# Dynamic Relationships among Phosphate Rock, Fertilisers and Agricultural Commodity Markets: Evidence from a Vector Error Correction Model and Directed Acyclic Graphs

[1*]Kehinde Oluseyi Olagunju, [2]Siyi Feng and [3]Myles Patton

[1]Economics Research Branch, Agri-Food and Biosciences Institute, BT9 5PX Belfast UK

[2]Independent Researcher, BT9 5PX Belfast, UK

[3]Department of Agriculture, Environment and Rural Affairs, Belfast, UK

*Corresponding author email address: Kehinde-Oluseyi.Olagunju@afbini.gov.uk

**Abstract**

The finite supply of phosphate rock, as well as rising fertiliser prices, are key topics in the discussion around global food system resilience. Our paper contributes to this discussion by conducting an analysis of the dynamic causal relationships between phosphate rock, fertilisers, and wheat prices to provide insights on how farmers and policymakers might respond to phosphate rock supply shocks for sustainable and resilient food systems. The linkages between 147 monthly price observations spanning from March 2007 to April 2019 were analysed by combining Directed Acyclic Graphs (DAG), a recently developed modelling technique, and a Vector Error Correction Model (VECM). The findings suggest that there are five long-run cointegrating relationships between these three key components of the food supply chain. Price shocks to the phosphate rock market, over a two-year period had a knock-on positive impact on phosphorus fertiliser prices and to a lesser extent on wheat prices. Interestingly, an increase in wheat price had a sizeable impact on both fertiliser and phosphate rock prices, providing empirical evidence that increases in the price of phosphate rock are driven by demand factors, as well as supply factors.

**Keywords**: Phosphate rock, agricultural commodity, fertilisers, directed acyclic graph, VECM

# 1. Introduction

The global food system is facing unprecedented stresses and shocks such as the climate crisis, resource depletion, population growth as well as changes to dietary patterns and agricultural land-use practices (Fanzo, 2019; Meyfroidt et al., 2019; Oyetunde-Usman et al., 2021; Steffen et al., 2015; Vermeulen et al., 2012; Wu et al., 2014). The continued and appropriate supply of essential plant nutrients required for crop growth underpins a viable food system but these nutrients must be used efficiently and sustainably (Dawson and Hilton, 2011; Stewart et al., 2005). Among many nutrients that plants require for growth, the element phosphorus is essential to crop performance.

Modern agricultural production systems are highly reliant on phosphorus in the form of mineral fertiliser derived mainly from a finite resource – phosphate rock - and global deposits are strongly skewed towards a few countries that are located in what has been termed "geopolitically unstable zones" (e.g., approximately 45% of global phosphate rock deposit is located in Algeria, Iraq, Jordan and Syria), making sustainable access and consistent supply uncertain (Blackwell et al., 2019; Cordell and Neset, 2014). With steadily increasing global demand for phosphate fertiliser in response to factors such as population growth, dietary change, and development of agro-fuel production (Blackwell et al., 2019; FAO, 2008; Khabarov and Obersteiner, 2017; Von Horn and Sartorius, 2009), the finite nature of this resource may lead to future shortages of inorganic phosphate fertiliser (Blackwell et al., 2019; Cordell and Neset, 2014).

A potential future scarcity of phosphate rock and growing demand for phosphate rock for fertiliser use has brought to fore two main discussion points. Firstly, scarcity might lead to rising prices of phosphate rock and fertilisers, which farmers, especially in developing countries, might not be able to afford, or invest in new resource alternatives, with implications for agri-food systems and global food security (Cordell et al., 2009; Khabarov and Obersteiner, 2017; Neset and Cordell, 2012; Van Kauwenbergh et al., 2013). Secondly, growing demand for phosphorus in farming might favour improper use of phosphorus fertiliser leading to increased inefficiency of use, wastage and losses to the aquatic environment (Elser and Bennett, 2011; Withers et al., 2020). Phosphorus rock supplies may not keep up with future demand if fertilisers are used unsustainably.

In an effort to address these concerns, the nature of the causal relationships between phosphate rock, fertilisers and agricultural commodity prices has received a lot of interest in recent times. However, due to the complexity of the interrelationships existing research studies have not offered a definitive direction. Some studies argue that the price of phosphate rock is driven by its scarcity leading to increase in phosphate rock price, with resulting impacts trickling down to the fertiliser and agricultural markets (Chowdhury et al., 2017; Cordell, 2010; Cordell et al., 2009; Vaccari et al., 2014; Von Horn and Sartorius, 2009) and described this as a dominantly "supply-driven" relationship. On the other hand, some explain that the reverse causal relationship is also important, with shocks in fertiliser and agricultural markets likely to have a knock-on impact on the phosphate rock market, leading to "demand-driven" price increases of phosphate rock (Cordell et al., 2009; Khabarov and Obersteiner, 2017; Mogollón et al., 2018). The argument being that increases in agricultural commodity prices tend to raise farmers' return on fertiliser use, and hence increase the demand for fertilisers, and consequently phosphate rock prices.

It therefore remains unclear whether the causal relationships between phosphate rock, fertilisers and agricultural commodity prices are supply or demand-driven (or both supply and demand-driven). Further evidence is required given the critical influence of the phosphate rock market on the global food system and food security (Chowdhury et al., 2017; Heckenmüller et al., 2014; Lyon et al., 2020), and an increasing policy focus on sustainable use of planetary resources and food system resilience (Cordell and White, 2014). A few empirical studies, for example O'Hara et al. (2015), Gnutzmann and Spiewanowski (2016), and Brunelle et al. (2015) have studied the relationship between fertilisers and agricultural commodity prices, but have not included the main resource inputs to fertilisers, such as phosphate rock.

In this paper, we employ a time-series estimation approach to analyse the causal relationship between phosphate rock, fertilisers and wheat prices, by combining a Vector Error Correction Model (VECM) with Directed Acyclic Graphs (DAG) in a dynamic framework. The fertilisers under consideration include the two most common phosphate fertilisers such as Triple superphosphate (TriP) and Diammonium phosphate (DAP) as well as other non-phosphate fertilisers used in agricultural production namely, urea and potassium chloride.

Our paper makes important contributions to the literature and policy debate. Firstly, this study provides the first attempt to apply a combination of VECM and DAG approach, a recent and powerful modelling technique, to investigate the contemporaneous causality and dynamic interrelationships among phosphate rock, fertilisers and wheat prices. The applied DAG explores the inherent causal information contained in the data to test for contemporaneous causation among the markets (Pearl, 1995; Spirtes et al., 2000b). Secondly, our aim is to provide agricultural market participants and policy analysts with a clear picture of what drives increases in phosphate rock price as well as providing a comprehensive perspective of price interdependence and directions of causation between phosphate rock, fertilisers and wheat prices that are relevant to a viable and resilient agri-food system based on sustainable use of resources.

## 2. Literature review

Various time series techniques have been employed in applied economics studies to empirically examine the dynamic relationship between multiple variables (Bakhtavoryan et al., 2014; Swanson and Granger, 1997). One of the most common approaches used is Vector autoregression (VAR) which models endogenous variables as a function of their past values (Sims, 1980). The widespread acceptance of VAR is attributed to two main reasons. First, the VAR approach offers a simple way to characterise data without any requirement of invoking *a priori* assumptions based on economic theory to restrict the dynamic relationships between variables; that is, it can accommodate zero-restriction identification condition (Awokuse and Bessler, 2003; Bakhtavoryan et al., 2014; Cooley and Dwyer, 1998a; Xu, 2018). Second, VAR can be readily transformed to explain evolution of systems, and therefore, can represent the complex interactions in real world markets and how they function (Awokuse and Bessler, 2003; Cooley and Dwyer, 1998a).

Previous studies that examined the interaction of agricultural commodity price developments with market fundamentals include, for example, a study by Rezitis (2015) that analysed the relationship between agricultural commodity prices, crude oil prices and exchange rate using VAR and Granger causality tests concluded that there exist bidirectional causality effects between international agricultural prices and crude oil prices. Tuan (2010) also employed a similar technique as Rezitis (2015) to analyse the relationship between international prices, import prices and domestic prices of phosphate fertilisers in Vietnam and found that the Vietnamese phosphate fertiliser prices are well integrated into world phosphate fertiliser prices. Similarly, studies such as Gnutzmann and Spiewanowski (2016) applied a VAR cointegration approach to examine the impact of changes in crude oil price on the causal relationship between fertiliser and food prices. They found that fertiliser prices have a significant impact on food prices much more than direct energy prices.

