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Electricity incentives for agriculture in Saudi Arabia. Is that relevant to remove them?☆

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ABSTRACT

Saudi Arabia has been implementing the domestic energy price reform (EPR) and fiscal reform since the end of 2015 under the Fiscal Balance Program (FBP), one of the key realization programs of Saudi Vision 2030 (SV2030). The EPR aims to increase the rational consumption of energy and budget revenues by gradually removing energy incentives across the economy by 2025 (FBP, 2019). This study assesses the impact of electricity incentives that the government provided for the development of the agricultural sector in the pre-reform period to find out how large its magnitude was and to determine whether removal of them in the sector is a relevant measure to take. We found that while these incentives had both short and long-run positive impacts on the agriculture growth, the magnitude of these impacts was quite small (the long-run elasticity is between 0.04 and 0.07 and the short-run elasticity is around 0.09–0.11). We also found that investing in capital stock and technological progress would lead to more and sustained development than a continuation of the government's electricity incentives in the sector. Additionally, we found that increases in temperature, primarily resulting from carbon emissions of fossil fuel consumption, is harmful to the sector's development. These empirical findings support the ongoing policy for the implementation of gradual removal of electricity incentives and suggest that some mitigation measures should be considered for the sector. In policy implementations, decision-makers should consider that the sector is capable of absorbing shocks, including policy interventions within two years.

1. Introduction

Environmental conditions in Saudi Arabia are harsh, with extreme temperatures and low precipitation, which are challenging for the cost-effective development of the agricultural sector (Tuncalp and Yavas, 1983; Elhadj, 2004, among others). This implies significant government support for the sector to survive. Al-Shaya et al. (2012) states that agriculture accounted for 85% of the country's water consumption, rising to 88% in 2014, according to FAO Aquastat (Brown et al., 2018). This figure in itself gives an idea of the difficulty of agricultural development in Saudi Arabia. However, the development of the agricultural sector is important for three critical reasons (Tuncalp and Yavas, 1983; Baig and Straquadine, 2014).

First, there is the issue of food security. Tuncalp and Yavas (1983), Lovelle (2015) and Fiaz et al. (2018) note that Saudi Arabia has a growing dependency on imported food to meet its demand. According to the Global Food Security Index, the country position worsened from the 28th most secure country in terms of food supply in 2012 to 32nd most secure in 2018 (GFSI, 2019). Agricultural products accounted for roughly 11% of the country's total imports between 1988 and 2014 (SAMA, 2018). Saudi Arabia needs to import around 80% of its food requirements (Al-Subaiee et al., 2005). All other factors remaining constant, this percentage is expected to rise as the Kingdom's population increases due to a high fertility rate and rising immigration from neighboring countries. Saudi Arabia's average per annum fertility rate and population growth rate were about 4% and 3%, respectively, between 1988 and 2014 (WB, 2018; UN, 2018). Although Saudi Arabia has enough foreign reserves from its oil exports to meet its import needs, including those for agricultural products, it is important to produce some agricultural products domestically so as not to be heavily dependent on the rest of the world (Tuncalp and Yavas, 1983).

Second, the development of Saudi Arabia's agriculture sector would, to some extent, help prevent further rural migration to urban cores (Tuncalp and Yavas, 1983; Baig and Straquadine, 2014). The Kingdom's

☆ The literature interchangeably uses the words 'subsidy' and 'incentive'. We believe is it appropriate to use the word 'incentive' in our study here.

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rural population as a share of its total population declined from 24.7% in 1988 to 17.1% in 2014 (WB, 2018; UN, 2018). A continuation of this trend could lead to environmental and economic problems. For example, a larger urban population will demand more energy and other resources for transportation, industry, and services, in turn causing pollution levels to rise and using more oil domestically – leading to less oil being available for export. This migration of rural populations to urban areas will also decrease the agricultural labor force and, consequently, agricultural production (Tuncalp and Yavas, 1983). In fact, the contribution of the agricultural sector to GDP (and non-oil GDP) reduced from 3.2% (7.8%) in 1988 to 2.4% (4.3%) in 2014 (GaStat, 2018). Agricultural employment as a share of total employment also fell from 7.0% in 1988 to 4.2% in 2014 (GaStat, 2018).

Last, the development of the agricultural sector is part of the economic diversification strategy oil-dependent economies often adopt, as it can help to curb some negative consequences of oil dependence, such as the so-called 'Dutch disease' (see Tuncalp and Yavas, 1983; Hasanov 2013).

All of the above issues are core elements of Saudi Vision (2030), a strategic roadmap for the Kingdom (NTP, 2017).

The agricultural sector's development depends on a number of factors, including capital stock, the labor force, available technologies, and climate conditions, among others. However, it is a commonly accepted view that Saudi Arabia's agricultural sector cannot develop at the desired level without government support given the nature of the sector. The Saudi government has introduced long-term interest-free loans, easy credit schemes, helping farmers to design responsible farming plans and improve cereal, fruit and vegetable production, to raise their living standards, and established duty-free imports for agriculture-related raw materials and machinery to improve sector's productivity. The government also provides incentives for the prices of electricity, fuel, and water in the sector (FAO, 2007; 2009; Al-Shaya et al., 2012; Bailey and Willoughby, 2013).

Napoli et al. (2016) state that government incentives have a role not only in developing the Saudi Arabian agricultural sector but also, and more importantly, in determining its structure. Energy incentives are key government support since energy is crucial to the agricultural production process. Modern agriculture uses machinery and equipment that require energy at different stages of production. Direct energy is consumed by crop, livestock, and animal production, the manufacture of fertilizers, pesticides, and the packaging and transport of crops use energy indirectly. Continuous energy supply is key to achieving sustainable agricultural development. Energy incentives in the Saudi agricultural sector are mainly manifested in low energy prices. For example, between 1988 and 2014, the electricity price was on average 0.10 Saudi riyals (SAR) per kilowatt (kW) in Saudi Arabia, but 0.20 SAR/kW in the United States, taken as an international benchmark price. The energy at half the price of the international benchmark level offers strong support to the agricultural sector's development. Low energy prices, however, can also lead to the inefficient use of energy resources (see Mehrara, 2007; IMF, 2004, 2013). Some studies raise concerns about the costs of incentives, including electricity incentives, criticizing them as being unreliable and unpredictable, leading to poor service, environmental pollution and hindering social programs (WB, 2001; Birner et al., 2007; Strand, 2010; Badiani et al., 2012). Napoli et al. (2016), among others, argue that implicit and explicit incentives for the agriculture sector may not be sustainable in the long run.

According to International Energy Agency (IEA) statistics, Saudi agricultural electricity consumption expanded about eightfold between 1988 and 2014, from 0.05 million tonnes of oil equivalent (Mtoe) to 0.39 Mtoe, respectively (IEA, 2018). This figure is in itself very high and prompts the question, how much does such substantial electricity consumption, partly boosted by energy incentives, contribute to the development of Saudi Arabia's agriculture? To answer this requires an analysis of the numerical impact of electricity incentives on agricultural production. This kind of assessment can help decision-makers enhance their understanding of the role of these incentives in agricultural development. Such numerical assessments and thereby an adequate evaluation of the roles of incentives and the effects of their removal are especially important for the government in the successful implementation of EPR and fiscal reform (see Gonand et al., 2019; Hasanov, 2019, among others). In December 2015, the government announced that it had begun domestic EPR and fiscal reform as key initiatives of the FBP. The FBP has key pillars, namely EPR and Other Government Revenues, Rationalizing Government Expenditures, Household Allowance, Enabling Private Sector Growth. The main objective of the program is to achieve fiscal balance by 2023 and support the economic transformation and development in line with SV2030. It is projected that fiscal revenues and spending will constitute 1.154 billion Saudi Riyal (SAR) and 1.153 billion SAR, respectively in 2023. EPR and fiscal reforms are the central elements of the FBP. The objective of the EPR is to foster the rational consumption of energy and increase budget revenues without simultaneously undermining its social welfare goals. To be precise, it has the following four aims: Stimulate rational consumption of energy; Encourage the establishment of competitive investments in the industrial sector; Redirect and Rationalize support provided to eligible segments, Strengthen the general fiscal position. The EPR aims at gradually removing all types of energy incentives so that domestic energy prices reach international reference energy prices by 2025. As the main revenue components of the fiscal reform, the government introduced expat levies on non-Saudis and excise tax on harmful products in 2017, as well as a value-added tax in 2018 alongside raising other existing taxes, tariffs, and administrative fees. The details of the EPR and fiscal reform, including rationalizing government expenditures, as well as other aspects of FBP, can be found in FBP (2017, 2018, 2019) to save space.

Accordingly, the objective of our research is to investigate the role of electricity incentives in the development of the Saudi agriculture sector and to see how large its magnitude was in the pre-reform period and thereby identifying whether it is appropriate to remove them in the sector.

To do this, we applied cointegration and equilibrium correction modeling to the Saudi data in an augmented production function framework for the period 1988–2014.

Our findings showed that agricultural labor productivity establishes a long-run relationship with electricity incentives, capital, and technological changes. Although electricity incentives have positive effects on agricultural development both in the long- and short-run, these effects are very small: the long-run elasticity is between 0.04 and 0.07 while the short-run elasticity is around 0.09–0.11. We also found that capital per employee has significant and positive impacts on agricultural labor productivity (with the long- and short-run elasticities of 0.97 and 0.67, respectively). Technological progress can increase agricultural labor productivity by 1.10% each year according to our estimates. These impacts are much larger than those realized through electricity incentives. We further found that temperature increases, mainly caused by carbon emissions from fossil fuel consumption, have a negative impact on the sector's productivity. Lastly, empirical estimations indicated that any shock to the agriculture sector could be absorbed within two years.

The findings of the study above, in particular, the small effect of the electricity incentives, provide a straightforward answer to our research question: it would be relevant to remove the electricity incentives from the sector. It should be implemented gradually and with some mitigation. This conclusion evidenced from the empirical analysis supports the underlying EPR policy strategy of the government: the gradual removal of the energy incentives with some mitigation measures as highlighted in FBP (2017, 2018, 2019). The gradual removal of incentives is also relevant in the sense that it helps the economy, including the agriculture sector, transit smoothly, adapt to the new socio-economic environment, and be efficient. Removing electricity incentives will make additional resources available to the government that can be allocated for different projects in line with the objectives of the SV2030. As another policy choice, they also can be used for the development of renewable energy projects. This policy option has some advantages such as it generates additional electricity to meet demand, which reduces domestic use of fossil fuel that can be exported, mitigates environmental pollution, and thus is beneficial for current and future generations. In removing electricity incentives, policymakers may also be motivated by the fact that energy incentives encourage the wasteful use of water resources and cause burning more fuel to generate more electricity and thus more carbon emissions. Lastly, the policy of removing incentives can also be supported by economic theory, which articulates that although incentives can help sectors in the short-run, they can cause issues, such as market distortions, undesirable structural changes and disproportional development in the long-run.

This study contributes to the existing literature in some ways. First, to the best of our knowledge, this is the first study to investigate the role of electricity incentives for the Saudi Arabian agriculture sector by numerically estimating its effects in the long- and short-run. Second, this is also the first study, to the best of our knowledge, that estimates long- and short-run impacts of capital (and implicitly labor), technological progress, and temperature change on the agricultural sector as well as assesses the speed of adjustment for the sector. Mainly, as in line with its objective, the study adds value to the ongoing debate on EPR by empirically supporting the policy strategy of gradual removal of electricity incentives in the Saudi Arabian agriculture sector. Additionally, numerical assessments conducted in the study are useful as they inform Saudi policymakers about a big role of capital and technological progress and a small role of electricity incentives and labor that should be taken into consideration in designing long-term and short-run policy packages for the development of the sector. It also may encourage policymakers to think about the short-run but numerically large effect of temperature change caused by fossil fuel consumption and thus carbon emissions and take appropriate measures. Third, the study uses different estimation and test methods as well as small sample bias corrections to obtain more robust results. This is important for proposing well-established evidence-based policy recommendations. The numerical assessments and estimated specifications that this study provides can also be used for projecting and simulating future alternative development paths of the sector under different policy options. These projections would be useful to evaluate what role the sector can play in the future development of the whole Saudi economy. Such an evaluation would be important when it comes to diversification of the economy away from oil, a key development strategy in SV2030 that the country follows. Lastly, we hope that this study will encourage researchers to conduct similar studies for Saudi Arabia and other oil-exporting countries.

The rest of the paper is organized as follows: Section 2 reviews existing studies; Section 3 presents the theoretical framework of the study, while data and the methodology of the study are discussed in Section 4; Section 5 presents the empirical findings and Section 6 discusses these findings. Section 7 concludes the study with some policy implications. References section lists the studies used in the study. Appendix section contains additional information about the role of incentive, data description, econometric methodology and estimations for robustness to save space in the main text.

2. Literature review

Ideally, we should review studies that have estimated the impact of electricity incentives on agricultural development in Saudi Arabia. However, to the best of our knowledge, there are no such studies for Saudi Arabia. Accordingly, we opted to review other Saudi related studies that we considered relevant to our research objective. Additionally, we discussed the role of incentives in agricultural development generally and specifically for Saudi Arabia, then reviewed studies investigating the role of electricity incentives in the agriculture sector of developing economies in Appendix A.

Napoli and Tellez (2016) calculate water and electricity productivity for water extraction in the agricultural sectors of 41 countries, including Saudi Arabia. They conclude that the productivity of water, as well as the energy required for water extraction, is much smaller in the Gulf states, including Saudi Arabia, than other countries. This implies that the opportunity costs of water and energy used in agriculture are very high. They conclude that a better strategy would be to import water-intensive agricultural products, which would allow the Kingdom to reduce energy consumption in the sector and thus export more oil, gain more revenue, save domestic water resources and be more environmentally friendly. Although the work gives an idea of the roles of water and electricity in agriculture, it does not estimate the numerical impacts of the energy/electricity on the sector.

Napoli et al. (2016) investigate policy options to reduce water consumption, which would also reduce energy/electricity consumption, in the Saudi Arabian agricultural sector without further compromising food security or farm revenues, using 2013 data. The study just discusses the importance of energy/electricity incentives for the development of the sector without conducting any numerical estimations.

Elhadj (2004) conducts a cost/benefit analysis of the Saudi government's support for desert irrigation. For the cost components, the study discusses electricity and fuel incentives along with direct incentives, including for the agricultural sector through the government-owned Agricultural Bank. It also looks at import incentives, measured as the difference between the price that the Saudi agency, the Grain Silos and Flour Mills Organization, paid to local farmers and the price of importing wheat and barley between 1984 and 2000. The study concludes that the incentives might have caused the inefficient use of money and water. The study does not estimate the impacts of incentives, including electricity incentives, on agricultural production.

