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FERTILIZING GROWTH AGRICULTURAL INPUTS AND THEIR EFFECTS IN ECONOMIC DEVELOPMENT

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Abstract

This paper uses cross-country panel data to estimate the agronomic inputs that lead to cereal yield improvements and the consequences for developing countries' processes of structural change. The results suggest a clear role for fertilizer, modern seeds and water in boosting yields. It then estimates empirical links in developing economies between increased agricultural yields and economic growth; in particular, the spillover effect from yield growth to declines of labor share in agriculture and increases of non-agricultural value added per capita. The identification strategy for the effect of fertilizer includes a novel instrumental variable that exploits variation in global fertilizer price, interacted with the inverse distance between each country's agriculturally weighted centroid and the nearest nitrogen fertilizer production facility. Results suggest that a half ton increase in staple yields (equal to the within-country standard deviation) generates a 13 to 20 percent higher GDP per capita, a 3.3 to 3.9 percentage point lower labor share in agriculture five years later, and approximately 20 percent higher non-agricultural value added per worker a decade later. The results suggest a strong role for agricultural productivity as a driver of structural change.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

FERTILIZING GROWTH AGRICULTURAL INPUTS AND THEIR EFFECTS IN ECONOMIC DEVELOPMENT

John W. McArthur and Gordon C. McCord

INTRODUCTION

Agriculture's role in the process of economic growth has framed a central question in development economics for several decades (e.g., Johnston and Mellor 1961; Schultz 1968). While arguments differ regarding the specific mechanisms through which agricultural productivity increases might contribute to structural change in the economy, it has long been theorized that advances in the agricultural sector can promote shifts in labor to higher productivity sectors that offer higher real incomes. Empirical work in more recent years has helped inform the conceptual arguments and underscored the long-term growth and poverty reduction benefits from agriculture, especially for the most extreme forms of poverty (e.g., Gollin et al. 2007; Ravallion and Chen 2007; de Janvry and Sadoulet 2010; Christiaensen et al. 2011). At the same time, recent evidence has also underscored the role of the manufacturing sector in driving structural change and long-term convergence in incomes across countries (McMillan and Rodrik 2011; Rodrik 2013). This and other evidence regarding agriculture's relatively low value added per worker compared to other sectors (e.g., Gollin et al. 2014) has prompted some researchers to narrow the number of developing countries in which agriculture is recommended as a priority sector for investment in light of higher prospective growth returns in non-agricultural sectors (Collier and Dercon 2014). These debates present a first-order concern for understanding why some countries have not experienced long-term economic progress and what to do about it. If agriculture can play a central and somewhat predictable role within the poorest countries, then it is a natural candidate for targeted public investment.

The theoretical and empirical literature regarding structural change is vast, yet identifying the causal role of agricultural productivity is challenging because relevant indicators of structural change trend together in the process of development; impacts on labor force structure are likely to occur after a lag; and statistical identification is not amenable to microstyle experiments. Our contribution in this paper is to focus on the role of agricultural inputs as drivers of higher yields and subsequent economic transformation, using the unique economic geography of fertilizer production in our identification strategy. Large-scale nitrogen fertilizer production occurs in a limited number of countries around the world, owing partly to the fact that the Haber-Bosch process requires natural gas. Transporting this fertilizer to each country's agricultural heartland generates crosssectional variation due to economic geography, akin to Redding and Venables' (2004) model of "supplier access" to intermediate goods, which is estimated to affect income per capita. Our identification strategy exploits this variation in supplier access as well as temporal variation in the global fertilizer price to generate a novel instrument for fertilizer use. To our knowledge this is the first application of economic geography towards causally identifying the relationship between agriculture and structural change.

Our paper builds on the insights of Lagakos and Waugh (2013), which highlight the gaps in understanding of cross-country variations in agricultural productivity. A variety of studies have estimated sources of total factor productivity (TFP) in agriculture in the poorest countries, including in sub-Saharan Africa (e.g., Bates and Block 2013; Block 2014), but agriculture is such an input-intensive sector that TFP assessments only provide one piece of the overarching crop sector puzzle. Our econometric strategy proceeds in two parts. First, we empirically assess the inputs that contributed to increased productivity in staple

agriculture, as proxied by cereal yields per hectare, during the latter decades of the 20th century. Using cross-country panel data, this forms a macro-level physical production function for yield increases. We find evidence for fertilizer, modern variety seeds and water as key inputs to yield growth, controlling for other factors such as human capital and land-labor ratios. Second, we deploy our novel instrument to examine the causal link between changes in cereal yields and aggregate economic outcomes, including gross domestic product (GDP) per capita, labor share in agriculture, and non-agricultural value added per worker. We find evidence that increases in cereal yields have both direct and indirect positive effects on economy-wide outcomes. The results are particularly pertinent when considering economic growth prospects for countries where a majority of the labor force still works in agriculture.

The next section of this paper motivates the empirical work, drawing from the many contributions in the literature towards understanding structural change. Section 3 presents empirical models both for estimating the physical production function for cereal yields and for estimating the effect of yield increases on economic growth, labor share in agriculture, and non-agricultural value added per worker. Section 4 describes the data, Section 5 presents the results, and Section 6 concludes.

THE GREEN REVOLUTION AND STRUCTURAL CHANGE

At the most general level, agricultural output can grow through either increases in area planted (the extensive margin) or increases in output per area planted (the intensive margin). In the agronomic science community, primary emphasis is placed on the latter, with land productivity usually measured in tons of output per hectare. The term "green revolution" is typically used to describe the early stage where yields jump from roughly 1 ton per hectare to 2 or more tons per hectare. The term was coined following the advent of South Asia's rapid increases in cereal yields in the late 1960s and 1970s. Some researchers have argued that these green revolutions underpinned later stages of economic growth, and cite Africa's lack of a green revolution as a key reason why the region has not yet experienced greater long-term economic success (e.g., Diao et al. 2006).

In a stylized story of green revolutions, improvements in agricultural technology are achieved through the introduction of improved land management techniques or improved inputs, including germplasm and fertilizer, all of which boost yields and labor productivity (Murgai 2001; Restuccia et al. 2008). If food is relatively non-tradable beyond local markets, then increased staple food production leads to reduced food prices, increased real wages and hence lower poverty. As staple yields jump and basic food needs are met, crop production begins to diversify, including to nonfood cash crops for export, and so the virtuous cycle of commercial farming begins. With greater savings and access to finance, farms begin to substitute capital for labor, and freed up workers begin to look for wage employment, typically in nearby cities. To the extent that other sectors enjoy higher labor productivity, this is welfare enhancing. It is also possible (and we will test this empirically) that this structural change triggers even further increases in non-agricultural labor productivity. One potential mechanism is that after subsistence is surpassed, savings rates increase, and the subsequent capital accumulation increases worker productivity (Lewis 1954). In parallel, governments are able to collect revenues to finance growthenhancing infrastructure, such as roads and ports, which increases the worker productivity of manufacturing and services. Another mechanism may be that increased incomes improve health outcomes, which increase worker productivity, while also decreasing child mortality, reducing total fertility rates, increasing investment per child, and decreasing demographic pressures. Or, it may simply be that the non-agricultural sector enjoys increasing returns to scale due to fixed costs or learning-by-doing, which would imply that a green revolution and the resulting labor shift would accelerate productivity growth in these nonagricultural sectors. Although our paper will not be able to pinpoint which of these mechanisms is at work, our contribution is to provide a causal framework to evaluate whether higher staple yields trigger labor shifts away from agriculture as well as faster growth in non-agricultural labor productivity.

