly confirm that the relationship between macroeconomic uncertainty and oil prices changes across the three regimes identified after 1990. Notably, we also underline the existence of an indirect link between financial uncertainty and oil shocks residuals. Since financial uncertainty is not significantly correlated with oil price shocks, its effect on oil prices turns up through its relationship with macroeconomic uncertainty. The correlation between economic and financial uncertainties is essentially non-significant in the first subsample and only becomes significant after the financial crisis 2007.

Importantly, we identify an indirect link between financial uncertainty and oil shocks. While financial uncertainty does not exhibit a significant correlation with oil price shocks, its effects on oil prices manifest through its relationship with macroeconomic uncertainty. The correlation between economic and financial uncertainties remains non-significant in the first subsample but becomes significant following the financial crisis of 2007, echoing findings from recent studies such as those by Lyu et al. (2021).

Based on these findings, we estimate the following restricted matrices:

Pre-crisis period:

$$\tilde{K} \coloneqq \begin{pmatrix} k_{MM} & k_{Moil} & 0 \\ k_{oil\_M} & k_{oil\_oil} & 0 \\ 0 & 0 & k_{FF} \end{pmatrix}$$

Recovery period:

$$\tilde{K} + \tilde{\delta}_2 \coloneqq \begin{pmatrix} k_{MM} + \delta_{2,MM} & k_{Moil} & \delta_{2,MF} \\ k_{Oil\_M} + \delta_{2,Oil\_M} & k_{oil\_oil} + \delta_{2,Oil\_Oil} & 0 \\ \delta_{2,FM} & 0 & k_{FF} + \delta_{2,FF} \end{pmatrix}$$

Post covid period:

$$\tilde{K} + \tilde{\delta}_2 + \tilde{\delta}_3 \coloneqq \begin{pmatrix} k_{MM} + \delta_{2,MM} & k_{Moil} & \delta_{2,MF} + \delta_{3,MF} \\ k_{Oil\_M} + \delta_{2,Oil\_M} + \delta_{3,Oil\_M} & k_{oil\_oil} + \delta_{2,Oil\_Oil} + \delta_{3,Oil\_Oil} & \delta_{3,Oil\_F} \\ \delta_{2,FM} & 0 & k_{FF} + \delta_{2,FF} + \delta_{3,FF} \end{pmatrix}$$

The restrictions of the matrices across the three regimes are based on the assumptions initially set as well as the results of the correlations in Table 1. The response of financial markets to non-financial shocks was weak during the Pre-crisis period $(\widetilde{K})$. So, we assume that the responsiveness of financial uncertainty to oil chocs (k_{F_Oil}) and macroeconomic uncertainty (k_{FM}) equal zero. During this period, oil shocks are assumed also to not be linked to financial uncertainty $(k_{Oil\_F} = 0)$, and macroeconomic uncertainty does not respond to the effects of financial uncertainty$(k_{FM} = 0)$. Regarding the recovery period, the $(\widetilde{K} + \tilde{\delta}_2)$, restrictions imposed on the covariance matrix during states that macroeconomic uncertainty affect oil prices through $(k_{Oil\_M} + \delta_{2,Oil\_M})$. Oil shocks are assumed also to affect macro uncertainty through the parameter k_{MOil}. We assume that causality between the two sources of uncertainty can occur in both directions through the parameters $\delta_{2,MF}$ and $\delta_{2,FM}$. Lastly, in the post pandemic volatility regime, we assume that oil markets respond to financial uncertainty chocs directly through δ_{3,Oil_F} and indirectly through its impact on macroeconomic uncertainty via the parameters: $\delta_{2,MF} + \delta_{3,MF}$.

The described non-recursive SVAR specification allows for testing the exogeneity of macroeconomic uncertainty $(k_{MOil} = 0)$, as well as the one-way impact of financial uncertainty on macroeconomic uncertainty $(\delta_{2,FM} = 0)$.

3.4 On-impact and dynamic causal effects

Our SVAR model is built on the hypothesis that changes in covariance matrix $\Pi_{\mu,1} \neq \Pi_{\mu,2} \neq \Pi_{\mu,3}$ depends on three different volatility regimes. To deepen our analysis and for comparison purpose of our approach, we compare the IRFs generated by our model to those generated by the model developed by Lanne and L¨utkepohl (2008). The latter assumed constant autoregressive parameters in eq. (7), and the changes in the unconditional covariance matrix in the three volatility regimes are modelled by the simultaneous diagonalization:

$$\Pi_{\mu,1} = KK', \quad \Pi_{\mu,2} = KA_2K', \; \Pi_{\mu,3} = KA_3K'$$

Where the components of K are constant, $A_2 \neq A_3 \neq I_n$ are two diagonal matrices with positive elements on the diagonal.

Table 3 reports estimates of the structural parameters along with the standard errors. Panel A reports the estimates of the matrix specifications in Eq18 allowing for endogenous macroeconomic uncertainty effect, while Panel B refers to the specification with the two hypothesized restrictions: $(k_{MOil} = 0)$ and $(\delta_{2,FM} = 0)$ allowing for macroeconomic uncertainty exogenous effect. In the following, we first address the reciprocal causality issue, then we focus on the variable causal effects across the three volatility regimes generated by the estimated IRFs.

TABLE 3. Estimation results of the structural VAR model

Panel A: Model with endogenous macroeconomic uncertainty								
$\widetilde{K}$			$\widetilde{K} + \widetilde{\delta}_2$			$\widetilde{K} + \widetilde{\delta}_2 + \widetilde{\delta}_3$		
0.0124	0.0015	0	0.0041	0.0015	0.007	0.0041	0.0015	0.0129
(0.0006)	(0.1062)	-	(0.0012)	(0. 1062)	(0.001)	(0.0012)	(0. 1062)	(0.0007)
-0.0719	0.7385	0	-0.298	1.1951	0	-0.2194	4.8848	-0.6257
(0.1026)	(0.0327)	-	(0.2488)	(0.1089)	-	(0.5454)	(0.1939)	(0.5022)
0	0	0.0281	0.0185	0	0.0271	0.0185	0	0.0197
-	-	(0.0012)	(0.0128)	-	(0.0038)	(0. 0128)	-	(0.0022)
LR Test statistics: 5.3693								
P-value: 0.0482								

***Panel B**: Model with exogenous macroeconomic uncertainty*								
$\widetilde{K}$			$\widetilde{K}+\widetilde{\delta}_2$			$\widetilde{K}+\widetilde{\delta}_2+\widetilde{\delta}_3$		
0.0124	0	0	0.0113	0	0.0035	0.0113	0	0.0066
(0.0005)	-	-	(0.0004)	0	(0.0014)	(0.0004)	-	(0.0006)
0.0189	0.7417	0	0.0008	1.2316	0	0.0387	0.0199	-0.3063
(0.0443)	(0.0314)	-	(0.2167)	(0.0999)	0	(0.2386)	(0.1778)	(0.2516)
0	0	0.0281	0	0	0.0328	0	0	0.0271
-	-	(0.0012)	-	-	(0.0027)	-	-	(0.001)
LR Test statistics: 11.4375								
P-value: 0.0869								

Reverse causality/exogeneity.

With regard to the sample period, the results of both panels of table 2 confirm the evidence that macroeconomic uncertainty is an exogeneous source of oil markets shocks. Panel A presents the results of the specification allowing a reciprocal causal relationship between macroeconomic and financial uncertainty from the 1990s. The p-value of the LR statistic (0.048) shows that the model is not consistent with the data at the 5% level of significance. Under the three volatility regimes, the parameter of the effect of oil shocks on macroeconomic uncertainty to real economic activity shocks k_{M_oil} appears not statistically significant. This finding confirms the exogeneity of macroeconomic uncertainty. The parameter $\delta_{2,FM}$ appears slightly significant showing the evidence that financial uncertainty shocks affect macroeconomic uncertainty, while the reverse effect is not valid.

In Panel B of Table 2, we report the results of the specification, including the two restrictions ($k_{Moil}=0$) and ($\delta_{2,FM}=0$), see eq. (19). The p-value of the LR statistic (0.087) shows that the model supports our data at the 5% level of significance. The specification in Panel B states an asymmetric relationship between macroeconomic and financial uncertainty.

To test the endogeneity of financial uncertainty and its impact on Macroeconomic uncertainty, we invert the positions of U_F and U_M in our structural model[1]. This allows us to test the reciprocal role that uncertainty exerts on the model and how it propagates to oil markets. The results of the estimation strongly reject the model with an LR test statistic of 18.54 and a p-value of 0.00. This finding is consistent with Lyu et al. (2021) and supports our initial hypothesis that financial uncertainty does not directly affect oil prices. In our specification, financial uncertainty influences oil prices indirectly through macroeconomic uncertainty.

Contrary to Van Robays (2012), we find that macroeconomic uncertainty is exogenous to oil prices and has a positive impact on oil markets. Van Robays (2012) suggests that the endogeneity of macroeconomic uncertainty reported may indicate the asymmetric impact of financial and macroeconomic uncertainty shocks included in his approach. His findings also show that oil prices respond dynamically to uncertainty shocks, a feature that sets our analysis apart from previous studies. The exogeneity of macroeconomic shocks has been reported in their impact on the business cycle by Carriero et al. (2018) and Angelini et al. (2017). Using a non-recursive SVAR model with stochastic volatility, Carriero et al. (2018) test for the uncertainty effect and the business cycle by including measures of macroeconomic and financial uncertainty one at a time in their regressions. They assume constant impact coefficients and use an independent stochastic

[1] *The results of the estimations can be provided under request.*

process to model the system's volatility and identify shocks.

Impulse Response Functions (IRFs)

Figures 2-5 plot the implied IRFs over a 60-period (5-year) horizon for the three-volatility regime. Figure 2 plots the IRFs for the three volatility regimes under f = 1 (one-month uncertainty). The blue IRFs indicate the pre-financial crisis period, the green IRFs indicate the recovery period, and the brown IRFs indicate the post-COVID pandemic period. The figures on the first row show the response of macroeconomic uncertainty to the three structural shocks, the second row reports the response of oil prices, and the third row reports the response of financial uncertainty.

Two main comments can be inferred from Figure 2. First, the IRFs show time-varying dynamics across the three regimes. Although the uncertainty shocks affect oil prices in the three volatility regimes, the persistence of the responsiveness changes across the regimes. Second, the effect of macroeconomic uncertainty shocks on oil prices (Brown curve) is particularly highly persistent during the post-COVID period. Especially, macroeconomic uncertainty played a role in oil price volatility during this period.

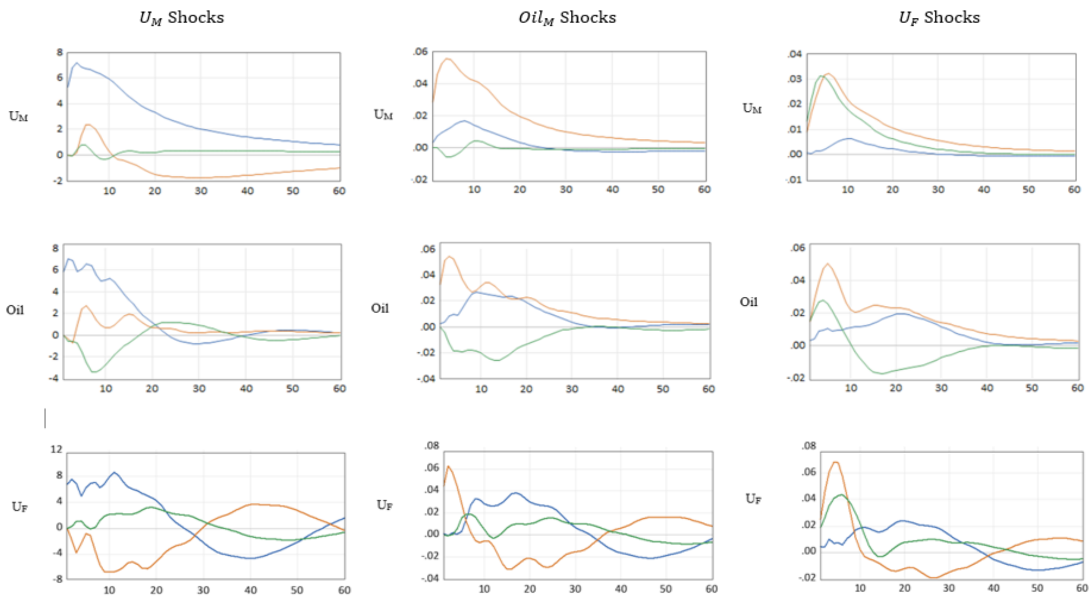


***Figure 3**: IRFs obtained from the baseline non–recursive SVAR for*

$$X_t := (UM_t, Y_t, UF_t)$$

The joint analysis of Figures 3 to 6 confirms the second hypothesis of the study, as it shows that the relationship between uncertainty and oil prices varies across the three volatility regimes identified. Ignoring the dependence of volatility regimes may lead to the estimation of compound effects that fail to reflect the dynamics of the relationships between uncertainty and oil prices embedded in the time series. Figures 4 and 5 show that the response of uncertainty to oil price instability changed considerably between the recovery period and the post-COVID period.

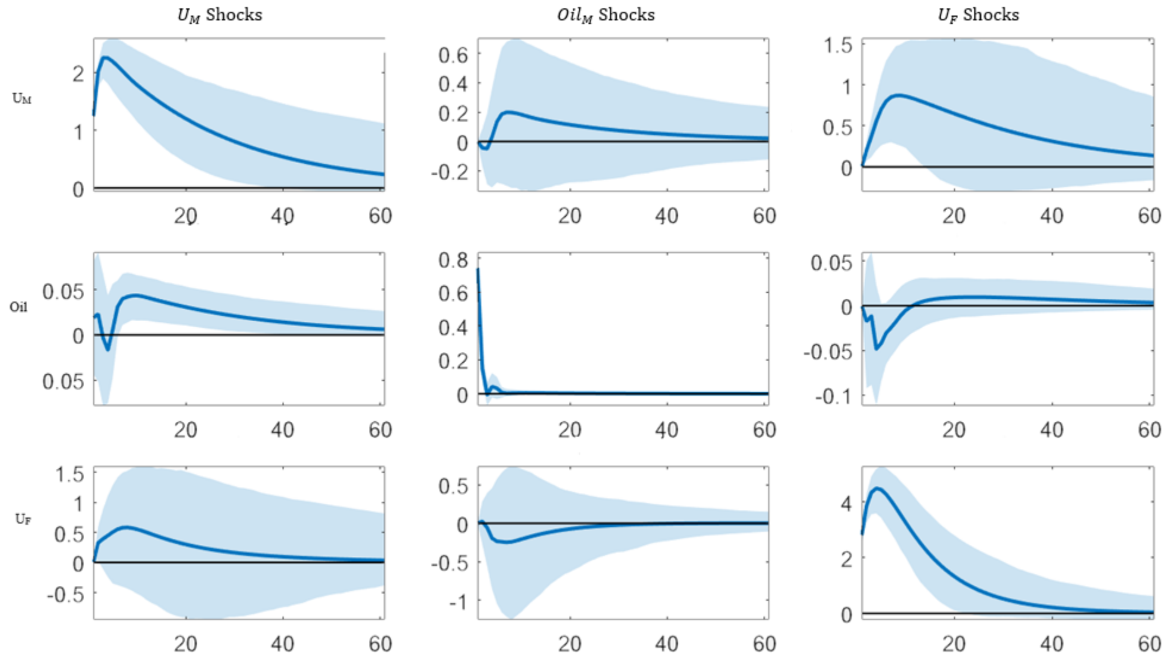


***Figure 4**: IRFs obtained in the first volatility regime (Pre–Crisis period, 1990M1–2007M12) from the baseline non–recursive SVAR for $X_t := (UM_t, Y_t, UF_t)$*