Grindle et al. (2015) conduct a similar study. They briefly discuss the roles of government incentives, including energy incentives, energy consumption, foreign direct investment and water in the development of agriculture and sustainable food production in Saudi Arabia. However, the study does not quantify the impact of the factors listed on either agriculture or food production.

Barany and Grigonyte (2015) consider incentives for energy products, including electricity, in different countries, including Saudi Arabia. However, the paper does not discuss sectoral energy/electricity incentives, including those for agriculture. A similar study is also conducted by Alyousef and Stevens (2011), in which they calculate electricity incentives for the Saudi agricultural sector, but only for 2010. They do not estimate the impact of the electricity incentives on the agricultural sector as this does not accord with the objective of their study.

Tuncalp and Yavas (1983) discuss the development of the agricultural sector in Saudi Arabia between 1973 and 1981, including direct incentives to farmers and import incentives for basic foodstuffs while Mousa (2017, 2018) reports on import incentives for some agricultural goods, such as wheat, barley, and corn for 2017 and 2018 for Saudi Arabia. Similarly, Al-Shaya et al. (2012) and Fiaz et al. (2018) discuss issues around Saudi Arabian agricultural development, including government initiatives, the production of and trade in agricultural commodities, water shortages and limited water resources, environmental challenges and capacity building while Baig and Straquadine (2014) look at agricultural expansion, sustainable agriculture and their impacts on rural development. None of the studies investigates the impact of energy/electricity incentives on agricultural development.

The overall conclusion from the literature review above is that although some studies discuss the roles of energy incentives and other inputs in the Saudi agricultural sector, none of them estimates the impact of energy/electricity incentives alongside other inputs, such as capital, labor on the sector's development. However, such numerical assessments are essential at least for two key purposes. First, the authorities cannot implement efficient measures for the development of the agricultural sector without having information on the numerical impacts of each factor. Second, the lack of numerical measures and estimated models would not make it possible to prepare reasonable projections and simulations for the future time paths of the agricultural development based on different assumptions for the impacting factors. This, in turn, would not make it efficiently feasible to evaluate how the agriculture sector is important in the development of the entire Saudi economy. This may be important to know when it comes to diversification away from oil, a key development strategy of SV2030 that the country is going to expedite. Our research addresses the above-mentioned gap in the literature on the Saudi Arabian agricultural sector by assessing the impact of electricity incentives alongside other determinants, namely capital, (and implicitly labor), technological progress, temperature change on the development of the sector.

3. Theoretical framework

It may seem that since the objective of this study is to explore the role of the government electricity incentives in agricultural production, a bivariate framework, where the latter is the only function of the former, is a relevant framework. However, from the econometric estimation perspective, such a bivariate framework may lead to biased results, due to what is known as the omitted variable problem. For example, Lütkepohl (1982) discusses that omitting relevant, for example, theoretically predicted variable(s) might lead to results ranging from spurious findings to non-causality in the Granger-causality analysis. Triacca (1998), Odhiambo (2009), Caporale et al. (2004), among others, show that a bivariate framework that omits relevant variable(s) in the analysis may also lead to a theoretically inconsistent sign and size of coefficients, as well as the wrong direction of causality. Accordingly, we use the Cobb-Douglas production function (CDPF) (Cobb and Douglas, 1928) in this study. Following Solow (1957), Sato and Beckmann (1968), Beckmann and Sato (1969), Sato and Thomas Mitchell (1989), Kim and Heshmati (2019) the CDPF augmented with technological change can be expressed as follows:

$$Y_t = A \cdot L_t^{\alpha} \cdot K_t^{\beta} \cdot e^{\gamma t} \varepsilon_t \tag{1}$$

Where, Y is real output and L and K are the labor and real capital, respectively; e is the natural number, i.e., the base of the natural logarithm; t denotes time, which is also a proxy for technological progress of unknown forms; ε is the error term; A, α, β and γ are coefficients to be estimated. α and β are elasticities of output relating it to labor and capital.

In this study, we employ a CDPF that represents the relationship between output per labor (Y^*) and capital per labor (K^*) assuming the constant return to scale hypothesis following the same studies above. It takes the following form:

$$Y_t^* = A^* \cdot K_t^{*\,\beta} \cdot e^{\gamma t} \cdot \varepsilon_t^* \tag{2}$$

One of the reasons for using (2) is to investigate labor productivity rather than overall output. Another reason is that (2) is a more relevant theoretical framework to underpin econometric estimations in the event that the number of observations is small since it has one variable less compared to (1).

The CDPF can be considered a relevant theoretical framework, because with or without the presence of incentive, agriculture output is a function of capital and labor, theoretically, among other factors such as land and weather. If we include a measure of incentive in (2), which is in line with our research objective and express it in the natural logarithm form for the purpose of econometric estimations, we will get the following form:

$$y_t^* = \alpha_0 + \alpha_1 k_t^* + \alpha_2 s_t + \alpha_3 t + \xi_t \tag{3}$$

Where, y^* and k^* are natural logarithm expressions of per labor output, which is productivity, and per labor capital in agriculture; s is the natural logarithm of agriculture incentive; ξ is the error term.

Note that a number of agriculture-related studies also employ the CDPF framework in their analysis, such as Felloni et al. (2000), Antle (1983), Yunhua and Xiaobing (2005), Faridi and Murtaza (2013), Evenson and Mwabu (2001), and Timmer and Block (1994), Tintner (1944). Biddle (2011) surveys agriculture studies that have employed the CDPF framework in their research.

4. Data and methodology

4.1. Data

We use the annual time-series data for agriculture gross value added per employment (GVA), agriculture gross capital stock per employment (CS), and electricity incentive in agriculture (ELS) for the period 1988–2014. We end our analysis in 2014 as our research objective is to estimate the impact of the electricity incentives on the agriculture sector in the pre-reform period. Such kind of approach is usual in empirical analyses (e.g., see Harvey and Durbin, 1986). The starting year of the period is dictated by the availability of the agriculture employment data. Appendix B describes the variables.

Fig. 1 illustrates the natural logarithm levels of the variables, denoted in small letters, and their first differences against time in years.

4.2. Methodology

We first check the stochastic properties of the given variables above. Enders and Lee (2012b) state that conventional Dickey-Fuller type unit root tests (URTs) are straightforward to use and do not have initial-value problems, unlike de-trending URTs. Hence, we use the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) and Phillips-Perron (PP) (Phillips and Perron, 1988) URTs. To get robust results and thus strong inferences about the stochastic properties of the variables, we also employ Enders-Lee (EL) (Enders and Lee (2012a, b) URT to account for multiple structural breaks in the data. Enders and Lee (2012a) show that their test performs reasonably well not only for smooth breaks but also for sharp breaks. Moreover, we follow Furuoka (2016) approach and augment EL test with level shift and pulse dummies to capture large breaks if they exist and if they cannot be captured by the Fourier approximation. As further robustness, we also use Furuoka (2016) critical values for testing the null hypothesis of the unit root when the time trend is included in the test equation as they are based on small samples compared to Enders and Lee (2012b) critical values.[1]

Once the integration order of the variables is identified, we test the existence of a cointegrating relationship using the Johansen method (Johansen, 1988; Johansen and Juselius, 1990, 1992). According to the cointegration concept, if we have *n* variables, then we can have at most an *n-1* number of cointegrating relations (Engle and Granger, 1987 inter alia). However, only the Johansen approach can discover this. Other cointegration methods such as the Engle-Granger (EG) (Engle and Granger, 1987) and Autoregressive Distributed Lag (ADL) bounds testing (Pesaran and Shin, 1998; Pesaran et al., 2001) methods can only reveal whether or not variables are cointegrated. Incorrectly determining the number of cointegrating relationships among the variables can lead to an omitted variable bias issue if the equilibrium correction term of the other cointegrating relationship is statistically significant in

[1] For example, the τ critical value from Enders and Lee (2012b) is −4.95 at the 1% significance level when time trend is included in the test equation and frequency for the trigonometric functions, $k = 1$ and number of observations, $T = 100$, the smallest sample size (see Table 1a of that paper). However, the τ critical value from Furuoka (2016) is −5.13 at the 1% significance level for the same specification of the test equation but $T = 50$ (see Table 3 of that paper). Thus, if one uses 50 number of observations and considers the Enders and Lee (2012b) critical value instead of Furuoka (2016), she/he over-reject the null hypothesis of unit root process by about 4%.

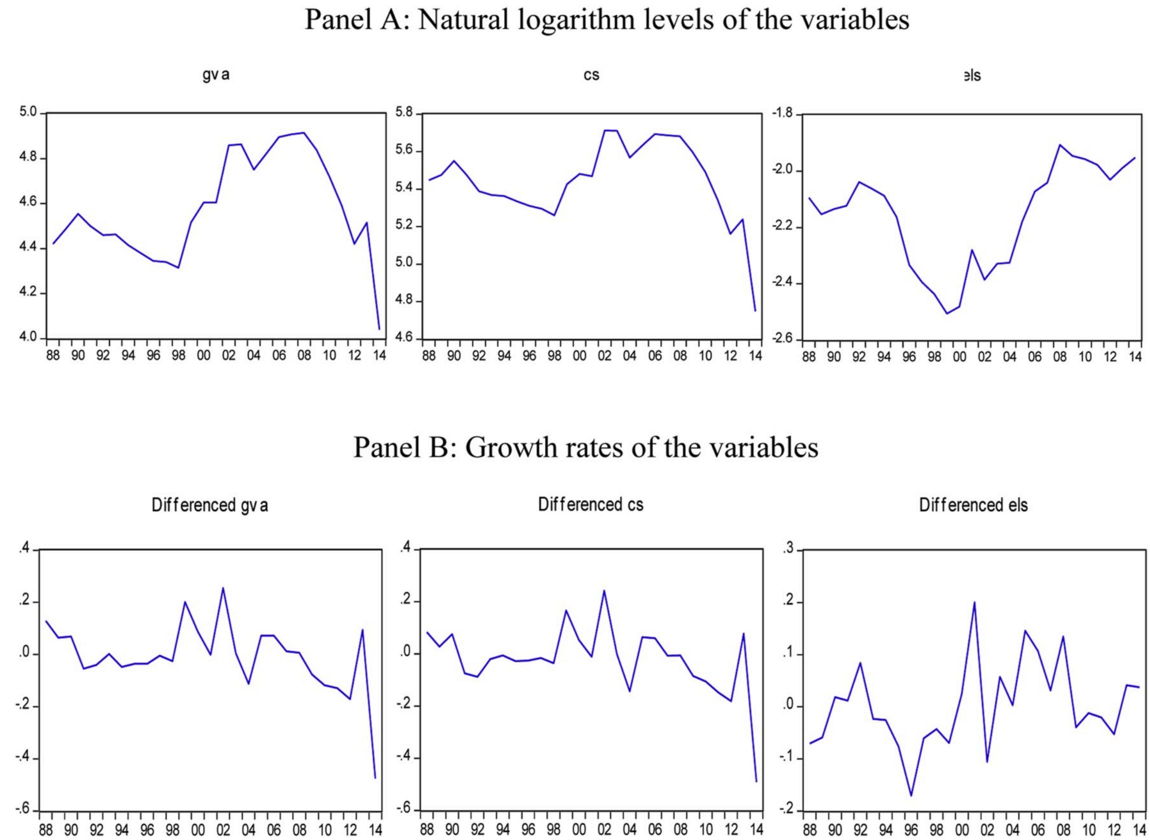

Fig. 1. Time profile of the variables.

the short-run specification of the variable in interest. Incorrect determination of the number of cointegrating vectors also may lead to information loss and inefficiency in the estimations. Once the Johansen method indicates one cointegrated relationship, then residual-based and/or single-equation-based cointegration methods such as the ADL bounds testing approach also can be applied as a robustness check. In both the tests, we apply small sample bias correction as further robustness. In order to take into consideration possible effects of the structural breaks in the dependent variable, if it is not captured by the explanatory variables, we also use the Fourier ADL type of cointegration test, which has been recently developed by Banerjee et al. (2017). The key advantages of this test over other cointegration tests designed to account for structural breaks such as Gregory and Hansen (1996), Westerlund and Edgerton (2007), Maki (2012), are that it can be applied without knowing prior information about a number of structural breaks, their occurrence dates, their types, whether they are endogenous or exogenous (Banerjee et al., 2017; Enders and Lee, 2012 a,b inter alia).

If the variables are cointegrated, then we use the Vector error correction model (VECM) alongside ADL (Pesaran and Shin, 1998; Pesaran et al., 2001), Fully modified ordinary least squares (FMOLS) (Phillips and Hansen, 1990), Dynamic OLS (DOLS) (Stock and Watson, 1993) and Canonical cointegrating regression (CCR) (Park, 1992) to estimate the level relationship between them in a robust way.

Once the long-run relationship is estimated and coefficients are found, we conduct a short-run analysis. An equilibrium correction model (ECM) will be applied to analyze the short-run relationships among variables.[2] In the case of the Johansen approach, and if all level variables except a variable of interest are weakly exogenous to the cointegration system, then we can estimate a single ECM of the variable of interest (de Brouwer and Ericsson, 1998, among others). We estimate the ECM in the General to Specific Modeling Strategy (GSMS) framework (Campos et al., 2005).

The descriptions of the tests and estimation methods are given in Appendix C.

5. Empirical findings

5.1. The URT results

In line with our methodology in this section, we first run the ADF and PP as well as EL tests to define the integration order of the variables. We perform the first two tests on the level and first difference of the variables. We also run the EL test for the level of the variables. The reason for this run is that the level of all three variables in Panel A of Fig. 1 demonstrates a drifting trajectory with more than one trend. For example, both *gva* and *cs* contain a downward trend during 1988–1998, and it is followed by an upward trend till 2008 and a downward one since then. For *els*, if we take a broader look, it has a downward trend during 1988–2000 and an upward trend since then. As discussed in the methodological section, such kind of breaks in the data can reduce the power of ADF and PP tests as these conventional tests cannot accommodate them, instead, the EL test can account for the breaks or non-linear trend. First, we ran general specifications of the tests, where we included both constant and trend as well as two lags of the dependent variables in all three tests. Additionally, we ran the EL test equations with a single frequency, k to be one and two for the trigonometric functions at a time and include shift dummy and pulse dummy variables following Furuoka

[2] Of course, this statement is true if the variables are cointegrated. Otherwise, short-run analysis is conducted by means of the VAR or ADL of stationary variables, where an error correction term is dropped, since the variables are not cointegrated.