For the purposes of illustration and to motivate our empirical work more specifically, we describe agriculture-driven structural change with a simple model following the long theoretical tradition starting with works including Rostow (1960); Johnston and Mellor (1961) and formulated mathematically by Laitner (2000); Hansen and Prescott (2002); Gollin et al. (2002, 2007), and others. We start with a country that has no trade in staple food products, and where the entire population (*L)* works in either the agriculture or non-agriculture sector $(L_A \text{ and } L_M \text{ respectively})$. The model is dynamic, but we dispense with the time subscript for simplicity of exposition.

$$
(1) \tL = L_A + L_N
$$

Following a strict version of Engel's law, consumers have a minimum food requirement (*ψ*) and then satiate immediately, such that food demand is exactly:

$$
(2) \tF = \psi L
$$

The agriculture sector produces food according to the following production function:

$$
(3) \tF = A_A L_A
$$

where A_A represents labor productivity, itself a function of TFP and agronomic input intensity. The market equilibrium for food implies that:

$$
(4) \t A_A L_A = \psi L
$$

This determines the proportion of the population in agriculture:

$$
\frac{L_A}{L} = \frac{\psi}{A_A}
$$

Note that (5) represents the third relationship explored empirically in this paper, as we will explicitly test whether increasing agronomic input use, which increases A_{μ} , leads to a decrease in the labor share in agriculture within the subsequent decade.

If the price of food is set as numeraire at 1, then farmer wages must equal A_A . The non-agricultural sector's production is:

$$
(6) \t N = P_N A_N L_N
$$

where P_N is the relative price of non-food items, and A_N is productivity in the non-food sector.

Wage equilibration across sectors means that wages in the non-agriculture sector must be A_a and the relative price of non-food items is (A_A/A_N) . Note that the relative price of non-food items goes up as agricultural productivity improves. To illustrate one possible mechanism linking productivity in the agriculture and non-agriculture sectors, let worker productivity in the non-agriculture sector increase through learning-bydoing with a simple linear function represented by *α*:

(7)
$$
\frac{\partial A_N}{\partial t} = A_N \alpha L_N = A_N \alpha (L - L_A) = A_N \alpha (L - \frac{\psi L}{A_A})
$$

$$
= A_N \alpha L (1 - \frac{\psi}{A_A})
$$

This expression relates the growth in productivity of the non-agricultural sector to agricultural productivity A_A . Increases in agricultural productivity result in faster non-agricultural productivity growth. Given that the data on non-agricultural productivity we use in our empirical exercise is the non-agricultural value added per worker (NAVA), we note that:

$$
(8) \t NAVA = \frac{N}{L_N} = P_N A_N
$$

Therefore NAVA is a function of both labor productivity and relative prices in the economy. The growth rate of NAVA is the following:

$$
(9) \frac{\partial N}{NAVA} = \frac{\partial P_N}{\partial t} + \frac{\partial A_N}{\partial t} + \frac{\partial A_N}{\partial t} = \frac{\partial P_N}{\partial t} + \alpha L(I - \frac{\psi}{A_A})
$$

The key point to note in this final expression is that a rise in A_A increases the growth rate of NAVA. This occurs both through increases in the relative price of non-food items (A_A/A_N) , and through accelerated learning-by-doing in the non-agriculture sector. This second component of growth in NAVA would not be instantaneous; it would have a time delay reflecting

the transition period for the labor force from agriculture to non-agriculture. This paper's empirical contribution to understanding the complexity of structural change is most closely related to equations (5) and (9): We test for a causal relationship between agricultural productivity, the labor share in agriculture and the growth rate of non-agricultural labor productivity. Since we are particularly interested in looking at whether structural change implies a real increase in NAVA (net of changes in relative prices), we use data on value added by sector in constant dollars.

The stylized facts support the theoretical link between staple crop yields link and economic growth. Figure 1 shows indexed regional trends in food production per capita across the developing world from 1961-2001.¹ The graph highlights the major growth in East Asia and the Pacific over the period, with per capita values nearly doubling, and considerable growth in Latin America and South Asia since the mid-1970s. Africa is the one region to have experienced a decline in per capita food production over the period, including a major decrease since the early 1970s and relative stagnation since 1980.

These trends are mirrored in Figure 2, which presents cereal yields per hectare from 1961-2001. Again, all developing regions except Africa experienced major sustained growth rates in land productivity over the period, despite varying starting points, and all except Africa more than doubled yields by 2001. East and Southeast Asia boosted yields from less than 1.5 tons

(t) per hectare (ha) in 1961 to more than 4 t/ha in 2001; Latin America's yields grew from 1.3 t/ha to greater than 3 t/ha; and South Asia's from 1 t/ha to nearly 2.5 t/ha. Africa had the lowest starting point at 0.8 t/ha, and still after 40 years had barely crossed the threshold of 1 t/ha, which was South Asia's starting level in 1961.

A simple Boserup (1965) hypothesis would argue that, relative to other regions, Africa's yield stagnation is a product of its land abundance, and yields will increase as land becomes scarce. There are three main reasons why this hypothesis does not hold, as described in McArthur (2013). First, the history of 20th century yield take-offs in the developing world was predomi-

nantly characterized by proactive public policies supporting a package of yield-boosting inputs, rather than by factor scarcity (Djurfeldt et al., 2005). These policies are thought to explain much of the regional variations in fertilizer use since 1960, as shown in Figure 3. Second, labor/land ratios vary tremendously across Africa but they are just as high or higher in many African countries than they were in pre-green revolution Asian countries. Third, land productivity is driven by the crucial latent variable of soil nutrients, which are being depleted at dramatic rates throughout Africa. High rates of soil nutrient loss strongly suggest that land pressures are not being surmounted by extensification.

Figure 4 compares the growth of cereal yields to growth in GDP per capita over the 1965 to 2001 period, indicating a strong positive correlation between the two variables. A novel relationship is presented in Figures 5 and 6, which compare initial cereal yield levels to subsequent GDP growth across developing countries, excluding fuel exporters and socialist economies.2 Figure 5 covers the full 1965 to 2001 period and Figure 6 covers only the latter portion from 1985 to 2001. The horizontal line marks zero average growth and the vertical line marks 2 t/ha of cereal yields. In addition to the overall positive relationship between initial yield and economic growth, it is noteworthy that no country in the sample experi-

enced negative average growth after reaching a yield threshold of 2 t/ha.3

Figure 7 presents a scatter plot similar to Figure 4 but shows growth in non-agricultural value added per non-agricultural worker on the vertical axis instead of GDP per capita, covering the period 1970-2001. The graph shows a clearly positive relationship between the two variables, even amidst a considerable degree of variation, and suggests that higher rates of progress in agricultural productivity are structurally correlated with higher growth rates in non-agricultural sectors.

Figure 4: Growth in GDP Per Capita Versus Growth in Cereal Yields,

EMPIRICAL MODEL

This paper's empirical strategy proceeds in two parts. The first focuses on establishing a country-level physical production function for cereal yields (in tons per hectare), in order to motivate the emphasis on agronomic inputs in a study of structural change. The second part focuses on identifying the impact of increased yields on economic outcomes and structural change, measured by GDP per capita, labor shares and non-agricultural value added per worker.