Although past studies have widely adopted some variation of a VAR model, the value of the results in terms of applied policy analysis has been questioned (Awokuse and Bessler, 2003; Cooley and Dwyer, 1998b; Swanson and Granger, 1997). This is attributed to the fact that the impulse response functions (IRF) and forecast error variance decompositions (FEVD) generated from a VAR model cannot offer any meaningful structural interpretation mainly because their innovations are not identified with the underlying structural errors[1]. The residuals of the covariance matrix in a VAR model often turn out to be non-diagonal, suggesting contemporaneous correlation among the errors (Swanson and Granger, 1997)[2]. Therefore, analysis of the evolution of economic shocks of the system caused *just* by an innovation in one variable may not be appropriate, as this innovation may occur at the same time as another innovation in the system (Swanson and Granger, 1997).

To overcome the no-restriction problem of VAR models, the covariance matrix of the residuals is orthogonalized by the application of the Choleski decomposition procedure. This decomposition procedure ensures the evolution of innovations in a unidirectional system by introducing a just-identified contemporaneous structure of innovations assumption (*i.e.* introducing a restriction that is sufficient to identify the underlying shocks) (Awokuse and Bessler, 2003). The application of this approach to estimate the dynamic relationship among agricultural commodity markets is growing (Akram, 2009; Awokuse and Bessler, 2003; Gou, 2017; Vo et al., 2019; Wei, 2019). One shortcoming of this approach is that its imposition of a just-identified contemporaneous structure of innovations is rarely consistent with economic theory or with the inherent casual path rooted in the data (Awokuse and Bessler, 2003; Awokuse and Duke, 2006). Hence, policy inference based on such modelling approach strongly

[1] The use of VAR models mostly centres around the computation of IRF and FEVD. Both IRF and FEVD track the changes in the system of equations that are caused by the evolution of economic shocks in the system.
[2] Errors, residuals, shocks and innovations are used interchangeably throughout the paper.

depends on the validity of the imposed just-identified structural form (Awokuse and Bessler, 2003; Swanson and Granger, 1997).

Sims (1986) argued that the application of ordering based on Choleski decomposition for analysing the causal relationship between economic variables that are correlated contemporaneously will yield significant differences for impulse response and corresponding FEVD. With this deficiency of the Choleski decomposition, Bernanke (1986) and Blanchard and Watson (1986) proposed orthogonalisation alternatives that allow the imposition of over-identification restrictions. Such models are popularly labelled as Structural Vector Autoregressions (SVARs) because they rely on prior economic theory as the source of their identifying restrictions. Specifically, Bernanke (1986)'s approach achieves identification through the assumption that distinct, mutually orthogonal and behavioural innovations drive the model. Unlike in pure VAR, the just-identified structure assumption for the innovations is relaxed under the Bernanke decomposition approach; it requires imposition of a particular causal ordering of the variables.

Given that theory may not necessarily produce a clear identifying structure for imposition of a particular causal ordering of the variables, an appropriate identification procedure can be achieved by modelling the contemporaneous innovations from VAR with the DAG, a recent method rooted in artificial intelligence and computer science, which is critical in offering sound inference in innovation accounting (Awokuse and Bessler, 2003; Awokuse and Duke, 2006; Spirtes et al., 2000a; Swanson and Granger, 1997).

For this study, we adopted the variation of the Bernanke decomposition approach that is based on a combination of a VECM and DAG modelling techniques[3]. This approach is data-driven and has become increasingly popular in applied economics studies that examine dynamic relationships between economic price variables; see in particular the studies by Xu (2018), Bessler and Akleman (1998), Bessler et al. (2003), Awokuse and Duke (2006) and Yu et al. (2007). Recently, Xu (2018) employed the Bernanke decomposition to examine the dynamic relationship between US corn cash and futures prices. Although the use of the combination of a VECM and DAG approach has been popular in recent years, to the best of our knowledge, our study is the first to apply this approach in investigating the interrelationship between phosphate rock, fertilisers (such as Triple superphosphate, Diammonium phosphate, urea and potassium chloride fertilisers), crude oil and wheat prices in a multimarket and intertemporal framework.

## 3. Methods of analysis

To achieve the objectives of the study, we employed two main estimation techniques: a multivariate time-series technique to capture the dynamic interdependence between phosphate rock, oil, different fertilisers and wheat markets, and, a graphical modelling analysis, DAG, to explore whether or not there are contemporaneous relationships between these markets.

[3] A VECM is a differenced VAR model, but also adds the error correction feature that accounts for both the short-run and long-run dynamics. It is more appropriate for analysis that involves variables that are nonstationary and cointegrated Engle, R.F., Granger, C.W., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica: journal of the Econometric Society, 251-276..

*3.1 Multivariate Cointegration Analysis*

Several studies that have analysed a set of interrelated variables have employed a VAR model. The specification of a VAR model with *k* lags of *J* variables are written as:

$$X_t = \sum_{i=1}^{k} \Gamma_i X_{t-i} + \mu + \varepsilon_t \quad (\text{for } t = 1, \dots, T), \tag{1}$$

where *X* indicates $(J \times 1)$ vector of series at time *t*, $\Gamma_i$ is a $(J \times J)$ matrix of coefficients relating series changes at lagged *i* period to current changes in series, $\mu$ is a $(J \times 1)$ vector of constants, and $\varepsilon_t$ is a $(J \times 1)$ vector of independent identically-distributed (i.i.d.) innovations ( known as error terms in many statistical models that are not based on time series). Equation (1) indicates that each of the *J* variables is a function of n lags of all *J* variables, including itself, a constant and a present innovation (error) term. According to Engle and Granger (1987), the procedure for testing interrelationships between a set of variables should not be based on VAR if some series in the set of evaluated variables are nonstationary and cointegrated. An attempt to employ VAR will yield misspecification error (Engle and Granger 1987). Rather it is more appropriate to adopt the VECM, developed by Johansen (Johansen, 1988, 1991; Johansen and Juselius, 1990). This is suitable to study both short-run discrepancies and long-run equilibrium for data series that are cointegrated. The VECM framework is specified as follows:

$$\Delta X_t = \mu + \boldsymbol{\alpha} ECT_{t-1} + \sum_{i=1}^{k-1} \tau_i \Delta X_{t-i} + \varepsilon_t \, for \; t = 1, \dots, T, \tag{2}$$

Equation (2) is a first-differenced VAR model with an inclusion of a lagged-level term. The $ECT_{t-1}$ , lagged-level component, represents the Error Correction Term and the $\boldsymbol{\alpha}$ represents a (*J* × *J*) coefficient matrix containing information of how lagged levels of prices respond to current changes which suggests that the coefficient matrix $\boldsymbol{\alpha}$ determines how many combinations of $X_t$ that are stationary (Bessler and Akleman, 1998; Bessler and Lee, 2002; Bessler et al., 2003).

The parameters in Equation (2) identify the short-run, contemporary, and long-run information among the price series. Specifically, the parameter, $\boldsymbol{\alpha}$, contains summary of information on the long-run association that exists between the *J* variables. In the case when the rank of $\boldsymbol{\alpha}$ is a non-negative number, *p*, and it is less than the number of variables, *J*, then $\alpha = \emptyset\beta'$, where $\emptyset$ and $\beta$ are $(J \times p)$ matrices. The $\beta$ matrix contains the cointegrating parameters and the matrix $\emptyset$ includes the information on the speed of adjustment. Conducting hypothesis testing on $\beta$ can identify long-term structure while hypothesis testing on $\emptyset$ and $\tau_i$ can determine the short-run relationships (Johansen, 1988, 1991; Johansen and Juselius, 1990). Moreover, the structural analysis of the parameter $\varepsilon_t$ can identify the contemporaneous structure, as detailed in Demiralp and Hoover (2003) and Bessler and Lee (2002).

It is widely acknowledged that meaningful interpretations of individual coefficients in Equation (2) – VECM are difficult (Sims, 1980). Consequently, innovation accounting may be most appropriate to describe dynamic interrelationships among price series (Lütkepohl and Reimers, 1992; Swanson and Granger, 1997). The innovation accounting technique involves application of the Johansen (1992)'s maximum likelihood procedure to estimate the parameters of Equation (1). The estimated VECM is transformed to a levels VAR and then inverted to a moving-average representation. The innovation accounting based on the moving-average representation is then computed to summarise the dynamic interdependencies among the prices series in the contemporaneous time.

The 'information on the contemporaneous structure of interdependence may be explored by examining the causal relationship among innovations in contemporaneous time *t*, across markets based on the variance-covariance matrix of innovations (residuals) from the

VECM' (Hoover, 2005; Spirtes et al., 2000b). The application of DAG provides data-driven evidence on ordering or 'structuring' in contemporaneous period *t*, based on the assumption that the information on the parameter $\varepsilon_t$ is causally satisfactory. Finally, a Bernanke ordering may be applied with the discovered order/structure obtained from the DAG (Bernanke, 1986).