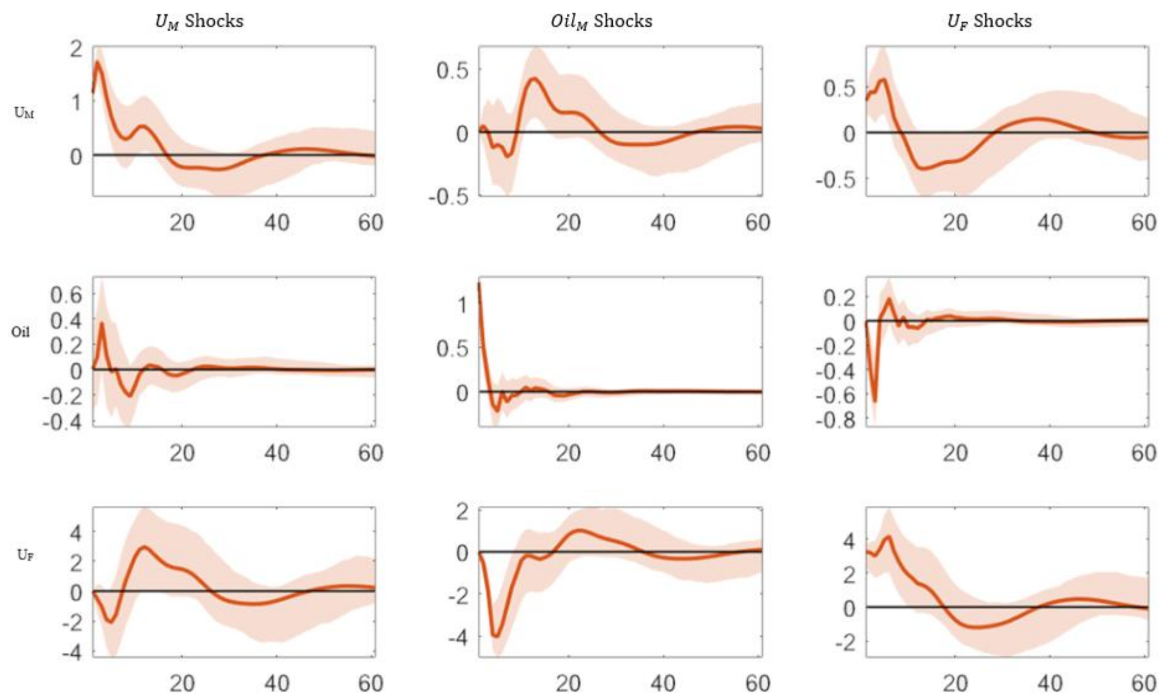


***Figure 5**: IRFs obtained in the first volatility regime (Recovery period, 1990M1–2007M12) from the baseline non–recursive SVAR for $X_t := (UM_t, Y_t, UF_t)$*

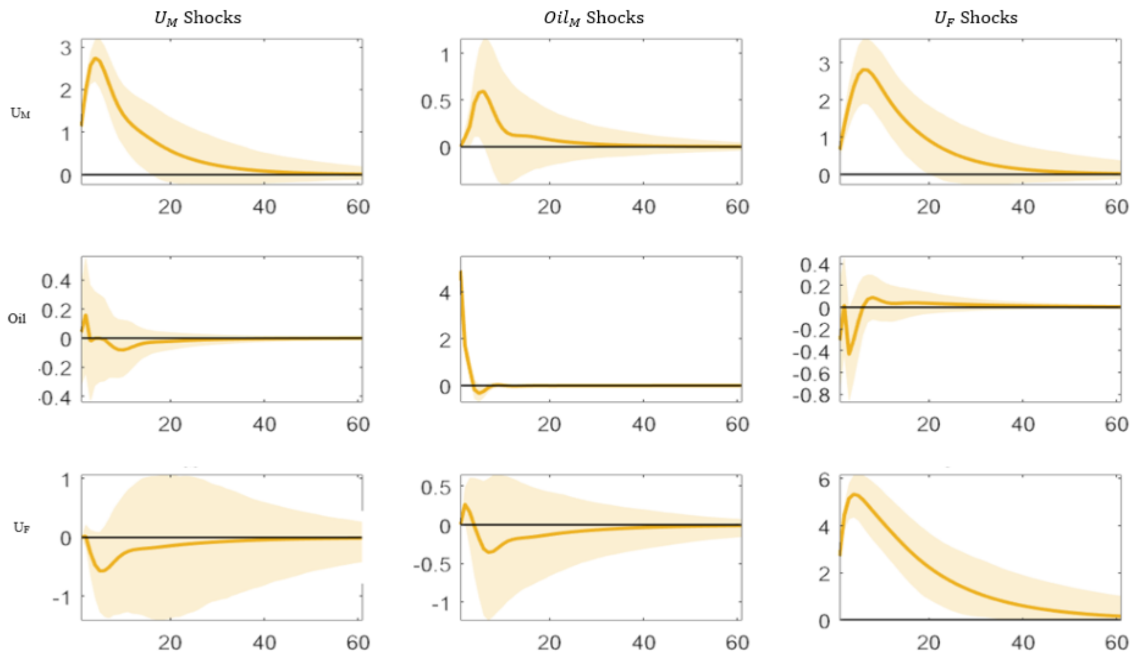


***Figure 6**: IRFs obtained in the first volatility regime (Post Covid period, 2007M1–2023M12) from the baseline non-recursive SVAR for $X_t := (UM_t, Y_t, UF_t)$.*

5. Conclusion and policy implications

This paper examines two controversial hypotheses about the relationship between uncertainty and oil prices. First, we tested whether uncertainty is an exogenous factor affecting oil markets, or rather, an endogenous factor influenced by oil price variations. Second, we examined whether the impact of uncertainty differs across volatility regimes. Both hypotheses were tested using a non-recursive, simultaneous SVAR model. The latter differs from previous models in that it can , accounting for the dynamics of uncertainty effects across regimes. Our specification also allows us to investigate the reciprocal causality relationship between uncertainty and oil prices.

Our results show that the effect of uncertainty on oil markets varies across volatility regimes. We also find that macroeconomic and financial uncertainty exerts an exogenous effect, rather than an endogenous effect, on oil prices. Macroeconomic uncertainty shocks are shown to increasing oil prices, especially during the post-COVID period. Financial uncertainty influenced oil markets by affecting macroeconomic uncertainty.

In summary, the estimation results presented in this article show that endogenous models are important tools for political analysts and economic agents seeking to understand fluctuations in crude oil prices. In particular, the extracted uncertainty factor can risk measure in oil markets. Modeling this latent factor can not only serve as an early warning signal of risk in the oil market, but it can also help understand the evolution of inflation, inflation expectations, and disagreements during periods of high uncertainty in the oil market. We leave the asymmetric endogenous effect of uncertainty on oil demand and supply to future work.

In light of our findings, we emphasize that the observed dynamics among macroeconomic, financial, and oil price uncertainty carry significant implications for policymakers and market participants. The increased correlation between macroeconomic uncertainty and oil prices, particularly during different economic regimes, suggests that policymakers should closely monitor macroeconomic indicators to anticipate potential oil price fluctuations. Furthermore, our results highlight the of integrated risk management strategies that account for the interconnectedness of these uncertainties. We recommend that future research explore more granular data to refine our understanding of these relationships and guide effective policy responses in volatile economic climates.

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عدم اليقين، أسعار النفط وأنماط التقلب: مقاربة جديدة للتحديد غير التكراري

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المستخلص:

خلال العقود القليلة الماضية، ركزت العديد من الدراسات على فحص التحركات المشتركة بين أسعار النفط وحالة عدم اليقين. في هذه الورقة، نطبق نهجًا جديدًا للتعرف غير التكراري لاختبار ما إذا كانت حالة عدم اليقين الاقتصادية والمالية تسبق أو تتبع التغيرات في أسعار النفط. في المقام الأول، نستكشف التفاعل بين حالة عدم اليقين وتغيرات أسعار النفط عبر أنظمة تقلبات مختلفة. تشير نتائجنا إلى أن حالات عدم اليقين الاقتصادية والمالية عوامل خارجية تؤثر على ديناميات أسعار النفط. علاوة على ذلك، وجدنا أدلة على أن تأثير صدمات عدم اليقين على سوق النفط يتكثف خلال فترات الاستقرار الاقتصادي أو المالي، مما يجعلها مصدرًا مهمًا للتقلبات الاقتصادية في سوق النفط. يمكن أن تساعد هذه النتائج المشاركين في سوق النفط على فهم أفضل لكيفية تأثير حالة عدم اليقين الاقتصادية والمالية على أسواق النفط، مما يوفر لهم أساسًا لاتخاذ قرارات تتعلق بإدارة المخاطر وتحسين المحافظ الاستثمارية.

الكلمات المفتاحية: أسعار النفط، التحديد، SVAR غير التكراري، صدمات عدم اليقين، نظام التقلبات.

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The AI Revolution in Labor: Navigating Job Transformation, Economic Impacts, and Skill Evolution

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Abstract: *This research paper analyzes the applicability of Artificial Intelligence (AI) as a transformative force across the world's labor market, job roles, and skill requirements across different economic sectors. We analyze how AI is changing not only employmentthe labor market and wages and income distribution. We find AI has, by nature, a dual purpose in the labor market. It causes unemployment in routine and low-skilled occupations, such as manufacturing and retail, but at the same time it creates high-skilled employment in IT-related fields. The economic effects of AI are similarly dual: an exacerbation of income inequality or the opening of new economic mobility pathways via expanded educational and skill-development opportunities. The impact of AI varies widely across sectors. The main discussion shows that while manufacturing has the highest risk of automation, healthcare and education face less job substitution than job augmentation. In addition, we locate an increasing need for technical AI skills on the one hand, and uniquely human capacities, including creativity and intelligence, on the other hand. We propose policy recommendations based on these insights, including ways to mitigate negative effects on lower-skilled workers. They are targeted at reskilling programs, education system reforms, and sector-specific transition strategies. Our work adds to the conversation about what the future of work might look like in an AI economy, and clarifies the pace at which we need to act to ensure that the rewards of AI are shared widely with society.*

Keywords: *Artificial Intelligence, Labor Markets, Job Transformation, Employment*.

JEL Code: *O33, J24, J21, E24*

1. Introduction

At the beginning of the twenty-first century, the speed of technological advances accelerated exponentially. Artificial intelligence (AI) has emerged as a driver of change across many industries of the global economy. Thus, as AI advances in its ability to perform more advanced activities and take over human work, we reach a turning point in labor and employment history. With the rapid integration of new technologies that include artificial intelligence in workplaces and labor markets, there has been a lot of debate among economists, policy makers, managers and workers about what these technologies mean for the future of work, the nature of work and indeed job creation in an economy that is shifting to the new era of increasing integration of artificial intelligence technologies.

There are several pathways through which the use of AI can shape labor markets. On the positive side, AI seeks to enhance business performance and efficiency through automation, decision support, and new business and economic opportunities. This technology revolution is likely to lead to the emergence of new businesses and professions that can create high-wage employment in society. On the negative side, such progress raises concerns on the creation of a large number of jobless citizens particularly the workers in sectors that are most likely to be exposed to automation. These two faces of AI are a major problem for societies around the world, on the one hand, to obtain the positive effects of applying AI, and on the other hand, to prevent the negative impact on employment and, consequently, the stability of the socioeconomic system.

The consequences of AI integration are observed across many sectors, including manufacturing, finance, healthcare, education, and others. While there are certain industries that are struggling to fight automation and, therefore, unemployment, there are other fields, which offer new vacancies related to automation but with human intervention. Flexible work is not just about changing the types of work available, but also the types of work required for success in the AI age.

However, it also has implications for the economy, especially for employment, wages, and income distribution, as well as for labor market indicators. However, as subgroups of AI technologies continue to emerge, there is huge concern that this might lead towards the other pole of attainment of equality and perpetuating of new injustices that previous technology may have assumed, conceptualized and solved.

Therefore, the purpose of this research is to discuss current literature on the effects of AI on labor forces and labor markets, while accounting for the opportunities and threats in this technological era. Thus, based on the analysis of the current literature and considering the possibilities of the present and potential tendencies, we would like to contribute to the discussion about work in the context of deep global integration with artificial intelligence.

This study aims to address the following main research question: What are the impacts of Artificial Intelligence (AI) on labor markets and job roles, and what are the skill requirements across the different sectors of the global economy? This overarching question is explored through the following sub-questions: (c) In what way is AI changing the ways we work now? (c) What are the possible long-term implications of widespread AI adoption for jobs and how work is performed? (c) What implications does AI have on wage structures and income inequality, as well as the structure and dynamics of labor markets? On the other hand, (d) what skills are required, and what are the educational needs in the presence of AI integration in the economy? (e) What are the specific impacts of AI on various industries, and what job types are affected by AI?.

Based on these research questions, we propose the following main hypothesis: It is changing the landscape of the labor market, fundamentally shifting the features of employment and skill demand and, in turn, the economics of the market, in general, across sectors. This central hypothesis is supported by the following sub-hypotheses: AI adoption increases job displacement in routine and low skilled jobs, generates new jobs in high skilled, AI related jobs; (b) A net positive effect of AI on employment in the long term is expected, but in the form of a change in the nature of jobs, especially of technology usage; (c) Adoption of AI affects wage polarization, where labor in high skills benefits while that in low skills may suffer wage depression; (d) When AI is embedded in the economy, demand for both technical AI related skills and uniquely human skills like creativity, and emotional intelligence increases; and (e) The impact of AI differs greatly across different industries, with some industries experiencing more job augmentation than replacement out of AI.

The paper is structured as follows: We first review the main literature on the topic. In section 3, we start by analyzing the current impact of AI on the ongoing disruption of employment experiences across sectors and grades of employment demand. Section 4 discusses the long-term impacts of the growth and evolution of the AI technologies on job markets and employment. The next part of our analysis will focus on the economic consequences of the use of artificial intelligence, including wage and income differences and its influence on the labor market. Following this, the paper provides a background on the changes in skills and education with the emergence of an AI-based economy. Section 6 provides deeper information on the extent of AI's impact across industries and occupational categories. Section 7 discusses the sector-specific effects of AI on various industries and job types. Section 8 concludes with the key findings. This paper will provide policymakers, businesspersons, educators, and employees with useful guidance on how to address labor in the context of emerging artificial intelligence systems.

2. Literature Review:

The effects of Artificial Intelligence on the labor market are one of the hottest and most hotly discussed and researched issues in the academic literature and within the policy-making process. While there is a rapidly growing body of literature on the subject, much remains uncertain about the extent and nature of the economic and employment effects of AI. This lack of consensus is further exacerbated by several factors,, including difficulties in measuring the impact of AI, differences in regional economic structures, and uncertainty about the path AI is likely to take. This brief section presents an attempt to articulate the state of the art of this discourse and to show how the field has advanced and where the main questions and debates lie today.

One of the first investigations in this context discussed the impact of AI at the aggregate level of an economy and its implications for employment. The work of Zhou et al. (2020) was among the first empirical assessments of the AI effect on one of the world's biggest economies – China. Their study revealed a nuanced picture: the places where AI caused displacement were at the same time accompanied by a rise in employment in other areas, specifically within technology-based industries. We have seen that the authors noted a positive net impact on employment in the early phase of AI application, though the balance could change as AI technologies develop and spread. On this basis, Frank et al. (2019) proposed a multidisciplinary framework for analyzing the AI labor-market effect. Their work was also a sign of a shift as they recognized the impossibility of easy positive or negative labeling of AI’s impact, because of increasing rates of AI development and integration in economies. They also pinpointed further on the effectiveness of the methods for assessing and predicting the impact of AI on employment and skills.

Over recent times, the researchers have shifted their focus towards understanding how the AI effects are a function of the economic system. A research work by Fatun and Pazour (2021) considered the effects of AI on employment with a focus on the Czech Republic. In their studies, they observed that when it comes to AI, one has to look at the structures of the regions to see what awaits the regions. The authors also established that the impacts of AI can differ with the structure and stage of development of an economy and its technology, implying that more targeted policy measures are needed to address what happens in specific labor markets.

In a similar context, Lane and Saint-Martin (2021) have provided a detailed investigation of the positive impacts of AI on the labor market. They incorporated prior studies, provided a complex view, and explained that, though the application of artificial intelligence increases productivity and taps the potential of new occupations, there is a potential threat of occupational automation and wage inequality. Most pointedly, they noted the polarizing effect of AI across industries, job types, and skill levels, and called for policies properly allocate the gains from AI.

Over recent times, the focus has changed, and it has become important for scholars to locate the value of AI in building and learning capacity. This area of the literature was thus expanded by Shiohira (2021) in a UNESCO study. From the study, it became clear that, to accommodate the dynamic nature of the job market driven by AI, education systems needed to change. This study also noted that preparation should be made for development not solely of rather specific efficient AI-compatible technical skills and knowledge, but also of higher-order problem solving, reasoning, and arguing abilities, as well as for enhancing values and competencies related to emotions and social interactions, and for broadening the conversation into the domain of educational policy as well.