Cereal Yield Production Functions

A panel data approach can be applied to identify a cross-country cereal yield production function. A baseline fixed effects approach is as follows:

(10)
$$
y_{ii} = \beta_0 + \beta_1 f_{ii} + \beta_2 p_{ii} + \beta_3 m_{ii} + \beta_4 l_{ii} + \beta_5 r_{ii} + \beta_6 d_{ii}
$$

$$
+ \beta_7 q_{ii} + \eta_i^{\gamma} + \varepsilon_{ii}^{\gamma}
$$

$$
\varepsilon_{ii}^{\gamma} = \mu_i^{\gamma} + \nu_{ii}^{\gamma}
$$

where y_{it} is the average cereal yield per hectare in country *i* in year *t*; *f* is the average fertilizer use per hectare; *p* is precipitation over a calendar year; *m* is the share of seeds that are modern varieties; *l* represents labor inputs; *r* is the share of arable land that is irrigated; *d* is average years of schooling as a measure of human capital; *q* is physical machinery per hectare; $\eta_{_t}$ is a time period dummy to flexibly capture global trends; $\mu_{_{i}}$ is a country fixed effect; and $v_{_{it}}$ is a random error term. The *y* superscript indicates a parameter specific to the yield equation, distinct from the economic growth equations below.

The linear approximation strategy is not without limitations. It was chosen over log-linear and log-log approaches since neither of the latter were found to provide a better fit with the data, and indeed most

countries with significant input use have pursued relatively linear fertilizer-yield trajectories, as shown in Figure 8. This linear relationship is somewhat at odds with the field-level agronomic data that show decreasing returns, but is likely an inherently limited product of the country-level unit of aggregation. This paper aims to present a first approximation of a country-level agricultural production function, which to our knowledge has not been previously done in the economics literature. Future research would be well placed to provide more refined estimates anchored in more specific crop types and input combinations, the latter captured for example through a range of possible interaction terms. With these points in mind, this paper's regression results provide information only on marginal additive effects of various inputs.

Instrumenting for Fertilizer Use

One might hesitate to interpret associations between agronomic inputs and yields in a causal framework; indeed, omitted variables such as farmers' agronomic know-how might be correlated with both yields and inputs and thus bias coefficients in the estimation. In order to assuage these concerns and improve identification in the case of fertilizer use, we construct a novel time-varying instrument. Our approach follows a similar spirit to the instrument presented in Werker et al. (2009). A valid instrument needs to be correlated with countries' fertilizer use and satisfy the exclusion restriction (not affecting yields through any channel besides fertilizer use). We use fluctuations in the global fertilizer price to generate temporal variation exogenous to conditions in any one developing country. In order to generate the cross-sectional variation in the instrument we exploit the fact that the production of nitrogen fertilizer is intensive in

natural gas usage and therefore produced in only a select group of facilities around the world, most of which are in developed countries. We contend that the distance fertilizer travels from these facilities to the agricultural heartlands of each developing country is valid cross-sectional variation that can be interacted with the global fertilizer price to generate a valid instrument for fertilizer use in developing countries. Specifically, we hypothesize that countries closer to fertilizer plants are more sensitive to the commodity's price variation relative to the transport costs that farmers incur.

The instrument satisfies reverse causality concerns (small emerging economies are unlikely to influence global fertilizer price), and the omitted variable bias concern is assuaged since a problematic omitted variable would need be to correlated with the global fertilizer price and have the same distance decay function from agricultural heartlands to global fertilizer production facilities. A specific concern that a reader might have is that fertilizer price fluctuations might be correlated to fossil fuel prices, which might affect economic outcomes through many channels. However, the correlations between crude oil prices

and phosphate, DAP, urea and potash prices are only between 0.11 and 0.38 over the period (using World Bank Commodity Price Data). Moreover, the correlation is only problematic if the specific distance decay function we use from agricultural centroids to nitrogen facilities matches the pattern of cross-country differences in fossil fuel prices, and there is no reason to believe that this will be the case.

We use a Geographic Information System (GIS) to calculate the agriculturally weighted centroid of each country, using data on percentage of each 5 arc-minute grid cell's area planted to staple crops (maize, wheat, rice, sorghum or millet) from Monfreda et al. (2008). Next, we geolocate 63 of the production facilities of the top fertilizer producers in the world (Agrium, CF Industries, EuroChem, IFFCO, Koch, Potash Corporation of Saskatchewan, Sinopec, TogliattiAzot, and Yara International). Although these are present-day facilities (ideally we would have beginning-of-period facilities to assuage endogenous location concerns), we remind the reader that most facilities are located in developed countries not in our sample, and many locate in proximity to natural gas deposits, so the issue is unlikely to have a big effect on our results. We then calculated the minimum costadjusted distance from each country's agriculturally weighted centroid to the nearest fertilizer production site. In order to adjust for relative transport cost between land and water, we use Limão and Venables' (2001) result that shipping a standard 40-foot container from Baltimore to different destinations around

Figure 10: Fertilizer Use in 1985 and Cost-Distance to Fertilizer Production

the world in 1990 costs \$190 for an extra 1,000 km by sea and \$1,380 for an extra 1,000 km by land. This indicates roughly a 1:7 cost ratio, which we use to optimize travel over sea and navigable rivers versus travel over land. The centroids, fertilizer production sites and optimal cost-distance function are mapped in Figure 9. The distance component of the instrumental variable is itself strongly correlated with fertilizer use across countries, as shown in Figure 10, which plots the log of fertilizer use per hectare at the 1985 sample midpoint against the indexed distance measure. The

correlation between the two variables in the graph is -0.63. Towards the top left of the scatter plot, a country like Vietnam (VNM) has an distance index value of 3,954 and a fertilizer value of 84 kg/ha, while Rwanda (RWA), towards the bottom right, has a distance value of 13,083 and a fertilizer value of 1.7 kg/ha.

The instrument allows us to employ the following twostaged least squared specification (using the vector X to summarize other covariates discussed above):

(11)
$$
f_{ii} = \alpha_0 + \alpha_1 IV_{ii} + \delta' X_{ii} + \lambda_i^{\gamma} + \xi_i^{\gamma} + \pi_i^{\gamma}
$$

$$
y_{ii} = \beta_0 + \beta_1 f_{ii} + \theta' X_{ii} + \eta_i^{\gamma} + \mu_i^{\gamma} + \nu_i^{\gamma}
$$

use (f) from the first regression, and better identified $\beta_{_I}$ is now estimated using the fitted value of fertilizer in a causal sense compared to equation (10) above.

Economic Growth Equations

It is trivial for higher agricultural productivity to be linked to higher economic growth in the same period, since agricultural output is included directly in national accounts. For example, if one holds fixed all prices and production levels in other sectors, a green revolution-style five-year doubling of output in a low-income country with 30 percent of GDP in food production would translate mechanically to a 5.4 percent annual real GDP growth rate.⁴ For a country with only 15 percent of GDP in food production, the same yield doubling would translate to 2.8 percent annual growth. Of course a major supply expansion would be expected to decrease the price of food, and the nominal measured growth rate would be much smaller—so 5 or 6 percent could be considered an upper bound on the direct contribution of increasing yields to economic growth. The arguments of Sachs et al. (2004) and McArthur and Sachs (2013) posit that increasing agricultural yields in low-income settings creates scope for increased savings, investment and TFP as food becomes cheaper and minimum subsistence requirements are met.