### *3.2 Directed Acylic Graphs and Algorithms of Inductive Causation*

The application of DAG was first introduced in artificial intelligence and computer science fields (Pearl, 2000), however its use in applied economics literature is growing. A DAG is a pictorial representation showing causal flow among a set of variables that are suggested to be related in theory or past studies (Yu et al., 2007). The causal flow is such that there is no directed cycles, that is, it is impossible to start at a node (or vertex) and follow a directed path back to the same node (Awokuse and Bessler, 2003; Awokuse and Duke, 2006). The nodes of DAG denote variables upon which data has been collected, and the line segments connecting nodes (popularly referred to as direct edges or arrows) are produced by estimating conditional statistical dependence or independence among the pairs of variables.

For illustration purpose, let us consider that the economic variables *X*, *Y*, and *Z* are in causal relations. The first scenario illustrates a *causal fork*, which assumes a relationship such that *Z* causes *X* and *Y*, depicted as: X←Z→Y. The existence of a common cause in *Z* means that the unconditional association between *X* and *Y* is non-zero, however the conditional association between *X* and *Y*, given the knowledge of the common cause *Z*, is zero. This implies that common causes screen off correlations between their joint effects. On the other hand, the second case illustrates the *inverted causal fork*, which assumes a relationship such that *Y* and *Z* cause *X*, depicted as: *Y*→*X*←*Z*. This suggests that the unconditional correlation between Y and Z is zero, while the conditional correlation between *Y* and *Z* given the common effect *X* is non-zero. In this case, common effects do not screen off association between their joint causes.

In line with Bessler and Lee (2002), DAG can be used for representing conditional independence as given by the recursive product decomposition formular:

$$Pr(x_1, x_2, x_3, \dots \dots, x_m) = \prod_{i=1}^{m} Pr(x_i |\, pa_i) \tag{3}$$

where *Pr* denotes the probability of variables $x_1, x_2, x_3, \dots \dots, x_m$; $pa_i$ represents the realisation of some subset of variables that precede ( come before in a causal sense) $x_i$ in order ($i$ = 1, 2, . . . , $m$); the notation $\prod$ denotes the product operator. Pearl (1986) proposed the concept of directional separation (*d-separation*) described as a "graphical characterisation of conditional independence" [see Verma and Pearl (1988) for proof of this proposition]. Pearl (1986) and (Pearl, 1995) revealed that the conditional independence relations implied by Equation (3) can be illustrated by the *d-separation*. In particular, the significance of *d-separation* is in the fact it shows the direction of flow between the causal graphs as well as the probability distribution of the data generating process (Pearl, 2000).

Several variants of search algorithms have been developed to implement the concept of *d-separation* particularly on observational dataset. Notable among algorithms developed is the PC algorithm by Spirtes et al. (2000b) for constructing DAG from observational data. The PC algorithm is an ordered set of commands that informs the direction of causal direction among variables based on a stepwise testing of conditional independence to remove statistically insignificant edges or causal links between variables and directing causal flow between variables. Specifically, it involves sequential removal of edges among a set of *N* variables (for example, innovations from VAR) based on zero correlation or partial correlation. The basic PC algorithm as well as its refined extension are available and can be estimated in TETRAD IV software (see http://www.phil.cmu.edu/projects/tetrad/).

To test whether the computed sample correlations conditional correlations are significantly different from zero, the Fisher's $z$ statistics was deployed. This can be presented as follows

$$(\rho(i,j|\,k),n) = \left[0.5\,\sqrt{n-|k|-3}\right]\, ln\left\{\frac{1+\ \rho(i,j|k|)}{1-\ \ \rho(i,j|k|)}\right\} \tag{4}$$

where $n$ denotes the number of observations employed in the computation of the correlations; $\rho(i,j|k|)$ represents the population correlation between series $i$ and $j$ which is conditional on series $k$ (eliminating the effect of series $k$ on each $i$ and $j$); and |k| represents the number of observations in $k$ ( that we condition on) . If $i, j$ and $k$ are normally distributed and r$(i, j|\,k)$ is the sample conditional correlation of $i$ and $j$ given $k$, then the distribution of z$(\rho(i,j|k|n) -$ z$(r(i,j|k|n)$ is standard normal. The application of DAG was first applied by Swanson and Granger (1997) to inform or provide casual flow on residuals from VAR. As in Swanson and Granger (1997), the casual flow/results suggested by DAG is employed for estimating the forecast error variance decompositions and impulse response functions. For additional details on DAG and its applications, see the studies conducted by Spirtes et al. (2000b) and Spirtes et al. (2000b).

## 4. Data

The data employed for analysis consists of monthly price data for the period from March 1999 to April 2019 for world prices of oil, phosphate rock (PhoRock), Triple superphosphate (TriP), Diammonium phosphate (DAP), urea, potassium chloride (Potass) and wheat. This data was obtained from the C.I.A. World Fact Book. All the price series are measured in US$ per metric tonne except oil price measured in US$ per barrel. The data set covers 240 observations, and all data series are converted into natural logarithmic form to reduce the variations without altering the overall characteristics and structure of the data. The description and summary statistics of the seven commodities and their prices are presented in Table A1 of the appendix and Table 1, respectively. Diammonium phosphate (DAP) have a higher mean than the Triple superphosphate (Trip) fertilisers. Notably, all the price series found their maximum values in 2008 (see Figure 1a in the appendex section), which indicates the global commodity price hikes. As one might expect, most of the price series are positively skewed, except for oil price series, and platykurtic.

**Table 1**. [a]Summary statistics of commodity price series

| Series | Mean | Median | Minimum | Maximum | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| Oil | 4.329 | 4.335 | 3.428 | 4.897 | 0.346 | -0.321 | -0.949 |
| PhoRock | 4.856 | 4.797 | 3.818 | 6.064 | 0.423 | 0.826 | 0.965 |
| TriP | 5.954 | 5.938 | 5.394 | 7.031 | 0.331 | 1.271 | 2.169 |
| DAP | 6.115 | 6.074 | 5.627 | 7.091 | 0.319 | 1.108 | 1.498 |
| Urea | 5.698 | 5.666 | 4.960 | 6.646 | 0.302 | 0.604 | 0.613 |
| Potass | 5.803 | 5.709 | 5.175 | 6.771 | 0.385 | 0.503 | -0.399 |
| Wheat | 5.489 | 5.469 | 4.955 | 6.086 | 0.265 | 0.006 | -1.055 |

[a]Values of price series are log transformed prices.

## 5. Results and Discussion

### *5.1 Unit roots tests*

In time series data analysis, it is important to ascertain whether data series are stationary at their levels, or after the data series has been first differenced. If two or more series are found to be stationary after first differencing, then it may be necessary to test for cointegration as there may be long-term relationships among the series. To examine the non-stationarity of the seven price series, we employed two univariate unit root tests: the augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1981) and the Phillips–Perron (PP) test (Phillips and Perron, 1988). However, these two tests are low power tests (Awokuse and Duke, 2006; Fedorová, 2016), and therefore we also applied the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992). The two former tests were used to test for the null hypothesis of a unit root while the latter was used to test the null hypothesis of stationarity. The combination of these three tests presents a more robust approach to determining the presence of unit root. In Table 2, we report the results of these three tests for both price levels and their first differences. The results show that the price series are stationary in differences but not in levels, suggesting the possibility of cointegrating relationships among the variables and the appropriateness of carrying out a multivariate cointegration analysis (Hansen and Juselius, 1995).