Zarifhonarvar (2024) investigated the influence of language models, including ChatGPT, on various occupations with a primary focus on those that require some degree of understanding. This research provided current information of just how current AI systems are changing the face of employment. This study focused mainly on the roles of employees affected by automation, claiming that whereas certain jobs are at a potential risk of being automated, there are new emerging roles that require assisted AI; this shows the level to which continual workforce transformation and rejuvenation are being exercised through reskilling programs.

It is clearly noticed that there are probable future research questions in this new area, given that the AI technologies are likely to advance further, such as the creation of new forecast models, the enhancement of the impact of the latter by sectors, and the consideration of the potential for the emergence of new categories of professions by AI. However, one must also realize that the development of AI is an ongoing process, which implies that its impact on the labor market must be assessed continuously to facilitate the right policy response.

Hence, let it be noted that the discussions and analyses of the effects of AI application in the labor markets were launched merely in the last decade; thus, it is possible to observe the course of more and more complex and refined understandings of the implications of Artificial Intelligence in this sphere. The social effect and the alterations that AI appears to be bringing in are therefore the subject of discussion in the future to direct future policies to encourage the positive use of AI while bearing in mind the negative impacts of employment and the structure of economies. In the following section, we will discuss in more detail the effects of AI on several aspects of labor markets.

3. The Current Impact of AI on Reshaping the Employment Patterns Across Different Sectors and Labor Skills:

The use of Artificial Intelligence (AI) in many different fields is practically revolutionizing employment around enterprise, occupation, and skill type. This means that this process of transformation is creating employment, but also treating employment as a structural change that displaces work and transforms the nature of work across the world.

In manufacturing, AI and Robotics technologies have been the most prevalent in skill displacement, especially for low-skilled employees. Using US data for the period 1990-2007, Acemoglu and Restrepo (2020) demonstrated that each additional robot per thousand employees reduces the employment-to-population ratio by approximately 0.2% and wages by 0.42%. This trend has continued in 2023, with the International Federation of Robotics stating that the average robot density in manufacturing worldwide reached a new high of 141 robots per 10,000 employees. But this displacement is not manufacturing subsectors. Automated assembly lines have been present in automotive manufacturing. Still, Aerospace or a specialized electronics industry demands skills that are far more complex than simple assembly line work but even here, but Aerospace or a specialized electronics industry demands skills that are far more complex than simple assembly line work. Still, even here, AI is supplementing the human element.

On the other hand, AI has created high-quality jobs in high-skilled occupations, especially in the IT sector and analytics. LinkedIn’s Jobs on the rise for 2023 highlights that AI and Machine learning specialist jobs have been on the rise for years growing at a compound rate of 32% per year from 2016 to 2023. There are new occupations, such as AI ethicists, data scientists, machine learning engineers, and robotics engineers, due to the increasing use of AI across various sectors of the economy. According to the Future of Jobs Report 2023 published by the World Economic Forum, the global economy is expected to generate 69 million fresh jobs by 2027, with several of the jobs associated with Artificial Intelligence and Data analysis.

Furthermore, another example of a particular sector in which the processes associated with AI is affecting the transformation of traditional professions is the financial sector. Certain individuals view AI as a threat to certain occupations, for example, call center agents and data clerks, while in fact it is enhancing human functioning at higher levels. For example, the JPMorgan Chase Company has digitalized contract interpretation through the Contract Intelligence (COiN) which operates on artificial intelligence and natural language processing to handle legal documents and give pointers to vital markers and clauses in mere seconds, an activity that once required 360000 working hours of the lawyers. It has not, however, led to grand-scale dismissal of lawyers; instead, lawyers have shifted to higher-level work that requires professional decision-making and creativity. However, a study done on Wells Fargo reported that 200,000 employees in the banking sector in the USA could lose their jobs to AI in the ongoing decade; it is a structural change that has happened in the banking sector in general.

As it is observed from the real area namely the healthcare industry, there are new professions on the one hand, and there are professions which are being replaced by AI on the other hand. The integration of AI in diagnosis, such as in Radiology, has not completely done away with Radiologists as was anticipated earlier. Instead, it has enlarged their facilities to turn the focus to other kinds of situations and meanings that each of them apparently finds less comfortable to handle. In his 2019 paper in Nature Medicine, Topol concedes that AI may ‘replace’ traditional healthcare practitioners in the broadest sense, but will actually generate new professional profiles, such as ‘clinical AI specialists’. It prevails in the job market, and the United States Bureau of Labor Statistics suggests that the growth of healthcare employment positions will be 13% between 2021 and 2031, which is above the average level for all occupations.

It is also noticed that the effect of AI on jobs has been a mixed bag in the Retail Sector, which means you have job elimination and job formation both simultaneously. The perks of such technologies, such as the self-check kiosks and the inventory-following robots, are making changes in the in-store roles, in the same manner as they are creating new roles and titles such as e-commerce specialists, data analysts, and customer experience designers. This new trend can be illustrated by an application such as Amazon Go, where there are no cashiers at all, but new positions in the spheres of technology and customer service. However, the notion of change is massive on retail employment; as per the Brookings Institute analysis of 2020 about 47% of the employees in retail will be affected by automation.

The application of artificial intelligence solutions is slowly entering the teaching duties in the education sector. Instead of replacing them, in the case of teaching positions, AI is merely redefining how people work. Other intelligent adaptive learning technologies, such as Carnegie Learning’s MATHia, are providing better prospects for devoted time to teacher intervention, allowing them more time with students and helping them discover what they need. This change implies that the teachers should develop new competencies in data analysis and in the formulation of student-centered teaching approaches. As for jobs in education, the effect is mixed: According to the U.S. Bureau of Labor Statistics, high school teachers are expected to add 4% from 2021 to 2031, but needless to mention new profiles like AI education specialist or learning experience designer.

Self-employment and independent contracting, that is part and parcel of the gig economy, have also not been left behind by the advances in AI. Currently, numerous popular firms like Uber and Deliveroo are using AI for tasks such as assigning, pricing, and creating new forms of employment, but at the same time raising issues concerning employment rights and guarantees. According to the World Economic Forum's Future of Work report, about 32% of workers worldwide are now classified as freelancers, temporary workers, or agency workers.

4. Long-term Effects of AI Adoption on Job Market and Work

The consequences of different kinds of AI on the future job market and the general nature of work are diverse and represent as much potential as risks. When looking at the future, we are presented with a continuum on which are a set of positive options for jobs and employment, varying from the very pessimistic outlook centered around the lack of work, up to the optimistic view that envisages a new type of human-technology relations at work.

This implies that one of the key issues of concern is on jobless future as pointed by several studies which indicated that the rise of robots is likely to lead to high levels of unemployment. Frey and Osborne's (2017) study predicted that nearly half of U.S. employment would be in high-threat occupations over the next two decades. For example, a recent analysis by the World Economic Forum of the Fourth Industrial Revolution presented the contention that while 85 million people may lose their jobs by 2025 because of the way the division of labor between humans and machines is changing, 97 million new positions may become available that are better suited to this new division. This suggests that whilst job loss through displacement is a genuine problem, job creation in the new economy might offset it.

The character of work practices themselves is likely to change dramatically. AI has been predicted to take over simple and repetitive tasks in different industries, thus modifying the required skills in the labor market. A 2021 McKinsey Global Institute report showed that up to 375 million workers, or 14% of the global workforce, may have to change occupations by 2030 due to digitalization, automation, and improvements in AI. This shift highlights the jobs that require human input such as creativity, emotions and other facets that make human beings to be different from robots hence cannot be easily replaced by technology in the near future.

Discussing such changes in light of AI is not to blame the technology for disruption; on the contrary, the healthcare sector offers an interesting example for understanding how work might be transformed without job elimination. Diagnostic and treatment planning involve the use of artificial intelligence tools in the current society. For instance, a study published in the British Medical Journal Nature in 2020 revealed that an artificial intelligence system beat human radiologists at detecting breast cancer. Instead of making their work redundant and replaceable, this technology is helping radiologists in enhancing their efficiency and doing more value-added analysis on cases that require their attention and spend more time with patients. This is evidenced by the US Bureau of Labor Statistics' expected job openings, which indicate that employment for radiologic technologists is expected to grow by 7% between 2019 and 2029, a higher rate than most general occupations.

Regarding manufacturing enterprises that have already experienced the dominance of automation, recent trends include 'cobots' – collaborative robots. Some of them are used to assist people with their tasks and increase efficiency and decrease the risks of accidents. According to the International Federation of Robotics report in 2021, firms installed cobot units even as the global economy declined by 11%. This trend suggests that the future of workforce will closer involve human and artificial intelligence in most careers.

In addition, the freelance economy, where independent workers use applications powered by artificial intelligence, is another change of work. Services such as Uber used 3.9 million drivers worldwide in 2020 and apply AI to everything from route selection to driver and passenger selection. Although these platforms have indeed provided jobs that can be done at convenient hours, they also have triggered issues to do with job insecurity and workers' remuneration. Consequently, the extent of the emergence of this AI-driven form of employment and its effect on the regular employment mechanisms is still disputed and investigated in the longer run.

On the other , which is seen firsthand, AI can complement human work rather than replace it, as seen in disciplines such as scientific research. In 2020, DeepMind produced an AI system able to identify the solutions to the protein folding problem, a dilemma no scientist has solved for the past thirty years. This accomplishment does not make human scientists obsolete; instead, it equips them with a stronger tool to accelerate research in areas such as pharmaceuticals and biotechnology.

However, the advantages and the obstacles relating to the input of AI may not be enjoyed or experienced by all the individuals or organizations engaged in a particular mundane. The Brookings Institution conducted a survey in 2021 that showed that AI exposure differs by demographic, with white-collar workers, who are usually paid better, having a higher risk of exposure to AI work applications. This raises some profound questions, namely the issue of fairness and the need for an AI policy that will put AI to work addressing the needs of the wider populace, not only the selected few.

Moving to the future, proposal which drew significant interest as the policy solution towards AI-induced employment erosion is the Universal Basic Income (UBI). Although it is still a highly polemic and debated topic, experiments regarding UBI implementation are underway in several countries. For instance, a trial of UBI implemented in Stockton, California over 2019-2021 enabled the establishment that assured income lessened income uncertainty, uplifted full-time employment, and gave a boost to mental health among the involved population. They may become more important in the future as various societies face AI-induced employment challenges.

In conclusion, one can state that the long-term consequences of increased usage of AI in businesses is going to be continuing and diverse. However, although people have reasonable concerns about job losses, the picture shows a viable future in which many professions will shift, but few will vanish completely. Hence, the success of the transition to AI-augmented reality depends on society’s capacity to adjust educational systems, labor market regulations, and economic models. Therefore, as we proceed; encouraging human-centric AI partnership or human-automation co-operation, another obvious task that would have to be achieved is the development or continuation of policies on skills enhancement, and perhaps most important investment or promotion of policies aimed at ensuring that risks posed by the rise of AI do not result in a negative long-term impact on workers and societies.

5. Economic Consequences of AI: Wage Structures, Income Inequality, and Labor Market Dynamics

It is clearly noticed that AI is making its way into the global economy and the future of wages, income, and the labor market. However, the effects of AI on wages are not the same in all sectors, and they differ from one sector to another. Currently, some labor force policies have yielded significant wage gains in the tech industry due to the scarcity of personnel in artificial intelligence. According to the study carried out by Stanford University in the year 2021, AI workers in the United States earn an average of $126,000 per year, while other computer and IT workers earn an average of $88,240 per year.

AI is also helping to support the ‘Winner Takes All’ market structures, especially in the technology market, which remains the most active in the AI field. In 2023, he top five Tech companies: Apple, Microsoft, Amazon, Alphabet, and Meta captured more than 25% of the market capitalization of the S&P 500, suggestive of the fact that a huge concentration of wealth is being garnered by those industries that lie primarily on the frontier of AI technologies. The phenomenon of industry structure characterized by a high level of Concentration Ratio has significant effects on competition in markets and on the distribution of incomes.

The role of AI in changing the dynamics of total available employment opportunities, Hence, the World Economic Forum’s report for the future of jobs titled “Future of Jobs Report 2020” anticipated that up to 85 million jobs may be displaced by automation and other forms of capital by 2025, but indicated that 97 million new jobs may be created. However, the new employment opportunities may not necessarily be located in the geographical areas where the displaced workers are domiciled, resulting in structural unemployment and requiring a significant amount of retraining.

However, AI also creates possibilities for new forms of a 'career track' in the economy. The use of AI to deliver online learning is making quality education more accessible. The use of AI to deliver online learning is making quality education more accessible, thanks to the growing democratization of education. For example, Coursera claimed to have 77 million learners across its portfolio in 2021, many of whom were enrolled in AI or data science programs. This would mean that there could be a decrease in barriers to entry for highly skilled technology vocations through these enhancements in education and skills training.

AI technologies are also making the industry more competitive by reducing enabling small businesses and new start-ups to overcome barriers across different fields, enabling them to compete fairly with large organizations. The use of AI in market analysis, customer relations, and product design is increasingly available to SMBs, which can promote innovation and, at the same time, economic growth.

Regulation of AI technologies and ways to measure progress towards algorithmic bias, or the absence of it, will be critical in mitigating harm from inequality. The issue of ethics will come into play in the design and implementation of the AI so that value is captured for the AI while at the same time the inequalities and disparities in society are not deepened.

Consequently, it is possible to outline that the changes that can stimulate can stimulate can stimulate that can be stimulated by AI are rather profound and versatile; the further development of AI will lead to changes in wage levels, income differentiation, and labor market features. With these possibilities, therefore, artificial intelligence poses real dangers of extending present inequities while at the same time opening the way to the construction of new forms of mobility. The final effect would therefore be relative to policy decisions and the way societies choose to deal with the transition to 'AI'. Further research will be needed to look into how these policies can be fine-tuned in order to make businesses and other institutions, such as governments and educational facilities, employ AI in a way that will benefit the economy and minimize the adverse effects.

6. Evolution of Skills and Education in an AI-Driven Economy

As such, artificial intelligence is changing the way work is done, and creating significant shifts in the foundational knowledge one needs to function and be able to get a job in the current labor market. As AI technologies developed and full-scale implementation of AI into various sectors rose, new skills emerged that have the potential to transform future education and training of personnel. It is therefore possible to note that, when discussing technical skills, they are relevant only in the sphere of AI-related fields. Referring to the professions in the list of the new emerging jobs for 2023 presented on LinkedIn, some of the most rapidly developing occupations include such positions as AI and Machine Learning Specialists, whose occupation rate has shown a 2016-2023 compounding annual growth of 32%. Yet another study, conducted by Stanford University in May 2021, established that the proportion of AI-related job offers increased by 21% annually between 2015 and 2021. Among all the technical competencies that are crucial are specialists who have been identified to be in high demand, and they include: machine learning, natural language processing, computer vision, big data and analytics, and cloud computing.

Surprisingly, there is a trend that the three or four growth components of artificial intelligence — factual, physical, and emotional —are actually making human skills more precious. According to the Future of Jobs Report 2023 of the World Economic Forum, the education and skill prerequisites expected for the future forecast are effective thinking, analysis, and innovation. This view was supported by a Deloitte's survey, which was conducted in 2022, where 74% of the executives who responded to the survey said that soft skills will be valued more when AI is scaled up. Current emergent competencies are flexibility and lifelong learning, emotional intelligence, critical and creative thinking, innovation/s, leadership and people competencies.

There is also an emerging acceptance of persons who can flip between technical and non-technical job markets. A study conducted by IBM in 2021 relative to the impact of the shift, ‘‘hybrid jobs ‘’ that entail a need for technical and soft skills are becoming more common, and are among the highest paid. This trend is evidenced by terms such as ‘AI Ethicist’, or ‘Human-AI Interaction Designer’ because they entail a combination of technology, ethics, and aesthetics.

These changes in required skills are posing a lot of pressure on the existing education systems. It is seen that educational institutions are now and then updating the syllabi in the field of Artificial Intelligence and Data Science. For example, the Massachusetts Institute of Technology (MIT) launched a $1bn project in 2018 to establish a new college focused on AI and its use. In 2023, more than eight hundred universities in the globe offer specialized AI degree programs. Technological changes are also happening at a fast and furious rate, and thus it has become necessary to learn continually.