This hypothesis can be examined, first, through a cross-country growth equation for GDP per capita and, second, through a cross-country growth equation for non-agricultural value added per non-agricultural worker. The former captures both the mechanical element of agricultural-to-GDP growth plus the indirect aspects of increased investment and higher TFP. The

latter captures increased investment and TFP more directly. In addition, we test the extent to which increases in agricultural productivity can trigger labor movement out of agriculture by estimating the effect of yield increases on the national labor share in agriculture.

The baseline fixed effect specification is constructed as follows:

(12) $g_{ii} = \rho g_{i, t-5} + \lambda_0 + \lambda_1 y_{i, \text{ lag } t} + \lambda_2 k_{i, t-5} + \lambda_3 r_{i, t-5}$ *+ ω* '*MAC*_{*i, t−5*} + $η_t^g$ + $ε_{it}^g$ $\varepsilon_{it}^{\ \ g} = \mu_i^{\ g} + \nu_{it}^{\ g}$

In equation (12), g_i is average real GDP per capita in the first set of specifications and non-agricultural value added per worker in the second; *yi, lag t* is cereal yield per hectare in previous years (the lag structure will be discussed below); *ki, t−5* is lagged aggregate physical capital per worker; *ri, t−5* is the total fertility rate as a proxy for demographic pressures and capital widening; *MAC_{ir−5}* represents a vector of standard macroeconomic variables used in the growth literature, averaged from years *t-5* to *t*; and the *g* superscript indicates a parameter specific to the growth equation. The main coefficient of interest is λ_{I} . Since the regression controls for country-specific effects, past period growth and initial income per capita within the period, a significant and positive value for $\lambda_{_I}$ would lend support to the importance of agricultural land productivity in boosting economic growth. As with the yield regression, we will use the instrument described above to improve identification of the causal impact of changes in cereal yield on GDP per capita and on non-agricultural value added per capita. We have established in the discussion around equation (11) that we have a valid instrument for fertilizer use—by extension the instrument is a valid instrument for yields as well.

Fixed effects estimators suffer from dynamic panel bias particularly pertaining to bias on the lagged dependent variable (Wooldridge 2002; Bond 2002). A complementary estimation strategy for the economic growth equations is therefore pursued through the use of Arellano and Bond's (1991) generalized method of moments (GMM) "difference" estimator, which purges the fixed effects. The GMM strategy takes a standard first difference transformation of equation (12), using lags as instruments:

(13)
$$
\Delta g_{ii} = \rho \Delta g_{i,t-5} + \lambda_1 \Delta y_{i,\log t} + \lambda_2 \Delta k_{i,t-5} + \lambda_3 \Delta r_{i,t-5} + \omega^2 \Delta M A C_{i,t-5} + \eta_i^s + \Delta y_i^s
$$

Note that the first difference is taken across five-year intervals in this construction, which holds as long as there is no autocorrelation within countries beyond

the first lag. Arellano-Bond AR(2) tests are therefore applied in all GMM specifications, as are Sargan tests. For completeness, we also test the Blundell and Bond (1998) "system GMM" estimator and find that it does not pass the Sargan specification. Moreover, it is more appropriate for random walk-type estimations and in this context may result in bias inherent in its application to cross-country regressions (Roodman 2009).

One other specification we employ is to study the effect of yield increases on labor share in agriculture. This follows the same logic as equation (12); however since the share of employment is a censored variable, we do not include a lag of the dependent variable as we do in the GDP or NAVA regressions. All the other independent variables, including the instrumented version of cereal yields, remain the same.

DATA

The estimation strategy draws upon a cross-country panel data set constructed for developing countries over the period 1960-2002. As described below, most of the values are constructed in five-year intervals over the period from 1965-2000, based on data availability. Descriptive statistics are presented in Table 1 and variables are described in more detail in the appendix. Much of the data comes from the World Bank's World Development Indicators (WDI), including cereal yield per hectare, fertilizer use per hectare, 5 share of agricultural land under irrigation and tractors per hectare. A new fertilizer measurement protocol was implemented after 2002, so that is the most recent year that can be included in a relevant time series, as reported in WDI 2006. The key cereal yield variable is defined as follows in the WDI: "kilograms per hectare of harvested land, and includes wheat, rice, maize, barley, oats, rye millet, sorghum, buckwheat and mixed grains. Production data on cereal yields relate to crops harvested for dry grain only. Cereal crops harvested for hay or harvested green for food, feed or silage and those used for grazing are excluded," (World Bank 2006). The data count double cropping as part of an annual yield measure rather than counting only the yield per harvest.

Human capital is estimated by Barro and Lee's (2012) measure of total years of schooling. Values of real GDP per capita in constant 2005 U.S. dollar terms are taken from Version 7.1 of the Penn World Tables (Heston et al. 2012). Labor-to-land ratios are estimated using data on agricultural labor force size from the FAOSTAT online database and merged with World Bank (2013) data on cereal area planted. The numerator and denominator are an imperfect match in this instance, particularly when non-food cash crops represent a large share of agriculture, but the variable is nonetheless available as a proxy for population pressures on land.

The cereal yield production functions include a historical measure of the introduction of green revolution technology from Evenson and Gollin (2003) and previously presented in Conley, McCord and Sachs (2007). The indicator describes modern variety (MV) crops planted as a percentage of all crops planted, weighted by area planted to those crops. As discussed above, it is well-established that the development of modern seed varieties suitable to Africa's unique crop mix and agroecological zones lagged behind the development of high yield varieties relevant to other regions by roughly two decades (Evenson and Gollin 2003), so this variable captures the highly relevant proliferation of MVs across countries. Data for the variable cover 85 countries from 1960 to 2000, taken in five-year averages.

Monthly gridded precipitation data are taken from the University of Delaware (Matsuura and Willmott 2012). Values are summed for each year and averaged over the country, and then converted to natural log form. This is an imperfect signal, since it is rain variability during the location-specific crop growing season that matters most, rather than precipitation across an entire year. Constructing such a location-specific precipitation variable focused on local growing seasons is beyond the scope of this paper.

For the growth equations, WDI data are used to measure average aggregate investment as a share of GDP, and government consumption as a share of GDP. Non-agricultural value added is from the WDI and is measured in constant 2005 U.S. dollars. We blend it with data from the FAOSTAT online data on non-agricultural labor force to create a measure of non-agricultural value added per worker in constant dollars.

Note: Values given for sample of five-year intervals from 1965-2000. Standard deviations indicated in parentheses.

