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Agricultural Research Spending in Sub-Saharan Africa (SSA): How Important are Political Economy Considerations?

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Agricultural Research Spending in Sub-Saharan Africa (SSA): How important are political economy considerations?

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Abstract: Given the centrality of the agricultural sector to employment and GDP, agricultural transformation, particularly increasing agricultural total factor productivity (TFP) through knowledge creation and assimilation, can be a foundation for structural transformation and sustainable growth in developing countries. Domestic agricultural TFP performance is influenced mainly by knowledge creation (concerted investments in agricultural R&D) and assimilation of knowledge created elsewhere (knowledge spillovers). Investing in knowledge creation and assimilation entails concerted political commitment, the absence of which depends on domestic political factors and results in low levels of agricultural research spending (evident in most SSA countries). Furthermore, knowledge spillovers from advanced economies to SSA countries have reduced considerably due to increased inapplicability in those developing countries. Islam and Madsen (2018) analysed patterns of knowledge creation and channels of knowledge spillovers in developing countries. We are interested in modelling the patterns of knowledge creation in and spillovers to the agriculture sector in SSA countries (with similar economic structures and institutional features), factoring in the salience of cross-section dependence. We investigate the relationship between agricultural inputs (including a measure of domestic knowledge creation) and agricultural output in a panel of 45 SSA countries covering the period 1960 – 2016. Data on agricultural inputs and output are obtained from the FAOSTAT database while data on knowledge creation is obtained from the ASTI database. The empirical analysis, applying the dynamic Common Correlated Effects Mean Group Estimator proceeds in three steps; estimating an agricultural production function, allowing for cross-country heterogeneity and the distorting impact of unobserved shocks, to obtain estimates of agricultural TFP. Second, we adopt a spatial econometric framework to the computed TFP estimates from the first stage to model alternative channels of knowledge spillovers. Third, we use novel methods in panel time series econometrics to test for the direction of causality between variables.

JEL classification: C21, C23, F35, F44, F63, H53, O33, Q16

Keywords: agriculture, agricultural transformation, knowledge spillovers, common factor model

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1. BACKGROUND AND JUSTIFICATION

The agricultural sector represents a substantial portion of employment and GDP in developing countries, and efforts to boost agricultural performance have positive spill-over effects – such as greater food security, lower poverty levels, better nutrition and higher incomes – into other sectors of the economy (Badiane and Collins, 2016; Beintema and Stads, 2017; AGRA, 2018; African Center for Economic Transformation, 2017). Extant literature discusses the potential galvanising impact of agricultural Research and Development (R&D) on improvements in agricultural total factor productivity (TFP hereafter) in developing countries (Fuglie and Rada, 2016; Evenson and Gollin, 2003). Historically, improvements in agricultural output have been achieved by intense cultivation on existing plots (Ruttan, 2002) or expanding plots under cultivation (Alston and Pardey, 2014). However, the effects of climate change, the natural bounds of agri-climatic geogreaphy, and population growth impinge on land availability and fertility (Fuglie and Rada, 2016; Alston and Pardey, 2014; Beintema and Stads, 2017) leaving agricultural R&D as the main source of improved agricultural TFP, hence improved agricultural performance. We posit that domestic agricultural TFP growth and performance can be influenced primarily by knowledge: by investing in knowledge creation and innovation (technological improvements) and implementing mechanisms to assimilate knowledge created elsewhere (Islam and Madsen, 2018; Pardey, Alston and Chan-Kang, 2013). An important prerequisite for investing in knowledge creation and assimilation is concerted government effort. Development stakeholders have begun to avail of the importance of politics in determining development outcomes: where there is political commitment from the 'top brass' of the domestic government, broad-ranging reforms to agricultural knowledge creation and assimilation are attainable. This political economy narrative lends itself to an important drawback of the agricultural sector in Sub-Saharan African (SSA) countries: underinvestment in local agricultural R&D (Mogues, 2015; Mogues and Do Rosario, 2016).