AI, in the first place, is being employed in the transformation of education delivery. According to a McKinsey research report published in 2023, the AI-assisted model of learning could increase student performance by about 30 percent. Carnegie Learning’s MATHia – an adaptive learning platform – was found to have boosted test scores in mathematics by as much as 11%provides evidence of AI’s effectiveness as a tool for improving education.

People and companies are adopting several measures to address shifts in required skills. There is significant capital expenditure on reskilling employees in organizations these days. For instance, Amazon announced in 2019 an additional $700 million over five years to restructure 100,000 of its employees to develop AI and other technical competencies by 2025. The Grow with Google program is Google’s action plan to impact at least 100 million people, providing resources to help job seekers and workers advance their careers since its inception in 2017. Many compact and specific educational courses, such as micro-credentials and Nano-degrees, are emerging at the present time. In 2023, Udacity claimed that more than 14 million students were currently taking its Nanodegree programs; the most popular tracks were artificial intelligence and data science. That is why, according to a 2022 study by Northeastern University, 68% of HR leaders claimed micro-credentials are the solution to the skills gap.

However, several challenges constrain the advancement of skills and education in an AI Economy. The literacy gap remains a problem, as a 2022 UNESCO report showed: 83% of students in low-income countries have no internet access for online classes, while only 10% of students in high-income countries don’t have internet access for online classes. This fast rate of advancement in technologies also bears some evidence of some of the challenges to education systems. Gartner report from 2023 revealed that today the half-life of a profession skills is five years, meaning that what one learns today may be obsolete in five years’ time. Moreover, as AI is applied more frequently, it becomes relevant to determine what is right or wrong in AI cases. A study conducted on 331 organizations in February 2022 by Deloitte disclosed the reality that only 35 percent of these organizations have precise and stringent AI ethics policies, but leadership is not fully proficient with these policies.

7. Sector-Specific Impact of AI on Industries and Job Types

The banking and financial services industry is one of those industries that have started using AI technologies mainly in the area of fraud and credit risk analysis. Decision Intelligence by Mastercard has now minimized the false negatives to as low as half and has also improved the ability to detect fraud. What has been done at JPMorgan Chase in legal document analysis by applying COiN is that some tasks that legal professionals were spending 360,000 hours per year doing have been automated and can be done in seconds. Flow strategies are also changing, JPMorgan estimated that such trading automation in the year 2020 was 60 percent from US equity, ten percent in 2000. Aladdin is the AI engine of BlackRock, the world’s biggest asset manager, which manages $21.4 trillion in 2023.

In finance however, efficiency is relatively; a report from Wells Fargo published in 2019 revealed that some 200,000 banking positions in the US can be automated through the application of Artificial Intelligence over the next decade. There are, however, new roles, and, according to the LinkedIn 2023 Jobs on the Rise report, 'Finance AI Specialist' is one of them.

Today, in the manufacturing industry, the Fourth Industrial Revolution is promoted with the help of AI in such segments as, for example, predictive maintenance or quality control. The McKinsey digital trends for 2021 revealed that, on average, artificial intelligence-enhanced prognostic maintenance in production reduced the overall annual maintenance cost by 10% and, in the most favorable cases, cut the time organizations spend maintaining their production processes by up to 20%. According to some Siemens customers, they were able to cut the frequency of unexpected breaks in half thanks to AI-based applications. In quality control, the company of BMW has adopted an image recognition system that is based on artificial intelligence to detect defects on the production line, whereby the company asserted that the system can accurately detect defects with 100% and also has increased productivity of manufacturing by 5 percent. While certain occupations are steadily automating, new occupations are emerging in the market as well. In a report published by the World Economic Forum in 2021, through the application of technology, human and machine working hours to complete current tasks may be equal; thus, the report indicated that 85million jobs may be automated while 97 million new roles may be generated. The number of industrial robot technicians employed in the U.S. is expected to increase by 12% between 2021 and 2031, as noted by the U.S.

New ideas of retail and e-commerce are emerging with the help of AI that offers high levels of personalization and efficient inventory management. McKinsey reported in 2019 that the AI recommendation engine at Amazon contributes to 35% of the company's overall sales. At Walmart, the inventory tracking uses artificial intelligence and machine learning to optimize the supply system; through it, the bakery losses have been cut by one third.

In education, AI is assisting in the creation of more efficient learning methods. For example, a Carnegie Learning adaptive mathematics software, "MATHia," which has the element of artificial intelligence, helps students raise their math test scores by as much as 11%. A 2023 McKinsey study shows that if AI is employed in learning and personalized, children could improve their performance by 30%. At Georgia State University, AI chatbots are used in administrative work to answer students' questions, reducing 'summer melt' from 28% to 7%. The impact of computers on jobs related to education is rather complex, as some of the secretarial tasks will be taken over by computers, while the jobs of teachers will remain open. The US Bureau of Labor Statistics projects that employment of high school teachers will increase by 4 percent between 2021 and 2031. Some of these are the AI education specialists, and learning experience designers, and a survey by EdTech Magazine showed that 86% of higher learning institutions plan to hire more IT staff to support and integrate AI and other technologies into their 2022 institutions.

8. Conclusion:

This study has examined the multifaceted impact of AI on labor markets, job transformation, and skill evolution, addressing our main research question: What influence is Artificial Intelligence (AI) having on labor markets, job roles, and skill requirements across different sectors of the global economy? insights that help us understand how AI will shape the future of work.

8.1 Key Findings:

We find strong support for our central hypothesis that AI adoption is changing the economic landscape, driving shifts in employment, skill demands, and the economic structures of many industries. Specifically:

1. Employment Patterns: In support of our first sub-hypothesis, we found evidence that AI is rewriting employment patterns across sectors. Additional robots per thousand workers reduce the employment to population ratio by about 0.2%. What's of special note, however, is that highly skilled fields related to AI are also growing rapidly, with the number of jobs for AI and Machine Learning specialists rising at a compounding rate of 32% per year between 2016 and 2023.

2. Long-term Job Market Effects: We find support for the second sub-hypothesis of our study, that there is a complex long-term impact of AI on employment. According to the World Economic Forum, 85 million jobs will be lost by 2025, compared to 97 million new jobs, but the overall picture is positive, with significant changes in job types.

3. Economic Consequences: For our third sub-hypothesis of wage polarization, we were able to show evidence of AI playing a part. Although computer and IT workers in the United States on average made $88,240 per year, poorly specialists earned about $126,000; this gap suggests that poorly handled AI could increase income inequality.

4. Skill Evolution: The research supports our fourth sub-hypothesis; there is a growing need for technical AI skills and uniquely human skills. As highlighted by a Deloitte survey, which boasts an impressive 74 percent of executives, the need for a balanced skill set in the AI-driven economy grows as increasingly soft skills are becoming more important, and AI-related job offers rise rapidly (21 percent yearly from 2015 to 2022).

5. Sector-Specific Impacts: Results on our fifth sub-hypothesis confirm that AI's impact differs significantly across sectors. Overall, job replacement risk is highest in manufacturing and retail, closely followed by the transportation and materials sector. At the same time, healthcare and education will proportionately gain more than they lose from automation.

8.2 Policy Recommendations:

Based on these findings, we propose the following policy recommendations, with a particular focus on mitigating negative impacts on lower-skilled workers:

1. Targeted Reskilling Programs: All this is to say, governments and industries should work together to create and fund comprehensive reskilling programs for lower-skilled workers at risk of displacement. , both in the technical domains pertaining to AI-augmented jobs and in soft skills to complement AI capabilities, should be the focus of these programs.

2. Progressive Taxation and Universal Basic Income (UBI): To reduce inequality, we need to tax profits from AI much more progressively than is now the case and commit resources (sufficiently) into UBI programs. A Stockton, California, UBI experiment demonstrated positive effects on employment and mental health and could be mirrored.

3. Education System Reform: We overhaul education systems to be more based on lifelong learning, critical thinking, and adapting. Bring in AI literacy as part and parcel of every level of education to equip the workforce for an AI–driven economy.

4. Sector-Specific Transition Strategies: Adapt solutions for sectors most likely to see AI-driven displacement. They could involve phased automation, as illustrated in job-sharing programs and in sector–specific job–sharing programs and in sector–specific training initiatives.

5. SME Support: Support small and medium-sized enterprises (SMEs) in the financial and technical adoption of AI technologies so that SMEs can remain competitive and employ individuals.

6. Ethical AI Development: Create solid regulatory foundations to underpin AI development and use, to emphasize the safeguarding of lower skill work where practical, as well as ethical facets of AI-made decisions.

7. Regional Development Initiatives: Establish targeted regional development programs with the aim of forming new economic opportunities for places worst affected by AI-driven displacements of jobs through attracting AI-related industries and helping local entrepreneurship.

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ثورة الذكاء الاصطناعي في سوق العمل: استكشاف التحولات في الوظائف والتأثيرات الاقتصادية وتطور المهارات

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المستخلص: تسعى هذه الدراسة إلى تحليل قابلية تطبيق الذكاء الاصطناعي (AI) كقوة تحويلية في سوق العمل العالمي، وتحديداً على أهم الوظائف الحالية والمهارات اللازمة في مختلف القطاعات الاقتصادية. يعتمد التحليل في هذا البحث على دراسة آثار الذكاء الاصطناعي ليس فقط على التوظيف، بل أيضًا على الأجور وتوزيع الدخل، وما هي حدة هذه الآثار على الاتجاهات والتوقعات لمستقبل سوق العمل. إذ توصلت الدراسة إلى أن الذكاء الاصطناعي يتميز بطبيعة ثنائية الغرض والتأثير في سوق العمل، فهو يتسبب في زيادة البطالة في الوظائف الروتينية ومنخفضة المهارة كما في قطاعي التصنيع والتجزئة، ولكنه في الوقت نفسه يخلق فرص عمل عالية المهارة في المجالات المتعلقة بتكنولوجيا المعلومات. كما أن الآثار الاقتصادية للذكاء الاصطناعي ثنائية بالمثل: فهي إما تُفاقم عدم المساواة في الدخل أو تفتح مسارات اقتصادية جديدة من خلال توسيع فرص التعليم وتنمية المهارات. في المقابل، يختلف تأثير الذكاء الاصطناعي بشكل كبير عبر القطاعات المختلفة، إذ يُظهر التحليل أنه بينما يواجه قطاع التصنيع أعلى المخاطر التي قد تنتج عن عملية الأتمتة، إلا انّ قطاعي الرعاية الصحية والتعليم يواجهان تعزيزًا للوظائف أكثر من استبدالها. بالإضافة إلى ذلك، يمكن ملاحظة بأنّ هناك تزايد للحاجة إلى المهارات التقنية المتعلقة بالذكاء الاصطناعي من جهة، والقدرات البشرية عالية المستوى والفريدة، بما في ذلك الإبداع والذكاء من جهة أخرى. وبناءً على ذلك، قدّمت الدراسة عدد من التوصيات المهمّة، أبرزها يتعلّق بطرق تخفيف الآثار السلبية على العمال ذوي المهارات المنخفضة. إذ تستهدف هذه التوصيات برامج إعادة التأهيل، وإصلاحات نظام التعليم، واستراتيجيات انتقالية خاصة بكل قطاع. من المهم الإشارة الى أن هذا الجهد البحثي يُساهم في النقاش المستمر حول مستقبل العمل في اقتصاد يعتمد على الذكاء الاصطناعي، ويوضح الوتيرة التي نحتاج إليها للعمل لضمان توزيع فوائد الذكاء الاصطناعي على نطاق واسع في المجتمع.

الكلمات المفتاحية: الذكاء الاصطناعي، أسواق العمل، التحول الوظيفي، التوظيف.

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Climate Smart Agriculture in Egypt: Assessing Food Security with CGE and IMPACT Models

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Abstract: *Climate change is a global threat and is expected to reduce crop yield and income. This study aimed to develop indicators for the 'triple-win' nexus of productivity, livelihood improvement, reduced GHG emissions, and water footprints for climate-resilient practices. Two models were used: the IMPACT Climate and Hydrology Model to examine the link between climate change and crop productivity and the Computable General Equilibrium (CGE) model to assess the effects of climate-smart agriculture (CSA) on the agricultural sector. By 2050, climate change is projected to significantly lower crop productivity in Egypt, increasing commodity prices and worsening consumption, income, terms of trade, and food insecurity. However, the combined scenario addressing climate change and CSA showed that adaptation measures can mitigate these impacts and deliver modest benefits. These indicators reveal that CSA can partially restore growth above the baseline, emphasizing the importance of incorporating CSA into agricultural investment plans. CSA not only responds to the challenges of climate change, but also offers immediate advantages, as its technological benefits outweigh the negative impacts of climate change. Thus, CSA has emerged as a viable strategy for agricultural investment and future resilience.*

Keywords: *CSA; Climate change; Agricultural productivity; IMPACT model; CGE Model.*

I. Introduction

Scientific data analysis in climate change. The negative effects of climate change include droughts, increased rainfall variability, desertification, and decreased land productivity [1]. Throughout the coming decades of the twenty-first century, the complex interrelationship between environmental change, on the one hand, and agricultural productivity, on the other, will become one of the most significant debates. (Mahmoud, 2019). Climate change is expected to have a negative impact on crop yields and income (Carleton & Hsiang, 2016), posing a significant challenge for hundreds of millions of people globally (Adesina, 2010). Egypt is no exception; climate change can have a variety of effects on agriculture and food security. Plant

[1] IPCC (2019). *Summary for policymakers. In: Climate change and land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. Shukla et al., (eds.). In press.

production is harmed by rising temperatures, as are extremely hot weather, extreme heat events, droughts, plant diseases, and pests. Land use also changes because of flooding caused by rising sea levels, seawater intrusion, and secondary salinization (Mahmoud, 2019). Furthermore, crop water requirements are expected to increase.

While the world struggles with the potential impacts of global climate change, much attention has been paid to adaptation options, particularly for farmers in developing countries. Climate-smart agriculture is one of the most promising adaptations in the developing world and has sparked considerable academic and research interest in recent times (Amadu et al., 2020; Marenya et al., 2020; Tesfaye et al., 2021). Furthermore, climate-smart agriculture (CSA) can amid climate change. CSA has three objectives: (1) improving agricultural productivity, (2) building resilience to climate change, and (3) reducing agriculture's greenhouse gas emissions (Lipper et al., 2014). For example, the Global Alliance for Climate Smart Agriculture envisions 500 million farmers using CSA technologies by 2030 (Carraro, 2016), which will result in significant improvements in land sustainability and poverty reduction.

The CSA approach was introduced in 2010 at the First Global Conference on Agriculture, Food Security, and Climate Change, and because it is relatively new, its economy-wide effects remain understudied. Most CSA economic studies are at the farm household level, estimating the determinants of CSA adoption and their impact on crop yields (Abd El Mowla & Abd El Aziz, 2020). Some studies have discussed the effects of CSA and its variants on irrigation systems (Fawzy & Shedeed, 2020). Despite high expectations and lofty or ambitious objectives, there is little quantitative evidence at scales beyond farm households on the economic advantages of CSA over traditional input-intensive technologies. The general consensus is that CSA increases farmers' food security and income (Thornton et al., 2018). In addition, quantitative estimates of the benefits and trade-offs of CSA technologies are required to support investment planning and priority setting, especially at the national, subnational, and farm levels. We assessed the opportunity costs of CSA by comparing it with input-intensive technologies. There are a few studies dealing with the economy-wide effects of CSA on Egyptian agriculture, e.g., (Fawzy & Shedeed, 2020; Abd El Mowla & Abd El Aziz, 2020).

As previously mentioned, climate change poses substantial threats to Egypt's economic growth, food security, and poverty reduction prospects, owing to its high exposure to biophysical effects and limited adaptive capacity. Egypt hosted the UN Climate Change Conference COP27, which sought to address environmental and climate change issues across all sectors, not just agriculture, but this paper focuses only on agriculture. Therefore, it is necessary for Egypt to integrate adaptation plans into its development strategies to address the unavoidable impacts of climate change. Rational adaptation planning requires a forward-looking empirical assessment using a quantitative approach to assess the potential effects of climate change on economic performance by comparing the benefits and costs of conceivable adaptation measures. The main objective of this study is to analyze the potential economic and social impacts of deteriorating weather conditions on economic growth and food security in Egypt, with detailed analysis of their impacts on rural and urban households. The exclusive focus on agricultural performance is through the consideration of additional impact channels and the use of a newly built social accounting matrix that provides a holistic account of the agricultural sector, coupled with a highly diversified population, thereby utilizing a general equilibrium model that captures the potential effects of climate change and the adaptation strategy on food security in Egypt for different households.