The sample includes only developing countries with available data, since the main drivers of growth in high-income economies are assumed to be innovation and increasing returns to scale, not agriculture. We use the middle of sample time period (1985) for country classification. The World Bank income ceiling for developing country status in 2012 was \$12,615, and given that the WDI's GNI per capita data is in 2000 U.S. dollars, we deflate the ceiling to \$9,699, and then keep only countries that had below that income in 1985 (keeping all post-1985 observations regardless of their income trajectory). The sample excludes small economies—defined as those with populations of less than 1 million in 1985—and developing economies in Europe, since their agricultural trajectories have been part of the process of temperate latitude technology transfer and were also affected by Soviet-era socialism. We exclude IMF-designated fuel exporters (Algeria, Angola, Congo, Iran, Libya, Nigeria, Oman, Trinidad and Tobago, and Venezuela) and major diamond producers (Botswana, Guinea and Namibia). This leaves 75 countries with data on cereal yields and fertilizer, though we limit the sample in the reduced form cereal yield specifications to 69 countries that have data on all variables. In the estimations for economic growth, labor share and non-agricultural value added we opt for keeping a consistent number of countries that have data for all variables, thus forming an unbalanced panel of 58 countries. The entire sample spans 1965-2000; however, the economic growth, labor share and NAVA estimations include lagged variables which limit the sample period from 1975-2000. The 75-country sample and 58-country subsample are listed in Table 2.

** These 17 countries are not in the 58-country sample for GDP, Labor Share, and NAVA regressions.*

RESULTS

Cereal Yield Production Functions

Table 3 presents results for fixed-effect regressions that consider cereal yield per hectare as the dependent variable, covering five-year intervals over the period 1965-2000. For each representative observation, yields, precipitation, fertilizer, irrigation, tractors and the labor-land ratio are averaged across three years (*t-1*, *t* and *t+1*) in order to focus on structural shifts as opposed to year to year volatility. Column I presents a simple pooled OLS with year dummies. The coefficient on fertilizer is 7.85 and strongly significant, implying that a 1 kg/ha increase in fertilizer is associated with higher yields of nearly 8 kg/ha. In the absence of country fixed effects, we expect this coefficient to be biased upward, since country-specific characteristics such as capital stock and other agronomic inputs are likely to be positively correlated with both fertilizer use and yields.

Column II introduces country fixed effects, and the fertilizer coefficient drops considerably to 4.54. Column III adds (the natural log of) precipitation. The fertilizer coefficient is nearly unchanged at 4.49, and precipitation is significant with a coefficient of 0.39. This coefficient is large, since it implies that for a country like Rwanda with average yields of 1.1 tons per hectare, precipitation of 1082 mm and a standard deviation of 39 mm, a one standard deviation increase in precipitation would be associated to yield increases of 1.4 tons. As mentioned in the data description section above, this is likely an underestimate of precipitation's effects, limited by the measurement error inherent in the annual construction of the precipitation variable. In an unreported regression, we run year-to-year yields on fertilizer and precipitation and find a consistent coefficient of 0.3 on the precipitation variable.

Column IV introduces another critical element of the green revolution package, modern variety seed use, which is significant at the 1 percent level and substantive in magnitude. This is a pure productivity effect. A marginal 1 percentage point increase in modern seed use is linked to an extra 10 kg per hectare yield, independent of fertilizer. The inclusion of the seed variable results in a slight decline in the fertilizer coefficient to 3.4, substantiating the point that fertilizer-seed packages have complementary effects in boosting yields.

To round out the production function with a measure of labor, Column V adds the agricultural labor-land ratio. Both the agricultural labor and land variables are imperfectly aligned to the dependent variable since they include land and labor allocated to noncereal crops, including root staples and cash crops. The variable is nonetheless insignificant and has no perceptible effect on the other variables. It is worth noting that this table reports results for a consistent set of observations in all estimations, where the limiting variable in terms of data availability is the tractors variable. When Column V is allowed to include all countries with available data, the larger sample results in a significant association between labor-land ratio and yields, where the coefficient is -0.42 and significant at the 10 percent level. We opted for being conservative and presenting a consistent sample across specifications to ease interpretability of coefficients.

Column VI introduces irrigation, the other main source of water for cereal crops. Column VII introduces human capital measured in average total years of schooling. Column VIII introduces the tractors variable to test for the effects of high-cost physical machinery. While these three variables have the expected positive sign, they are not statistically significant in the presence of country and time fixed effects.

*Notes: Standard errors in parentheses, clustered by country. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. (1) All variables except schooling and modern seeds are three-year means measured at five-year intervals, e.g., "1970" measures means over 1969, 1970 and 1971. The subsequent value averages over 1974, 1975 and 1976. (2) Constant terms, year dummies and country dummies not reported to save space.*

Instrumenting for Fertilizer Use

The results in Table 3 show that agronomic inputs of fertilizer, rainfall and modern seeds are strongly associated with yields, even after controlling for labor-land ratio, irrigation coverage, human capital and physical capital in agriculture. In order to gain a better causal estimate, however, we employ an instrumental variable framework to assuage biases due to omitted variables or endogeneity. Table 4 shows the results of estimates on yield using the IV framework. The sample increases to up to 75 countries when not limited to the availability of irrigation, tractor and schooling variables as in the regressions of Table 3, though only 70 countries have data on precipitation, modern seeds and our instrument.

Column I repeats the country fixed effects regression from Column IV in Table 3, using the larger sample. Column II then instruments fertilizer use with the fertilizer price-distance instrument in the first stage, resulting in a strongly significant coefficient and a first stage F-statistic of 14.83, above the usual threshold

*Notes: Standard errors in parentheses, clustered by country in both first and second stages. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. All variables except schooling and modern seeds are three-year means measured at* five-year intervals, e.g., "1970" measures means over 1969, 1970 and 1971. Constant terms, country dummies, time dummies *not reported.*

value of 10 for strong instruments. The coefficient of -2.26 indicates that increases in global fertilizer price cause lower fertilizer use, in a pattern consistent with countries nearer fertilizer production sites experiencing larger proportional shocks. To get a sense of magnitudes, the mean of the instrument is 0.53, and the standard deviation is 0.06. One can consider a price shock of 10 percent and compare a country roughly one standard deviation below the instrument mean (Brazil, at a cost-distance of 10520) with one roughly a standard deviation above (South Korea, at a costdistance of 1545). The -2.26 coefficient and 10 percent price increase imply that Brazil would experience a 23

kg/ha decrease in fertilizer use, 6 while Korea would experience a 29 kg/ha decrease. Given that Brazil's fertilizer use in the sample averages 62 kg and ranges from 10 kg to 111 kg, while Korea averages 387 kg and ranges from 174 kg to 530 kg, the magnitude of the price effect seems plausible. In Column III, the secondstage regression results in a coefficient for fertilizer of 9.39, suggesting that a 1 kg/ha increase in fertilizer causes a 9 kg/ha increase in yield. Note that this is more than twice the magnitude of the fixed effects regressions of Table 3, suggesting that measurement error might have been attenuating the estimates in the reduced form.

Columns IV and V repeat the instrumented first and second stages with controls for precipitation and modern seeds. The sample shrinks from 75 to 70 countries, and both the coefficient on the instrument in the first stage and on fertilizer in the second stage reduce in magnitude. Fertilizer has a consistent and slightly reduced coefficient of 8.78, still highly significant beyond the 1 percent level. Precipitation also has a positive coefficient in the second stage, though it is significant only to the 10 percent level. Modern seeds are fertilizer responsive, and the variable is highly correlated to fertilizer use (as evidenced in the first stage), which is likely why the variable is insignificant in the second stage. Regardless, these specifications provide some confidence that the instrument for fertilizer use is valid and strong, and that fertilizer is an important macro determinant of cereal yields even after controlling for other agronomic inputs of production. This provides evidence for the causal statement that countries facing greater barriers to fertilizer access will have a more difficult time boosting cereal yields.