**Table 2**. Unit root tests on levels and first differences of monthly prices of variables

| Series | Without trend | | | With trend | | |
|---|---|---|---|---|---|---|
| | ADF[a] | PP[b] | KPSS[c] | ADF[a] | PP[b] | KPSS[c] |
| **Panel A: Test with price levels** | | | | | | |
| Oil | -2.386 | -2.139 | 1.439 | -2.628 | -1.329 | 0.178 |
| PhoRock | -2.057 | -1.046 | 1.392 | -1.014 | -2.110 | 0.392 |
| TriP | -2.006 | -0.980 | 1.268 | -1.006 | -1.180 | 0.368 |
| DAP | -1.071 | -1.166 | 0.896 | -2.031 | -1.866 | 0.596 |
| Urea | -2.077 | -0.425 | 1.616 | -2.027 | -2.145 | 0.616 |
| Potass | -1.741 | -0.618 | 2.611 | -1.041 | -1.113 | 0.681 |
| Wheat | -2.126 | -0.926 | 2.523 | -0.017 | -0.926 | 0.569 |
| **Panel B: Test with first differences** | | | | | | |
| Oil | -7.862 | -5.239 | 0.073 | -1.024 | -0.429 | 0.060 |
| PhoRock | -6.257 | -8.146 | 0.092 | -1.057 | -1.046 | 0.392 |
| TriP | -4.347 | -5.680 | 0.061 | -1.006 | -0.980 | 0.368 |
| DAP | -5.842 | -7.066 | 0.096 | -0.071 | -1.166 | 0.596 |
| Urea | -3.502 | -4.115 | 0.016 | -0.077 | -0.425 | 0.616 |
| Potass | -10.598 | -6.218 | 0.281 | 0.041 | -0.618 | 0.105 |
| Wheat | -9.017 | -4.116 | 0.103 | -0.017 | -0.926 | 0.569 |

[a] The choice of the number of lags is based on the Schwarz information criterion (SIC). We obtain similar outcome on the confirmation of unit root when other criteria such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The critical values of the ADF test with a constant but without a trend at the 1%, 5% and 10% significance levels are −3.43, −2.86 and −2.57, respectively, while the critical values of the ADF test with a constant and a trend at the 1%, 5% and 10% significance levels are −3.96, −3.41 and −3.12, respectively.

[b] The critical values of the PP test with a constant but without a trend at the 1%, 5% and 10% significance levels are −3.43, −2.86 and −2.57, respectively, while the critical values of the PP test with a constant and a trend at the 1%, 5% and 10% significance levels are −3.97, −3.42 and −3.13, respectively.

[c] The critical values of the KPSS test with a constant but without a trend at the 1%, 5% and 10% significance levels are 0.74, 0.46 and 0.35, respectively, while the critical values of the KPSS test with a constant and a trend at the 1%, 5% and 10% significance levels are −3.43, −2.86 and −2.57, respectively.

### *5.2 Cointegration test*

Following the results from the unit root tests, we conducted cointegration analysis to ascertain the number of cointegrating relationship that exits among the seven price variables (Johansen, 1992). Table 3 presents the results of the Johansen's trace and maximum eigenvalue tests for the co-integration rank of price series. Before the procedure for both tests could be conducted, it is important to determine the optimal lag length, denoted as *k* in Equation (1). The optimal lag length adopted is *k*=2. This was based on Schwarz information criterion. The test results as presented in Table 3 show that there are five long-term cointegrating relationships among the price series at the 5% significance level.

**Table 3.** Johansen's trace and maximum eigenvalue tests for the co-integration rank of price series

| Rank | Panel A: Trace test | | Panel B: Maximum Eigenvalue test | |
|---|---|---|---|---|
| | Statistics | Critical values at 5%[a] | Statistics | Critical values at 5% [a] |
| 0 | 82.07 | 44.91 | 60.85 | 56.91 |
| 1 | 62.41 | 39.43 | 49.74 | 42.43 |
| 2 | 48.70 | 33.32 | 45.21 | 31.32 |
| 3 | 38.95 | 27.14 | 30.15 | 28.14 |
| 4 | 25.83 | 21.07 | 22.31 | 19.07 |
| 5* | 11.17 | 14.90 | 9.58 | 15.02 |
| 6* | 2.59 | 8.18 | 7.48 | 8.18 |

[a] The critical values estimated are from MacKinnon et al. (1999).

*5.3 Contemporaneous causality and dynamic relationship among price series*

Following the application of the PC algorithm DAG to the variance-covariance matrix of the residuals from the VECM presented in Equation (2), we report in Figure 1 the contemporaneous causal relationship among the seven price series. The DAG produced are based on 5% and 30% significance levels, however, the DAG with the latter level of significance appeared to produce a more reasonable causal graph. The graph based on the 5% significance level suggests that the data on the price series are not sufficiently rich to yield a clear causal graph in the contemporaneous period. Studies conducted by Awokuse and Bessler (2003) and Awokuse and Duke (2006) established that DAG with less restrictive levels of significance enhances retention of edges or relationships between price series. Besides, Spirtes et al. (2000b) suggest that less restrictive significance levels may lead to improvement performance of casual structure particulary in small samples. As a result, we based the inferences on the 30% DAG so as not to be overly restrictive in terms of identifying possible instantaneous relationships among the price series.

Figure 1 shows that the seven markets considered (Oil, PhoRock, TriP, DAP, Urea Potass and Wheat) are interconnected in contemporaneous time (i.e. within a month[4]), suggesting that each of the price series will respond to shocks in other markets. Specifically, the DAG algorithm shows that there is no directed edge towards phosphate rock price, indicating that phosphate rock price is exogenous. Moreover, the phosphate rock price causes changes in wheat, DAP and oil prices, suggesting that shocks in the phosphate rock market in the short-term may have an impact on prices of wheat and DAP fertiliser. This supports the findings by Khabarov and Obersteiner (2017) and Cordell et al. (2009) that price spikes in the global fertiliser markets, as well as the rapid growth in dairy and cereal prices in 2007, may be partly attributed to price changes in the phosphate rock market in the same year.

The analysis also shows that the DAP fertiliser price is affected by phosphate rock and other fertiliser prices (including TRIP, POTASS, UREA). This is not surprising given that DAP is the world's most widely used phosphorus fertiliser ( that also contains some N) and shocks in its prices may likely have widespread effects. The DAP fertiliser price is affected by oil prices which may be attributed to increased transportation costs and/or the costs of fertiliser production, which requires sulphuric acid as well as ammonia. In particular, ammonia production uses large quantities of natural gas, and subsequently its price is strongly influenced

[4] Further knock-on impacts may occur on other markets beyond this timeframe. The full interconnected impacts between all markets are captured using the IRFs.

by any shocks in energy costs (Chowdhury et al., 2017; Von Horn and Sartorius, 2009). The wheat price is affected by phosphate rock, oil and Potass fertiliser prices, which supports the argument that the oil price plays a significant role in explaining shocks in the prices and associated volatility of agricultural commodities (Nazlioglu et al., 2013; Vo et al., 2019). The price of urea is found to be affected by oil, Trip and Potass prices.

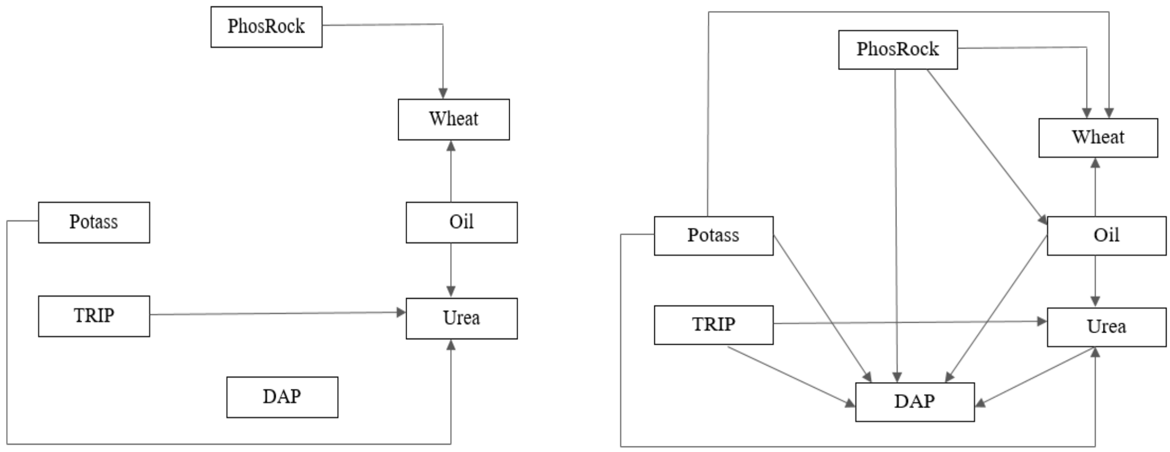



**Figure 1**. Causal Flows on Innovations from vector error correction model on Price Series based on PC algorithms at significance level 0.05 (left) and 0.30 (right) within one month.

Based on the results obtained from the VECM model in Equation (2) combined with the causal relationship in Figure 1 (based on 30% significance level DAG), we generated two moving average (MA) presentations for each of the price series at alternative time horizons, which include the FEVD and IRF. These MA presentations are then used to examine the dynamic interdependence among the price series. Table 4 presents the FEVD for successive time horizons which explains the percentage variation of a price series that is due to innovations by itself and the other six price series. These numbers partition the variation in each class at horizons of one, six, twelve, eighteen and twenty-four months ahead so as to identify how the impact varies over time. The 24 month time period provides sufficient time to ensure the full effects are captured.