(2016) .[3] We specified *k* to be one for the *gva* and *cs* test equations while *k* to be two for the *els* test equation based on the sum squared of residuals of the estimated test equations. The null hypothesis of no non-linear trend or break can be rejected as the sample F-values of 14.90, 13.26 and 14.93 for the *gva*, *cs* and *els* test equations, respectively are greater than the critical F-value at the 1% significance level, which is 12.21 (See Table 1a in Enders and Lee, 2012b). Table 1, below, reports final specifications of the ADF, PP and EL tests and their results for the level and first difference of the variables.[4]

The ADF and PP tests result evidently fail to reject the null hypothesis of unit root for the level of the variables, while strongly rejecting the null hypothesis for the first difference between them. According to the EL test results, the null hypothesis of unit root cannot be rejected for *gva*, *cs* and *els* as the test sample values in Table 1 are smaller than the respective critical values at 1%, 5% and 10% significance levels in Table 1a of Enders and Lee (2012b), i.e., −4.95, −4.35 and −4.05 in absolute terms. Even if one considers critical values from Furuoka (2016) calculated for small samples, the test sample values in Table 1 are still considerably smaller than the critical values at different significance levels in absolute terms, meaning that the null hypothesis of unit root cannot be rejected.[5] To conclude, the results indicate that *gva*, *cs,* and *els* are not stationary at their level, but the first differences of them are stationary. In other words, the variables are integrated in order one, i.e., I(1). Note that the time profiles of the variables illustrated in Fig. 1 are also in favor of the I (1) process. In this regard, the results from the UR tests are confirmed by those from the graphical analysis.

5.2. The cointegration test results

Since our variables appear to be I(1) processes, we can test for the cointegration that is a long-run relationship between them.[6] By following the methodological instruction of the Johansen approach (Johansen, 1988; Johansen and Juselius, 1990; Juselius, 2006; Enders, 2015), we first build a VAR of *gva*, *cs* and *els*. Section D1 in Appendix D describes the estimation details of the VAR. The VAR successfully passes all the residual diagnostics and stability tests, as indicated in Panels A through D in Table 2, below.

Then we transform the VAR to a VECM to test for cointegration and to estimate the long-run relationship among the variables. We perform the Johansen cointegration test on the VECM. The details of the cointegration test options are discussed in Section D1 of Appendix D. According to the test results, there is only one cointegrated relationship among *gva*, *cs,* and *els* even after small sample bias correction as Panel F of Table 2 reports. We also check statistical significance, stationarity and weak exogeneity of *gva*, *cs,* and *els*. The results documented in Table D1 of Appendix D indicate that they are non-stationary (which supports URT results in Table 1) and statistically significant and only *cs* is weakly exogenous to the cointegration relationship.

As discussed in the methodological section, we also run the Fourier ADL cointegration test that accounts for multiple structural breaks or non-linearity in the cointegration test. The estimation results are reported in Appendix D Section D2. We conclude that a conventional ADL and bounds testing approach developed by Pesaran et al. (2001) should be used to test for cointegration and estimate level relationship as the null hypothesis of no non-linear trend cannot be rejected in the Fourier ADL method framework. We did so and reported the obtained long-run coefficients in Table 3. In the ADL estimations, the maximum lag order of two was set for *gva* and *cs*, *els*, and the ADL (1,0,2) specification is selected by Schwarz information criterion among 18 candidate specifications. The selected ADL(1,0,2) successfully passes the post-estimation tests, including residuals serial correlation, normality, heteroskedasticity as well as misspecification and stability (the results of the tests are available from the authors under request). Bounds test for cointegration using ADL(1,0,2) yields the sample F-value of 503.392. This value is hugely greater than the respective upper bound critical F-values of Pesaran et al. (2001) and even those of Narayan (2005) calculated for small samples. Hence, we reject the null hypothesis of no cointegration and conclude that there is a cointegrated relationship between *gva* and the explanatory variables. The ADL finding of the cointegrated relationship among the variables supports the finding of the Johansen cointegration test.

5.3. The long-run estimation results

Since the Johansen test discovers not more than one cointegrated relationship between the variables, there is no information loss, and we can also run the ADL, FMOLS, DOLS and CCR methods alongside the VECM in estimating coefficients as a robustness check. Table 3 documents the estimation results.

The general conclusion from Table 3 is that all five methods produce very similar and statistically significant coefficients, which indicate the robustness of the assessments. Across methods, the coefficients of *gva* with respect to *cs* are 0.97 on average, while the trend is about 0.01. Regarding the electricity incentive elasticity of agricultural productivity, the dynamic methods VECM and ADL produce numerical values around 0.04, while static methods yield about 0.07.[7]

As the last exercise in the long-run analysis, we performed additional long-run estimations and cointegration testing by including two more variables, namely rainfall (*RF*) and temperature change (*TCH*) in the analysis to ensure that our estimation findings are robust and thereby the policy recommendations that we propose are well-grounded. The results are given in Section D3 of Appendix D. They show that neither *TCH* nor *rf* is part of the long-run relationship of *gva*. Therefore, we can conclude that the long-run relationship that we obtained for *gva* in Table 3 is robust.

5.4. The short-run estimation results

Finally, we estimate single equation ECMs. Again, the FMOLS, DOLS and CCR methods yield very close long-run coefficients, as reported in Table 3. It is reasonable to think that the long-run residuals, i.e., error correction terms (ECT) calculated based on those coefficients would lead to considerably close ECM specifications, especially the speed of adjustment (SoA) coefficients. Therefore, we calculate only one ECT, *ect_EG*, by averaging the respective long-run coefficients from the FMOLS, DOLS, and CCR and estimate one ECM for them. Alongside this,

[3] Enders and Lee (2012a, b), and Furuoka (2016) among others discuss that it is recommended to keep *k* small. This further amplified by the small number of observations we have. A shift dummy variable, taking unity for 1999–2014 and zero otherwise, and a pulse dummy variable, taking unity in 1999 and zero otherwise, included in the EL test of *gva* and *cs* but they became statistically insignificant in the final test specifications, whose results are reported in Table 1. A shift dummy variable, taking unity for 2001–2014 and zero otherwise and a pulse dummy variable, taking unity in 2001 and zero otherwise included in the EL test of *els* and they became statistically significant in the final test specification.

[4] We did not run the EL test for the first difference of the variables as their graphical illustrations in Panel B of Fig. 1 suggest stationary processes and do not demonstrate any breaks or other type of non-linearity.

[5] The critical values are −5.13, −4.44 and −4.10 at 1%, 5% and 10% significance levels to compare the test results of *gva* and *cs* (see Table 3 on page 19 of Furuoka, 2016). The critical values are −5.14, −4.31 and −3.88 at the 1%, 5% and 10% significance levels to compare the test results of *els* (see Table 3 on page 20 of Furuoka, 2016).

[6] It could still be meaningful to test for cointegration, even if the regressors were be a mix of I(1) and I(0) processes, according to the concept behind the ADL bounds testing approach.

[7] Note that we could not run DOLS with sufficient numbers of lags and leads due to the small number of observations. Hence, it was run in a static case.

Table 1
The UR test results.

Variable	ADF test					PP test					EL test					
	Test value	C	*t*	N	*l*	Test value	C	*t*	N	*l*	Test value	C	*t*	N	*l*	*k*
gva	0.376		x		0	0.423		x		0	−3.05		x		1	1
cs	0.514		x		0	0.828		x		0	−2.70		x		1	1
els	−1.438		x		0	−1.581		x		0	−0.16		x		1	2
Δgva	−4.069**		x		0	−4.170**		x		0						
Δcs	−4.250**		x		0	−4.344***		x		0						
Δels	−4.253***			x	0	−4.269***			x	0						

Notes: ADF, PP and EL denote the Augmented Dickey-Fuller, Phillips-Perron and Enders-Lee tests, respectively. Maximum lag order is set to two, and optimal lag order (*l*) is selected based on the Schwarz criterion in the tests. *k* is the selected frequency for the trigonometric functions. ***, **, and * indicate a rejection of the null hypotheses at the 1%, 5%, and 10% significance levels, respectively. The critical values for the ADF and PP tests are taken from MacKinnon (1996), while those for the EL are taken from Furuoka (2016). Estimation period: 1988–2014. The final UR test equation can include one of the three options: intercept (C), intercept and trend (*t*) and none (N). x indicates that the corresponding option is selected in the final URT equation based on statistical significance.

Table 2
The VAR residual diagnostics, stability and cointegration tests results.

Panel A: Serial Correlation LM Test [a]

Lags	LM-Statistic	P-value
1	14.143	0.117
2	15.508	0.078*
3	11.175	0.264

Panel D: VAR Stability Condition

Root	Modulus
0.838-0.314i	0.895
0.838+0.314i	0.895
0.302-0.620i	0.690

Panel B: Normality Test [b]

Statistic	χ^2	d.f.	P-value
Skewness	3.740	3	0.291
Kurtosis	0.910	3	0.823
Jarque-Bera	4.650	6	0.589

Panel E: Johansen Cointegration Test Summary

Data Trend:	a) None	b) None	c) Linear	d) Linear	e) Quadratic
Test Type:	No ***C*** and ***t***	Only ***C***	Only ***C***	***C*** and ***t***	***C*** and ***t***
Trace:	1	0	0	1	1
Max-Eig:	0	0	0	1	1

Panel C: Heteroscedasticity Test [c]

White	χ^2	d.f.	P-value
Statistic	94.981	90	0.339

Panel F: Johansen Cointegration Test Results for Version d

Null hypothesis:	$r = 0$	$r \leq 1$	$r \leq 2$
λ_{trace}	51.477**	17.807	5.765
$\lambda^{a}{}_{trace}$	40.034*	13.849	4.483
λ_{max}	33.670**	12.041	5.765
$\lambda^{a}{}_{max}$	26.185**	9.364	4.483

Notes: [a] The null hypothesis in the Serial Correlation LM Test is that there is no serial correlation at lag order h of the residuals; [b] Normality Test is Doornik-Hansen system normality test with the null hypothesis of the residuals are multivariate normal; [c] White Heteroscedasticity Test takes the null hypothesis of no cross terms heteroscedasticity in the residuals; χ^2 is Chi-squared; d.f. means degree of freedom; P-value means probability value; ***C*** and ***t*** indicate Intercept and trend; *r* is rank of Π matrix, i.e., number of cointegrated equation; λ_{trace} and λ_{max} are the Trace and Max-Eigenvalue statistics, while $\lambda^{a}{}_{trace}$ and $\lambda^{a}{}_{max}$ are adjusted version of them; ** and * denote rejection of the null hypothesis at the 5% and 10% significance levels respectively; Critical values for the cointegration test are taken from MacKinnon et al. (1999); Estimation period: 1988–2014.

Table 3
Long-run estimates from the methods.

Methods	*cs*	*els*	*Trend*	*Intercept*
	Coef. (Std. Er.)	Coef. (Std. Er.)	Coef. (Std. Er.)	Coef. (Std. Er.)
VECM	0.945***	0.047**	0.011***	−1.185
	(0.025)	(0.017)	(0.000)	
ADL	0.963***	0.044**	0.011***	−1.248***
	(0.023)	(0.021)	(0.000)	(0.108)
DOLS	0.988***	0.073***	0.011***	−1.337***
	(0.022)	(0.027)	(0.001)	(0.134)
FMOLS	0.984***	0.071***	0.011***	−1.256***
	(0.017)	(0.021)	(0.000)	(0.105)
CCR	0.967***	0.070***	0.011***	−1.234***
	(0.023)	(0.019)	(0.000)	(0.133)

Notes: The dependent variable is *gva*; Coef. and Std. Er. are coefficient and standard error; Standard errors are in parentheses; *, ** and *** indicate significance levels at 10%, 5%, and 1%. The same coefficients in the trend and zero standard errors are the results of three digits rounding. The reported elasticities for *cs* are the estimated ones minus 2 times of their standard errors to be consistent with the theoretical discussion in section 3. Estimation period: 1988–2014.

we calculate two additional ECTs, one from the Johansen and another from the ADL long-run coefficients. Thus, we have three ECMs to estimate. We employ the general-to-specific modeling strategy, as discussed in the methodological section. Each general specification includes two lags of Δgva, Δcs, Δels, one lag of the *ECT* and contemporaneous values of Δcs as well as the intercept term.[8] Although neither *TCH* nor *rf* provides additional information in explaining the long-run behavior of *gva*, we still consider them for the short-run relationship as further robustness. Such consideration is also theoretically reasonable as some variables have only short-run effects but not the long-run. In doing so, we additionally include *rf* and the stationary transformation of *TCH*, i.e., the de-trended series of it, denoted as *TCH_DT* in the general ECM specifications, to see whether they can provide additional information in explaining the short-run behavior of Δgva. Final ECM specifications are selected by excluding statistically insignificant regressors while passing all the residual diagnostics and misspecification tests. Table 4 reports the resulting final specifications and test statistics.

[8] As discussed above, since *els* is not weakly exogenous to the cointegration system, to avoid inefficiency of the estimations we do not include a contemporaneous value of it in general ECM specifications.

Table 4 documents that the selected final ECM specifications successfully pass the post-estimation tests. The SoA coefficients across the three ECMs are quite close to each other. Additionally, they are negative and statistically significant, indicating that the short-run disequilibrium adjusts to the long-run equilibrium path and, therefore, the cointegrating relationship among the variables is stable. The table presents that all the remained variables in the final specifications are statistically significant and theoretically interpretable. Hence, we can use the results in the final ECM specifications to explain the short-run behavior of agriculture productivity and to derive policy recommendations.

6. Discussion of the empirical findings

In this section, we discuss the results of our empirical analysis. According to the unit root test results, documented in Table 1, agricultural productivity, capital and electricity incentives are non-stationary variables, meaning that their mean, variance and covariance change over time. They are not mean-reverting processes, and it is, therefore, difficult to predict future values for them. Additionally, non-stationarity assumes that any shock from policymakers, or socioeconomic and other processes, to these variables may involve a permanent change. Since the variables are non-stationary with stochastic trends, there is a possibility that they share a common stochastic trend. This is called a long-run relationship, i.e., cointegration. Tables 2 and 3 report that agricultural productivity, capital and electricity incentives are cointegrated, meaning that there is a meaningful relationship between the levels of these variables, which can be interpreted using economic theory. Hence, it is useful to estimate numerical values for this relationship and use these as a basis for policy recommendations.