Economic Growth Equations

Growth in GDP Per Capita

As mentioned earlier, short-term increases in yield should appear directly in the GDP accounts if land under cultivation is relatively fixed in the short term, and agricultural output constitutes a sizable share of GDP. Table 5 presents fixed effects OLS estimators for equation (12), covering five-year growth periods from 1965 to 2000. Consistent with the growth literature (Caselli et al. 1996), the coefficient on lagged GDP per capita is close to 0.7, suggesting a convergence coefficient of approximately -0.06 per annum. Barro and Sala-i-Martin (2004) summarize the debate on the true underlying meaning of this coefficient, which is not our main variable of interest and therefore not discussed in detail here.

Our main variable of interest is a lagged value of cereal yield, which has a very large and significant coefficient of 0.08 in the first column of Table 5. The within-country standard deviation of yields is 0.5 tons, so we proceed to interpret the instrumented yield coefficient in terms of a marginal increase of 0.5 tons. The coefficient implies that a half ton per hectare increase in yields is linked to a 4 percent increase in GDP per capita. The implied long-run coefficient on yields is 0.29.7 The remaining variables are standard in cross-country growth equations. Investment over the previous five years is positively correlated with growth, while inflation, government consumption as a percentage of GDP, and total fertility rates are all negatively correlated with growth. Note that Column I does not limit the sample, while Column II limits the sample to the 58 countries that have data on non-agricultural value added per worker. For consistency we retain the 58-country sample moving forward. Note that keeping this consistent sample throughout the analysis implies limiting the time period to starting in 1970, since the NAVA estimations involve longer lags in the independent variables. In unreported results, allowing a larger sample in Table 5 leads to consistent coefficients on the yield variable, however these are not always significant at 5 percent levels.

We employ the instrumental variables framework to look at how shocks to yield through the fertilizer channel might show up in GDP, both contemporaneously and with a lag. Column III instruments for yields using the same instrument described above, and then GDP per capita is regressed on the fitted value for yields in Column IV. The first stage indicates a good instrument, with a strongly significant coefficient of -31.84 and an F-statistic of 8.76. In the second stage (Column IV) the coefficient on yield is significant at the 5 percent level and equal to 0.35, four times larger than the OLS regression of Column I. The magnitude implies that a 0.5 ton increase in yield leads to 19 percent higher GDP per capita.8 This increase in the

*Notes: Standard errors in parentheses, clustered by country in both first and second stages. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. All variables are three-year means measured at five-year intervals, e.g., "1970" measures means over 1969, 1970 and 1971. The subsequent value averages over 1974, 1975 and 1976. Constant terms and country dummies not reported to save space.*

coefficient from fixed effects to the 2SLS specification might be due to attenuation bias due to measurement error in the reduced form, or else to omitted variables that are correlated to high yields and low GDP per capita growth. For example, overly pro-rural government policy could boost yields but hurt the economy as a whole.

In Columns V-VI of Table 5, we control for the other elements of standard growth regressions (investment, inflation, government consumption and the total fertility rate). The first stage coefficient on the instrument continues to be very significant and has an F-statistic of 12.34, while the second-stage coefficient on yield is now 0.25. This implies that a half ton increase in ce-

real yields leads to a 13 percent higher GDP per capita, even when controlling for five-year lag of GDP. While this may seem like a surprisingly large result, one should keep in mind that in the 1960s agriculture constituted over 30 percent of GDP in many countries. In fact, in an unreported result, when we limit the sample in Regressions V-VI to the 30 countries above the median in terms of percentage of GDP in agriculture in 1960 (median 27 percent), the coefficient on yield in the second stage is 0.41. This is consistent with the theory that yields increases should boost GDP more in agriculture-dependent countries.

of Columns III-IV in order to explore the lag structure of this causally identified effect of yield shocks on GDP, and found an effect in the contemporaneous year as well as one and two years later. The lagged coefficients with 95 percent confidence intervals are graphed in Figure 11, and suggest a statistical relationship between a three-year moving average of GDP per capita centered at time *t* with a yields *t*, *t-1* and *t-2*. We opt to present our estimates using yield centered at *t-1*.

Labor Share in Agriculture

Note that Table 5 uses a one-year lagged value of yield, keeping in mind that both the GDP and yield variables are both three-year moving averages. We tested from zero- to five-year lags in the specification

An important way to evaluate whether increases in agricultural productivity are producing economy-wide effects is to test whether they lead to a shift in the labor force away from agriculture as predicted in the

structural change models described earlier. In Table 6 we employ similar specifications as in Table 5, this time using the labor share in agriculture as the dependent variable. The mean share in the sample is 52 percent. Columns I-III use OLS with country and year fixed effects, while IV-VII instrument for yields. We first examined the lag structure, as shown in Figure 12. Note that higher (instrumented) yields are correlated with lower labor shares in agriculture contemporaneously and during the next five years before the effect dissipates. We therefore use a five-year lag on yields in the Table 6 estimations in order to look for evidence of agriculture-led structural change.

Column I in Table 6 indicates the strong association between labor share in agriculture and lagged yield, even controlling for country and year fixed effects. The coefficient of -3.32 indicates that a 0.5 ton increase in yields is associated with a 1.65 percentage point lower share of the labor force in agriculture five

*Notes: Standard errors in parentheses, clustered by country in both firts and second stages. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. All variables are three-year means measured at five-year intervals, e.g., "1970" measures means over 1969, 1970 and 1971. The subsequent value averages over 1974, 1975 and 1976. Constant terms, year dummies, and country dummies not reported to save space.*

years later. In following the GDP and NAVA specifications, Column II adds investment and inflation as controls. Neither is significant, and the coefficient on lagged yield does not change. Column III adds government consumption and the fertility rate. Government consumption is positively correlated with labor share in agriculture, which might be an indication of excessive government intervention in the economy delaying structural change. Higher fertility is also associated with a higher labor share in agriculture in subsequent years; in general, higher fertility increases demand for food and thus for agricultural labor, while in the reverse causal direction agrarian societies tend to have higher fertility rates due to low returns to education and demand for labor on the farm.

Columns IV and V instrument for yields, again using the fertilizer price-distance variable. The instrument continues to be strongly correlated with the endogenous yield variable, and in the second stage the coefficient on yield increases to -7.73. This would suggest that a 0.5 ton increase in yields causes the labor share in agriculture to decrease by nearly 3.9 percentage points in the next five years. The result is consistent when controlling for investment, fertility rate, inflation and government consumption in VI-VII.

Growth in Non-Agricultural Value Added

Another trenchant way to explore the broader economic growth effects of yield increases in developing countries is to test the links to economic activity entirely outside of agriculture. Table 7 does this by replicating the same basic growth specification as the GDP and labor share tables but instead tests nonagricultural value added per non-agricultural worker (NAVA) as the dependent variable. Given that we expect a delay between having a boost in yields and spillovers to the non-agriculture sector, and that there is no theoretical prior on what the lag structure is, we first plot out the lag structure of (instrumented) cereal yields on non-agricultural value added per worker.

Figure 13 shows the results of regressions of nonagricultural value added per worker tested against 15 respective lags (from *t* to *t-15*) of instrumented cereal yields. Two things are evident when comparing this graph to the one relating cereal yields and GDP per capita. First, the statistical signal is weaker (note that we are using 90 percent confidence intervals in this graph, so the relevant results should be treated with appropriate caution). Second, the statistically significant impact of yields on the non-agricultural sector productivity occurs with a longer lag (about eight to 10 years). This longer delay might indicate that the relationship between yields and non-agricultural value added per worker might occur through slower-moving channels such as movement of labor from agriculture to non-agriculture as opposed to faster channels, such as relative price changes or increases in food immediately generating disposable income for investment in other sectors.