As a result, one of the goals of this study was to develop indicators of the triple-win nexus of productivity, contributions to livelihood and household income, and reductions in GHG emissions and water footprints for each climate-resilient practice or set of practices. So is the farmer's viewpoint about the adaptability of scaling up these practices. Potential roadblocks and policies that can undermine wider adoption are likewise generated, as are support policies and ancillary services. Furthermore, policy modelling of upscaling the production and value-adding chains of prioritized adaptation technologies emphasizes their effects on the agriculture and food sectors, as well as on the economy-wide income and employment effects in other sectors of the economy. Similarly, CSA's potential contribution to achieving development goals, such as poverty alleviation.

The remainder of this paper is organized as follows. Section 2 provides a non-technical description of the analytical framework and models; Section 2.1 discusses future climate prediction and its impact on productivity, and Sections 2.2 and 2.3 discuss the theoretical basis of the ADAPTs and Computable General Equilibrium (CGE) models, as well as the data sources on which those models rely. Section 3 examines the hypotheses chosen to identify future climate scenarios. Section 4 presents the baseline and simulation results and explores the net impact of the simulated economic outcomes in the presence of policy-led adaptation measures. Finally, Section 5 presents the conclusions and recommendations.

II. METHODS

The economy-wide modelling component of this study involves linking a CGE model to a range of climate change impact models to generate quantitative estimates of impacts on agriculture and livestock in Egypt (as shown in Figure 1). The study relied on two main models in order to analyze the climate impact and explore options for the future of climate smart agriculture: IMPACT with the Climate and Hydrology Model is used to analyze the relationship between climate change and crop productivity; second, the CGE model is used to emphasize the effects of CSA on the agriculture and food sectors and economy-wide income and employment effects on the other sectors of the economy (as shown in Figure 1).

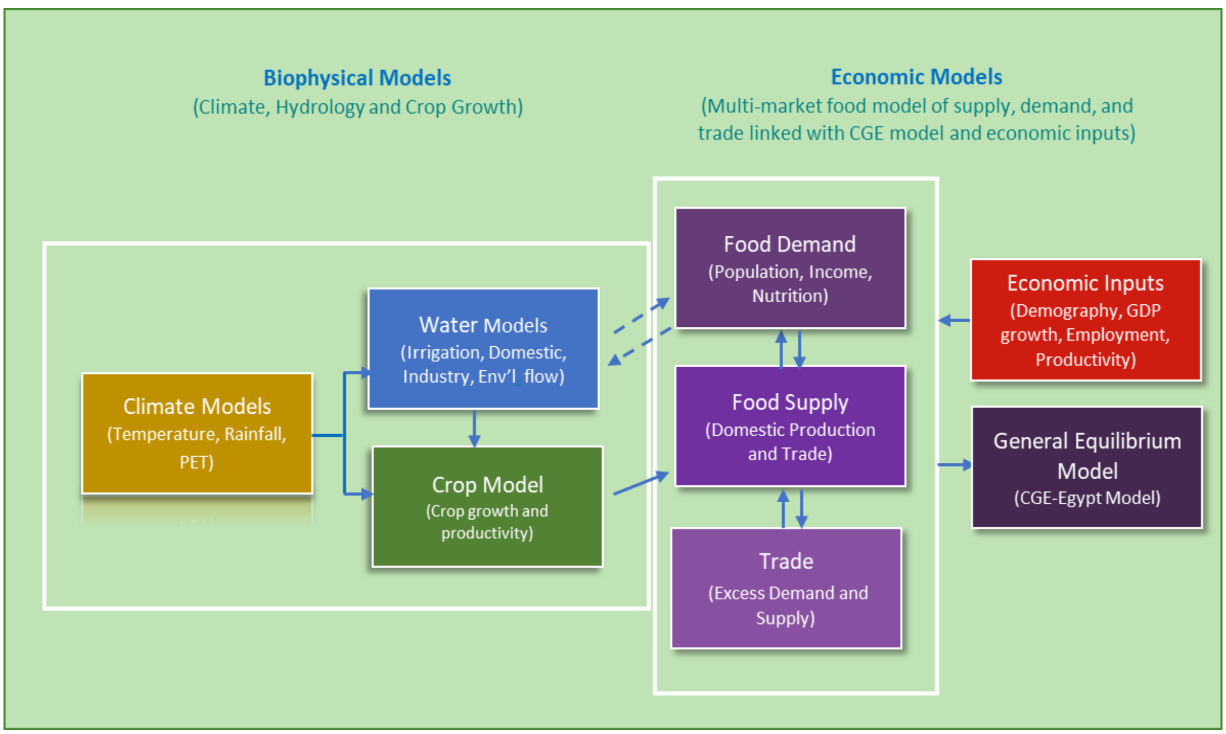

Figure 1. Graphical representation of biophysical-economic models.

III. Change in crop production due to climate change (Climate crop model). And Scenarios for upscaling climate-smart agriculture adaptation: policy and operational framework

It is clear that the agricultural sector in Egypt is particularly vulnerable to the harmful effects of climate change. Additional negative impacts are expected to worsen as the agricultural sector and agroecological systems deteriorate, as they are of great importance to the Egyptian economy.

a. Change in crop production due to climate change

Table 1 clarifies the potential impacts of climate change on the productivity of major crops in Egypt and concludes that climate change could reduce domestic yields of food crops, which are projected to decline by 10.29 percent by 2050. Maize (16.16 percent), sugar crops (11.96 percent), fruits and vegetables (11.66 percent), and rice (8.78 percent) were expected to experience the greatest decline in biophysical yield. The productivity decline is less for wheat (2.81 percent), whereas biophysical impacts result in a small increase in productivity for roots and tubers (0.47 percent). Estimates of climate change impacts on animal-source food production (e.g., meat, dairy, and eggs) were derived indirectly from their effects on animal feed and are thus conservative. Moreover, the model does not include any estimate of climate-induced heat stress effects on animals, which may negatively affect productivity. This study was based on the IMPACT model results and previous literature, and these results were used to direct the shock to the CGE model.

Table 1. Changes in productivity due to climate change, biophysical and economic effects of climate change, Egypt by 2050.

Commodities	Biophysical effects				Combined Biophysical and Economic Effects	
	Heat Stress	Water Stress	Salinity	Cumulative Effects	Egypt	Rest of World
	--------------- % change from NoCC -------------------------					
All food crops	-4.94	-4.14	-1.55	-10.29	-6.17	-5.24
All cereals	-4.66	-2.57	-1.59	-8.59	-10.36	-7.74
Maize	-12.86	-2.46	-1.36	-16.16	-19.54	-17.66
Rice	-5.81	-1.59	-1.58	-8.78	-8.53	-5.61
Wheat	2.27	-3.25	-1.78	-2.81	-0.56	0.82
Fruits and vegetables	-4.73	-5.88	-1.48	-11.66	-8.28	-1.95
Oilcrops	-6.98	-3.18	-1.53	-11.31	-12.08	-6.69
Pulses	-5.46	0.04	-1.57	-6.92	-9.98	0.01
Roots and tubers	0.26	-0.29	-1.79	0.47	3.56	-4.58
Sugarcane	-6.66	-4.19	-1.56	-11.96	-13.28	-10.39

Source: Estimates derived from IMPACT results.

There has been a decline in domestic supply caused by the effects of climate change on productivity. The prices of agricultural commodities are expected to increase by varying amounts, highlighting price levels. Table 2 shows the projected price increases for agricultural commodities. The results show increases in the prices of agricultural commodities. Moreover, although cereals and wheat crops are a significant part of Egypt's agricultural economy, vegetables and fruits also play an essential role in rural livelihoods. The expected increase in the prices of cereals (+14), maize crops (+22.8%), rice crops (+18.7%), wheat crops (+2.5%), fruits and vegetables (+10.2%), in Egypt, will create a problem for food security. Therefore, we must learn about CSA techniques that can reduce the impact of climate change, which is discussed in more detail in the next section.

Table 2. Changes in Prices due to climate change, Egypt by 2050.

Food commodities	Prices of Food		
	No Climate Change	With Climate Change	Change
	------- US$/mt --------		%
All meat products	3,411	3,581	5.0
Beef	4,203	4,317	2.7
Lamb	4,540	4,609	1.5
Poultry	2,780	3,024	8.7
Dairy	588	594	1.1
Eggs	2,539	2,685	5.7
All cereals	268	305	14.0
Maize	212	260	22.8
Rice	427	507	18.7
Wheat	286	293	2.5
Fruits and vegetables	1,184	1,305	10.2
Oilseed crops	552	662	20.0
Pulses	1,132	1,217	7.5
Roots and tubers	448	518	15.8
Sugar	412	442	7.4

Source: Estimates derived from IMPACT results.

b. Scenarios for upscaling climate-smart agriculture adaptation: policy and operational framework

This section identifies adaptation measures for Egypt's agriculture due to future climate change. The latter are in the agricultural sector.

This study used the IMPACT model developed by IFPRI (Robinson et al., 2021) with a scenario-based approach to assess the effectiveness of various technology suites in mitigating the impacts of climate change on the agricultural sector. However, they combine complementary technologies to obtain additional productivity increases and cost savings. Technologies from several technology bundles tend to be more complementary than technologies within the same bundle, which can be mutually exclusive (an exception is combined heat and drought stress tolerance). The joint application of complementary technologies, also called technology stacking, combines technologies from each bundle — soil fertility, seed technology, crop protection, and water management. Stacking technologies, as simulated, increased productivity by 10.4 percent for rice, 19 percent for maize, and 7.8 percent for wheat (Table 3, last column).

Table 3. Yield effects of moderate adoption of a suit of climate-resistant technologies for staple foods, Groups, Egypt, by 2050 (moderate adoption rate)

Food commodities	Yield effects of Climate Change	Minimum Yield change to counter Climate Change	Suite of climate-resilient technologies				
			Seed Technology	Soil Fertility Mgt	Irrigation and Water Mgt	Crop Protection	Stacked Technology
	% from NO CC	-------------------- '% change from climate change scenarios --------------------------					
All food crops	-6.2	6.6	9.9	4.7	1.7	3.7	13.2
All cereals	-10.4	11.6	7.2	7.3	1.5	3.1	12.7
Maize	-19.5	24.3	13.6	10.1	1.4	3.0	19.0
Rice	-8.5	9.3	7.3	3.5	1.7	3.5	10.4
Wheat	-0.6	0.6	1.4	5.9	1.6	3.4	7.8
Fruits and vegetables	-8.3	9.0	12.4	6.0	2.0	4.6	16.5
Oilseed crops	-12.1	13.7	8.8	4.7	1.6	3.3	12.2
Pulses	-10.0	11.1	5.8	3.0	1.6	3.6	9.0
Roots and tubers	3.6	-3.4	4.3	2.3	1.6	2.3	6.6
Sugar	-13.3	15.3	8.5	4.3	1.6	3.3	11.6

Source: IMPACT simulations.

IV. Simulating economywide effects

Baseline scenario: The difference between the baseline projection and the policy shock reflects the impact of a policy change, derived from simulations for both the policy scenarios and the baseline. Initially, information on the future benchmark equilibrium under normal conditions is required to develop scenarios. The "business-as-usual" scenario serves as a reference path for the growth of the Egyptian economy, representing a steady-state equilibrium in the absence of irrigation development project impacts (a fictitious baseline without CSA technology). It used a baseline for comparison with the irrigation development project scenario. This "business-as-usual" scenario assumes that the 2015 trends continue until 2050. The baseline is not a forecast but rather a continuation of past trends. Therefore, the baseline is meant to provide a reasonable approximation of trends and expectations based on available information. To simulate the baseline, population and labor supply grow at a 2.44% annual rate, farmland expands at a 1% annual rate, and capital stocks accumulate at a 3.0% annual rate. In the counterfactual baseline scenario (without the CC effect and CSA technology), the economy is growing steadily at a long-run growth rate of 5.27% (Figure 2). Look at figure 3, which shows that exports and investment demand must rise by 8.14% and 5.26%, respectively.

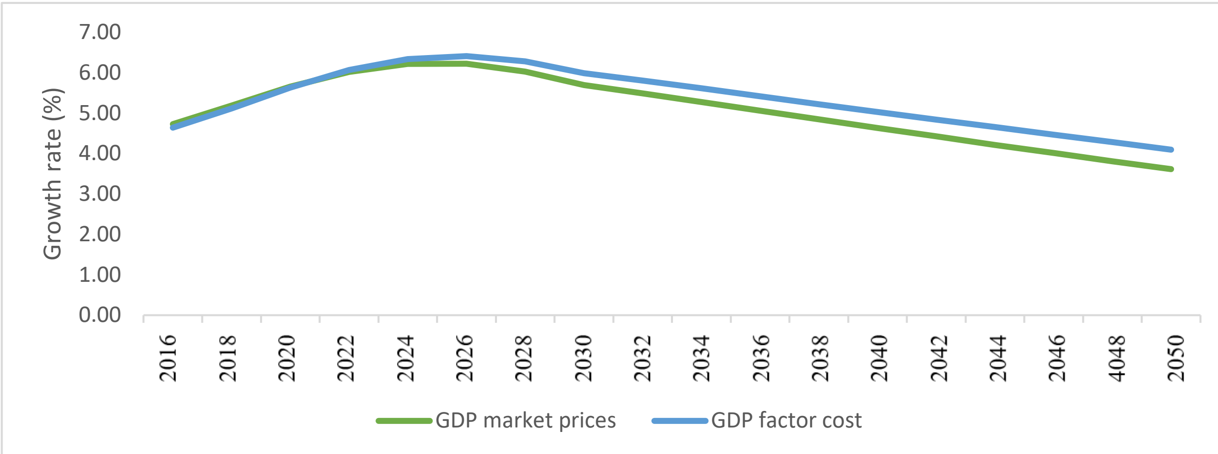

Figure 2. Gross Domestic Product (GDP).
Source: results of CGE model.

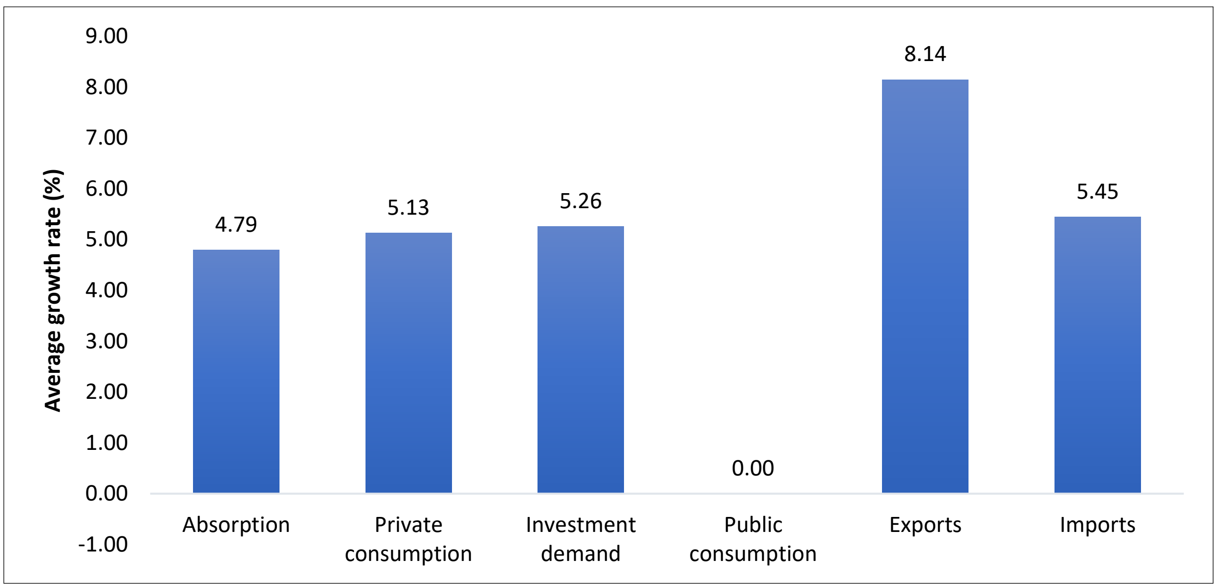

Figure 3. Macroeconomic Results.
Source: results of CGE model.