Consistent with the results from the DAG analysis, the phosphate rock price is wholly explained by innovations to its own price and is not driven by any other markets at least initially, implying that price shocks in the phosphate rock market are largely exogenous and supply-driven at least in the immediate short-run (Blackwell et al., 2019; Von Horn and Sartorius, 2009). This result suggests that potential restrictions to phosphate rock mining attributable to geopolitical instability in the mining regions of the world could disrupt phosphate rock global supply leading to a shortage in phosphate rock, with a knock-on impact on the phosphate rock price (Blackwell et al., 2019; De Ridder et al., 2012; Von Horn and Sartorius, 2009). After 6 months, the variation in the phosphate rock price is still primarily influenced by its own price (72.12%), followed by two main phosphorus mineral fertilisers, TRIP price (13.84%) and DAP price (8.66%). However, the influence of other markets gradually emerges after twelve months, with 3.33% of the variation in the phosphorus rock price attributable to the wheat price. After two years, the phosphorus rock price is still influenced by its own price (53.43%), but the demand market for phosphate rock which includes wheat, TRIP, and DAP prices accounted for 34.82%. This suggests the demand market for fertiliser and wheat production becomes increasingly important in explaining phosphate rock price over time, and that shocks in the global phosphate rock market are demand-driven, as well as supply-driven (Von Horn and Sartorius, 2009). The large contribution of TRIP and DAP fertilisers in explaining variability in the phosphate rock price after the first month is in line with changes in demand for mineral phosphorus fertiliser for agricultural production, thereby constituting pressure on phosphate reserves and consequently phosphate rock price (Chowdhury et al., 2017).

Simailr to the DAG analysis, the TRIP price is initially 100% exogenous thereafter the TRIP market starts interacting with other prices. After 12 months, variation in TRIP price is influenced by its own price (55.49%), wheat price (10.17%), phosphate price (2.74%), Urea price (11.27%), DAP price (5.91%) and Oil price (1.10%). After 18 months, uncertainty in TRIP price is attributed to itself, wheat, urea and oil prices. Hence the TRIP fertiliser price appears to be influenced more heavily by the demand for fertiliser in the wheat industry than by the supply of phosphate rock. Given that farmers operate on small margins, increases in agricultural commodity prices tend to raise farmers' return on investment in fertiliser use and thus fertiliser demand, and consequently fertiliser prices. For example, Khabarov and Obersteiner (2017) found that a massive import of fertilisers to India to meet increasing crop demand contributed significantly to the global price spike in phosphorus fertiliser in 2007.

Consistent with the direction of causality obtained in the DAG analysis, the variation of the wheat price was largely associated with the wheat price itself (94.07%) and modestly attributed to phosphate rock price (2.35%), crude oil price (3.361%) and potass fertiliser price (0.21%). After 24 months, variation in wheat price was found to still be influenced by its own price (93%). Variation in the DAP price series is initially largely influenced by its own price (65.81%), TRIP fertiliser (28.74%) and phosphate rock price (4.48%). However, after twelve months, the DAP fertiliser price is largely driven by TRIP price (37.49%), oil price (20.27%), wheat price (12.86%) and prices of other fertilisers (Potass - 4.80%, Urea - 7.69). This pattern was maintained throughout the 2-year time horizon and suggests that the DAP price is susceptible to large volatility shocks not only from itself but also from other markets. These include the increased price of oil and energy necessary for the production and transportation of DAP, excessive fertiliser demand for biofuel production, and increased excise on phosphate fertiliser exports (FAO, 2008, 2011; Scholz et al., 2014).

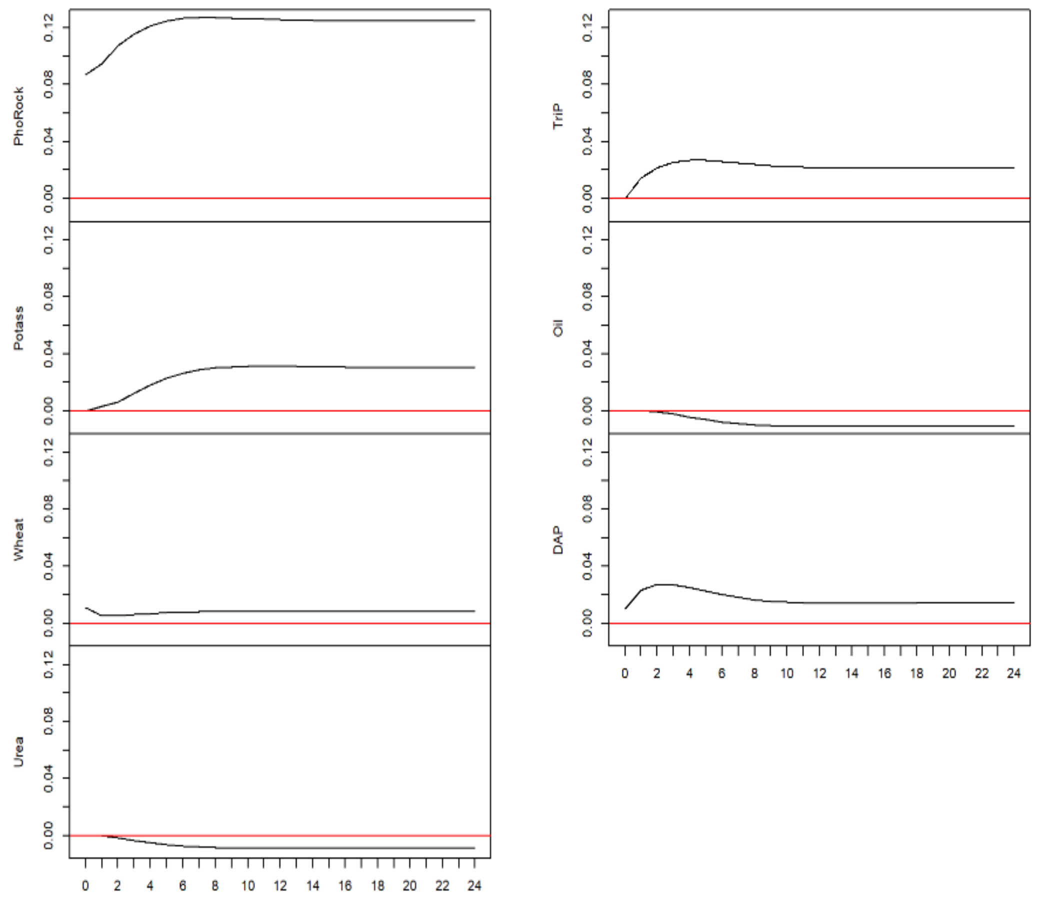
The results from the impulse response function (IRF) are presented in Figures 2(a) – (g) and indicate that shocks to the phosphorus rock market have a knock-on positive impact on phosphate fertiliser markets and to a lesser extent the wheat market.  A 10% increase in the phosphate rock price results in a 2% increase in the TRIP price and a 0.8% increase in the wheat price. The IRF for the TRIP price indicates that a 10% increase in the TRIP price results in a 4% increase in the Urea price. The IRF for the wheat price shows that a shock to the wheat price has sizeable positive impacts on phosphate rock and fertiliser prices. A 10% shock in the wheat price has impacts ranging from 2.5% to 5% on fertiliser prices, and 4% on the phosphate rock price. This finding provides support for the policy paper by Khabarov and Obersteiner (2017) which argued that the phosphate rock price increases in 2008 could largely be attributed to demand shocks and phosphate scarcity. The findings from the IRF are consistent with the FEVD results.