This study attributes low spending on domestic agricultural research to an absence of high-level domestic political commitment towards R&D, with such lack of commitment plausible for three reasons. First, the benefits (outcomes) of agricultural research accrue in the medium to long-term making them less attractive to politicians with uncertain time horizons in power. As a result, politicians prefer to prioritize overt, albeit less profitable investments (such as infrastructure investments, agricultural input subsidies) whose benefits accrue within a shorter period of time and whose successes are easily attributable to them (Benin, McBride and Mogues, 2016; Mogues, 2015). Furthermore, the human resource capacity of most of the small African countries is low and declining, with governments investing increasingly less in human resources. This is particularly rife in francophone West and Central African countries. Second, (economic and political) elites' incentives and interests towards agricultural transformation, and how elites bargain among themselves. In developing countries, the economic elites involved in agriculture are typically large-holder farmers although the bulk of farmers are smallholders who are constrained in their ability to leverage their collective power in influencing policy toward agricultural research (Benin and Bingwanger-Mkhize, 2012; Birner and Resnick, 2010). Third, endogeneity of *ex post* policy impact; with agricultural performance influencing the availability of future resources (Birner and Resnick, 2010). A history of weak agricultural performance reduces government's resources to agriculture, while simultaneously undermining incentives to invest in agriculture.

Agricultural Science and Technology Indicators (ASTI) data for the period 2000 – 2014 shows two key patterns: first, palpable heterogeneity in growth in agricultural research spending with the larger countries recorded substantial growth in said spending. Countries experienced positive (Sierra Leone, Zimbabwe, Uganda), stagnant (Mauritius, Kenya, Cote d'Ivoire), and negative growth (Guinea, Togo, Gabon) over the period. Second, the levels of domestic investment in agricultural R&D have been lagging behind investments in other agricultural inputs such as training, irrigation and farm support and subsidies (Beintema and Stads, 2017). This is somewhat counterintuitive given the documented benefits of agricultural research in reducing poverty more than other pro-poor spending, in addition to higher returns of agricultural research compared with other agricultural investments (Thirtle, Lin and Piesse, 2003; Benin, McBride and Mogues, 2016; Fan, Nyange and Rao, 2012; Fan and Zhang, 2008). The biggest spenders on agricultural research for the 2000 – 2014 period were Nigeria, South Africa, Kenya, Ghana, Uganda, Ethiopia, Tanzania, Cote D'Ivoire, Senegal and Burkina Faso while most West and Central African countries spent considerably less. The growth in agricultural research spending amongst the aforementioned biggest spenders – particularly Ghana, Uganda, Nigeria, and Kenya – was driven mainly by salary increases rather than by investments in research, infrastructure or equipment.

The African Union and United Nations, through the Comprehensive Africa Agriculture Development Program (CAADP) of the New Partnership for Africa's Development (NEPAD), agreed that member countries should spend at least 10 percent of their budget on agricultural investment in order to achieve 6 percent sectoral growth per year (Lynam, Beintema, Roseboom and Badiane, 2016; Beintema and Stads, 2017). Furthermore, NEPAD set a target for countries to spend 1 percent of their agricultural GDP on research and development (Beintema and Stads, 2017). Agricultural production growth, however, outstrips agricultural research spending in SSA countries. The agricultural intensity ratio – agricultural research spending as a share of agricultural GDP (AgGDP) – has dropped steadily over the years; with approximately 81% of SSA countries (29/36) for which data were available investing less than 1 percent of their agricultural GDP on research (Beintema and Stads, 2017). Mauritius (5.8 percent) and Namibia (3.1 percent) recorded the highest intensity ratios in 2014, while Madagascar, Gabon and Chad recorded lowest (0.2 percent). While standard intensity ratios shine spotlight on temporal domestic efforts in agricultural innovation (or lack thereof), they do not incorporate crucial structural, policy and institutional factors in measurement, making universal targets unrealistic. Furthermore, a higher agricultural intensity ratio may emanate from reduced agricultural output rather than higher investment. Even when (weighted) multi-factored indexes are used (Nin Pratt, 2016) there is considerable cross-country heterogeneity and countries still underinvest in research (with the 1 percent investment deemed unattainable). We posit that underinvestment is due to political economy factors, as discussed below.

An easy path to economic transformation in developing countries and specifically in SSA, premised on the salience of agriculture, is through agricultural transformation. Agricultural transformation entails the shift of agriculture from low productivity agricultural employment – largely subsistence, farm-oriented and characterized by underutilization of inputs on large farms – to high productivity agricultural employment that is largely commercial and dominated by small-scale commercial farms (ACET, 2017; AGRA, 2018; Jayne, Chamberlin and Benfica, 2018). This consists of two processes: first, modernization of farming by running farms as a business while increasing agricultural productivity through knowledge creation, and second, strengthening the links between farms and other sectors of the economy (Jayne *et al.,* 2018; ACET, 2017). Increasing productivity of the main agricultural inputs – labour and land – results from increased technological change, brought about by domestic investments in agricultural R&D and the inevitable spill-overs from agricultural R&D investments in other countries (see paragraphs above). Thus, our paper will provide econometric evidence on the first process of agricultural transformation.