Given the lag structure evidence, Table 7 shows results for non-agricultural value added regressions using a nine-year lag on cereal yield (later we repeat this specification with a 10-year lag). Column 1 presents the fixed-effects regression with no controls. The nine-year lagged value on cereal yields is positively associated with increases in non-agricultural worker productivity, with a coefficient of 0.05, although only significant at the 10 percent level. This implies 0.5 ton per hectare yield increases are associated with a 2.5 percent higher non-agriculture productivity level around nine years later. Column II adds investment and inflation; the lag NAVA coefficient drops from 0.88 to 0.73, similar to the coefficient in the GDP regression, while the yield coefficient is 0.06 and falls just short of the 5 percent significance level. Investment rates are positively correlated with non-agricultural productivity growth, while inflation is negatively correlated. Column III adds government consumption and the total fertility rate. The coefficient on yield remains consistent at 0.03, although it is not significant in this specification. Government consumption is negatively correlated to non-agricultural productivity growth, while the total fertility rate is insignificant.

The rest of Table 7 employs the same identification strategy as in the GDP per capita regressions. We instrument for yields using the global price of fertilizer interacted with the inverse distance from agriculturally weighted centroid to nearest nitrogen production facility. The two-staged least squares results in Columns IV-V employ no macroeconomic controls; the instrument is highly significant in the first stage, and the F-statistic of 10.89 indicates that the instrument is strong. In the second stage, the coefficient on the instrumented lagged cereal yield is significant and rises in magnitude to 0.37. This suggests that an exogenous half ton increase in cereal yields leads to a 20 percent higher non-agricultural productivity nine years later, which translates to a 2 percent higher growth rate of annual productivity per worker.

Regressions VI and VII add investment and inflation over the previous five years as controls. The results are consistent: the instrument is significant and has an F-statistic of 11.32; and in the second stage the coefficient on the instrumented cereal yields is significant at 5 percent levels. Its magnitude of 0.35 suggests that a 0.5 ton increase in yields increases

Notes: Standard errors in parentheses, clustered by country in both first and second stages. *, **, and *** represent 19%, 8%, and 1% significance levels, respectively. All variables are three-year
means measured at five-*Notes: Standard errors in parentheses, clustered by country in both first and second stages. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. All variables are three-year means measured at five-year intervals, e.g., "1970" measures means over 1969, 1970 and 1971. The subsequent value averages over 1974, 1975 and 1976. Constant terms, year dummies, and country dummies not reported to save space.*

non-agricultural productivity by 19 percent in around nine years. Investment and inflation are significant and have the expected signs. Finally, Regressions VIII and IX complete the set of standard macroeconomic growth variables by adding government consumption and the lagged total fertility rate. The first stage results are largely unchanged, with the instrument still highly significant and with an F-statistic of 7.01. The second stage coefficient on cereal yields drops slightly to 0.26, suggesting that 0.5 ton boost in cereal yields leads to a 1.4 percent higher annual growth rate in non-agricultural productivity. Column IX does not quite achieve statistical significance on yields. In Columns X-XI we drop the government consumption variable and find that the second stage yield coefficient returns to 0.36 and achieves 10 percent

significance. Overall, Table 7 provides cautious but consistent results suggesting that exogenous half ton increases in yields lead to approximately 20 percent higher non-agricultural value added per worker a decade later. This lends empirical support for the potential role of agriculture in promoting structural change.

Robustness Checks

In order to test the robustness of results, particularly those linking yield increases to non-agricultural labor productivity, we conduct the following tests and report them here: adding region- or country-specific linear trends to the regressions; testing 10-year lags on yield instead of nine-year lags; and running the regressions using GMM instrumentation.

Table 8 adds region-specific linear trends to the IV regressions of Table 7 using World Bank defined regions of East Asia and the Pacific, Latin America and the Caribbean, Middle East and North Africa, South Asia, and sub-Saharan Africa. Column I shows that the instrument is still strongly correlated to yields

after controlling for country and year fixed effects and now regional linear trends. The F-statistic, however, drops to 4.56, suggesting that the instrument is less strong after partialing out regional linear trends. Indeed, the second stage shows that the instrumented lagged value for cereal yields is no longer

*Notes: Standard errors in parentheses, clustered by country in both first and second stages. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. All variables are three-year means measured at five-year intervals, e.g., "1970" measures means over 1969, 1970 and 1971. The subsequent value averages over 1974, 1975 and 1976. Constant terms, year dummies, and country dummies not reported to save space.*

significant, although it maintains a similar magnitude (0.55 compared to 0.37), which suggests consistency given that the regional linear trends are reducing the variation available for regression. Regressions II and III add investment and inflation, and then IV and V add government consumption and the total fertility rate. The results are qualitatively similar: The instrument is still highly correlated to cereal yields, though the F-statistics on the instrument are hovering at only around 4.5. Second-stage estimates of the coefficient on cereal yields exhibit consistency in sign and magnitude with the results on Table 7; The coefficient is now 0.40 and consistent with the 0.36 in Table 7 Column XI, though with less precision here. We interpret these results as supporting our overall findings, even if the variation absorbed by the regional trends leads to imprecise estimates. For completeness, we tested country-specific linear trends, but doing so absorbs too much variation (each country has only eight time periods) and neither first nor second stage regressions are able to identify relationships between the key variables.

We further test robustness by changing the specifications in Table 7 from nine-year lags on yield to 10-year lags. As explained above, we chose nine-year lags because the statistical signal was strongest at that lag; nevertheless, we employ 10-year lags to assuage concerns of a spurious nine-year correlation. Columns I-III in Table 9 replicate the fixed effects OLS regressions in I-III in Table 7; the results are essentially unchanged, and the 10-year lag on cereal yield displays even stronger significance than the nine-year lag in Table 7. Columns IV-V introduce the instrumented version of yield with a 10-year lag; the first stage continues to show a strong correlation between the instrument and yield (with an F-test of 15.48). The second stage coefficient on yields is 0.33, which is consistent with the coefficients in Table 7, however with a 10-year lag the coefficient in Column V is not significant. Columns VI-VII introduce investment and

inflation; the coefficients are essentially the same as in Table 7 and the instrumented yield now achieves 10 percent significance. Columns VIII-IX introduce government consumption and total fertility; again the results match those of Table 7, though the coefficient on yield remains consistent but is no longer significant at the 10 percent level. Finally, just as in Table 7, Columns X-XI drop the government consumption variable and report a coefficient of 0.35, now significant at the 10 percent level and consistent in magnitude with Table 7. Overall, the results using a 10-year lag on yield remain highly consistent with the results in Table 7, though the statistical threshold for significance is not passed in two of the second stage specifications.