**Table 4.** Forecast error variance decompositions results based on the DAG derived from PC algorithms

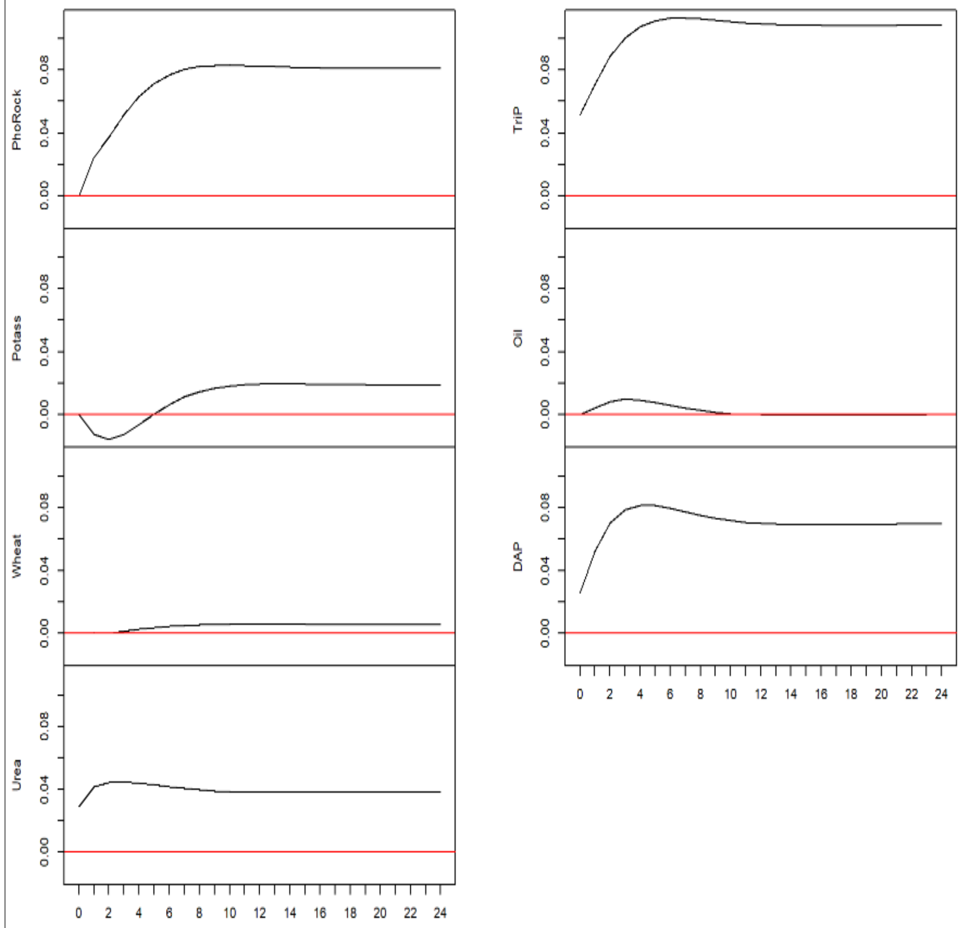
| Horizon (month[a]) | PhoRock | TriP | Potass | Oil | Wheat | DAP | Urea |
|---|---|---|---|---|---|---|---|
| PhosRock[b] | | | | | | | |
| 1 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 72.122 | 13.844 | 0.195 | 0.631 | 1.091 | 8.661 | 3.456 |
| 12 | 58.048 | 18.504 | 0.485 | 2.677 | 3.326 | 10.437 | 6.522 |
| 18 | 54.730 | 19.561 | 0.570 | 3.459 | 4.055 | 10.477 | 7.147 |
| 24 | 53.434 | 19.990 | 0.604 | 3.768 | 4.341 | 10.484 | 7.379 |
| TriP[b] | | | | | | | |
| 1 | 0.000 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 3.402 | 61.291 | 0.809 | 9.078 | 7.347 | 7.348 | 10.725 |
| 12 | 2.743 | 55.493 | 1.098 | 13.310 | 10.168 | 5.914 | 11.274 |
| 18 | 2.492 | 54.534 | 1.160 | 14.510 | 10.842 | 5.343 | 11.119 |
| 24 | 2.384 | 54.168 | 1.185 | 15.010 | 11.116 | 5.095 | 11.043 |
| Potass[b] | | | | | | | |
| 1 | 0.000 | 0.000 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 3.250 | 1.862 | 63.929 | 0.328 | 2.600 | 17.854 | 10.177 |
| 12 | 6.133 | 1.871 | 39.682 | 0.470 | 5.018 | 27.289 | 19.536 |
| 18 | 6.497 | 2.245 | 34.123 | 0.859 | 6.285 | 28.213 | 21.778 |
| 24 | 6.613 | 2.356 | 32.090 | 1.014 | 6.786 | 28.528 | 22.613 |
| Oil[b] | | | | | | | |
| 1 | 0.000 | 0.000 | 0.000 | 100.000 | 0.000 | 0.000 | 0.000 |
| 6 | 0.070 | 0.370 | 0.062 | 97.254 | 1.748 | 0.101 | 0.396 |
| 12 | 0.320 | 0.196 | 0.059 | 96.801 | 1.848 | 0.581 | 0.194 |
| 18 | 0.438 | 0.128 | 0.049 | 96.718 | 1.713 | 0.821 | 0.132 |
| 24 | 0.491 | 0.095 | 0.044 | 96.696 | 1.645 | 0.928 | 0.101 |
| Wheat[b] | | | | | | | |
| 1 | 2.355 | 0.000 | 0.206 | 3.361 | 94.078 | 0.000 | 0.000 |
| 6 | 0.648 | 0.045 | 0.249 | 2.382 | 95.046 | 1.128 | 0.502 |
| 12 | 0.669 | 0.185 | 0.203 | 2.480 | 93.766 | 1.707 | 0.990 |
| 18 | 0.670 | 0.241 | 0.183 | 2.587 | 93.296 | 1.865 | 1.158 |
| 24 | 0.668 | 0.264 | 0.174 | 2.636 | 93.091 | 1.935 | 1.232 |
| DAP[b] | | | | | | | |
| 1 | 4.481 | 28.736 | 0.168 | 0.420 | 0.000 | 65.802 | 0.393 |
| 6 | 4.497 | 38.432 | 4.169 | 13.853 | 9.132 | 21.107 | 8.810 |
| 12 | 2.999 | 37.497 | 4.808 | 20.274 | 12.178 | 14.549 | 7.695 |
| 18 | 2.529 | 37.558 | 5.086 | 22.239 | 12.866 | 12.708 | 7.014 |
| 24 | 2.302 | 37.633 | 5.228 | 23.166 | 13.180 | 11.816 | 6.674 |
| Urea[b] | | | | | | | |
| 1 | 0.000 | 7.657 | 2.515 | 2.500 | 0.000 | 0.000 | 87.328 |
| 6 | 0.071 | 9.009 | 0.259 | 14.917 | 2.429 | 0.206 | 73.109 |
| 12 | 0.213 | 8.234 | 0.135 | 17.584 | 2.919 | 0.530 | 70.386 |
| 18 | 0.277 | 7.879 | 0.102 | 18.301 | 2.973 | 0.682 | 69.787 |
| 24 | 0.306 | 7.708 | 0.085 | 18.642 | 2.997 | 0.752 | 69.509 |

[a] Month one is the contemporaneous period. [b] This subsection in the table shows how the variance of a particular series is explained by price innovations from the seven series listed in the first row. The numerical results are in percentage representations.

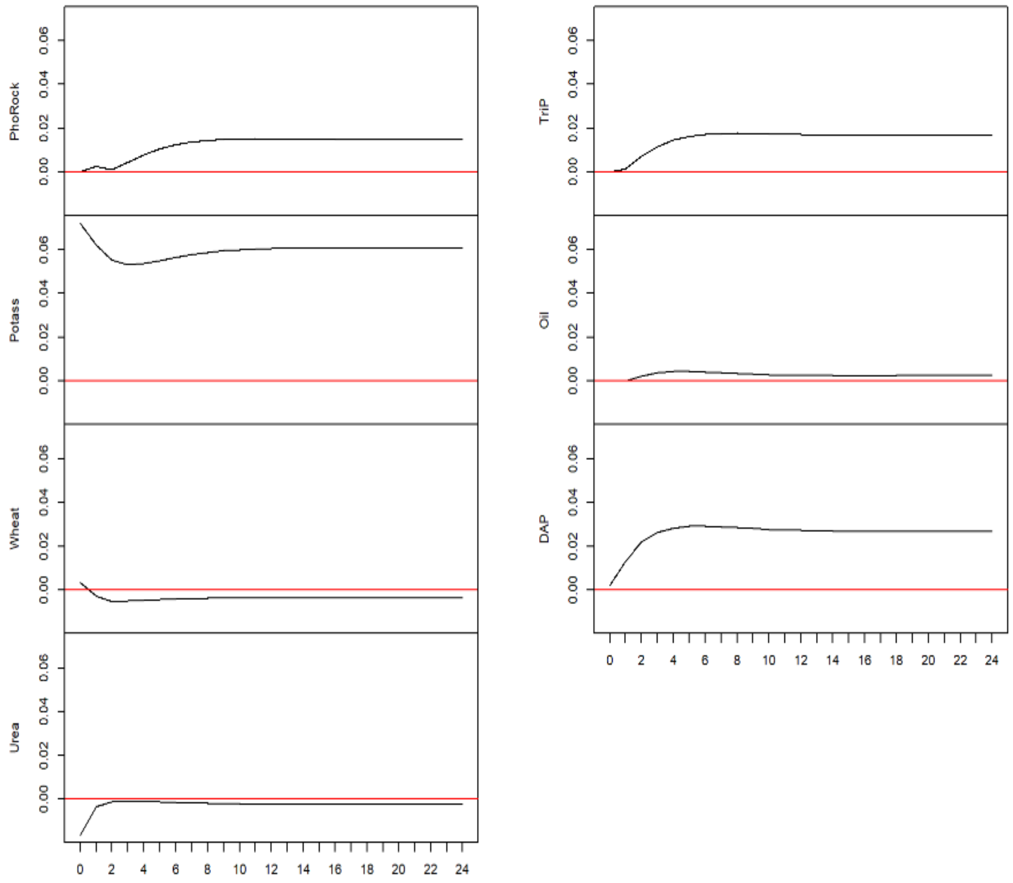
**Figure 2**. Impulse Response Functions of Each Prices to a one-time Only Shock in innovations in another price