This study will make use of annual data for 45 SSA countries covering the period 1960 to 2016, proceeding in four steps. First, we will estimate a heterogeneous agricultural production function following Griliches (1979), augmented with a measure of domestic R&D (to incorporate private returns to knowledge). We will employ a common factor approach which accounts for cross-country heterogeneity, the presence of genuine agricultural knowledge spill-overs and unobserved common shocks. The focus of this first step is to establish drivers of aggregate agricultural output, and obtain unbiased estimates of agricultural TFP (see Eberhardt, Helmers and Strauss, 2013). This allows circumventing the use of standard TFP measures (such as the Malmquist TFP index). Second, we extract agricultural TFP estimates by computing residuals from the macro panel equations – which incorporate distortions created by international business cycles, distortions for which each country is affected independently and has a unique response – and apply novel macro econometric techniques to model alternative mechanisms for agricultural spill-overs (Islam and Madsen, 2018; Ertur and Musolesi, 2017). Third, model heterogeneity is explored further by splitting the sample into economic development groups, geographical groups, spectra of state-business relations (Sen and Te Velde, 2009) and by volatility of donors' agricultural research funding (Stads and Beintema, 2015). Fourth, we will use novel methods in panel time-series econometrics (Canning and Pedroni, 2008; Eberhardt and Presbitero, 2015) to test for the direction of causality between R&D (and other inputs), agricultural TFP and output.

There is considerable research on agricultural production functions and studies focusing on the productivity of agricultural R&D investments (Block, 2014; Lusigi and Thirtle, 1997; Nin Pratt, 2015; Thirtle, Lin and Piesse, 2003; Eberhardt and Teal, 2013; Fuglie, 2015, 2017). Extant empirical literature on knowledge spillovers comprises mostly micro level studies that focus on single geographical areas or specific crops and a few macro-level studies (Guiterrez and Guiterrez, 2003; Johnson and Evenson, 1999; Schimmelpfennig and Thirtle, 1999; Islam and Madsen, 2018). Some of such micro level studies include: Barrett *et al.,* (2004) and Moser and Barrett (2006) on rice farming in Mozambique; Suri (2011) on hybrid maize in Kenya; Gine and Yang (2009) on maize and groundnuts in Malawi among others. Furthermore, some studies focus on the political economy aspect of investment, or lack thereof, in agricultural R&D (Mogues, 2015; Mogues and Do Rosario, 2016; Benin *et al.,* 2016; Benin and Binswanger-Mkhize, 2012; Mogues, Fan and Benin, 2015).

2. MODEL

2.1 The Agricultural Production Function

We follow Griliches (1979) in discussing an R&D augmented production function: including net agricultural output, standard inputs labour and capital, as well as a measure of domestic agricultural R&D (a measure of knowledge capital).

Equation 1

For simplicity, we assume equation (1) takes a Cobb-Douglas functional form and the current state of technical knowledge is treated as a compliment to the standard inputs. Griliches (1979) shows that the level of knowledge capital is a function of current and past levels of domestic R&D expenditures – in this study we posit that these expenditures are low due to a lack of political commitment – from which a measure of R&D capital stock can be obtained.

Thus, using the Cobb-Douglas functional form, equation 1 can be rewritten as:

Equation 2

Where A is a constant, t represents a linear time trend, and e is the stochastic error term. The parameters we are interested in estimating. Augmenting equation 2 with a measure of R&D capital stock and taking the natural logarithm of all observable variables, we obtain:

Equation 3

Where is a time-specific effect assumed to be differ across countries (motivating heterogeneous technology parameters). e is the error term which contains random shocks to agricultural production and knowledge accumulation.

2.2 Knowledge Spill-overs

A major challenge with the production function above is assuming away the potential for agricultural R&D spillovers across countries. Knowledge spillovers are an important source of agricultural productivity differences across countries (Islam and Madsen, 2018; Alston, 2002).