We estimated the impact of capital, electricity incentives, and technological progress proxied by time trend on agricultural productivity, employing five different long-run estimators, VECM, ADL, DOLS, FMOLS, and CCR, as a robustness check. The results, tabulated in Table 3, show that there is a theoretically expected and statistically significant numerical relationship. Before proceeding to an interpretation of the results, it is worth mentioning that numerical values, i.e., elasticities, from the different estimators are very close to each other, indicating the robustness of the empirical parameters.

Table 4
Final ECM estimations and test results.

Method	Johansen	ADL	EG
Panel A: The final ECM specifications			
Regressor	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
ect_JOH_{t-1}	−0.509*** (0.125)	–	–
ect_ADL_{t-1}	–	−0.561*** (0.129)	–
ect_EG_{t-1}	–	–	−0.607*** (0.136)
c	0.152*** (0.035)	−0.555*** (0.130)	−1.406*** (0.317)
Δgva_{t-1}	0.335** (0.152)	0.353** (0.148)	0.384** (0.148)
Δcs_t	0.996*** (0.022)	0.992*** (0.021)	1.005*** (0.021)
Δcs_{t-1}	−0.298* (0.159)	−0.325** (0.155)	−0.348** (0.155)
Δels_{t-1}	0.102** (0.040)	0.105** (0.039)	0.090** (0.037)
TCH_DT_t	−0.020** (0.007)	−0.020** (0.007)	−0.020** (0.007)
Panel B: Statistics, residuals diagnostics and model stability test results			
SER	0.0142	0.0138	0.0136
F_{AR}	0.905 [0.422]	0.699 [0.510]	0.710 [0.505]
F_{ARCH}	1.092 [0.306]	0.010 [0.325]	0.843 [0.368]
F_{HETR}	0.536 [0.775]	0.402 [0.869]	0.424 [0.854]
JB_N	0.258 [0.879]	0.452 [0.798]	0.206 [0.902]
F_{FF}	0.600 [0.448]	0.404 [0.532]	0.170 [0.685]

Notes: Dependent variable is Δgva_t; *ect_JOH*, *ect_ADL*, and *ect_EG* are the error correction terms, i.e., the residuals from the long-run relationships of the Johansen, ADL and Engle-Granger methods. *SER* is the standard error of regression; F_{AR}, F_{ARCH} and F_{HETR} denote F statistics to test the null hypotheses of no serial correlation, no autoregressive conditioned heteroscedasticity, and no heteroscedasticity in the residuals; JB_N and F_{FF} indicate and Jarque-Bera and F statistics to test the null hypotheses of normal distribution and no functional form misspecification, respectively. Probabilities are in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Estimation period: 1988–2014.

In Table 3, according to the dynamic and static estimators a 1% increase (decrease) in the electricity incentive leads to a 0.04–0.07% increase (decrease) in agricultural productivity in the long-run. Apparently, the long-run elasticities are quite small but statistically significant. Our interpretation for this finding is that the sectoral long-run growth effects of the electricity incentives are minor but they are needed. The following observations would support this finding. Although general economic theory articulates that in standard economies, incentives can lead to market distortion and a lack of competitiveness of the subsidized companies or fields in the long-run, the picture is different in Saudi Arabia (Goodwin, 1992; von Moltke et al., 2004). First, because Saudi agriculture takes place in a desert environment with very high temperatures and very limited rainfall, it is very hard to keep this sector alive without government support. Second, the Saudi agricultural sector is run by a limited number of players. In other words, there is no quite interest in economic agents in doing business and investing in the agriculture sector. Third, if the government did not support the development of the sector, then people employed in the sector, as well as those living in the rural area, would migrate to the urban areas massively, which would not be favorable in terms of economic diversification, environmental concerns, and sustainable development. Lastly, earlier studies such as Elhadj (2004), Al-Shaya et al. (2012), Napoli et al. (2016), Grindle et al. (2015), Alyousef and Stevens (2011), Tuncalp and Yavas (1983) and Mousa (2017, 2018) make general observations about the positive effect of different types of government incentives on the country's agriculture sector.

According to Table 3, there is almost a one-to-one relationship between productivity and capital in the Saudi agricultural sector in the long-run. In other words, all other factors being constant, a 1% increase (decrease) in capital will result in a 0.97% increase (decrease) in agricultural productivity. This finding is consistent with economic theory, as the production function concept predicts a positive association between capital and output, as discussed in the theoretical framework section of this paper. Since this is an expected relationship between these two variables, we do not interpret it in detail. The obtained numerical values for the capital elasticity of agricultural productivity are consistent with the nature of the sector in Saudi Arabia. As discussed earlier, because of the harsh climate conditions and desert environment, the sector is very capital intensive. The large capital elasticity implies a low labor elasticity of the Saudi agricultural output in the case of constant return to scale assumption.[9] Two things would mainly explain lower labor elasticity: again, the nature of the sector, which does not allow labor force to contribute more to the output; the sector is not labor-intensive, unlike in other countries. Its share in total employment was just about 6% on average for 1988–2014. Although we are not aware of any studies assessing the long- or short-run effects of capital on the agricultural sector in Saudi Arabia, studies dedicated to other countries also find a positive impact of the former on the latter. These include Timmer and Block (1994) for Kenya, Felloni et al. (2000) for China, Faridi and Murtaza (2013) for Pakistan and Antle (1983) for 47 less developed and 19 developed countries.

Finally, it was found that technological progress is positively related to agricultural productivity. Agricultural productivity has grown on average by 1.10% (0.011*100) per annum due to technological progress. This is a quite reasonable finding and does not need a detailed explanation given that both theoretical and empirical studies are in agreement that technological progress is one of the key drivers of productivity increase.

[9] $\alpha = 1 - \beta = 1 - 0.97 = 0.03$.

Short-run results from the final ECM specifications, documented in Table 4, show that one percentage point increase in the growth rate of the electricity incentive in the previous year raises the agricultural productivity growth by 0.10 percentage point in the present year. Noticeably, the short-run impact of the electricity incentive is greater than that in the long-run. This is consistent with the economic theory, as it articulates that incentives can foster economic growth in the short-run and they can also cause market distortions and a lack of competitiveness in the longer term.

As Table 4 presents, the cumulative short-run impact of capital on productivity is positive, and it is smaller than that in the long-run. Numerically, a one percentage point increase in the growth rate of capital leads to a 0.67 percentage point increase in agricultural productivity growth. This is also consistent with economic theory: investment has a long-lasting and lagged effect on output, and this effect is larger in the long-run and less pronounced in the short-run.

Table 4 further reports that if the temperature deviates 1 Â°C hotter than its trend line, then the agricultural productivity growth will decline by about 2.01 percentage points. This finding is reasonable for Saudi Arabian agriculture. As discussed earlier, Saudi Arabia has harsh climate conditions with extremely high temperatures, and this is one of the key problems for the agriculture sector. Figure D1 illustrates that over time the average temperature change in Saudi Arabia trends up, meaning that it gets hotter. Obviously, such increased temperature is harmful to the agriculture sector. Temperature increases and global warming are mainly caused by man-made greenhouse gas emissions, which is the key factor for environmental pollution. In this regard, our finding implies that man-made greenhouse gas emissions exert a negative effect on agricultural development. Our interpretation of the short-run effect of the temperature change would be as follows. The impact of temperature always exists, but the point is that when temperatures rise above previous levels, this exerts a statistically significant negative effect on the sector according to the short-run estimation results. However, authorities and farmers take relevant measures to protect the sector, especially plant growing, from this negative effect over time, and hence, the negative effect becomes not statistically significant in the long-run.

Table 4 tabulates SoA coefficients to be quite close to each other from the methods employed and being an average of −0.56. It shows that if there are shocks to agricultural productivity, 56% of the disequilibrium caused by these shocks will be corrected toward the long-run equilibrium path over the course of one year. This is quite a fast adjustment and, among other things, implies that policy measures in the agricultural sector would not have a permanent shock effect and that the sector is capable of absorbing them in a short time horizon.

Finally, it should be noted that all the estimated coefficients across the final ECMs in Table 4 are very similar to each other, indicating the robustness of the obtained short-run parameters. Unfortunately, we are unable to compare the numerical values we obtained in this research with those from other studies as we could not find any prior econometric studies on this topic for Saudi Arabia.

7. Conclusion and policy implications

The agriculture sector in Saudi Arabia requires energy inputs at different stages of production, from land preparation to harvesting and packaging. These energy inputs are essential for the sector's development, given the features of the sector formed by the harsh environmental conditions, extreme temperatures and low precipitation in the country. Historically, the government has subsidized energy consumption, among other inputs of the sector. However, it is difficult for the government to provide the same levels of support to agriculture as it used to given that the low oil price environment currently prevails and it entails low oil export revenues for the public finance. In addition, the government has started implementing domestic energy price and fiscal reforms at the end of 2015 in line with the FBP, one of the key realization programs of SV2030 (FBP, 2017, 2018, 2019).

Given this contextual background, this research examined the role of electricity incentive in the development of the agricultural sector in the pre-reform period to find out how large its magnitude was and thereby to determine whether their removal is a relevant policy measure to take.

We have examined the impact of electricity incentives on the Saudi Arabian agriculture sector in the long- and short-run using the augmented production function framework. We employed different tests, estimation methods, as well as small sample bias corrections to achieve more robust results and, as a result, well-grounded policy recommendations. Our empirical analysis shows that there are long-run and short-run agricultural productivity effects of electricity incentives, capital, and technological changes. It additionally shows that temperature increases, mainly caused by the carbon emissions from fossil fuel consumption, have a short-run inverse effect on agricultural development. The estimation results from different methods are also very similar, which indicates the robustness of the results obtained.

The findings from the empirical analysis, especially the small magnitude of the influence of the electricity incentives, answer to our research question: it would be a relevant policy strategy to remove the electricity incentives from the sector. Because the effect is small but exists, the gradual removal of electricity incentives with some mitigation measures seems a relevant policy option for the government to consider for the sector. It appears that the answer derived from the empirical analysis supports the underlying EPR policy strategy that the government implements. Precisely speaking, a gradual phasing out of energy incentives, i.e., increasing the domestic energy prices to the level of the international prices, with the mitigation measures is the policy measure that the Saudi government has been implementing since the end of December 2015. The gradual removal of energy incentives also helps for a smooth transition and gives some time for the sectors of the economy to adapt to the new environment. Hence the negative effect of removing the energy incentives should be minimal. In addition, the National Transformation Program 2020 (NTP), the other SV2030 realization program, highlights initiatives for the sustainable development of the agriculture sector (NTP, 2017). Moreover, the FBP (2019) outlines that government agencies such as the General Authority for Small and Medium Enterprises, Ministry of Finance should take appropriate policy measures to support small and medium enterprises (SMEs) and thereby to mitigate potentially harmful effects of the EPR by means of different direct and indirect ways such as returning government fees collected from SMEs, starting indirect lending to SMEs and raising the capital of the bail program "Kafalah" (FBP, 2019). The SMEs in the agriculture sector should also be included in the mentioned support programs given the importance of the sector regarding food security, keeping a balance between the rural and urban population, and maintaining its share in total employment, diversification of the Saudi economy as well as the features of the sector in Saudi Arabia mentioned above.

Removing electricity incentives will make additional resources available to the government. These could then be used for different purposes, in line with the objectives of the SV2030, such as strengthening the government's fiscal position, supporting social welfare or economic development. Among other key directions in SV2030, the available resources can also be used to accelerate the energy transition by investing in or financing technological enhancement and renewable energy projects, which generate additional electricity to meet demand by lowering domestic use of oil that can be exported and bring additional revenues, mitigate environmental pollution that is beneficial for current and future generations. In this regard, promotion for solar energy generation seems to be one of the relevant projects to consider because of the geographically strategic location of the Kingdom, such as being located in the so-called 'sunbelt' and having one of the world's highest solar irradiation, year-round clear skies as well as the abundance of desert land that can accommodate infrastructure for solar energy (see, e.g., discussion in Almasoud and Gandayh, 2015).

It is a commonly accepted idea that electricity incentives encourage the extensive use of water resources and result in burning more fuel to generate more electricity and, thus, more carbon emissions. It could be that phasing out the energy incentives will help to preserve water resources and decrease environmental pollution. This is consistent with the strategic goals and targets for the Ministry of Environment, Water, and Agriculture highlighted in the (NTP, 2017). This can also help achieve domestically and internationally committed environmental mitigation targets. The positive environmental outcomes of removing the energy incentives could outweigh any depressive effects on the agriculture sector, as our research found these effects to be very small.

It should be noted that, as economic theory postulates, while energy incentives can help sectors in the short-run, they can create some challenges, such as market distortions, the irrational use of resources, undesirable structural changes, or disproportional development of the sector relative to others in the long-run. The gradual removal of electricity incentives should help rationalize the Saudi agricultural sector and make it more efficient and competitive over time. Both of these support the Kingdom's economic diversification strategy, a key target of the SV2030 (NTP, 2017; FBP, 2019).

In addition to the policy implications above regarding the electricity incentives and its removal, which is the main interest of this study, the empirical findings of this research also can inform policymaking regarding the roles of capital (and implicitly labor), technological progress and temperature change in the development of the sector. The sector is very capital intensive due to the country's desert environment and harsh climatic conditions. We think that this is one of the reasons why we found a statistically significant and quite large impact of capital on agricultural development in the country, whereas we found the implicit effect of labor to be very small. It would be a better policy to encourage capital stock turnover towards those that are highly energy efficient, which is in line with one of the objectives for the Ministry of Environment, Water and Agriculture highlighted in the NTP (2018): developing sustainable and highly efficient production systems for plants, livestock and fishery and increasing the value-added of these target products. At the same time, the authorities should set up measures to increase the role of the labor force in the sector's development, although it is not an easy task.

The policymaking process should aim to accelerate technological development, as this, according to the findings of this study, plays a positive and significant role in the development of the agricultural sector in Saudi Arabia. Decision-makers might wish to allocate more financial and human resources to research and development activities. Moreover, they might wish to take the necessary measures to attract more foreign direct investment, perhaps by creating a technological development and modern investment parks in the sector. As a policy option, authorities may consider recycling the energy incentive removal revenues back to the sector to foster innovation activities.