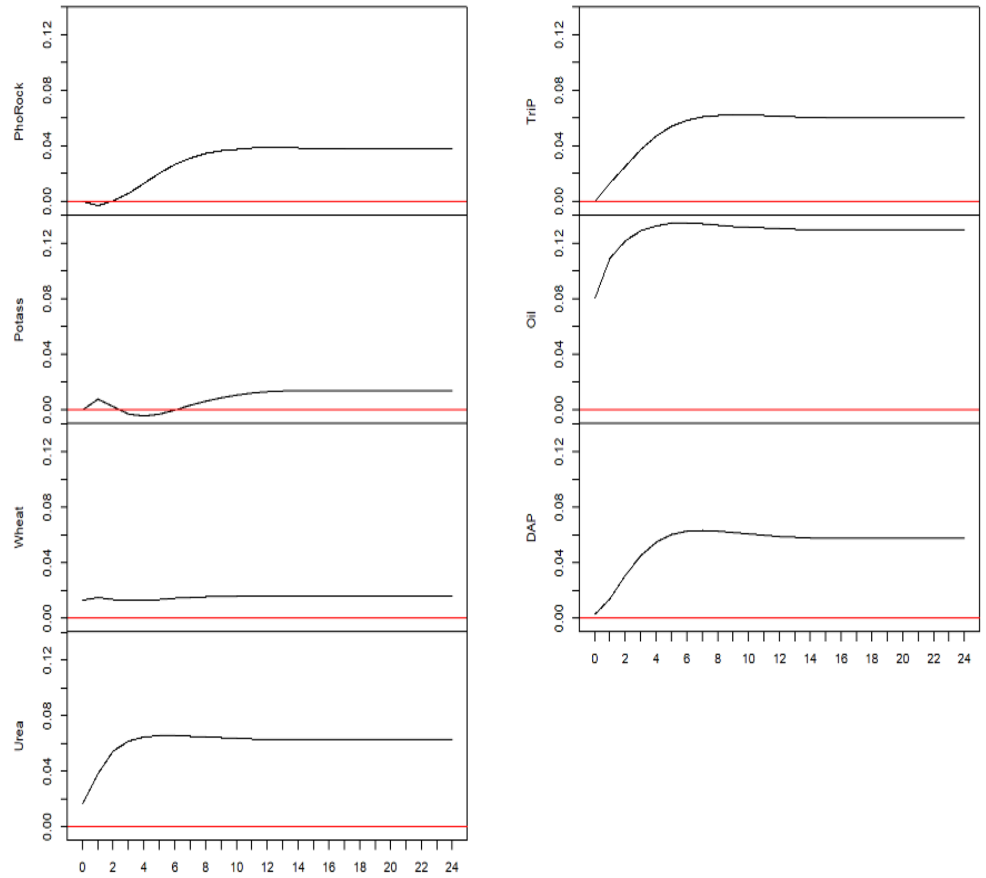

2(a) Impulse response over 24 months from Phosphorus Rock Shock



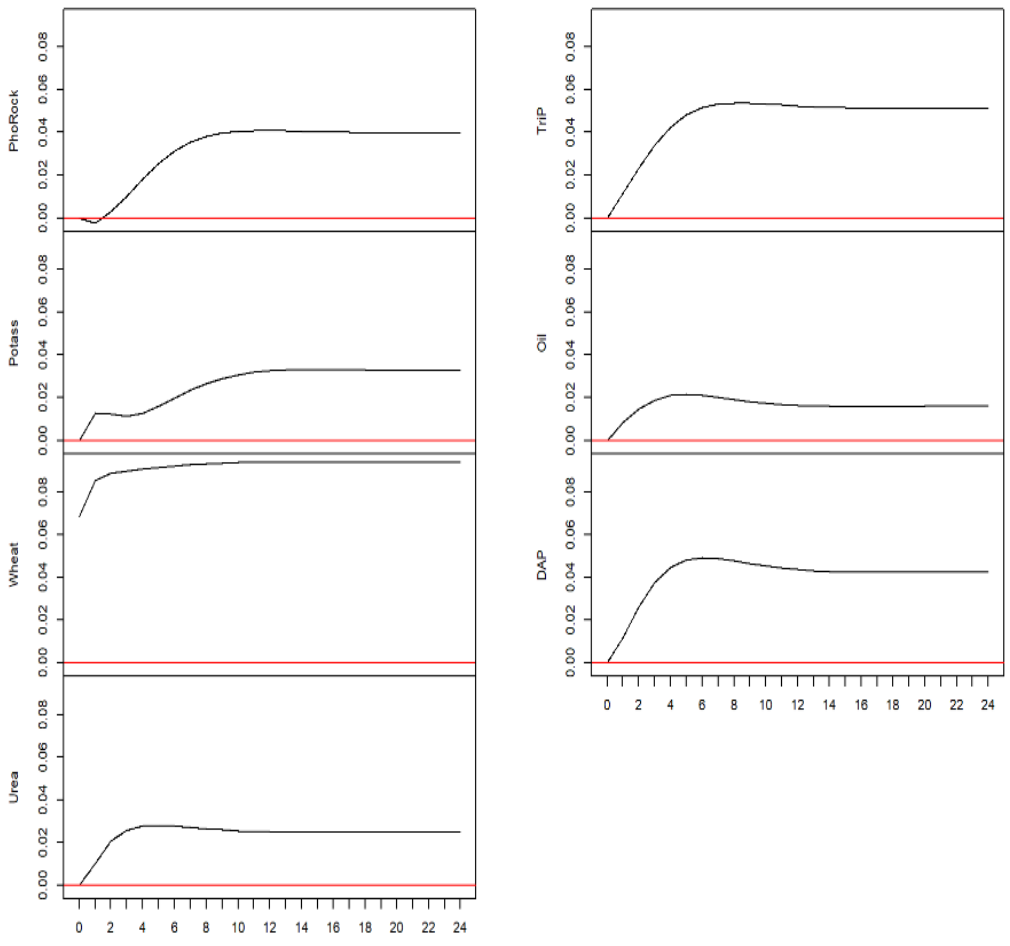

2(b) Impulse response over 24 months from TRIP shock



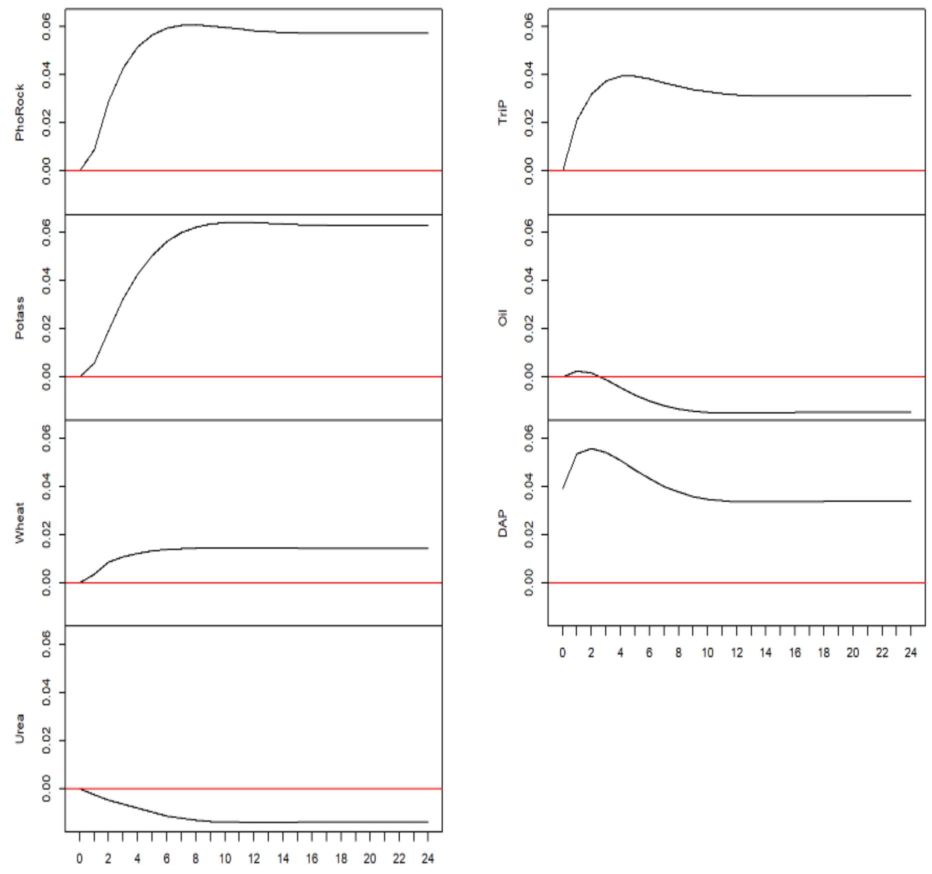

2(c) Impulse response over 24 months from POTASS shock



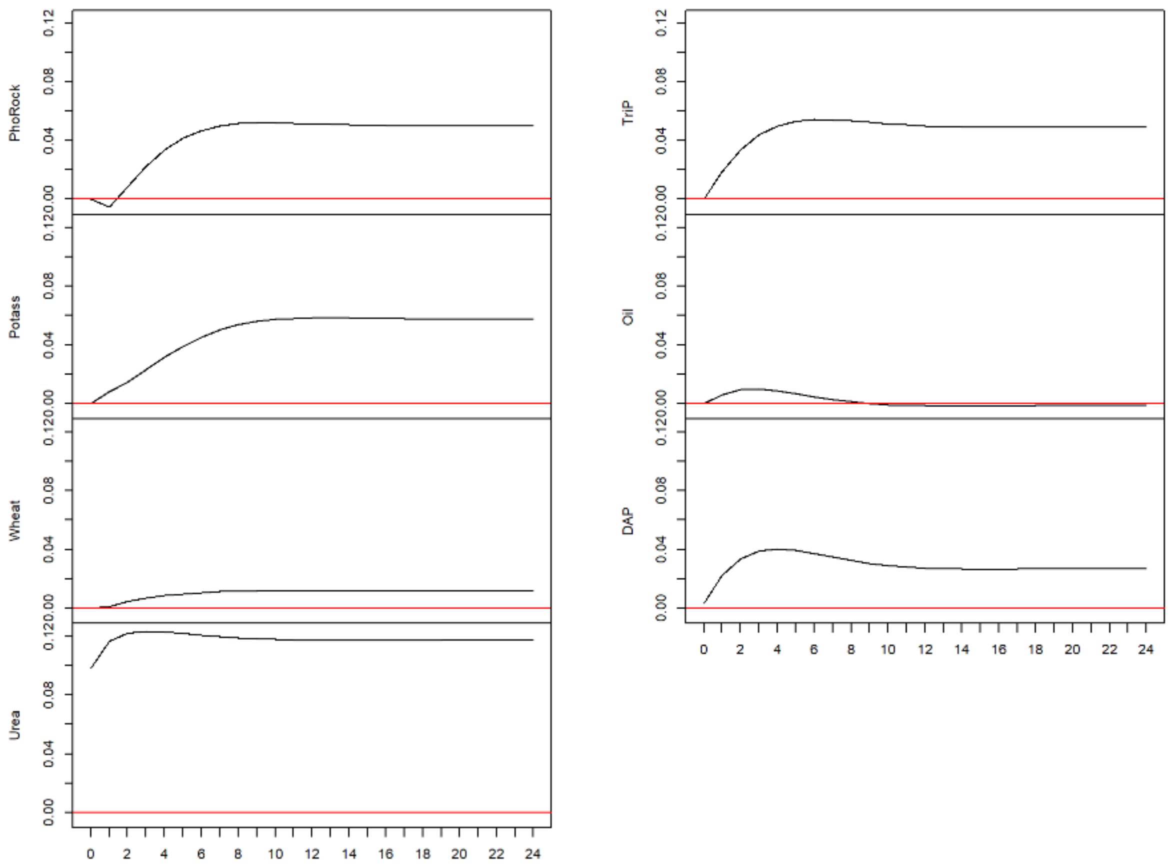

2(d) Impulse response over 24 months from OIL shock




2(e) Impulse response over 24 months from WHEAT shock




2(f) Impulse response over 24 months from DAP shock




2(g) Impulse response over 24 months from UREA shock

## 6. Conclusion

The finite supply of phosphate rock as well as rising fertiliser prices are key topics in the discussion around global food system resilience. The inter-relationships between phosphate rock, phosphate fertilisers and agricultural commodity prices are critical to understanding how farmers and policymakers might respond to future phosphate rock supply shocks and increase phosphorus-use efficiency for sustainable global food systems. This study applied a combination of a VECM and DAG analysis to examine the dynamic interdependence between phosphate rock, fertilisers and wheat prices. Applying DAG to the well-established VECM allows us to address issues surrounding dynamic patterns of price series using both forecast error decompositions and impulse responses.

Our results indicate five complex cointegrating relationships among phosphate rock, fertiliser and wheat markets. The DAG analysis indicates that the price of phosphate rock affects wheat and DAP prices, but that the phosphate rock price is not initially driven by any other markets, and is therefore most vulnerable to its own phosphate supply constraints. However, in the longer-run a shock to the wheat price will have sizeable knock-on impacts on phosphate rock and fertiliser prices. This suggests that hikes in phosphate rock prices are driven by demand factors as well as supply factors. Given the finite supply of phosphate rock, the continued demand for fertilisers for crop production may lead to an increase in phosphate rock prices.

Moreover, the finding that higher phosphate rock prices are likely to lead to a new equilibrium in the agricultural sector, with higher output and input prices, suggests that future phosphate rock price shocks will be partially offset in the long-run by higher output prices. The extent to which producers are likely to adjust phosphorus use in response to future input/output price changes depends on the behavioural response of farmers[5]. As a result, policymakers cannot necessarily rely on higher phosphate prices to solve the problem of excessive phosphorus use in the event of phosphate rock scarcity in the future. Policy initiatives should be directed to ensuring increased use efficiency of phosphorus fertilisers, for example, through improved nutrient management planning. This would help to preserve the finite phosphate rock resource, while also dampen increased demand, including excess demand in response to short term high commodity prices. Also, the policy advice on increased use efficiency of phosphorus fertilisers would help address supply side price hikes, especially when commodity prices are