3. CONCEPTUAL FRAMEWORK

Technical aspects of agricultural reform are important in supporting transitions to improved agricultural performance. Of equal, or even more importance, is the political commitment towards reform: elites have the power to either advocate for or stymie agricultural reform efforts. The success or failure of pushing the agricultural transformation agenda depends crucially on elites' vision for agriculture's contribution to development, and their commitment to the vision within a broad country-level development strategy. Governments decide to either invest in knowledge creation (agricultural R&D) and facilitating the adoption of knowledge created elsewhere (assimilating knowledge spillovers), or not to invest, subject to their resource (budget and/or time) constraints. This decision is influenced domestic elites' interests and incentives (i.e. the characteristics of agreements between elites and their proclivities for long-term investments) as well as the nature of their research systems and agricultural research funding sources.

First, there is a lengthy time lag between allocation of resources to provide a good or service, and the time when that good or service is created (Mogues, 2015; Mogues and Do Rosario, 2016). Agricultural research investments easily encapsulate this time lag as their benefits and measurable outcomes are typically realised in the long-run (Benin *et al.,* 2016). This is often an issue with leaders worried about their political survival since uncertainties about leaders' stay in power means they will prefer overt investments that can easily be connected to the policymakers' efforts, thus increasing their political capital. The latter type of investments – such as subsidized agricultural inputs – tend to have shorter time lags between investment and benefits. Furthermore, post-graduate (tertiary) qualifications are salient for the success of agricultural research programs since it allows for the conception, execution, management of research and effective communication with agricultural stakeholders (Beintema and Stads, 2011, 2017; ACET, 2017). However, investing in the capacity of researchers to the doctoral and post-doctoral levels is a long-term commitment which an incumbent government may not be inclined to engage in. Beintema and Stads (2017) show that such underinvestment in human capital is particularly strong in francophone West and Central Africa. Empirically, this is reflected in the difference between short-run (direct) and long-run (total) effects.

Third, agricultural reform involves a redistribution of government resources which creates winners and losers (losers usually prefer the *status quo* as reform may redistribute resources away from them). To illustrate, consider a spectrum of large-holder and smallholder farmers which can be extended into urban and rural groups, respectively. The large-holder farmers are usually the economic elites who can influence agricultural policy (through state-business relations) directly by obtaining political positions and indirectly by lobbying for special treatment. Large-holder farmers are more financially empowered to exert influence for policies benefitting them; and they also have greater educational endowments and access to information which they can use to influence policy in their favour (Binswanger and Deininger, 1997; Mogues, 2015). Two testable hypotheses emanate from the following discussion: (i) differences in agricultural performance for countries within a spectrum of state-business relations (SBRs), SBRs measured following Te Velde (2006); and (ii) differences in agricultural performance between large-holder and smallholder farmers, land-holding proxied by the average amount of capital employed and the level of technology spill-overs.

Fourth, most National Agricultural Research Systems (NARSs) in SSA are relatively small, private sector-exclusive, and highly fragmented in terms of the number of individual agencies. Small NARSs, with considerable capacity constraints, tend to focus on the same range of issues with their larger neighbours and struggle to absorb knowledge from larger neighbouring countries (Beintema and Stads, 2017). Furthermore, institutional fragmentation makes coordination across multiple research agencies (and also between research agencies and other stakeholders) cumbersome and it impinges on the use of scarce resources, significantly eroding research-influenced agricultural performance and future agricultural investments. This is exacerbated by highly unstable donor funding, with dependency on donor funding extremely high among West African countries (Beintema and Stads, 2017). Unstable funding constrains the advancement of technical change, while also impinging on the ability to absorb technology and knowledge spillovers. Additionally, donors fund significant chunks of non-salary related expenditures such that once they wrap up the projects the recipient countries are expected to scale back their activities. Low agricultural performance can influence future policy choices in terms of how much domestic investment can be allocated to agriculture. Empirically, this is can be tested using novel (panel) time-series tests for the direction of causation between R&D and output (Canning and Pedroni, 2008; Eberhardt and Presbitero, 2015).