This would also be useful information for policymaking that, over time, the average temperature change in Saudi Arabia trends up, and this has a negative effect on the development of the agriculture sector. Obviously, policies cannot impact this factor directly. Still, it should be taken into consideration that the continuation of the current trend implies that the sector will be hurt by this significantly. The temperature increase and overall global warming are mainly caused by man-made greenhouse gas emissions. Hence, the authorities should implement measures to decrease man-made greenhouse gas emissions, which can curb further temperature increases and, thus, the negative effect on the agriculture sector. Since the main part of the man-made greenhouse gas emission is carbon emissions resulting from fossil fuel energy consumption, removing energy incentives in the entire economy, including in the agriculture sector, seems a relevant measure to take.

Last but not least, policymakers may want to be aware that the findings of our research suggest the Kingdom's agricultural sector is capable of absorbing shocks. This implies that any shock, including those that could be caused by the implementation of the policy measures, would be only temporary and should disappear within two years.

CRediT authorship contribution statement

Fakhri J. Hasanov: Conceptualization, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing - original draft. **Sa'd Shannak:** Conceptualization, Data curation, Investigation, Project administration, Software, Validation, Visualization, Writing - review & editing.

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Appendix A. The role of government incentives in agricultural development

A1. Government incentives and agricultural development

Policymakers and stakeholders design their interventions to meet societal welfare requirements and increase fiscal strength. Government incentives are one of the policy interventions that have been adopted in both developing and developed countries. These types of interventions play a role in economic and social development by controlling prices and shielding people from high price fluctuations for essential commodities (Sowa and Edpri, 2007). In general, government incentives aim to encourage investment in certain sectors to make local commodities more competitive than foreign ones and to reduce the reliance on imports, which is very important for food security.

Although government incentives might sound good for consumers in a non-free market scenario, they are essentially a transfer of revenues from taxpayers to business owners. Those not in receipt of government incentives, therefore, lose out twice and are also forced to compete with those that do receive them (Amegashie, 2006). Typically, wealthy countries can afford domestic government incentives, but, in some cases, domestic government incentives could make developing countries poorer by artificially bringing down prices for their goods in the global commodity markets. Developing countries that cannot afford to lower production costs for their farmers by providing government incentives, or any other type of support, could lose their market share, and this, in turn, would slow down economic activity, lower incomes and increase poverty.

Agriculture is an example of a sector that cannot survive without government support in many countries. Government incentives are given to farmers in rural and remote areas to raise their income and reduce migration from rural areas to urban areas. Usually, the government incentives the agriculture sector receives include providing low-priced inputs, government incentives that guarantee certain purchase prices when the market price does not cover farmers' production costs and government incentives that facilitate the export of products (Gottschalk et al., 2007). Most studies on government incentives for agricultural refer to the World Trade Organization's Doha Development Round in 2001. This meeting aimed to rationalize agricultural government incentives in many developed nations, including the U.S. and Europe (Anderson and Martin, 2005; Bouet et al., 2005). Agriculture is vulnerable to many factors that governments might, at times, have control over, such as technological innovation and fuel prices. Other factors that they might have no control over include their geographical location, weather conditions, and resource availability. As the factors impacting the agricultural sector that cannot be controlled exceed those that governments can control, it is clearly essential that the sector is supported. There is a need to understand the basis on which the government incentives are given, whether they are working or not, if they face any fiscal or political constraints, and if they correct market failures by achieving efficiency and equity, and reducing potential tradeoffs.

Shah and Verma (2008) and Gulati and Pahuja (2015), among others, recommend that to reduce water and energy resource wastage resulting from electricity incentives, policymakers might consider some of the following policy options:

- Give farmers a choice to either limit the total hours of subsidized power supply or to follow a scheme where they receive long hours of supply. Still, the government incentive is based on the quantity of electricity used rather than the hours of supply.
- Provide electricity incentives only during irrigation seasons and phase them out during rainy seasons.
- Provide electricity incentives based on consumption, avoiding a flat rate.
- Apply gradual increases to flat rates so as to approach the real cost of supply.
- Provide electricity incentives based on intelligent scheduling and management of rationed power supplies, such as providing incentives for off-peak consumption.

A2. Impact of the government incentives on the economy

Government incentives are usually provided with the aim of correcting and reducing market failures (Koski and Pajarinen, 2010; Wren, 1994). An efficient government incentive with the right amount given to the right sector would correct market failure and align social and private costs and benefits. They tend to provide a positive impact in the short-term but might exert a negative effect on the long-term (Gustafsson et al., 2016, inter alia). On the other hand, government incentives are costly policy options and may cause complex economic distortions if they are not well planned. It is necessary to phase out government incentives when they start to cause inefficiencies, diminish social welfare, and impede the efficient allocation of resources. Failure to change behavior in the ways expected through government incentives, or incentivizing activities that would take place anyway without them means that, in those cases, government incentives represent wasted resources (McKenzie and Mintz, 2011). Phasing out government incentives is a politically difficult decision to make, and only very few countries choose to do so (Victor, 2009). Government Incentives also distort price signals and create uncertainty over investment decisions. Among other things, phasing out government's energy incentives can bring about substantial reductions in environmental pollution (Morgan, 2007).

A3. Government Incentives and the agricultural sector in Saudi Arabia

Gupta et al. (2002) state that the average government incentive in major oil-exporting countries was 3.0% of GDP and 15.2% of government expenditure in 1999. The IEA reported 37 countries subsidizing domestic energy prices, and, as might be expected, most of them are net oil exporters who provide a large amount and number of government incentives. Saudi Arabia is ranked second in the world, following Iran, and is followed by Russia (IEA, 2010). The Saudi Arabian agriculture sector is no exception. The country's harsh climate, characterized by high temperatures during the day, an abrupt drop in nighttime temperatures, and very low annual rainfall, make it a very challenging place to grow crops without major government support (Almazroui et al., 2012). Despite much skepticism, Saudi Arabia's total agricultural production skyrocketed between 1983 and 1993, with total wheat production rising from 148 thousand tonnes to 4.1 million tonnes. This was facilitated by significant agricultural incentives of the government to encourage local production as (SAMA, 2018) statistics show. The abundance of natural fossil fuels and the substantial revenues the country receives from exporting them has enabled Saudi Arabia to offer the agriculture sector higher government incentives, in the form of lower prices for electricity and other energy products, such as diesel.

Agriculture consumes energy in many ways: through pumping water from deep groundwater wells, farm machinery, cultivation, and harvesting, or in the manufacture of fertilizers and chemical pesticides, which require significant amounts of energy. Saudi Arabia has been able to keep local fuel prices well below international benchmarks through government incentives. The 2017 gasoline price (0.24 US$/liter) was almost 58% lower than the average international price of 0.58 US$/liter, and the price of diesel (0.20 US$/liter) is 68% lower than the average international price of 0.63 US $/liter. Although these government incentives are often criticized for boosting energy use, their actual impacts, and the extent to which subsidized prices affect total consumption remains debatable and difficult to estimate.

Poultry and dairy products account for the biggest share of energy consumption in the agricultural sector, as they must be produced, processed, packaged, distributed, and stored at a low temperature using a continuous stream of cold air. The dependence of the food supply chain on energy makes food prices vulnerable to any changes in energy prices, particularly electricity, as it is the main source of energy used to run food processing refrigeration systems (Canning, 2011). Therefore, it has become increasingly crucial to assess the impact of government incentives for electricity on the agriculture sector as they contribute to the sector's overall productivity and, eventually, to the national economic growth. Despite the prevalence of energy incentives in Saudi Arabia, there is little existing research offering guidelines and tools to assess the impact of these government incentives on the agriculture sector.

This topic has attracted researchers in the Gulf Cooperation Council (GCC) countries following the recent fall in oil prices. The available literature focusing on the GCC is very limited, and the bloc has not been a focus of research over the past few decades, despite its major role in many economies. The lack of research on energy incentives in the Saudi agricultural sector can be explained in three ways:

- -First, there is a lack of data on agricultural electricity incentives, and the problem is complex, with no clear methodology for assessment.
- -Second, there has been no urge to conduct research in this area because oil prices have been around $100 per barrel for decades. Saudi Arabia's substantial oil revenues have paved the way for more government incentives.
- -Third, electricity consumption in the agricultural sector is small in comparison with other sectors, such as service and industry in Saudi Arabia.

The current decline in oil revenues was one of the reasons for several oil-exporting countries, including Saudi Arabia, to reform their domestic energy prices, rationalize spending and re-consider government incentives. This could have different impacts on the welfare of communities and the profitability and competitiveness of different sectors, including agriculture. Measuring the impact of government energy incentives in an economy in the short- and long-run could also help policymakers to design their reform plans better.

A4. Government electricity incentives in the agriculture sector of developing economies

Since we could not find a sufficient number of studies investigating the effects of energy/electricity incentives by government on the development of the agricultural sector in the case of Saudi Arabia, in this sub-section we review the papers that examine this relationship in the case of other developing countries by following the anonymous referee's comment. Although the majority of the studies examining energy/electricity incentives in the agriculture sector are found for India as it is the 5th largest economy in the world in terms of energy subsidy expenditures (UNEP, 2008; WB, 2010; IEA, 1999; Sharma et al., 2015), we tried to include studies devoted to other developing countries' agriculture in this review as well.

The main objective of these government incentives, including electricity incentives, was to improve economic growth, sustain food security, increase electricity coverage, and reduce the cost of irrigation. Several studies have shown that electricity incentives are very effective in increasing agriculture production (Badiani and Jessoe, 2011, 2013). It also plays an important role in sustaining food security (Singh, 2000) and secures additional incomes in rural areas (Briscoe and Malik, 2006). On the other hand, these electricity incentives come with a high initial cost as it adds additional burden to government budgets as well as contributes to the unreliable and intermittent electricity service problems in developing countries (WB, 2001). It is urged that electricity incentives restrict the funding available for other social programs (Birner et al., 2007). For instance, the amounts of incentive spent on electricity are greater than those going to education and health care (Birner et al., 2007). Increasing electricity incentives has resulted in increasing the rate of groundwater pumping for irrigation and thus depleting aquifers, which, in turn, has resulted in several environmental problems (Badiani and Jessoe, 2011, 2013). These environmental problems are summarized in water quality and quantity problems as over groundwater extraction might result in comprising drinking water quality and the availability of water for irrigation, as well as greenhouse gas emissions in the long run (Gandhi and Namboodiri, 2009). These energy incentives have also shifted crop mix in different parts of the world and had led to a shift toward the water and energy-intensive crops.

Ziaabadi and Mehrjerdi (2019) examined the impact of removing electricity and fossil fuel incentives on the Iranian agriculture sector during 1974–2015. Employing cointegration and equilibrium correction methods, they concluded that these incentives have a positive impact on the sector. Therefore, removing them should be gradual and with support policies.

Farajzadeh and Bakhshoodeh (2015) analyzed the impacts of the energy price reform in Iran, applying a Computable General Equilibrium (CGE) model to 2008 data. They found that removing the energy incentives, including electricity incentives will not shrink agriculture share in GDP as this sector is not heavily energy-intensive compared to other sectors.

Solaymani and Kari (2014) explored the impact of energy price reform on the Malaysian economy, including its agriculture sector. They concluded that energy incentives removal would be favorable for oil-producing sectors, whereas other sectors, as well as aggregate exports and imports, would be negatively influenced.

Javid and Qayyum (2014) found the positive impact of electricity consumption on agricultural productivity in Pakistan using structural time series econometric method over the period 1972–2012. They also found statistically insignificant elasticity for the electricity price and discuss that the insignificance is because the electricity consumption in the agricultural sector of Pakistan is hugely subsidized.

Jiang and Lin (2014) examined the effects of energy, including electricity incentives, on different sectors of the Chinese economy, including agriculture, using the price-gap approach in the CGE model in 2008. The authors suggested that the energy incentives are important for the development of the agricultural sector and, hence, should be kept temporarily. Very similar research also carried out by Lin and Jiang (2011) applying the same approach and model to 2007 data. They concluded that removing energy incentives by implementing EPR is important in China. Although this will result in a significant reduction in energy consumption and carbon emissions, the sectors will be negatively affected. Hence, some portion of the energy incentive savings should be reallocated back to the sector in order to mitigate its harmful effect.

Azamzadeh et al. (2013) investigated the impact of energy incentives on the Iranian agriculture sector. Cointegration and equilibrium correction methods are applied to the annual data spanning over the period 1974–2008 in the production function framework. They estimated that price elasticity of energy demand in agriculture was inelastic, and hence, removing the energy incentive would reduce energy consumption and also agriculture output slightly. It was suggested that energy price reform should be implemented gradually, and some mitigation measures should be taken by the government.

Singh (2012) studied the trends in the consumption of electricity, the cost recovery, and the its incentive in Punjab, India's agricultural sector. He found that electricity incentives had increased irrigated rice land by 47%, which made it the most profitable crop. Cotton as well became profitable in Punjab due to electricity incentives. While this work did not find a statistically significant link between electricity incentives and agriculture productivity, it demonstrated that electricity incentives have indeed increased agriculture production.

Rajwindar (2012) concluded that the central government should adopt some criteria to phase out electricity incentives in Punjab as the supply of electricity in the state is irregular. Furthermore, farmers prefer a regular supply of power even if they have to pay for it. This policy, if implemented, will reduce state electricity burden and save electricity that can be allocated to other sectors.

Zaman et al. (2012) examined the causal relationship between energy incentives, energy consumption, electricity consumption and the agricultural value added share in Pakistan's GDP from 1975 to 2010 using time series econometrics. They found that energy incentives Granger cause energy consumption but not electricity consumption while the latter one causes agriculture value added to increase.

Kaur and Sharma (2012) analyzed the impact of electricity incentives in Punjab, India state from 1996-97 to 2011–12. He concluded that the state government had given electricity at almost free of charge rate to farmers, and that resulted in reducing the cost of agricultural production. Furthermore, large farmers benefited from this electricity incentive much more than small farmers as their consumption is much higher due to the larger agricultural areas.

Sidhu et al. (2011) studied the impact of electricity incentives on groundwater depletion and climate change. They found that 60% of total electricity consumption goes to groundwater extraction in Punjab, which in turn impacted the grid and industrial productivity negatively. Additionally, they concluded that the electricity incentive had an indirect negative impact on the climate of the region.

Similarly, Liu and Li (2011) also applied the price-gap approach to assess the impacts of the government incentives for different energy products, including electricity on the sectors of the Chinese economy, including agriculture in 2007. The study concluded that removing energy incentives would reduce energy consumption, but there would still be social and economic costs. It was suggested that the removal of the energy incentives should be implemented gradually, and incentives for coal should be cut first before cutting any other energy product incentives.