The Egyptian agricultural sector constitutes 11.7% of the GDP, 25.4% of employment, 6.7% and 4.3% of imports and exports, respectively. An in-depth examination of the agriculture sector, the crop sub-sector, and livestock are the two most significant components, accounting for about 6.3% and 4.3%, respectively, followed by fishing at 1.1%. Also, crops dominate agricultural trade, with 8.6% imported, whereas 2.6% of all agricultural products consumed in Egypt are exported (Table 4).

Table 4. Structure of the National Economy

	Share of total (%)				Export/	Import/
	GDP	Employment	Exports	Imports	output (%)	demand (%)
All sectors	100	100	100	100	7.5	12.8
Agriculture	11.7	25.4	4.3	6.7	2.6	8.6

	Share of total (%)				Export/	Import/
	GDP	**Employment**	**Exports**	**Imports**	**output (%)**	**demand (%)**
Crops	6.3	14.9	4.3	6.5	4.7	14.2
Livestock	4.3	9.5	0	0.2	0	0.7
Forestry	0.1	0.1	0	0	0	0
Fishing	1.1	0.9	0	0	0	0
Industry	31.3	24.8	48.6	67.9	7.2	17.3
Mining	9.1	0.3	14.4	5.9	16.2	11.8
Manufacturing	16.1	11	32.7	59.7	7.9	23.3
Agro-processing	3.7	3.5	4.4	7.4	4.2	12
Other manufacturing	12.4	7.5	28.3	52.3	9.2	27.1
Other industry	6.1	13.5	1.5	2.3	0.9	2.3
Services	57	49.8	47.1	25.5	8.9	7.8
Trade and hotels	17.8	14.2	16.3	5.3	10	5.5
Transport & communication	7.8	8.4	25.3	11.2	35.6	28.4
Finance & business	16	4.7	4.3	7.7	2.9	8
Government services	13.1	18.9	1.2	1.2	1	1.6
Other services	2.4	3.7	0	0	0	0

Source: Authors' compilation

V. Results

a. An Adverse impact of climate change on the Egyptian economy by 2050.

The climate change scenario examines the adverse effects of climate change on crop productivity, which gradually increases from 2050 onward. According to future productivity and price shocks, as described in tables 1 and 2. Accordingly, GDP is an essential tool for assessing the macroeconomic impacts of climate change on agriculture. Moreover, GDP is essential for estimating changes in the Egyptian economy, with agriculture accounting for approximately 11.7% of GDP. In this new context, the impact of climate change on yields will lead to direct and indirect economic impacts, including reductions in employment, income, imports, savings, and investments. These effects were captured in the CGE results as described below. Table 5 shows the percentage deviations from the benchmark growth path for macroeconomic indicators by 2050. The decrease in crop yields would reduce GDP and agri-GDP by 1.28% and 5.21%, respectively, relative to the baseline. A similar decrease in the present value of domestic absorption (household consumption, gross investment, and government consumption) is expected, amounting to approximately 0.55%. Private consumption and investment demand were expected to decrease by approximately 0.45% and 1.12%, respectively. However, CPI will rise by about 0.01%; this is to reduce supply (total production resulting from low productivity) and increase prices.

Table 5. Impacts of climate change and CSA on macro aggregates (deviations from baseline growth path by Percentage).

Indicators	Effects of Climate Change	Effects of Climate Smart Agriculture and Climate Change
	% From NO CC (Baseline)	
GDP	-1.28	0.34
Agri-GDP	-5.21	1.86

Indicators	Effects of Climate Change	Effects of Climate Smart Agriculture and Climate Change
	% From NO CC (Baseline)	
Absorption	-0.55	0.16
Private consumption	-0.45	0.14
Investment demand	-1.12	0.26
Exports	-0.74	0.21
Consumer price index	1.01	0.72
Investment	-1.40	0.29
Private savings	-0.51	0.14
Direct taxes	-0.86	0.26
Factor taxes	-1.49	0.53

Source: Authors' compilation

In addition, to understand the actual effects of low productivity (resulting from climate change), it is essential to households and examine differences in impacts across household types. Figure 4 illustrates the impact of higher prices on the commodity demand for all household groups.

Consumption among farming households and rural, poor households appeared to be most isolated from climate shocks. This is because the increase in prices (Table 2) exceeds the effect of the decrease in productivity (Table 1), so farming households, who own the land, also benefit from the high price. Non-farming households were the most vulnerable. We clearly distinguish the impact of the spread of food insecurity at different household levels.

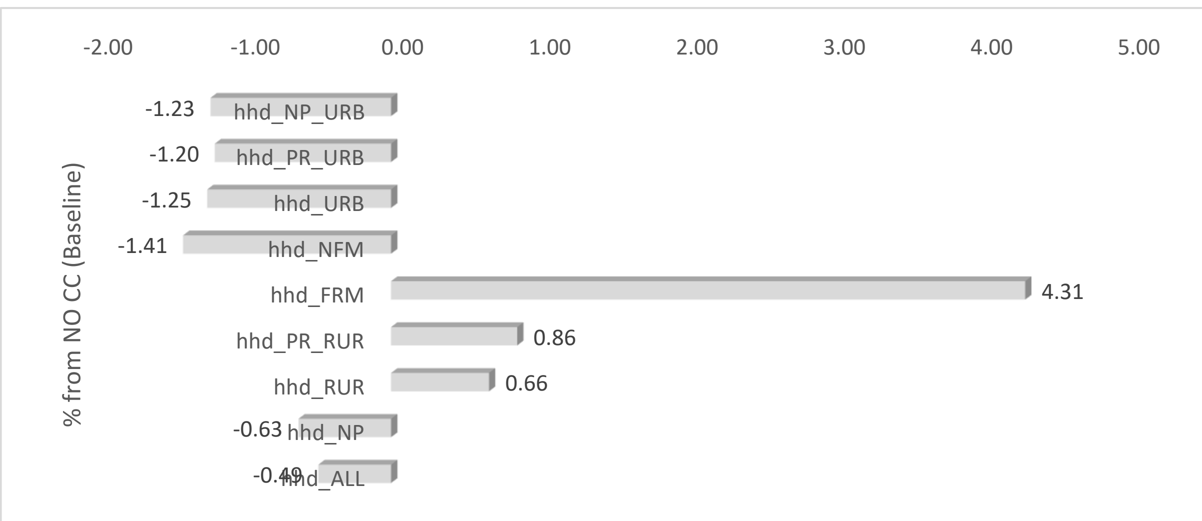

Figure 4. Change in consumption by household group (deviations from baseline growth trajectory by percentage). Source: results of CGE model.

Furthermore, a decrease in productivity and an increase in prices have a further impact on income, as shown in Figure 5. Income volatility disproportionately affects the non-poor, reducing the total income of non-farming households by approximately 0.9 percent. In contrast, the least vulnerable to income reduction are the farming households (because they are the ones who will reap more income from climate change), by about 5.16% as compared to the baseline.

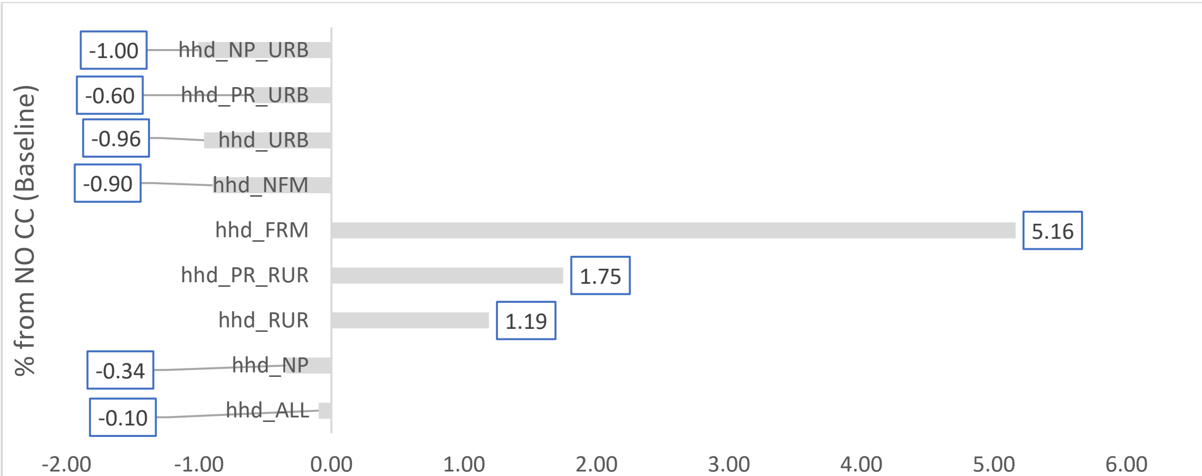

Figure 5. Change in income by household group (deviations from baseline growth trajectory by percentage). Source: results of the CGE model.

Consequently, climate change has reduced both output and domestic consumption, leading to food insecurity, as measured by the value of food production (applied to the model in the current scenario) and the value of consumption (see Figure 3). Moreover, the expected increase in commodity prices will persist, and the risk of food insecurity in Egypt will rise.

Otherwise, due to the contraction in domestic output, domestic demand would be met by increased imports (total agricultural imports will increase by 3.3%). Furthermore, import volume in almost all crops increased compared to the baseline, except for Pulses, Cotton, and other fruits, as shown in Table 6.

Table 6. Impacts of climate change and CSA on imports (deviations from baseline growth path by Percentage).

	Effects of Climate Change	**Effects of Climate Smart Agriculture and Climate Change**
	% from NO CC (Baseline)	
AGRICULTURE	3.03	-3.07
Crops	3.09	-3.11
Food crops	3.36	-3.58
Maize	0.69	-3.51
Wheat and barley	4.18	-4.96
Pulses	-2.77	0.12
Other roots	-6.49	-1.46
Tobacco	1.24	-0.36
Cotton and fibers	12.43	-1.42
Other fruits	17.04	-3.58
Leaf tea	-3.73	0.79
Coffee	-1.45	0.36

Source: results of the CGE model.

On the export side, lower productivity and higher domestic commodity prices may translate into lower competitiveness in global markets. Overall, Egypt will face a notable 23.27% drop in agricultural exports. Likewise, exports of almost all crops, except other roots, pulses, and other vegetables, are increasing compared to the baseline, as shown in Table 7.

Table 7. Impacts of climate change and CSA on Exports (deviations from baseline growth path by Percentage).

	Effects of Climate Change	**Effects of Climate Smart Agriculture and Climate Change**
	'% from NO CC (Baseline)	
AGRICULTURE	-23.27	9.04
Crops	-23.27	9.04
Food crops	-23.39	9.29
Other cereals	-10.77	14.37
Pulses	5.08	0.37
Other roots	5.24	9.00
Other vegetables	0.73	9.49
Cotton and fibers	-20.31	2.65
Other fruits	-32.11	9.67

Source: results of the CGE model.

Finally, the results of this scenario in the medium term by 2050 suggest that the impacts of climate change will be significant, as many crops in Egypt will have lower productivity. Commodity prices will rise, with the most visible effects on consumption, income, terms of trade, and food insecurity.

b. Impact of climate–smart agriculture scenario with climate change on the Egyptian economy by 2050.

Our integrated modelling approach coupled biophysical and economic models to simulate the economy-wide effects of crop technologies in Egypt with and without climate change and CSA technologies. Our approach allowed us to disentangle some of the complexities involved in assessing the yield and economic effects of crop technologies at the national scale. The first step in coupling biophysical and economic models is to assess how the biophysical model simulates different technologies (using the DASSAT and IMPACT models). Then, we used the AIDA model to simulate the effects of expanding farm production within existing CSA technologies, as shown in Table 4. TFP growth in each agricultural product group, such that the total agricultural GDP is 1.86 percent higher in each value chain scenario than in the baseline scenario.

Climate change shocks and proposed mitigation policies (CSA) are implemented, as described in Section 3 (Tables 1, 2, and 3). These findings should be considered to maintain an appropriate picture of the impact of climate change results. Our results suggest that synergies exist among technologies, with yield gains exceeding climate change losses (reduced productivity), depending on the combination of technologies applied in CSA. This is greater than the impact of climate change on all yields, except for sugarcane, which will suffer a small yield shortfall due to the combined effects of climate change and climate-smart agriculture, by about -0.36 percent.

Conversely, the simulations yield a wide range of results for economic and environmental variables at the Egyptian economy level. Furthermore, the simulation results on the effects of CSA and climate change on Egyptian agriculture were analyzed in two stages: first, changes in overall macro-variables and impacts at different household levels. As mentioned earlier in the methodology section, each result is compared presented as a percentage relative to the baseline, with the change reported as a percentage.

First, from an economy-wide perspective (Table 5, last column), the main finding is that GDP gains about 34% from the application of CSA technologies in the face of climate change relative to the baseline. It is also worth noting that climate-smart agriculture exceeded the effects of climate change (a decrease in GDP by 1.28 percent compared to the baseline), which indicates the effectiveness of overcoming the negative effects of climate change and achieving a few gains at the level of both GDP and agri-GDP. This indicates that CSA techniques have the potential to partially correct the domestic price trajectory. This increases the absorption rate by about 0.16 percent (-0.55 percent, the impact of the climate change scenario) relative to the baseline because of a decrease in the general price level, as reflected in the CPI.

Second, after identifying the overall impact of climate change-induced productivity changes in agriculture and CSA on the macroeconomic indicators, these CSA interventions were assessed on a sector-by-sector basis. When the set of economy-wide linkages is considered to assess their impacts at the sectoral level, as expected, CSA interventions reduced food prices. This will lead to an increase in consumption rates for all households, except farming households, whose consumption will decrease (Figure 6) due to the decline in crop prices.

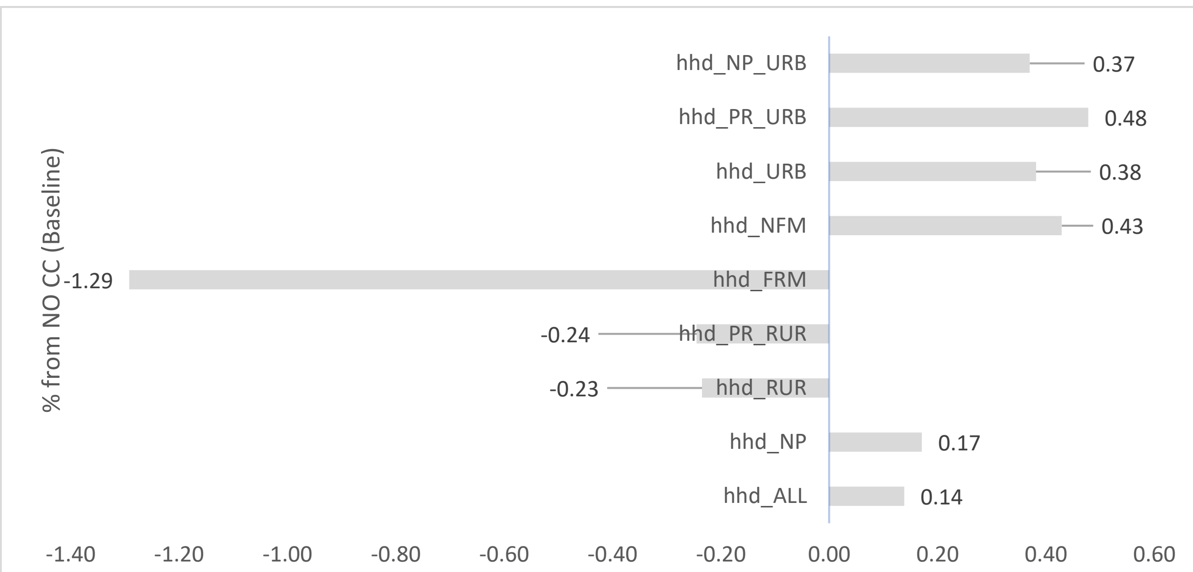

Figure 6. Change in consumption by household group (deviations from baseline growth trajectory by percentage). Source: results of CGE model.

In addition, to understand the actual effects of climate change and adaptation measures, it is essential to consider the differences in impacts across household types. Figure 7 shows the changes in household income resulting from the increase in productivity in the agricultural sector. The same figure also shows that the improvements in income are relatively small, but they are better than in the climate change scenario for all families, except for agricultural families, because of the decrease in the general level of prices, which is negatively reflected in their income.