4. DATA

All data used in this study will be obtained from the Food and Agricultural Organisation's (FAO) FAOSTAT and the IFPRI/CGIAR Agriculture Science and Technology Indicators (ASTI) databases. We collect annual data for 45 SSA countries covering the period 1960 to 2016: the time-series very long to exploit the full potential of the dynamic econometric model we propose in the next section. From the FAOSTAT database we obtain data for net agricultural output instead of agricultural value-added (as the latter might be influenced by R&D at different stages of production), labour (economically active population in agriculture), tractors in use (agricultural capital stock in sensitivity analyses) and arable and permanent crop land. Data on agricultural R&D expenditure, from which we obtain a measure for R&D stock (the main independent variable of interest) is obtained from the ASTI database. The ASTI database has no data R&D data prior to 1980. To obtain data on the years prior to 1980, we obtain data from the International Service for National Agricultural Research (ISNAR) database, a frontrunner to the ASTI database.

Public R&D in agriculture ignores private R&D investments (primarily due to data unavailability) although this is justifiable given the meagre contribution of the private sector to total expenditure in agricultural R&D in developing countries, particularly SSA (Beintema and Stads, 2017). A potential caveat with the data is heterogeneity in R&D, with complications in distinguishing between motives for R&D spending: not all R&D is focused on productivity, with other ventures including diversification of produce (risk reduction), food security and building resistance to pests. Even with a high level of granularity in the data it is impossible to distinguish the different motives of R&D within our sample period. Nonetheless, a fair assumption will that R&D intended productivity is less than R&D in the augmented production function.

5. EMPIRICAL STRATEGY

5.1 Heterogeneous Production Function

We estimate an R&D-augmented, Cobb-Douglas agricultural production function by adopting a multifactor error framework.

(1)

where and represent agricultural net output, capital stock, labour input, arable land, and public agricultural R&D stock respectively. The vector of agricultural factor input coefficients () differs across countries, but is constant over time. Equation (1) also includes country-specific intercepts, (agricultural TFP levels) and a vector of unobserved common factors () with country-specific factor loadings () to account for the evolution of agricultural TFP. These common factors are induced by strong shocks (such as the recent financial crisis, the food price crisis of 2008) and/or weak shocks that represent local spill-over effects such as deliberate international knowledge spill-overs in agriculture or externalities from innovation and production. We allow for the possibility that the growth of agricultural TFP not only differs across countries, but within countries over time (Eberhardt and Vollrath, 2018); with the main concern now being how to separate the country-time specific shock, , from the random error term, . However, we can model such country-specific unobservable evolution by adopting a multi-error factor structure for the error term, . Let

(2)

where the common factors, which are orthogonal to each other, can be a combination of a limited number of 'strong' factors () (following Stock and Watson, 2002) and an infinite number of 'weak' factors () (Chudik, Pesaran and Tosetti, 2011). Strong shocks like the global recession of the 1980s and the recent financial crisis are assumed to affect all countries, albeit to varying degrees. Weak shocks, (for example, the devaluation of the CFA franc in 1994 and the Arab Spring in 2011) on the other hand, affect only a sub-sample of countries so they represent localized (spill-over) effects. In addition, the unobservable factors not only drive inputs, but also output: creating an endogeneity problem (Kapetanios *et al.,* 2011). To elucidate

(3)

(4)

For and

From equation (3) we observe that if and then the error term and the regressors from equation (1) are correlated and the parameter is not identified unless (i) we can account for the unobservable factors in the error term , or (ii) provide a *valid* and *informative* set of instruments for potentially endogenous aid. Nonetheless, Bazzi and Clemens (2013) state that satisfactory instruments are unavailable. Furthermore, standard instrumental variables techniques are inappropriate in this set up due to the heterogeneous equilibrium relationships across countries (Eberhardt and Presbitero, 2015) and the omnipresence of unobserved common factors (Eberhardt and Presbitero, 2015; Temple and Van de Sijpe, 2017). The unobserved common factors can also be nonstationary, with implications for estimation and inference since both observable and unobservable processes in the model are now integrated (Kao, 1999; Eberhardt and Presbitero, 2015). In addition, equation (4) indicates that the factors can be nonstationary (), with implications for estimation and inferences.