Grossman and Carlson (2011) indicated that input incentives are the most expensive aspect of India's food and agricultural policy. They discuss that electricity is supplied directly to farmers at prices that are below the cost of generation.

Fan et al. (2008) discussed that small farms in India are often losing in the initial adoption stage of new technologies because of the increased supply of agricultural products from large farms that have benefited from new technologies pushes prices down. Therefore, electricity incentives, in addition to other types of energy incentives, are essential to help small farms adapt to new technologies.

Kamel and Dahl (2005) compared the economics of the present diesel generation technology versus hybrid power systems to produce electricity for a remote agricultural development area in Egypt. They found that the latter ones are less costly than the former ones, even with the high diesel fuel price incentives.

IEA (1999) examined the impacts of electricity incentives employing the price-gap approach for India and concluded that there are significant differences between end-user prices and reference prices of electricity for domestic and agricultural use, which promotes agriculture growth but also harms government budget and environment.

Appendix B. Description of the variables

Agriculture gross value added per labor (GVA)**.** This refers to goods produced in the agricultural and forestry sector in Saudi Arabia, measured in million SAR at 2005 prices and divided by employment. In other words, this measures agricultural labor productivity. The value-added for the agricultural and forestry sector in nominal million SAR and a price deflator for the sector with the base year of 2010 were retrieved from the General Authority for Statistics (GaStat, 2018). The deflator was first rebased to 2005 (*PDA*), and the added values at 2005 prices were then calculated. The purpose of rebasing from 2010 to 2005 was to be consistent with the base year of the capital stock variable that we use in the empirical analysis. Employment, measured in thousands, was also taken from the General Authority for Statistics (GaStat, 2018).

Agriculture gross capital stock per labor (CS). This is gross capital stock in the agriculture sector, divided by the sector's employment. It represents the total value of a producer's acquisitions, such as land, livestock, machinery and equipment, plantation crops. The data was obtained from the Food and Agriculture Organization of the United Nations (FAOSTAT, 2016) for the period 1992–2007, measured in million U.S. dollars (US$) at 2005 prices. We converted it into million SAR using a bilateral exchange rate of SAR against US$ (*ER*) taken from the Saudi Arabian Monetary Agency (SAMA, 2016) and also interpolated the values for 2008–2014. For brevity, we call the variable 'capital' throughout the paper.

We have noticed that FAOSTAT has changed the structure of its database since 2016. The gross capital stock data had been reported in a table format as a sum of its components in the previous database. However, the same data now is reported component-wise in different graphs not in a table in the new structure under the category of World Development/FAOSTAT Indicators (http://dsiweb.cse.msu.edu/demo/megatrend/index.aspx?sub=&db1=FAOSTAT&area1=194&dataset1=capital-stock&measure1=m6115&item1=23006&db2=FAOSTAT&area2=194&dataset2=capital-stock&measure2=m6115&item2=23007&db3=FAOSTAT&area3=194&dataset3=capital-stock&measure3=m6115&item3=23009&db4=FAOSTAT&area4=194&dataset4=capital-stock&measure4=m6115&item4=23010).

Government electricity incentive in agriculture (ELS)**.** We use the price gap approach to calculate the electricity incentive. This is a widely used method for measuring energy incentives. It calculates energy incentives as a difference between the reference and underlying prices. The theoretical foundation of the approach was developed by Corden (1956) and has been widely used in many studies, including those for agriculture, by international institutions and individual researchers (see McCrone, 1962; Larsen and Shah, 1992; OECD, 1998; IEA, 1999; 2008; Koplow, 2009; WB, 2010; Coady et al., 2010; Liu and Li, 2011; Lin and Jiang, 2011). The electricity incentive (*ELS*) is calculated using equation (4) below.

$$ELS = \frac{ELTUSA}{USGDPD} ER - \frac{ELTKSA}{PDA} \tag{4}$$

The reference price is constructed as the electricity tariff in the U.S. industrial sector, in which agriculture is included, measured in US$ per kilowatt-hour (kWh) (*ELTUSA*). It is deflated by the U.S. GDP deflator 2005 = 100 (*USGDPD*), and the resulting series is converted into SAR using *ER*. *ELTUSA* and *USGDPD* are collected from the U.S. Energy Information Administration (EIA, 2016) and the World Bank (WB, 2016), respectively. *ELTKSA* is the electricity tariff in the Saudi Arabian agriculture sector measured in SAR/kWh. It is taken from the Ministry of Environment, Water and Agriculture for the period 1974–1999 (MEWA, 2016) and the Electricity and Cogeneration Regulatory Authority for the period 2000–2014 (ECRA, 2016).

Appendix C. Econometric methods

C1. Unit root test

The Augmented Dickey-Fuller URT

According to the cointegration concept, if the variables are not stationary, and there is no long-run (cointegrating) relationship among them, then results from the regression of these variables are spurious. In this event, stationary conditions of the variables should be used in regression analysis. Alternatively, if there is a cointegrating relationship among the non-stationary variables, then the regression results are not spurious and can be interpreted as long-run parameters (Engle and Granger, 1987, inter alia).

Since most economic variables trend over time stochastically, it is important to check the stationarity of them, employing UR tests in order to prevent spurious results. In this study, we use the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981), one of the most widely used UR tests in empirical research. The ADF test equation, including also intercept and trend, can be expressed as below:

$$\Delta y_t = b_0 + vt + b_1 y_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta y_{t-i} + e_t \tag{5}$$

Here, y_t is a given variable to be tested for unit root; b_0 is a constant term; Δ indicates the first difference operator; i is the particular lag order; l represents the maximum number of lags; t is the linear time trend, and e_t denotes white noise residuals.

The ADF sample value is the t-statistic for b_1. If this value is smaller than critical ADF values in absolute terms at different significance levels, then the null hypothesis of UR cannot be rejected, and hence it is concluded that y_t is a non-stationary variable. Otherwise, if the value is greater than the critical ADF values in absolute terms, the null hypothesis of UR can be rejected, meaning that the variable is not non-stationary.

The Enders and Lee URT

The economic data is not free of structural breaks, and even in some instances multiple breaks with different types can occur in a given time series. Perron (1989, 2006) shows that the results of the conventional unit-root tests can be misleading as they lose power if they ignore structural break, which is part of the Data Generating Process (DGP). To address this issue, URTs accounting for structural breaks have been developed by Perron (1989), Perron and Vogelsang (1992a, 1992b), and Vogelsang and Perron (1998) as well as Lee and Strazicich (2003). However, these tests can account for only one structural break, and the latter can accommodate two breaks at maximum. Two issues further complicate the problem: first, economic variables may have more than two breaks in some instances as mentioned above and second, to develop URTs with multiple breaks such as Leybourne et al. (1998), Kapetanios et al. (2003) is inefficient because it is difficult to properly estimate the number and the size of multiple breaks. It also comes with the cost of consumption of more degrees of freedom, as discussed by Prodan (2008), Enders and Lee (2012a, b). To this end, Enders and Lee (2012a, b) developed a URT that can approximate multiple breaks using a Fourier series. The key advantages of the test over the ones mentioned above are that there is no need to have prior information about the number of breaks, their types, occurrence date, whether they are endogenous or exogenous, among others.

The EL URT test equation generally can be expressed as below:

$$\Delta y_t = \alpha_0 y_{t-1} + \alpha_1 + \alpha_2 t + \sum_{i}^{l} \beta_i \Delta y_{t-i} + \sum_{k}^{n} \phi_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k}^{n} \varphi_k \cos\left(\frac{2\pi kt}{T}\right) + v_t \tag{6}$$

Where, $\alpha_0, \alpha_1, \alpha_2, \beta_i, \phi_k, \varphi_k$ are the parameters to be econometrically estimated; t is the time trend; i is the particular lag order; l is the maximum lag order; sinand cos are the sin and cos trigonometric functions; k is a particular frequency; n is the number of cumulative frequencies; T is the number of observations; $\pi = 31416$; v is the stationary error term.

Enders and Lee (2012a,b) discuss that it is recommended to first estimate a modified version of (6), in which instead of summing frequencies, a single frequency k is considered. Such specification can be written as the following:

$$\Delta y_t = \alpha_0 y_{t-1} + \alpha_1 + \alpha_2 t + \sum_{i}^{l} \beta_i \Delta y_{t-i} + \phi \sin\left(\frac{2\pi kt}{T}\right) + \phi \cos\left(\frac{2\pi kt}{T}\right) + v_t \tag{7}$$

Enders and Lee (2012a,b) explain that the reason for giving a preference to (7) is that as a practical matter, it is not possible to consider a large value for n. Including more frequencies in the test equation will consume more degrees of freedom, and this can lead to a considerable loss in test power due to the over parameterization issue. Moreover, Enders and Lee (2012a) and Becker et al. (2006) show that often the test equation with a single frequency, even $k = 1$, can do a reasonable approximation for the break of unknown form. Furthermore, Furuoka (2016) also prefers (7) to (6) and considers only one and two single frequency in his empirical testing for unit root.

As Enders and Lee (2012a, b) discuss, optimal frequency, k can be selected based on the smallest value of sum squared of residuals of the estimated regression equations.

If the trigonometric terms are jointly equal to zero, i.e., $\phi_k = \varphi_k = 0$ in (6) or $\phi = \varphi = 0$ in (7) from the F-test, it means that there is no non-linear trend or break in the DGP of a given variable, and thus, the conventional ADF described above is recommended to use. Otherwise, there is a non-linearity or break in the DGP of a given variable, and thus the trigonometric terms should be included in the URT equation of (6) or (7). F-statistic here is non-standard if unit root exists in the DGP of a given variable and therefore, standard F-test critical values cannot be used, and one should compare his/her sample F-statistic with the special critical F-statistics given in Tables 1a and 1b of Enders and Lee (2012b) depending on whether the linear trend is present or absent in the URT equation.

The null hypothesis of unit root and the alternative hypothesis are $\alpha_0 = 0$ and $\alpha_0 < 0$, respectively. If t-value of α_0 is greater than a corresponding τ critical value at a given significance level in absolute terms, then the null hypothesis can be rejected. Otherwise, one fails to reject the null hypothesis of unit root.

Also, for testing the null hypothesis of unit root, special critical values for τ calculated and reported in Tables 1a and 1b by Enders and Lee (2012b) have to be used. Note that the smallest number of observations that Enders and Lee (2012b) and Furuoka (2016) considered in calculating the critical values are 100 and 50, respectively. As a result, critical values from the latter are higher than those from the former at any significance level. Therefore, if time trend is included in the test equation, one should use Furuoka (2016) critical values for the samples being smaller than 50 observations to avoid over-rejection of the null hypothesis of unit root.

C2. Cointegration methods

The Johansen cointegration method

The vector error correction model (VECM) developed by Johansen (1988) and Johansen and Juselius (1990) can be expressed as follows:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta y_{t-i} + \mu + \varepsilon_t \tag{8}$$

Where, y_t is a $(n\ x\ 1)$ vector of the n endogenous/modeled variables in interest, μ is a $(n\ x\ 1)$ vector of constants, Γ is a $(n\ x\ (k\text{-}1)$ matrix of short-run coefficients, $\varepsilon_t$is a $(n\ x\ 1)$ vector of white noise residuals, and Π is a $(n\ x\ n)$ coefficient matrix.

In the case that the matrix Π has reduced rank, meaning: $0 < r < n$, then it can be divided into these two elements: an $(n\ x\ r)$ matrix of loading coefficientsα, and an $(n\ x\ r)$ matrix of cointegrating vectorsβ. The α coefficient represents the importance of the cointegration relationships in the system's individual equations and the speed of adjustment to equilibrium, while the β coefficient shows the long-term equilibrium relationship, so that $\Pi = \alpha\beta'$.

When testing for cointegration using Johansen's reduced rank regression approach, the following logic applies: first, the process involves estimating the matrix Π in an unrestricted form, and, second, testing whether the restriction implied by the reduced rank of Π can be rejected. Namely, the rank of Π, which is determined by the number of its characteristic roots different from zero, characterizes the number of the independent cointegrating vectors.

A variable is considered to be significant if the null hypothesis of corresponding β is zero can be rejected, while stationarity or trend stationarity of a variable assumes that $(1\ \ 0\ \ 0)^{/}$restriction on long-run coefficients cannot be rejected.

Furthermore, the variable is considered weakly exogenous if the null hypothesis of corresponding $\alpha = 0$ cannot be rejected. The assumption of weak exogeneity assumes that disequilibrium in the long-run relationship does not feed back into a given variable. Additional and detailed information about these tests can be found in Johansen and Juselius (1990) and Johansen (1992a, 1992b). According to de Brouwer and Ericsson (1998), one can move to single equation ECM instead of VECM if the long-run determinants of the variable being studied are weakly exogenous to the cointegration system.

Small sample bias correction in the Johansen test

Reinsel and Ahn (1992) and Reimers (1992) proposed rescaling the sample maximum Eigenvalue and Trace statistics by $\frac{T-kn}{T}$ a factor to account for small sample bias. Where k is the lag length of the underlying vector autoregression (VAR) model in levels, while n and T are the numbers of endogenous variables and observations, respectively.

Autoregressive distributed lag (ADL) bounds testing model

We use the ADL method to estimate level relationships between the non-stationary variables and then apply the Bounds testing method of cointegration developed by Pesaran and Shin (1998) and Pesaran et al. (2001) in this study. According to Banerjee et al. (1986), the ADL is particularly superior (efficient) to the VAR/VECM method, especially when the number of observations is small. The ADL approach also has other advantages, such as ease of performing; estimating long- and short-run coefficients simultaneously; and bounds testing is applicable regardless of whether regressors are I(1) and I(0) or a mixture (Pesaran et al., 2001; Frimpong Magnus and Oteng-Abayie, 2006). Since we have a relatively small number of observations, the method is appropriate for our empirical analysis. According to Pesaran et al. (2001), the method can be performed at the following stages:

a) Construction of an unrestricted ECM:

$$\Delta y_t = c_0 + \theta y_{t-1} + \theta_{yx} x_{t-1} + \sum_{i=1}^{n1} \varpi_i \Delta y_{t-i} + \sum_{i=0}^{n2} \phi_i \Delta x_{t-i} + u_t \tag{9}$$

Where y is a depended variable; x is an explanatory variable; u - denotes white noise errors; c_0 is for a drift coefficient; θ and θ_{yx} indicate long-run coefficients, and ϖ_i and ϕ_i are short-run coefficients; i indicates lag length; $n1$ and $n2$ are the maximum number of lag lengths and not necessarily equal to each other.