Finally, Table 10 presents a NAVA growth framework using GMM instrumentation and finds similar agricultural productivity effects on value added in nonagriculture sectors. Column I runs difference GMM and finds that a 10-year lag on yield is associated with subsequent increases in non-agricultural value added per worker, significant just short of 5 percent levels. The coefficient of 0.1 suggests that a 0.5 ton increase in yields leads to a 5 percent higher non-agricultural labor productivity 10 years later, which translates to a 0.5 percentage point higher growth rate. Note that this magnitude lies between the fixed effects coefficients of 0.05-0.06 and the IV coefficients of 0.27- 0.37 in Table 6, adding support to the overall results. The specification in Column I passes the Sargan test for overidentification of instruments with a p-value of 0.43. Column II employs the Blundell-Bond "system" GMM estimator, though this does not pass a Sargan test under any relevant specification, so we prefer to interpret only difference GMM specifications. Column III adds the fertilizer price instrument to the exogenous variables in the specification, and finds similar results to Column I. Again, the estimation passes a Sargan test, and the AR(1) test is satisfied with a pvalue of 0.09.

Notes: Standard errors in parentheses, clustered by country in both first and second stages. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. All variables are three-year
means measured at five-y *means measured at five-year intervals, e.g., "1970" measures means over 1969, 1970 and 1971. The subsequent value averages over 1974, 1975 and 1976. Constant terms, year dummies, and* Notes: Standard errors in parentheses, clustered by country in both first and second stages. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. All variables are three-year *country dummies not reported to save space.*

*Notes: Robust standard errors in parentheses. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. All variables are three-year means measured at five-year intervals, e.g., "1970" measures means over 1969, 1970 and 1971. The subsequent value averages over 1974, 1975 and 1976. Constant terms, year dummies, and country dummies not reported to save space. Regression (III) includes the instrument as an exogenous variable in the specification.*

DISCUSSION AND CONCLUSIONS

Our analysis documents the strong positive links between agronomic inputs—fertilizer, water and modern seeds—and cereal yields per hectare, even after a variety of controls are introduced. We employ a combination of fixed effect, instrumental variable and Arellano-Bond GMM estimators to posit a causal economy-wide link between, first, input use and yields, and, second, yields and various measures of economic growth and structural change. We construct a novel instrument exploiting the economic geography of fertilizer production, which together with global fertilizer price fluctuations allow us to study economic growth and structural change in a statistically causal framework. The cross-country substantiation of both agricultural yield production functions and their links to various dimensions of economic growth and structural change are novel empirically. Taking the coefficients from Table 4, a representative country with yields of 1 t/ha that introduces an input package to jump from, say, 15 kg/ha to 65 kg/ha (0.05 tons) of fertilizer use would be expected to see an average yield jump of 147-470 kg/ha; while increasing from 10 to 50 percent use of modern seed would be expected to increase yields by 480 kg/ha.

On the economic growth side, the instrumental variable results suggest that boosting yields from 1.5 t/ha to 2.0 t/ha is linked to a range of 13 to 19 percent increase in income per capita, a 3.3 to 3.9 percentage point lower share of labor in agriculture five years later, and approximately 20 percent higher non-agricultural labor productivity after roughly one decade. The estimated effects are identified based on exogenous variation in fertilizer prices, and are robust to the inclusion of controls for investment and standard macroeconomic policy indicator variables. The results suggest that land productivity promotes growth both

by supporting changing labor shares and by increasing total factor productivity. Regressions focused on marginal effects of individual variables are, of course, not intended to evaluate nonlinear outcomes guided by Leontief-style agricultural production functions and discontinuous policy functions, so the regression results might underestimate the potential effects of yields. The results might also be constrained by issues of heterogeneity in cross-country production functions (Eberhardt and Teal 2012).

The evidence in this paper points to strong potential yield and growth effects resulting from policy efforts to support adoption of a green revolution-type package of inputs in economies with low agricultural productivity and a large share of the labor force still in agriculture. The results suggest a particularly strong role for fertilizer, which is highly consistent with field station agronomic evidence. Fertilizer's high private return on experimental plots and in the field suggests some sort of market failure that policy can address; scholars debate whether the failure is due to credit constraints or non-rational behavior on the part of farmers (Duflo et al. 2008, 2011). Regardless, the evidence presented in this paper suggests social returns from fertilizer use that exceed the immediate private returns, furthering the case for policy efforts.

It is worth briefly describing the main concerns about increasing fertilizer use. One set is environmental. These are legitimate and require foresight in policy planning, but as Palm et al. (2004) have indicated, countries should not simply avoid fertilizers for environmental reasons, since soil degradation induced by fertilizer omission poses much a greater risk to agricultural production. A second class of concerns focuses on inequality and the potential scale bias of modern inputs. Hayami and Ruttan (1985) review the evidence on the alleged scale bias in the Asian green revolution and find that the evidence does not support this allegation. A third set of concerns focuses on both the challenges of governments implementing input support programs and also the challenges of exiting from them in due course. Though there is evidence that subsidy programs can be successful (Dorward and Chirwa 2011), there is also evidence that they can be subject to elite capture, and there is concern that their fiscal drag effects can far outlive their usefulness (e.g., Pan and Christiaensen 2012; Pauw and Thurlow 2014).

While our results provide some evidence for a causal link from agricultural productivity increases to structural change and higher non-agricultural labor productivity, we can only speculate on the mechanisms through which these effects play out. Nevertheless, our novel identification of a causal link from yield increases to labor composition shift and non-agricultural productivity increases rules out models where structural change is driven solely by "pull" forces from growing non-agricultural sectors. To the extent that our results show that yield increases contribute to increases in non-agricultural labor productivity growth, this suggests that structural change involves more than just the satiation of food needs and the movement of labor into other sectors. This labor share shift somehow accelerates labor productivity growth. One possible mechanism might be increasing returns in the non-agricultural sector, perhaps through learning-by-doing as in the example modeled in Section 2 of this paper. Perhaps increased food production lowers average prices and frees up consumers' resources for other consumption and for productive public and private investments, raising labor productivity elsewhere. Or perhaps higher availability of staple foods promotes improved health and labor productivity across sectors. Identifying more precise causal pathways between staple yields and structural change forms an important topic for future work.

APPENDIX

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ENDNOTES

- 1. The variable for fertilizer use was redefined in 2002 (FAO's survey methodology changed and some countries shifted from a crop year to a calendar year basis). We therefore limit our analysis from 1961-2001 in order to maintain consistency. All graphs and regressions exclude more recent years accordingly.
- 2. The sample is more fully described in Section 4.
- 3. The threshold is only marginally affected by the inclusion of fuel exporting and socialist economies, with only Cuba, North Korea and Venezuela falling just under the vertical line in the lowerright quadrant of Figure 6. Romania and Saudi Arabia fall in a similar location on the graph if the sample is further expanded to include Europe and higher income countries.
- 4. That is, doubling output from 30 units of 100 total to 60 units of 130 total $(= 100 + 30)$ gives an

aggregate annual growth rate of 5.4 percent over five years.

- 5. Note that there is a mismatch between the cereal yield and fertilizer variables: Fertilizer use is reported as the average use over all arable land, which introduces measurement error into our specification if fertilizer use in cereals and noncereals is not consistent. To assuage this concern, we controlled the estimations below for the percentage of total agriculture planted to cash crops. The cash crop variable was not significant in any of the specifications and had no effect on the point estimates discussed below.
- 6. Calculated as follows (units in tons): -2.26* ln(110/100) / ln(10520).
- 7. $0.29 = 0.08 / (1 0.72)$
- 8. $0.19 = exp(0.5 * 0.35) 1$

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