Following the political economy arguments in section 3 we argue that a dynamic model is more appropriate in estimating the impact of agricultural inputs on agricultural output and the subsequent analysis of agricultural knowledge spillovers. Given the temporal dimensions of investments in agricultural R&D (including the long-term benefits of investing in agricultural education), within the confines of entrenched bureaucratic inertia, a dynamic model such as an error correction model (ECM) is suitable. The ECM allows for a difference between short-run and long-run returns to local (through the R&D stock) and foreign (through spill-overs) knowledge investments; such that it is not necessary to specify the variable lags through which R&D affects output as is common in the literature (Alston and Pardey, 2001; Griliches, 1994; Fuglie, 2017). This is crucial as it demonstrates persistence in policy and productivity evolution; sitting perfectly with political economy considerations. Thus we employ an unconditional error correction model (ECM) of the form:

(5)

where and (inputs) are the same as described above. The expression in brackets represents the potential cointegrating relationship we seek to identify, represents the long-run equilibrium (cointegrating) relationship between the independent and dependent variables, the represent the short-run adjustment dynamics and indicates the speed of convergence of the economy to its long-run equilibrium. We employ the dynamic Common Correlated Effects Mean Group (CCEMG) estimator which uses (weighted) cross-section averages (CSAs), in addition to lags of CSAs of the dependent and independent variables constructed to filter out the unobserved common factors and omitted elements of the cointegrating relationship as follows:

(6)

where the terms and represent the coefficients on the CSAs and lags of CSAs, respectively.

Kapetanios *et al.,* (2011) and Coakley, Fuertes and Smith (2006) show that the estimator is consistent in the presence of structural breaks, nonstationary common factors and the presence of multiple common factors while Chudik and Pesaran (2015) demonstrate that the estimator gains consistency after lagging the CSAs up to .

Another key novelty of the empirical analysis will be (i) incorporating R&D expenditures at the transnational level by focusing on funding for CGIAR research; and (ii) knowledge transfers from countries now occupying a larger world market share of agricultural R&D investments. The CGIAR funds research in 15 institutes across the globe with the aim of producing high-quality public goods, demonstrating how their results can trigger development outcomes and assessing the impacts of those outcomes (Roy-Macauley, Izac and Rijsberman, 2016). These CGIAR institutes cannot influence agricultural performance except through research (to develop innovations and technologies in developing countries) so their funding cannot be included as an independent variable in agricultural production functions. Instead, funding for CGIAR research can be included in the production function as an 'observed' common factor: which means it enters the production function just as a cross-section average.

The frontier of agricultural R&D investments was historically pushed by advanced economies, with significant benefits (Pardey, Alston and Chan-Kang, 2013; Alston and Pardey, 2014). However, the specificity of knowledge creation in the advanced economies, in addition to the difference in agro-climatic conditions across regions reduced the potential for knowledge spill-overs from the advanced economies to Sub-Saharan Africa. Nevertheless, advanced economies contribute increasing less to global agricultural R&D spending while large developing countries in South America and South Asia have gained more prominence in the global agricultural R&D scene. This geographical shift in R&D performance might ensure increased knowledge spill-overs to SSA agriculture, thus entering the production function as a cross-section average. To capture this increased potential for 'South-South' knowledge spillovers, we obtain data from the main emerging market players in South (East) Asia and Latin America; focusing on those with the largest agricultural R&D spending (Pardey *et al.,* 2013). From the spending data of these countries, an R&D stock variable will be created () and only the cross-section average of this variable will enter the production function (termed R&D share) like the CGIAR variable above).

5.2 Spill-over Analysis

We also conduct spatial spill-over analysis following Eberhardt and Teal (2013). Using the dynamic production function (accounting for unobserved heterogeneity and the presence of global shocks) we can extract TFP from the results by computing the residuals from the dynamic CCE equation (with cross-section averages) as such:

(7)

Note that for and we use the CSAs (to account for global shocks and unobserved heterogeneity) instead of the country-series. We then analyse the TFP using spatial econometric methods that allow for alternative channels of knowledge diffusion (geographical distance, trade volumes) and test the empirical significance.

5.3 Endogeneity and Causality

Endogeneity is prevalent when estimating causal relationships between variable inputs and output. The agricultural production function may be influenced by confounding factors. Unobservable country-specific factors may confound the impact of agricultural inputs on output, creating an endogeneity. Furthermore, dire agricultural performance may influence investment in domestic agricultural R&D. This simultaneity arises when weak (strong) agricultural performance reduces (increases) government's resources to agricultural research and undermines (boosts) elites' incentives to invest in agriculture. Thus, interest is in investigating if governments' investments in agricultural research is in response to the level of agricultural performance, or if the investment is independent of the level of agricultural performance.