It is noteworthy that one of the main points in the ADL estimations is to correctly specify the lag length of the first differenced right-hand side variables (Pesaran et al., 2001). The optimal lag length can be specified by minimizing Akaike and Schwarz information criteria while removing the serial autocorrelation of residuals (Pesaran et al., 2001). Following the Schwarz information criterion is recommended in the case of small samples (Pesaran and Shin, 1998; Fatai et al., 2003).

b) Cointegration test. The null hypothesis of no cointegration is $\theta = \theta_{yx} = 0$ respectively. If the F-value of the test is greater than the upper bound critical value at a given significance level, then the null hypothesis of no cointegration can be rejected, and the alternative of cointegration can be accepted. If the sample F-value is smaller than the lower bound critical value at a given significance level, then the null hypothesis of no cointegration cannot be rejected. If the sample F-value is between the upper band and lower band F critical values, then the test result is inconclusive. The distribution of F statistic is not standard, and, therefore, the standard F critical values table cannot be used. The F critical values tabulated by Pesaran et al. (2001) should be used for testing cointegration.

c) After determining a cointegration relationship between the lagged level variables, the next step is to calculate the long-run coefficient of x using the following equation (10):

$$b = \frac{\theta_{yxx}}{\theta} \tag{10}$$

Following the estimation of the long-run coefficients, a final ECM can be estimated by substituting lagged level regressors with lagged level error correction term (ECT_{t-1}) in equation (9).

$$\Delta y_t = c_0 + \lambda ECT_{t-1} + \sum_{i=1}^{n} \varpi_i \Delta y_{t-i} + \sum_{i=0}^{n} \phi_i \Delta x_{t-i} + u_t \tag{11}$$

Where, $ECT_t = y_t - bx_t$; $\lambda < 0$.

As a small sample bias correction in the bounds test for cointegration, usually Narayan (2005) critical values are used.

Fully Modified OLS

If the variables are cointegrated, the estimates of coefficients using ordinary least squares (OLS) are consistent and efficient (Engle and Granger, 1987). However, these coefficients are problematic in terms of using conventional inference, such as t-statistic. This is due to the absence of the dynamics in a static equation, which makes the coefficients and their standard errors biased. Moreover, Banerjee et al. (1986) argued that the bias would be significantly large in the small samples. Consequently, new approaches such as FMOLS, DOLS, and CCR have been developed to overcome the problems mentioned. Utkulu (2012) provided a comprehensive review of these methods. In brief, Utuklu (2012) indicated that these methods could be classified into two clusters: dealing with a correction of OLS estimates of long-run parameters such as FMOLS and CCR (Park and Phillips, 1988; Phillips and Hansen, 1990; Engle and Yoo, 1990) and putting dynamics in the static equation by using lag and lead of difference of the variables such as DOLS (Banerjee et al., 1986; Wickens and Breusch, 1988; Saikkonen, 1991; Phillips and Loretan, 1991; Charemza and Deadman, 1992; Cuthbertson et al., 1992; Inder, 1993). Inder (1993), among others, considers that using dynamic methods is preferable to apply a correction to the long-run parameters, but can cause over-parameterization, especially in small samples. Hence, we use all three methods in the empirical analysis.

FMOLS was initially proposed by Phillips and Hansen (1990). This approach involves the use of a semi-parametric correction to reduce the problems caused by the long-run correlation. The FMOLS is asymptotically unbiased. This approach uses preliminary estimates of the symmetric and one-sided long-run covariance matrices of the residuals. This can be explained mathematically as follows:

Let $\hat{u}_{1t}$ be the residuals obtained after estimating equation (9). The may be obtained indirectly as $\hat{u}_{2t} = \Delta\hat{\varepsilon}_{2t}$from the levels regressions

$$X_t = \hat{\Gamma}'_{21}D_{1t} + \hat{\Gamma}'_{22}D_{2t} + \hat{\varepsilon}_{2t} \tag{12}$$

or directly from the difference regressions

$$\Delta X_t = \hat{\Gamma}'_{21}\Delta D_{1t} + \hat{\Gamma}'_{22}\Delta D_{2t} + \hat{u}_{2t} \tag{13}$$

Let $\hat{\Omega}$ and $\hat{\Lambda}$ be the long-run covariance matrices computed using the residuals. Then we may define the modified data

$$\hat{y}_t^{+} = y_t - \hat{\omega}_{12}\hat{\Omega}_{22}^{-1}\hat{u}_2 \tag{14}$$

And an estimated bias correction term

$$\hat{\lambda}_{12}^{+} = \hat{\lambda}_{12} - \hat{\omega}_{12}\hat{\Omega}_{22}^{-1}\hat{\Lambda}_{22} \tag{15}$$

The FMOLS estimator is given by

$$\hat{\theta} = \begin{bmatrix} \hat{\beta} \\ \hat{\gamma}_1 \end{bmatrix} = \left(\sum_{t=2}^{T} Z_t Z_t'\right)^{-1}\left(\sum_{t=2}^{T} Z_t y_t^{\,+} - T\begin{bmatrix} \hat{\lambda}_{12}^{+\,\prime} \\ 0 \end{bmatrix}\right) \tag{16}$$

Where $Z_t = (X_t', D_t')'$. The key to FMOLS estimation is the construction of long-run covariance matrix estimators $\hat{\Omega}$ and $\hat{\Lambda}$.

Labeling the alternatives available for computing $\hat{\Omega}$ and $\hat{\Lambda}$ in advance will help define the scalar estimator

$$\hat{\omega}_{1.2} = \hat{\omega}_{11} - \hat{\omega}_{12}\hat{\Omega}_{22}^{-1}\hat{\omega}_{21} \tag{17}$$

which may be interpreted as the estimated long-run variance of u_{1t}conditional on u_{2t}. The degree-of-freedom correction to $\hat{\omega}_{1.2}$also might be applied, if needed.

The Wald statistic for the null hypothesis $R\theta = r$

$$W = (R\hat{\theta} - r)'(RV(\hat{\theta})R')^{-1}(R\hat{\theta} - r) \tag{18}$$

with

$$V(\hat{\theta}) = \hat{\omega}_{1.2}\left(\sum_{t=2}^{T} Z_t Z_t'\right)^{-1} \tag{19}$$

has an asymptotic χ_g^2-distribution, where g is the number of restrictions imposed by R.

Dynamic OLS

The Dynamic OLS (DOLS) approach was proposed by Saikkonen (1992) and Stock and Watson (1993) to construct an asymptotically efficient estimator. The main objective of this estimator is to eliminate the feedback in the cointegrating system. This method includes lags and leads of ΔX_t in the level regression:

$$y_t = X_t'\beta + D_{1t}'\gamma_1 + \sum_{j=-q}^{r} \Delta X_{t+j}'\delta + \vartheta_{1t} \tag{20}$$

The main assumption of this method is that adding q lags and r leads of the differenced regressors soaks up all of the long-run correlation between u_{1t} and u_{2t}. Note that the least-squares estimates of $\theta = (\beta', \gamma')'$ using equation (20) have the same asymptotic distribution as those obtained from FMOLS and CCR. The asymptotic variance matrix of can be estimated by computing the usual OLS coefficient covariance, but substituting the usual estimator for the residual variance of $\vartheta_{1t}$with an estimator of the long-run variance of the residuals. An alternative way is to involve a robust HAC estimator of the coefficient covariance matrix.

Canonical Cointegrating Regression

The canonical cointegrating regression (CCR) was proposed by Park (1992). This approach is closely related to FMOLS. It employs stationary transformations of the (y_t, X_t') data in order to obtain least squares estimates to remove the long-run dependence between the cointegrating equation errors and the stochastic regressors innovations. It also follows a mixture of a normal distribution that is free of non-scalar nuisance parameters and permits asymptotic chi-square testing, as is the case with the FMOLS method.

Similar to FMOLS, the CCR method starts by obtaining estimates of the innovations

$\hat{u}_t = (\hat{u}_{1t}, \hat{u}_{2t}')'$ and corresponding consistent estimates of the long-run covariance matrices $\hat{\Omega}$ and $\hat{\Lambda}$. Unlike FMOLS, CCR requires a consistent estimator of the contemporaneous covariance matrix.

We extract the columns of $\hat{\Lambda}$ corresponding to the one-sided long-run covariance matrix of and (the levels and lags of) as in Park (1992):

$$\hat{\Lambda}_2 = \begin{bmatrix} \hat{\lambda}_{12} \\ \hat{\Lambda}_{22} \end{bmatrix} \tag{21}$$

And transform the (y_t, X_t') using

$$X_t^* = X_t - (\widehat{\Sigma}^{-1}\widehat{\Lambda}_2)'\widehat{u}_t$$

$$y_t^* = y_t - \left(\widehat{\Sigma}^{-1}\widehat{\Lambda}_2\widehat{\beta} + \left[\begin{array}{c} 0 \\ \widehat{\Omega}_{22}^{-1}\widehat{\omega}_{21} \end{array}\right]\right)'\widehat{u}_t \tag{22}$$

where the $\widehat{\beta}$ are estimates of the cointegrating equation coefficients, typically the SOLS estimates used to obtain the residuals.

The CCR estimator is defined as ordinary least squares applied to the transformed data

$$\left[\begin{array}{c} \widehat{\beta} \\ \widehat{\gamma}_1 \end{array}\right] = \left(\sum_{t=1}^{T} Z_t^* Z_t^{*'}\right)^{-1} \sum_{t=1}^{T} Z_t^* y_t^* \tag{23}$$

Where, $Z_t^* = (Z_t^{*'}, D_{1t}^{*'})'$.

Park (1992) shows that the CCR transformations asymptotically eliminate the endogeneity caused by the long-run correlation of the cointegrating equation errors and the stochastic regressors innovations. He also shows that CCR transformations are simultaneously correct for asymptotic bias resulting from the contemporaneous correlation between the regression errors and stochastic regressors. Therefore, estimates based on the CCR can be considered fully efficient and have the same unbiased, mixture normal asymptotic as FMOLS.

The Fourier ADL cointegration method

The method is developed in Banerjee et al. (2017). In the case of one regressor, for simplicity, the test equation can be written as follows:

$$\Delta y_t = c_0 + c_1 t + \psi(y_{t-1} + \omega x_{t-1}) + \sum\nolimits_{k=1}^{n}\phi_k \sin\left(\frac{2\pi kt}{T}\right) + \sum\nolimits_{k=1}^{n}\varphi_k \cos\left(\frac{2\pi kt}{T}\right) + \sum\nolimits_{i=1}^{l1}\beta_i^{'}\Delta y_{t-i} + \sum\nolimits_{i=0}^{l2}\beta_i^{''}\Delta x_{t-i} + \chi_t \tag{24}$$

Where, $c_0, c_1, \psi, \omega, \phi_k, \varphi_k, \beta_i^{'}, \beta_i^{''}$ are the parameters to be estimated econometrically; t is the time trend; sinand cos are the sin and cos trigonometric functions; k is a particular frequency; n is the number of cumulative frequencies; T is the number of observations; $\pi = 31416$; i is the particular lag order; $l1, l2$ are the maximum lag orders; χ is the white noise error term.

Due to the same reasoning discussed for (6) and (7) above, one may prefer a single frequency version of (24), which can be expressed as below:

$$\Delta y_t = c_0 + c_1 t + \psi(y_{t-1} + \omega x_{t-1}) + \phi \sin\left(\frac{2\pi kt}{T}\right) + \varphi \cos\left(\frac{2\pi kt}{T}\right) + \sum\nolimits_{i=1}^{l1}\beta_i^{'}\Delta y_{t-i} + \sum\nolimits_{i=0}^{l2}\beta_i^{''}\Delta x_{t-i} + \chi_t \tag{25}$$

The optimal frequency, k can be specified according to the smallest value of sum squared of residuals of the estimated equations, as discussed in Enders and Lee (2012a, b). Banerjee et al. (2017) compare different ADL specifications of using different frequencies and different lag orders of the variables based on the Schwarz and Akaike information criteria.

The null hypothesis of no non-linear trend or break assumes that the trigonometric components are jointly equal to zero, i.e., $\phi_k = \varphi_k = 0$ in (24) or $\phi = \varphi = 0$ in (25) from the F-test. If this is the case, then the conventional ADL-based bounds test (Pesaran et al., 2001) or t-test (Banerjee et al., 1986) for cointegration is recommended to employ. Otherwise, there is a non-linear trend or break in the DGP of the variable of interest, and, therefore, the trigonometric components should be included in the ADL cointegration test equation of (24) or (25). The sample F-value should be compared with the critical F-values documented in Tables 1a and 1b of Enders and Lee (2012b) depending on whether a linear trend is included or not in the ADL cointegration test equation.

The null hypothesis of no cointegration and the alternative hypothesis of cointegration are $\psi = 0$ and $\psi < 0$, respectively. If the t-value of ψ is greater than a corresponding t critical value at a given significance level in absolute terms, then the null hypothesis of no cointegration can be rejected, and the alternative of cointegration can be accepted. The t critical values reported in Tables 1a, 1b, 2a and 2b of Banerjee et al. (2017) should be considered if the null hypothesis of no non-linear trend or break can be rejected. Otherwise, if the null hypothesis cannot be rejected, then the ADL cointegration test equation of (24) or (25) becomes the conventional ADL equation and, hence, critical values tabulated for the conventional ADL cointegration test should be used (e.g., Table A1 in Banerjee et al., 2017).

ECM estimation using GSMS

As mentioned in the main text, we estimate ECM in the framework of GSMS for the short-run analysis. This contains two main stages. First, a general/unrestricted ECM is estimated, with the maximum lags of the explanatory and dependent variables as well as contemporaneous values of the explanatory variables, alongside one lag of ECT, which is constructed using the residuals of the long-run relationship. The maximum lag order for a general ECM can be specified using several methods, such as information criteria (e.g., the Akaike, Schwarz), time-dependent rule, as well as the based on the frequency of the time series used. Perron (1989) suggests that if the frequency is quarterly and the number of observations is small, then the maximum lag order of four should be chosen. Alternatively, in the case of a small number of annual observations, one or at most two lags can be considered as a maximum lag length. Second, an attempt is made to get a more parsimonious ECM specification by excluding statistically insignificant variables, while comparing standard error of regression statistics of the last and the previous specifications and performing a battery of post-estimations tests such as autocorrelation, serial correlation, normality, heteroscedasticity, and misspecification tests on the last specification. Details of GSMS are discussed in Campos et al. (2005) inter alia.