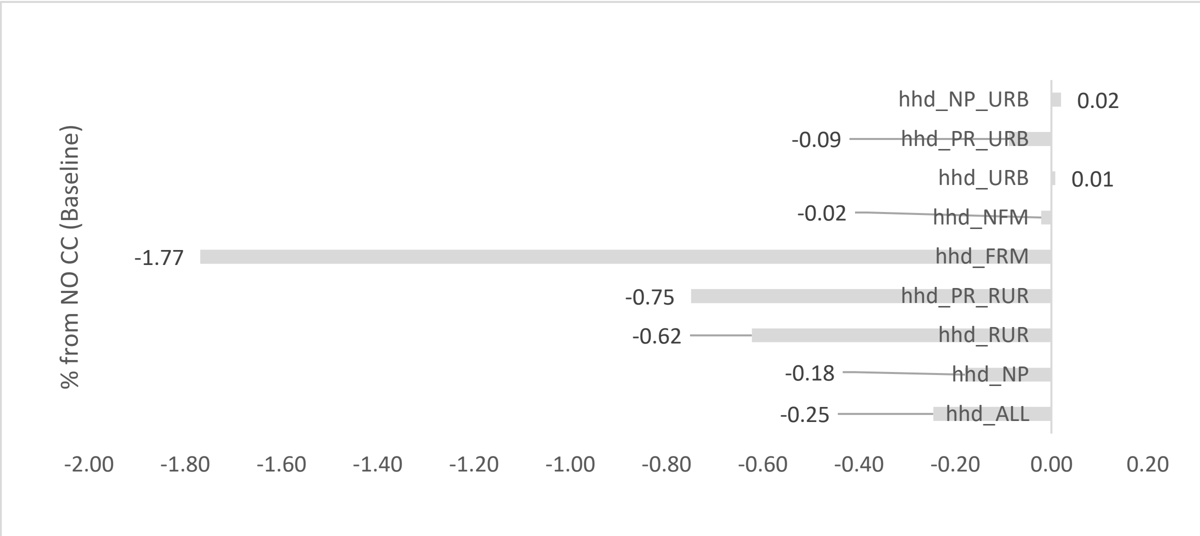

Figure 7. Change in income by household group (deviations from baseline growth trajectory by percentage). Source: results of CGE model.

At the trade level, Table 6 (second column) indicates a decrease in agricultural imports in general by about 3.07 percent, as well as a decrease in grain imports by about 3.11 percent. In addition, wheat and corn imports decreased at rates slightly greater than 3.5. This indicates the success of climate-smart agriculture techniques in mitigating the harmful effects of climate change and reducing dependence on external sources for these crops, even if by a small percentage. As for exports, CSA overcomes the obstacles of low productivity (due to climate change) and makes Egyptian crops more competitive in global markets (as a result of low domestic prices). This entails achieving a surplus at the local level that can be exported. Therefore, agricultural exports and food crops increased by approximately 9.04 percent and 9.29 percent, respectively (see Table 7, second column).

Finally, all the indicators discussed in this study indicate that adaptation measures through climate-smart agriculture exceed the effects of climate change and achieve relatively few benefits. Moreover, it indicates that the adaptation measures under consideration have partially succeeded in restoring growth above the baseline, which is sufficient considering the expectations of the study period. However, the study did not address or analyze some aspects, such as evaluating the effects of climate-smart agriculture techniques one by one at the national and sectoral levels, and determining the priorities among those technologies. Future work is needed to clarify individual components (costs) in more detail of the broader adaptation strategy in some other aspects outside investment in irrigation, such as specific technologies for livestock and water management, changes in planting dates, and crop varieties. This will require the development of an institutional framework and legislation for Egyptian agriculture to fully implement necessary adaptation measures through climate-smart agriculture and other technologies.

VI. Conclusion and Recommendations

There is an international consensus that climate change poses an imminent threat to global development. Climate change is expected to negatively impact crop yield and income. As the world grapples with potential problems caused by global climate change, much attention has been paid to adaptation options, particularly for farmers in developing countries. Climate-smart agriculture is one such adaptation that has shown promise in the developing world and has sparked much recent academic interest. Egypt is no exception; undoubtedly, global warming has put Egypt among the countries predicted to be affected by climate change.

As a result, one of the goals of this study was to develop indicators of the triple-win nexus of productivity, contributions to livelihood and household income, and reductions in GHG emissions and water footprints for each climate-resilient practice or set of practices. So is the farmer's viewpoint about the adaptability of scaling up these practices. Potential roadblocks and policies that can undermine wider adoption are likewise generated, as are support policies and ancillary services. Furthermore, policy modelling of upscaling the production and value-adding chains of prioritized adaptation technologies emphasizes their effects on the agriculture and food sectors, the economy as a whole. Likewise, CSA's potential contribution to achieving development goals, such as poverty alleviation, is enormous.

Hence, this study links a dynamic computable general equilibrium (CGE) model to produce quantitative estimates of the impacts on agriculture in Egypt. The study relied on three main models in order to analyze the climate impact and explore options for the future of climate smart agriculture: IMPACT with the Climate and Hydrology Model to analyze the relationship between climate change and crop productivity; second, an ADAPT model for analyzing the structure of the agricultural sector in Egypt, at the national and sub-national levels; and finally, the CGE model to emphasize the effects of CSA on the agriculture and food sectors and economy-wide income and employment effects on the other sectors of the economy.

It should also be noted that the analysis of the results occurred in two stages: the first stage reviewed the baseline (without the impact of scenarios), while the second stage dealt with two scenarios, namely, the scenario of the impact of climate change on the Egyptian agricultural sector and another scenario that reviewed the combined impact of both climate change and climate-smart agriculture.

The results of the climate change scenario for the medium term, by 2050, suggest that climate change impacts will be significant, and many crops in Egypt will have lower productivity. Commodity prices will rise, with the most visible effects on consumption, income, terms of trade, and food insecurity. On the other hand, the results of the combined scenario that addresses the impact of climate change and climate-smart agriculture, all the indicators discussed in the study indicate that adaptation measures through climate-smart agriculture exceed the effects of climate change, as well as achieve some relatively few benefits. Moreover, this indicates that the adaptation measures under consideration have partially succeeded in restoring growth above the baseline, which is sufficient.

Overall, CSA appears to be a beneficial option for agricultural investment. Second, CSA is motivated to cope with the realities of climate change. However, CSA is also an option today outweigh the climate change effects.

Based on the above, the study recommends the following: focus on scaling up climate-smart agriculture practices that achieve the triple-win objectives of improving productivity, enhancing livelihoods, and reducing greenhouse gas emissions and water footprints. Prioritize practices such as conservation agriculture, improved irrigation techniques, and resilient crop varieties that have demonstrated success in Egypt under changing climatic conditions. Training programs and extension services should be developed to empower farmers with the knowledge and skills needed to adopt CSA practices. In particular, smallholder farmers are more vulnerable to climate change. Incentivizing adoption through financial mechanisms, such as subsidies, insurance schemes, and access to credit, lowers the barriers to implementing these practices.

However, it is crucial that agricultural policies be revised to create an environment that enables the widespread adoption of CSA. This could involve reforming subsidy programs to prioritize CSA-friendly inputs, providing tax breaks for sustainable farming technologies, and introducing regulations that mandate efficient water use and soil management. In addition, it will increase investment in research institutions and technological innovation to develop new CSA technologies suited to Egypt's climate and agricultural conditions. Support should also be directed toward models such as IMPACT and ADAPT to refine predictions of climate impacts on crops and to assess the economic viability of CSA interventions at national and subnational levels. Implement robust monitoring systems to assess the impact of CSA practices on productivity, livelihoods, and environmental sustainability. Use dynamic computable general equilibrium (CGE) models to regularly analyze economy-wide impacts and adjust policies as necessary to ensure long-term success and facilitate access to climate finance from international sources (e.g., the Green Climate Fund) to support CSA initiatives in Egypt. Develop public-private partnerships to increase investments in resilient agricultural infrastructure and innovation.

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الزراعة الذكية مناخياً في مصر: تقييم الأمن الغذائي باستخدام نماذج CGE وIMPACT

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المستخلص: يُشكل تغير المناخ تهديدًا عالميًا، حيث يتوقع أن يؤدي إلى تراجع إنتاجية المحاصيل وتناقص الدخل الزراعي. لذا، تهدف هذه الدراسة إلى تطوير مؤشرات تربط بين زيادة الإنتاجية، وتحسين سبل العيش، وتقليل انبعاثات الغازات الدفيئة، وذلك من خلال تطبيق ممارسات زراعية ذكية مناخياً تتوافق مع التغيرات المناخية. لذلك استندت الدراسة على نموذجين رئيسيين وهما: نموذج (IMPACT) لدراسة العلاقة بين تغير المناخ وإنتاجية المحاصيل، ونموذج التوازن العام (CGE) لتقييم تأثير ممارسات الزراعة الذكية مناخيًا (CSA) على مستوي القطاع الزراعي والاقتصاد الكلي. تناولت الدراسة سيناريوين رئيسين، حيث يتناول السيناريو الأول الأثار الاقتصادية لتغيرات المناخ، وتُظهر التوقعات أنه بحلول عام 2050، سيسبب تغير المناخ انخفاضًا كبيرًا في إنتاجية المحاصيل في مصر، مما سيؤدي إلى ارتفاع أسعار السلع الأساسية، وتفاقم استهلاك الغذاء، وتراجع مستويات الدخل، وتراجع مستويات التجارة، مما يفاقم حالة انعدام الأمن الغذائي. إلا أن السيناريو الذي يجمع بين آثار تغير المناخ والزراعة الذكية مناخيًا أظهرت أن تبني تدابير التكيف يمكن أن يخفف من هذه الأثار السلبية لتغيرات المناخ، بل يُحقق فوائد ملموسة، وأشارت المؤشرات إلى أن الزراعة الذكية مناخيًا قادرة على استعادة جزء من النمو الزراعي بما يتجاوز خط الأساس وأثار تغيرات المناخ، مما يبرز أهمية دمج ممارسات الزراعة الذكية مناخيًا في خطط الاستثمار الزراعي بمصر. إن الزراعة الذكية مناخيًا لا تواجه تحديات تغير المناخ فحسب، بل تقدم أيضًا فوائد مباشرة، حيث تتفوق مزاياها التكنولوجية على التأثيرات السلبية المحتملة لتغير المناخ. وبالتالي، تُعد الزراعة الذكية مناخيًا استراتيجية فعالة لضمان الاستثمار الزراعي المستدام في الحاضر والمستقبل.

الكلمات المفتاحية: الزراعة الذكية مناخيًا؛ تغير المناخ؛ إنتاجية المحاصيل؛ نموذج IMPACT؛ نموذج CGE.

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Modeling the Future of Saudi Arabia’s Economy: An Assessment of Time Series Forecasting Methods Up to 2030

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Abstract: *This paper compares three well-known time series forecasting models, ARIMA (autoregressive integrated moving average), NAR (nonlinear autoregressive), and RNN (recurrent neural network), to predict what Saudi Arabia's GDP will be by 2030. Given the nation's significant economic transformation under its Vision 2030 reform plan, accurate GDP forecasting becomes crucial for strategic planning and policy formulation. The study uses historical economic data, augmented by global economic conditions and national economic policies, to model and forecast future economic scenarios. We utilize the ARIMA model for its proficiency in handling linear time-series data with seasonal variations, and we explore the NAR and RNN models for their capacity to process nonlinear dynamics and complex temporal dependencies, respectively. The paper evaluates each model's predictive accuracy using root mean square error (RMSE) and coefficient of determination (R2), providing a comprehensive overview of their performance in forecasting Saudi Arabia's GDP. The findings aim to guide policymakers and economic stakeholders in selecting the most appropriate forecasting tool, given Saudi Arabia's dynamic, rapidly evolving economic landscape. The results show that ARIMA models are good at. Still, RNN models, especially those with LSTM architectures, are better at predicting long-term economic trends, which is important for making sureshort-term predictions. Still, RNN models, especially those with LSTM architectures, are better at predicting long-term economic trends, which is important for ensuring that the strategic goals of Vision 2030 are met.*

Keywords: *Economic Forecasting, Machine Learning, Neural networks, NAR, RRN, ARIMA*

Introduction

As the world's largest oil exporter, Saudi Arabia's economy presents unique dynamics influenced by both global energy markets and domestic economic policies. The nation's Gross Domestic Product (GDP) is a critical barometer for assessing the health and trajectory of its economy. Accurately forecasting Saudi Arabia's GDP is essential for policymakers, investors, and economic planners to make informed decisions that align with the country's strategic objectives, particularly the Vision 2030 reform plan aimed at economic diversification and sustainable development.

This paper aims to forecast Saudi Arabia's GDP 2030, leveraging historical economic data and employing sophisticated econometric models. The study is particularly timely, as it coincides with significant global economic shifts and major domestic reforms in Saudi Arabia, including initiatives to reduce oil dependency, enhance private-sector growth, and develop public service sectors such as health, education, and infrastructure.

The forecasting methodology centers on the Autoregressive Integrated Moving Average (ARIMA) model, renowned for its effectiveness in modeling and forecasting time series data. This model will be calibrated to account for seasonal variations and external economic shocks, providing a robust framework for predicting future economic outcomes. Additionally, this paper will explore the implications of various global and local economic scenarios on Saudi Arabia's GDP, offering a comprehensive outlook and valuable insights into the potential economic future of the nation (Ashour & Abbas, 2018; Ashour & Helmi, 2024; Mubarak Samer Mohammed Jaber and Ashour, 2024).

In recent years, several studies have focused on time series forecasting using three major approaches: ARIMA, NAR, and RNN models, each addressing data processing challenges uniquely. ARIMA models are well-known for their ability to effectively model linear, stationary time series. In 2018, they found widespread use in settings characterized by seasonality and clear trends, providing reliable forecasts within these limits. ARIMA's restrictions become clear, though, when considering non-linear data properties. In this context, NAR models and their enhancements, such as NNAR (Neural Network-based Nonlinear Autoregressive Models), serve as robust substitutes. These models utilize neural networks to capture the complex dynamics present in the data. Comparative investigations, including those by Zhang in 2023, have shown that when data reveal non-linear trends, NAR models can outperform ARIMA models. Recurrent neural networks (RNNs), especially those with LSTM (long short-term memory) or GRU (gated recurrent unit) architectures, have made it much easier to predict the future. They excel at presenting complex variations and long-term dependent data. Gers's 2024 research shows that RNNs have a better capacity than conventional statistical models to learn from past data in a manner much greater than their capacity. Comparative research on these models reveals that none of them consistently outperforms the others under all circumstances. ARIMA might be better suited for scenarios requiring short-term precision, for example, but RNNs may be better suited for situations requiring an awareness of complicated patterns over longer periods. The forecasting goals and the type of data should guide the model selection(Ashour et al., 2020, 2023; Hameed Ashour & Abbas, 2023).

The objective of this study is not only to forecast future economic conditions but also to assess the influence of Saudi Arabia's economic policies and external economic factors. The objective of the findings is to enhance the strategic planning anticipated opportunities and challenges.

Method

ARIMA model

A well-liked method for predicting time series is the ARIMA model, which stands for Autoregressive Integrated Moving Average. It the three main components: moving average (MA), autoregressive (AR), and differencing (I). The autoregressive component (AR) considers an observation's correlation with a predetermined number of lag observations. It presupposes that one may infer a variable's future value from its previous value. To make a non-stationary time series stationary, one uses the differencing component. It entails taking differences between consecutive observations to remove any trend or seasonality from the data. An observation's dependence on the residual error of a moving average model applied to lag observations is considered by the moving average component (MA) (Ashour & Al-Dahhan, 2020, 2021). You can write the ARIMA model as ARIMA (p, d, q), where d is the differencing order. Q represents the order of the moving average component. With the right parameter values for p, d, and q, the ARIMA model can accurately forecast time series by capturing their underlying patterns and characteristics. Common methods for identifying the model parameters include examining partial and autocorrelation plots, estimating parameters using maximum likelihood estimation, performing a grid search, and evaluating the model using goodness-of-fit metrics. Figure 1 shows the approach of the ARIMA model(Ashour & Al-Dahhan, 2020; Munim et al., 2019; Wirawan et al., 2019).