In a (panel) time-series context, endogeneity is dealt with by exploiting the temporal dimension of the data. If the inputs and outputs are both nonstationary and co-integrated, then tests for weak exogeneity (i.e. the direction of long-run causality) are applicable (Eberhardt and Presbitero, 2015; Canning and Pedroni, 2008). If the government, in their agricultural research spending decisions respond to changes in revenue performance in receiving countries, this implies R&D is endogenous for the long-run equilibrium; suggesting some kind of behavioural impact of R&D on agricultural output for the donors. If governments do not respond to such changes in their allocation decisions but R&D influences output, R&D is weakly exogenous or *long-run forcing* (Lloyd, McGillivray, Morrissey and Opoku-Afari, 2009).

Provided there exists a cointegrating relationship between the inputs and outputs the Granger Representation Theorem (Engle and Granger, 1987) states that at least one variable must adjust to maintain an equilibrium relation; and the variables can be represented in the form of a dynamic ECM. For a pair of cointegrated variables, we can then test for weak exogeneity in the following models:

(8)

(9)

where is the disequilibrium term constructed using the cointegrating relationship between the variables (represents deterministic terms obtained after estimating equations 8 and 9). The disequilibrium term represents how far the variables are from the equilibrium relationship, with the error correction mechanism then indicating the speed of adjustment following a deviation from the long-run equilibrium (Canning and Pedroni, 2008). Each variable may react to its lagged differences, as well as lagged differences of other variables in the cointegrating relationship. The Granger representation theorem implies that at least one of the adjustment coefficients , , must be non-zero if a cointegrating (equilibrium) relationship between the variables is to hold (Canning and Pedroni, 2008 p. 512). If then has a long-run causal impact on and if then has a long-run causal impact on . If both and are non-zero then and determine each other jointly.

The ECM regressions are estimated at the country-level and empirical estimates of are investigated using standard -ratios, given that all the variables in the ECM regressions (8) and (9) are stationary (Canning and Pedroni, 2008; Eberhardt and Teal, 2013). Following Canning and Pedroni (2008) we present the group-mean statistic (hereafter) which averages the from individual country estimations of equations (8) and (9) and the test for the null of 'no long-run causal impact' is computed from the averaged -ratio from country regressions (). The statistic follows a standard normal distribution under the null hypothesis of 'no causal impact'.

6. EXPLORATORY ANALYSIS

We explore, further, the relationship between agricultural inputs and output in the context of agricultural production functions. We use dummy variables to group countries with similar characteristics. First, heterogeneity by level of agricultural research spending. Second, countries are split by level of development – least developed countries (LDCs) and other low income countries (LICs) – following the World Bank's income classification. Third, heterogeneity geographical location. The World Bank has initiated a regional approach to finance agricultural research in SSA through its regional productivity programs. Three are already operational: WAAPP (for West Africa), EAAPP (for East Africa), and APPSA (for Southern Africa) while discussions are underway to launch another, the CAAPP (for Central Africa). Our disaggregation aligns perfectly with the regional programs as we split the countries into four different groups comprising West Africa, East Africa, Southern Africa and Central Africa. There is empirical evidence that the different regions display heterogeneity in investment and macroeconomic data (Beintema and Stads, 2017; Roseboom and Faherty, 2016). Fourth, (i) differences in agricultural performance for countries within a spectrum of state-business relations (SBRs), SBRs measured following Sen and Te Velde (2009); and (ii) differences in agricultural performance between large-holder and smallholder farms, land-holding proxied by the average amount of capital employed. Fifth, the level of donor dependence for agricultural research funding. While most national governments in Africa fund their NARIs, a considerable amount of them rely on funding from donors, development banks and SROs (Beintema and Stads, 2017); more so than in other developing regions (Stads, 2016; Stads *et al.,* 2016). Large year-on-year fluctuations in agricultural research funding negatively affect poverty reduction and productivity growth, while also impinging on countries' ability to absorb technological and knowledge spillovers. We follow Stads and Beintema (2015) in quantifying volatility in agricultural research funding across countries: the standard deviation of the logarithmic growth of agricultural research spending over the period 2000 – 2014. Sixth, various measures of political commitment. Brinkerhoff (2000, 2010) and Birner, Naseem, Pray and Anderson (2018) developed and updated, respectively, an analytical framework to evaluate political commitment. (i) average budgetary resources spent on agriculture, that is the average government expenditure on agriculture as a percentage of total government expenditure. (ii) the agriculture orientation index (AOI) for government expenditures, calculated as the ratio of agriculture's share of government spending to agriculture's contribution to GDP. (iii) a related measure will be the agricultural intensity ratio (see section 1).

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