[5] While farmers responded to sharp increases in phosphate rock prices byreducing phosphorus use in 2008, it is unclear whether producers may respond in the same manner to further phosphate price increases.

unchanged, and therefore minimise impacts on farmers' production decisions that ultimately impairs food supplies to semi-subsistence farmers and stresses poorer consumers in developing and medium income countries.

While the present study focused on the relationship between phosphate rock, fertilisers and wheat prices, it is important to highlight that caution should be shown in generalising our findings to other agricultural commodities because they might respond at least slightly differently to market shocks. Considering this limitation, future research may be required to ascertain how other commodities may respond to shocks in phosphate rock price and vice versa.

**Acknowledgements**

The study was conducted as part of the RePhoKus project "The role of Phosphorus in the Resilience and Sustainability of the UK food system" funded by the the Global Food Security's 'Resilience of the UK Food System Programme' with the UK's BBSRC, ESRC, NERC, and the Scottish Government. Authors wish to thank Erin Sherry, Paul Caskie, Julia Martin Ortega and Paul Withers for their insightful comments on the earlier drafts of this paper.

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## APPENDIX

**Table A1**. Description of commodity price series

| Commodity | Unit | Description of price series | Chemical formula of fertilisers |
|---|---|---|---|
| Oil | US$ per barrel | UK Brent 38° API | NA* |
| Phosphate rock(PhosRock) | US$ per metric tonne | Casablanca (Morocco), contract, f.a.s., 70% BPL | NA* |
| Triple superphosphate (TriP) | US$ per metric tonne | pre Oct 2006, US Gulf, f.o.b.; post Tunisian origin, spot, f.o.b., bulk granular | $Ca(H_2PO_4)_2 .H_2O$, 45% $P_2O_5$ |
| Diammonium phosphate (DAP) | US$ per metric tonne | US Gulf, spot, f.o.b., bulk | $(NH_4)_2HPO_4$, 18% N, 46% $P_2O_5$ |
| Urea | US$ per metric tonne | Black sea, spot, f.o.b., bulk | $CH_4N_2O$, 46% N |
| Potassium chloride (Potass) | US$ per metric tonne | Vancouver, spot, f.o.b., standard grade | KCl, 63% $K_2O$ |
| Wheat | US$ per metric tonne | Export price delivered at the US Gulf port, no.1, hard red winter, ordinary protein | NA |

Note: NA means not applicable

**Figure 1A**. Trends of price variables