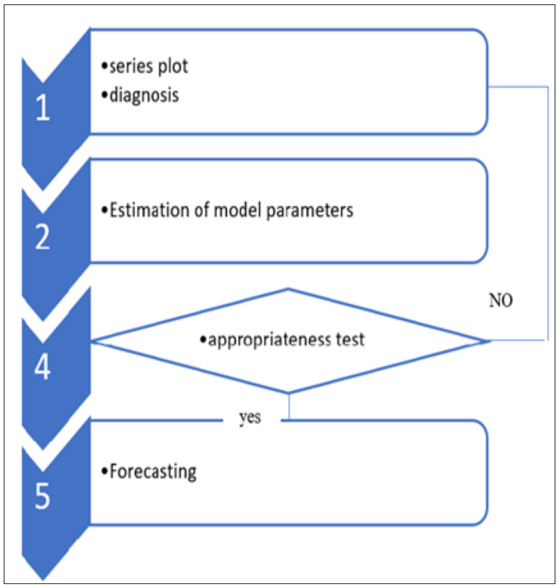

Figure 1. Architecture of ARIMA

NAR model

Nonlinear autoregressive (NAR) models are a more advanced version of traditional autoregressive methods. They are designed to understand the nonlinear dynamics common to many time-series datasets. Unlike linear models, such as ARIMA, which may fail to capture complex patterns, NAR models incorporate nonlinear functions of past values, making them highly effective in fields like finance, meteorology, and engineering, where data behavior is dynamic and complex. These models vary from polynomial NAR, which uses polynomial functions of past values, to neural network NAR (NNAR), which employs neural networks to model nonlinear dependencies. The challenge in using NAR models lies in requires advanced techniques such as optimization algorithms and regularization to ensure robustness and accuracy. Despite these challenges, NAR models' ability to improve forecasting in nonlinear scenarios makes them invaluable tools for advanced time series analysis. NAR models are expressed as(Ashour, 2022; Ferdiansyah et al., 2023) .

$$X_t = f(X_{t-1}, \dots, X_{t-p}) + \epsilon_t \qquad (1)$$

where f is a nonlinear function, x time series data, p is the order of the model, and ϵ is noise.

RNN model

Recurrent neural networks (RNNs) are specialized artificial neural networks optimized for processing sequential data, making them highly suitable for analyzing time-series data. In contrast to conventional feedforward neural networks, recurrent neural networks (RNNs) have cyclic connections, enabling them to retain a memory of past inputs and efficiently capture temporal interactions. By leveraging this feature, recurrent neural networks (RNNs) can effectively represent intricate temporal patterns, hence improving their effectiveness in a wide range of applications, including financial forecasting, weather prediction, anomaly detection in industrial environments, and healthcare outcome prediction. Recurrent neural networks (RNNs) are great at handling variable sequence lengths and remembering past events. This makes them reliable tools for studying and predicting things that change over time. Novel techniques, including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), have been developed to address issues encountered by conventional RNNs, such as vanishing gradients(Hossain et al., 2023; Lazcano et al., 2023). Long Short-Term Memory (LSTM) models include memory cells and gating mechanisms, such as input, forget, and output gates, to regulate the flow of information and preserve long-term patterns. Group Regression Units (GRUs) streamline this architecture by merging forget and input gates into a unified update gate, thereby reducing complexity while maintaining the capacity to represent long-term relationships. These improvements have broadened the scope of applications for recurrent neural networks (RNNs) and enhanced their ability to capture temporal dependencies. Nevertheless, recurrent neural networks (RNNs) also pose challenges, particularly due to their substantial computational requirements and the potential for overfitting. requires substantial computational resources and time. Recurrent Neural Networks (RNNs) can overfit because of their complex structure and ability to show complex temporal connections. This means that they need careful regularization and validation methods. Notwithstanding these obstacles, the advantages of employing RNNs to record and predict complex time-dependent patterns surpass the problems. These tools will remain essential for data scientists and machine learning experts specializing in time series analysis. Continuous improvements in processing capabilities and optimization techniques are further improving the feasibility and effectiveness of recurrent neural networks (RNNs), therefore guaranteeing their substantial contribution to the future of time series forecasting and analysis. The functioning of the RNN model is illustrated in Figure(Ashour, 2022; Ashour & Al-Dahhan, 2021; Ferdiansyah et al., 2023).

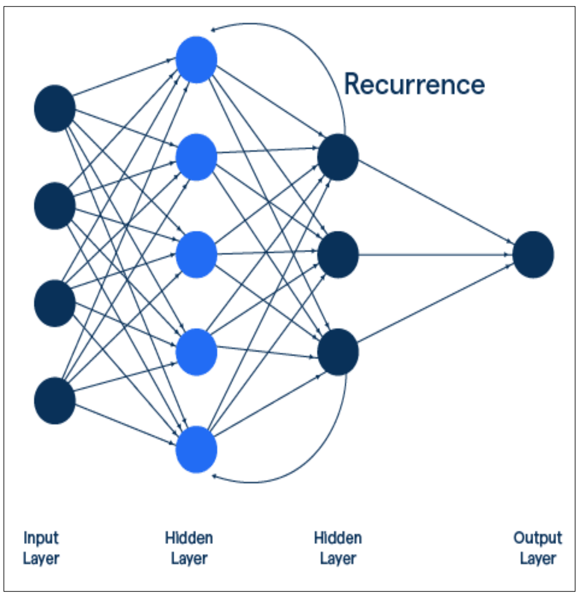

Figure 2. Architecture of the recurrent neural network.

Evaluating accuracy

To determine how effective prediction models are in time series analysis, it is necessary to assess their performance. Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) are two popular performance measures. These measures shed light on the models' precision and ability to explain data. I will demonstrate how to calculate these measures. It stands for Root Mean Square Error: When comparing anticipated and observed values, the root mean squared error (RMSE) is a good metric. We calculate it using the following formula(Ashour & Alashari, 2022; Minu et al., 2010):

$$RMSE = \sqrt{\frac{\sum(actual - predict)^2}{n}} \qquad (2)$$

Where n is the total number of data points in the time series, actual and predicted are the predicted and actual values, respectively. R^2: Determination Coefficient. One measure of how well the predicted data fits the data is the coefficient of determination, which goes by several names, such as R-squared and R^2. The formula for its calculation is

$$R^2 = 1 - (SSR/SST) \qquad (3)$$

Specifically, SSR stands for the unexplained variance in the projected data, while SST is the overall variation in the observed data. To decipher the findings, the better the match between the anticipated and observed values, with fewer errors, the lower the RMSE number. A higher R^2 value implies that the projected values explain a larger fraction of the variation in the observed data, which in turn suggests that the model is performing better (Abdul et al., 2023; Ferdiansyah et al., 2023; Lazcano et al., 2023).

Results

Figure 3 illustrates data on Saudi Arabia's Gross Domestic Product (GDP) from 1960 to 2023, demonstrating significant economic growth driven by expansions in the industrial and service sectors alongside abundant natural resources, such as oil. The data highlights periods of substantial increase, often associated with surges in oil prices or expanded production, while downturns reflect the economy's sensitivity to global crises such as oil price declines and global economic slowdowns, particularly evident during the pandemic and other global economic disruptions.

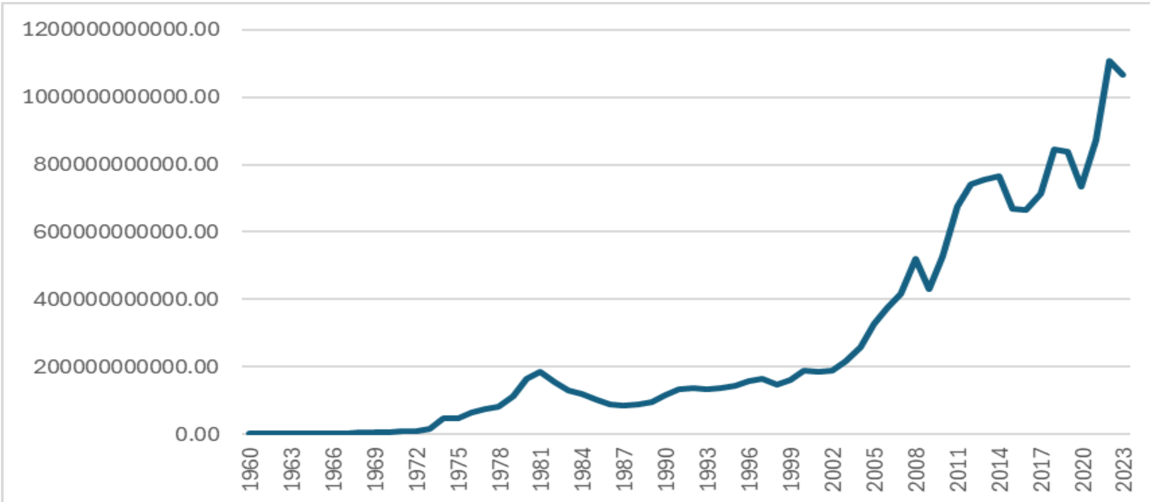

Figure.3 Saudi Arabia's GDP

Table 1 displays the results of the ARIMA analysis, indicating that ARIMA (1,0,0) is the best model. The table shows that the ARIMA model has a significant relationship.

Table 1. Statistics model

Model	Number of Predictors	Model Fit statistics			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	RMSE	Statistics	DF	Sig.	
VAR00001-Model_1	0	.954	.954	6.569E+10	12.643	17	.760	0

The ARIMA model results displayed in the table indicate a robust performance, with an R-squared value of.954, suggesting that the model accounts for 95.4% of the variance in the data. The high RMSE value might initially appear concerning, but its significance is context-dependent and should be evaluated against the scale of the data. Additionally, the Ljung-Box test results, with a p-value of.760 indicates no significant autocorrelation in the model residuals, suggesting that the residuals are random and demonstrating the model's predictive accuracy. Overall, the model appears to perform well, effectively handling the data without any outliers, showcasing its high efficacy in capturing the underlying data patterns.

The performance indicators for ARIMA, NAR, and RNN are presented in Table 2.

Table 2. Key Performance Metrics

Method	**RMSE**	**R^2**
ARIMA	65694884915.53	0.954
NAR	490977214666	0.960
RNN	20696000000	1.000

Table 2 presents the performance metrics for three forecasting methodologies: ARIMA, NAR, and RNN. The table utilizes two primary performance indicators, the root mean square error (RMSE) and the coefficient of determination (R^2), to evaluate each method.

ARIMA (Autoregressive Integrated Moving Average): This method, used for analyzing time series data, shows excellent performance, with an R^2 of 0.954. However, it has a relatively high RMSE, suggesting larger average prediction errors.

NAR (Nonlinear Autoregressive): As a form of neural network, it exhibits the highest RMSE among the methods, indicating the largest predictive errors, with an R^2 of 0.96. This could imply a slightly better fit to the data's variance than ARIMA.

RNN (Recurrent Neural Network): This type of neural network achieves a perfect R2 of 1, indicating highly accurate predictions.

These results are useful in assessing the effectiveness of each method for analyzing and forecasting time series data. The significance of each metric may vary depending on the specific context of use. Overall, these metrics suggest that the RRN models possess excellent predictive ability, effectively adapting to complex datasets and proving highly reliable in forecasting. This reliability is indispensable in decision-making processes where the cost of prediction errors is high, underscoring the models' applicability in critical and dynamic environments.

The seven-year prediction is in Table 3.

Table 3. Prediction value

year	prediction
2024	1549133993996.17
2025	1702164118944.95
2026	1870311218430.86
2027	2055068612277.26
2028	2258077136868.38
2029	2481139717470.31
2030	2726237380068.51

The data depicted in Table 3 provides a comprehensive forecast of a specific variable for ten years, revealing a notable and large upward trend in projected values from 2024 to 2033. Each successive year observes a consistent upward trajectory, indicating a robust pattern of expansion throughout the decade. The projected values commence at an estimated 1.549 trillion in 2024 and exhibit a consistent upward trend, reaching roughly 2.726 trillion by 2030. The observed exponential growth trajectory implies that the underlying model predicts substantial growth or accumulation in the measured variable. This could potentially indicate economic growth, population growth, technological advancements, or other sector-specific escalations, depending on the specific context of the data presented. The observed growth trend may suggest a compounding effect, in which the rate of expansion itself may exhibit an upward trajectory over time. Alternatively, a multitude of causes could gradually amplify or gain greater influence for the decade. The forecasts play a crucial role in the formulation of long-term plans and strategies across several domains, including corporations, government policies, investment strategies, and other applications that rely heavily on the ability to anticipate future circumstances. The assess stakeholders' preparedness and adaptive approaches to mitigate or alleviate the consequences of this anticipated expansion.

Conclusion

In the Conclusion of this paper, three well-known time series forecasting methods: ARIMA, NAR, and RNN—were carefully looked at. Each had its pros and cons in predicting the future and in the reliability of its models. With its ability to find patterns in time series data through a mix of differencing, autoregression, and moving-average components, the ARIMA model has shown impressive predictive power, even though its RMSE values indicate it makes more mistakes. On the other hand, the NAR model, by incorporating nonlinear dynamics, offers a significant improvement in handling complex patterns that are particularly prevalent in chaotic data sets. However, it also suffers from the highest predictive errors among the three models.

The RNN model stands out with the lowest RMSE and a perfect R^2 score, showcasing its exceptional ability to model temporal dependencies and complex interactions in time series data. This makes RNNs particularly valuable in environments where accurate forecasting can significantly impact decision-making processes. Moreover, advancements in neural network architectures, such as LSTM and GRUs, have further enhanced the RNN's ability to capture long-term dependencies without succumbing to issues like the vanishing gradient problem.

Comparing these models using key performance metrics such as RMSE and R^2 shows that time series analysis technologies are continually evolving. It also shows how important it is to choose the right model based on the data set's unique features and needs. Future research should continue to refine these models, address their respective weaknesses, and explore hybrid approaches that can leverage the strengths of each to improve overall forecasting accuracy.

This exploration not only enhances our understanding of time series modelling but also contributes to the broader field of predictive analytics, where forecast future events is paramount. As demonstrated by the predictive outputs, the ongoing advancements in time series modelling are likely to play a crucial role in shaping strategies across various sectors, making this an exciting area for further academic inquiry and practical application.

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نمذجة مستقبل الاقتصاد السعودي: تقييم لأساليب تنبؤ السلاسل الزمنية الى عام 2030

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المستخلص: للتنبؤ بالناتج المحلي الإجمالي للمملكة العربية السعودية بحلول عام 2030، يناقش هذا البحث ثلاثة نماذج معروفة للتنبؤ بالسلاسل الزمنية ARIMA :(المتوسط المتحرك المتكامل الذاتي الانحداري)، و NAR(الانحدار الذاتي غير الخطي)، و RNN(الشبكة العصبية المتكررة). بالنظر إلى خطة الإصلاح الطموحة لرؤية 2030 الهادفة إلى التحول الاقتصادي، يعد التنبؤ الدقيق بالناتج المحلي الإجمالي ضروريًا للتخطيط الاستراتيجي الفعال وتطوير السياسات. يستخدم الدراسة بيانات اقتصادية تاريخية مدعومة بالظروف الاقتصادية العالمية والسياسات الوطنية لنمذجة السيناريوهات المستقبلية. نختار نموذج ARIMA لفعاليته في إدارة البيانات الخطية مع التقلبات الموسمية، ونستكشف النماذج NAR و RNN لقدرتها على التعامل مع الديناميكيات غير الخطية والتبعيات الزمنية المعقدة. نقيّم دقة التنبؤ لكل نموذج باستخدام خطأ المتوسط التربيعي الجذري (RMSE) ومعامل القرار .(R2) تشير النتائج إلى أنه، بينما يبرع نموذج ARIMA في التنبؤات قصيرة المدى، فإن نماذجRNN ، وخاصة تلك التي تستخدم هياكلLSTM ، تتفوق في التنبؤ بالاتجاهات الاقتصادية طويلة المدى. هذا التمييز حاسم للتوافق مع الأهداف الاستراتيجية لرؤية 2030، مما يساعد صانعي السياسات والأطراف المعنية بالاقتصاد في اختيار النهج الأنسب للتنبؤ .

الكلمات المفتاحية: التنبؤ الاقتصادي، التعلم الآلي، الشبكات العصبية، NAR، RNN، ARIMA.