Appendix D. Some estimation results

D1. The VAR estimation

We include *gva*, *cs* and *els* as endogenous variables. We also include intercept and trend in the VAR as exogenous variables since the URTs results and graphical illustrations suggest that they are the part of the DGP of the variables. Additionally, we include the pulse dummy variable, taking unity in 2014 and zero otherwise, as an exogenous variable in the VAR to capture a sharp decline in *gva* and *cs* in 2014, illustrated in Fig. 1 that causes huge outliers in the residuals of the variables' equations. The dummy variables appears statistically significant. We set the maximum lag to two. The lag exclusion test and the Akaike and Hannan-Quinn information criteria suggest two lags, while the Schwarz information criterion indicates one lag as optimal.

However, the residuals of the VAR with one lag have serial correlation, which is a serious problem in the VAR analysis. Moreover, the VAR with one lag does not seem informative because the VECM transformation of it will have zero lag, meaning that we restrict the system so as not to have short-run dynamics, which is a strong constraint. Therefore, we specify two lags as optimal. Now, the VAR passes all the residual diagnostics and stability tests successfully as reported in Panels A-D of Table 2. Since the VAR is stable and the residuals of it are free of serial correlation, non-normality and heteroscedasticity, we transform it to a VECM and test for cointegration and to estimate long-run/level relationship among the variables. We first carry out the Johansen cointegration test. We check for cointegration in all the possible combinations of the deterministic regressors, i.e., in the five test equations. The reason for doing so is that economic theory predicts that some economic relations include both deterministic elements, while others include neither. For example, purchasing power parity or Fisher equation concepts assume that either intercept or trend might not be part of the relationships. On the contrary, the production function concept states that both may have a significant role in the production process; that is, one captures total factor productivity and another is for technological development. Panel E in Table 2 reports the results of the test for all the possible combinations of intercept and trend in cointegrating space. According to the results, the Trace and maximum Eigenvalues indicate cointegrated relations among the variables when both trend and intercept are included in the space, while only the Trace statistic suggests cointegration when neither is included. We do not think that version e, where we have intercept and quadratic trend in the cointegration equation, can be the case, because, first, it is not consistent with the Cobb-Douglas production function concept that we use in this study as a theoretical framework and, second, none of our variables in the analysis contain quadratic trends as unit root test results concluded that they are I(1) processes. Having intercept and linear trend in the relationship is in line with the Cobb-Douglas production function concept. Thus, we focused in more detail on the cointegration test type d, where we have intercept and a linear trend in the long-run equation. The test results, presented in Panel F of Table 2, show that both the Trace and maximum Eigenvalues test statistics reject the null hypothesis of no cointegration, whereas they fail to reject the null hypothesis of more than one long-run relationship. As discussed in the methodological section, we correct the test statistics for small sample bias. The adjusted statistics also yield the same results: *gva*, *cs,* and *els* establish only one cointegrating relation.

We further test statistical significance, stationarity and weak exogeneity of the level variables in the VECM. The test results are reported in Table D1, below.

Table D1
The significance, stationarity and weak exogeneity tests results

Panel A: Statistics for testing the significance of a given variable in the cointegrating space [a]			
	gva	*cs*	*els*
χ^2 (1)	17.477***	15.048***	3.925**
Panel B: Multivariate statistics for testing stationarity [b]			
	gva	*cs*	*els*
χ^2 (2)	15.052***	17.515***	26.779***
Panel C: Weak exogeneity test statistics [c]			
	gva	*cs*	*els*
χ^2 (1)	4.070**	1.822	6.427**

Notes: the null hypothesis is that a given variable is statistically insignificant; [b] the null hypothesis is that a given variable is (trend) stationary; [c] the null hypothesis is that a given variable is weakly exogenous; ** and *** denote rejection of the null hypotheses at the 5% and 1% significance levels respectively. Estimation period: 1988–2014.

The results in Panel A indicate that *gva*, *cs,* and *els* are statistically significant, while according to Panel B, the variables are not stationary. It is noteworthy that the results of the multivariate test for stationarity here confirm the results from the univariate UR tests reported in Table 1. The weak exogeneity test results in Panel C show that *gva* and *els* are not weakly exogenous to the cointegration relationship, whereas *cs* is. The results imply that if we proceed from VECM to a single equation ECM, because of endogeneity, we should not have contemporaneous values of *els*, or we should use a two or three-stage OLS or a system of contemporaneous equations rather than OLS.

D2. The Fourier ADL estimation and testing results

We estimated equation (25) using maximum lag order of two of the variables and consider Schwarz information criterion to select optimal lag lengths as it is preferable in small samples (see, e.g., Pesaran and Shin, 1998). Also, we consider five single frequencies, i.e., $k = 1,2, \ldots,5$ at a time following Banerjee et al. (2017) in the estimations. The estimation results are documented in Table D2.

Table D2
Estimation results from fourier ADL

k	ψ	t-stat	*SBC*	*ADL(l1,l2,l3)*
1	−1.101	−6.277	−5.279	ADL(2,2,2)
2	−1.001	−44.831	−5.266	ADL(1,0,0)
3	−1.121	−6.153	−5.296	ADL(2,2,2)
4	−0.915	−50.346	−5.440	ADL(1,0,0)
5	−0.989	−47.446	−5.208	ADL(1,0,2)

Notes: The dependent variable is Δgva_t; k stands for single frequency; t-stat is the t-statistics of ψ, i.e., the coefficient on gva_{t-1}; *SBC* means Schwarz information criterion; *ADL(l1,l2,l3)* indicates Schwarz-based selected optimal lag lengths for $\Delta gva, \Delta cs, \Delta els$, respectively; Estimation period: 1988–2014.

As we mentioned in Appendix A, Banerjee et al. (2017) select both frequencies and optimal lag length for the variables based on information criteria, Schwarz and Akaike, whereas Enders and Lee (2012a, b) select frequencies based on the sum of squared residuals of the regressions. If we follow Banerjee et al. (2017) approach, then the preferable ADL estimation will be the one reported in the fifth row of Table D2 , where $k=4$ as it has the smallest *SBC* value of −5.440. We test the null hypothesis of no non-linear trend for this ADL specification, and the sample F-value is 7.580. The corresponding critical F-values from Table 1a of Enders and Lee (2012b) are 12.21, 9.14 and 7.78 at 1%, 5%, and 10% significance levels, respectively. It appears that the null hypothesis of no non-linear trend cannot be rejected, and, hence, we should estimate a conventional ADL for the cointegration test and parameter estimate. If we follow Enders and Lee's (2012a, b) approach in selecting the optimal frequency, then ADL estimation in the fourth row, where $k = 3$ is the optimal specification as its sum of squared residuals is the smallest. We again test the null hypothesis of no non-linear trend for this ADL specification, and the sample F-value is 1.568. Obviously, we cannot reject the null hypothesis of no non-linear trend and, therefore, a conventional ADL for the cointegration test and parameter estimate should be considered. Our explanation for why the null hypothesis of no non-linear trend cannot be rejected is that *gva* and *cs* both demonstrate very similar time trajectories, including breaks, as illustrated in Fig. 1, above. In this regard, any non-linearity or break in *gva* as a dependent variable in ADL estimations is captured by those in *cs* as an independent variable and, hence, there is no need for any trigonometric components to capture them. Thus, regardless of whether we follow Banerjee et al. (2017) approach or Enders and Lee (2012a, b) approach, the null hypothesis of no non-linear trend cannot be rejected. Hence, it is recommended to use a conventional ADL-based bounds test or t-test for cointegration, as Banerjee et al. (2017) state.

D3. Additional long-run estimations and testing for robustness check

In this section, we carry out additional estimations and testing to ensure that our estimation findings are robust and, thereby, the policy recommendations that we propose are well-grounded.

One may think that, unlike the production process in other sectors of an economy, agricultural production can also be affected by factors other than capital, labor and technological progress. In this regard, one may mainly consider factors such as agricultural land area, livestock, rainfall, temperature change, and fertilizer indicators. The capital stock data that we use in this study includes land, livestock, plantation crops, machinery, and equipment, as we discussed in the Data section above. We tried to consider fertilizer indicators. However, only the available data of such indicators for Saudi Arabia we found from FAOSTAT starts in 2002. Considering these indicators will considerably shorten our estimation sample, which is already small, and thus the efficiency of the estimations will decrease remarkably. Instead, we found sufficient data for rainfall (*RF*) and temperature change (*TCH*) in Saudi Arabia. They are worth considering to examine whether they can provide any statistically significant information in explaining the long- and short-run developments of Saudi agriculture. For Saudi Arabia, we collected *TCH* from the FAO database while *RF* is calculated averaging the monthly average values obtained from the World Bank Group, Climate Change Knowledge Portal. Table D1 and Fig. D1 illustrates the time profile of both the variables over the period 1988–2014.

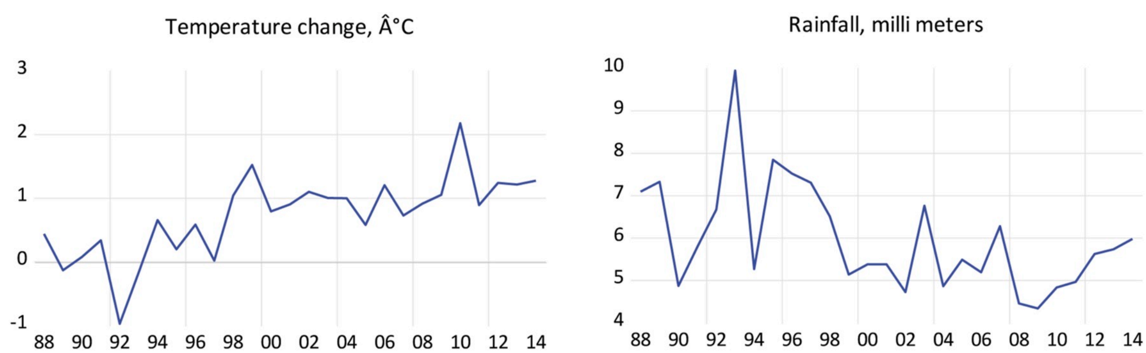

Fig. D1. Rainfall and temperature change for Saudi Arabia.

The figure portrays that *TCH* has an upward trend while *RF* demonstrates a quite stationary pattern over the period. Figure D1 also shows that the temperature change variable has pretty small and sometimes negative values, ranging about in the interval of −1 and 2 while the rainfall variable has relatively large positive values compared to the former one over the period. Hence, we consider the level of the former one, i.e., *TCH* and the natural logarithmic level of the latter one, i.e, *rf* in the testing and estimations. Here, *rf* means the natural logarithmic expression of *RF*.

We run the ADF URT on the variables since none of them demonstrates a broken trend or level. Based on a visual inspection of the graphical illustration of the variables, we include intercept and trend in the ADF test equations of *TCH* and intercept in the test equation of *rf*. We also include two lags of the dependent variable in each equation, and the Schwarz information criterion decides the optimal lag length. The ADF test sample value for *TCH* is −4.856. This value is greater than the respective critical values from MacKinnon (1996) at any significance level in absolute terms. Hence, we reject the null hypothesis of unit root and accept that *TCH* is a trend stationary process. As for *rf*, the ADF test sample value is −3.784, and this is greater than the respective critical values from MacKinnon (1996) at any significance levels in absolute terms. Therefore, we reject the null hypothesis and accept the alternative hypothesis that *rf* is a stationary process, i.e., I(0). Thus, we find that *TCH* is a trend-stationary process, and *rf* is an I(0) process.

We extend our long-run modeling framework by including *TCH* and *rf* there to examine whether they can provide any additional information in explaining *gva*. As we concluded above about the stochastic properties of the variables, *gva*, *cs*, and *els* are all I(1) variables whereas *TCH* and *rf* are not. In such cases, one should prefer ADL-based cointegration analysis because Pesaran et al. (2001) show that the ADL bounds testing approach can handle cointegration analysis where the regressors are a mixture of I(1) and I(0) variables. To this end, we consider a specification, where *gva* is a function of the four regressors and the deterministic components of intercept (*C*) and trend (*t*). We set the maximum lag orders of the variables at two, and the Schwarz information criterion selects the optimal ones. Table D3 presents the ADL bounds testing cointegration test and level estimation results.

Table D3
ADL estimation and test results.

Selected specification:	*ARDL(2,2,2,0,1)*	
Test results of the residual diagnostics, misspecification and cointegration		
F_{SC}	0.014	[0.909]
F_{ARCH}	0.017	[0.899]
F_{HETR}	1.193	[0.373]
JB_N	1.225	[0.542]
F_{FF}	2.150	[0.166]
F_W	5.623^{AB}	
Estimated long-run elasticities and SoA		
Regressor	***Coefficient***	***Standard error***
cs	0.977***	0.0246
els	0.030	0.021
rf	0.036	0.024
TCH	0.010	0.017
C	−1.455***	0.260
t	0.011***	0.001

Notes: *gva* is the dependent variable; $F_{SC}, F_{ARCH}, F_{HETR}, F_{FF}$ *and* F_W denote F statistics to test the null hypotheses of no serial correlation, no autoregressive conditioned heteroscedasticity, no heteroscedasticity in the residuals and no functional form misspecification and no cointegration in the Wald test, respectively; JB_N indicates the Jarque-Bera statistic to test the null hypotheses of the normal distribution of the residuals. Values in brackets are the probabilities of the associated tests; [A] indicates that the sample statistic is greater than the upper bound critical value of Narayan (2005) at the 5% significance level in the case of 30 observations, four regressors, intercept and trend in the long-run equation. [B] indicates that the sample statistic is greater than the upper bound critical value of Pesaran et al. (2001) at the 1% significance level in the case of 1000 observations, four regressors, intercept and trend in the long-run equation. *** means statistical significance at the 1% significance level; Estimation period: 1988–2014.

The selected ADL specification successfully passes the residual diagnostics tests, as well as the misspecification test and, hence, can be used for testing the existence of cointegration as Table D3 presents. We can reject the null hypothesis of no cointegration as the sample F value of 5.623 is greater than the respective Pesaran et al. (2001) and even Narahan (2005) upper bound critical values calculated for the small samples. The table further reports that the variables of our interest, i.e., *TCH* and *rf* are both statistically insignificant. This means that none of them provides additional information in explaining the behavior of *gva*. Even the inclusion of them weakens the statistical significance of the other explanatory variables. Thus, *TCH* and *rf* are not part of the long-run relationship of *gva*. Hence, we conclude that the long-run relationship that we estimate for *gva* in Table 3 is robust.

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