Trade and Agricultural Technology Adoption: Evidence from Africa

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Abstract

The incentives for and effects of widespread technology adoption depend on the trade costs separating producers from input and output markets. I incorporate the decision to adopt imported fertilizer into a model of agricultural trade between 230 regional markets in all 42 countries of continental sub-Saharan Africa. I use the estimated model to evaluate the most widely used agricultural technology adoption promotion policy: fertilizer subsidies. Greater adoption lowers local food prices substantially under existing high trade costs, but fertilizer subsidies only increase farmer incomes when trade costs are low.

1 Introduction

The widespread adoption of improved agricultural technology — the Green Revolution — has led to dramatic increases in per capita income in parts of the developing world since the 1960s (Gollin, Hansen, and Wingender 2018). While adoption of high-yielding varieties and inputs like fertilizer has been widespread in Asia and Latin America, adoption rates in sub-Saharan Africa have generally been much lower, and yields of staple cereal grains have not experienced increases comparable to other regions (figure 1) (World Bank 2007). The last 15 years have seen a renewed interest on the part of African governments, institutional donors, foundations, and researchers in understanding and overcoming the barriers to a Green Revolution in sub-Saharan Africa (Pingali 2012).

A farmer's decision of whether and how much of an input like improved seed or fertilizer to use depends crucially on the price of that input and the expected output price. Both input and output prices are pushed up or down by trade costs — the total costs involved in getting

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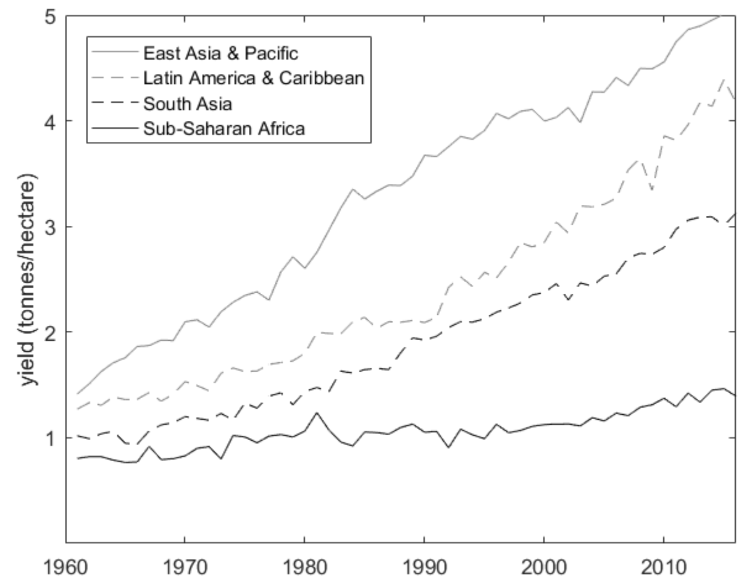

Figure 1: Cereal grain yield, 1961–2016

a product from a producer or trader in one location to a consumer or trader in another. Recent research has shown that trade costs in sub-Saharan Africa are much larger than elsewhere in the world (Atkin and Donaldson 2015; Teravaninthorn and Raballand 2009). Porteous (2017) estimates median trade costs for staple grains within African countries over 5 times higher than benchmark international freight rates. High trade costs — due to factors like poor infrastructure, policy barriers, and information costs — make output prices lower in net exporting regions and output prices higher in net importing regions. They also increase the price of inputs — many of which, like fertilizer, are almost entirely imported from outside of Africa.

How do trade costs affect the incentives for technology adoption? How do trade costs alter the potential effects of widespread technology adoption (a Green Revolution)? And how do trade costs affect the impact and cost of policies that governments use to promote adoption? This paper addresses these questions using an estimated dynamic model of storage and trade of the six major staple cereal grains between 230 regional hub markets in all 42 countries of continental sub-Saharan Africa developed by Porteous (2017). The model includes monthly storage in each of the 230 markets, monthly trade between them along 413 direct overland transportation links, as well as trade with the world market through 30 ports. The model parameters were estimated using monthly data from May 2003 to April 2013, and simulations of the model are run using production and world price realizations from that period.

In the baseline version of the Porteous model, production is treated as an exogenous endowment that is then allocated across time and space by representative competitive traders facing demand by representative consumers in each market and exogenous world prices. An important feature of demand for staple grains is that it is highly inelastic (Roberts and Schlenker 2013; Fally and Sayre 2018). I illustrate the potential implications this has for technology adoption using a simple simulation in which I double production in all 230 African markets. Under high trade costs, much of the extra production is stuck in remote markets, where inelastic local demand leads to a collapse in both food prices and agricultural revenues. When trade costs are lowered to an international benchmark, the average price decline is much smaller and revenues increase substantially as more of the extra production can be exported to other markets.

I proceed to fully endogenize production and the technology adoption choice by adding representative producers to the model. I focus on the choice to adopt urea, the most widely-used fertilizer in sub-Saharan Africa. I estimate a yield response function to urea by pooling observations from a review of the agronomic and economic literature. Like other fertilizers, urea is almost entirely imported into sub-Saharan Africa from the world market. I obtain local monthly urea prices for each of the 230 African markets in the Porteous model using world prices and per-kilogram trade costs along the least-cost route, which I then validate using an external dataset on urea prices from 69 markets in 16 countries. Implied baseline fertilizer use using my estimated local production functions and local fertilizer prices is significantly higher than that reported in the World Bank's nationally representative LSMS-ISA household surveys (Sheahan and Barrett 2017). This likely reflects extra uncaptured costs of fertilizer use including market-to-farm trade costs (Aggarwal et al. 2018), credit and risk (Dercon and Christiaensen 2011), complementary inputs (Beaman et al. 2013), and adulteration (Bold et al. 2017). I find that I have to double local prices to generate adoption rates consistent with household surveys, and I use these doubled prices in my subsequent simulations.

Fertilizer subsidies have emerged as the most prominent policy used by African governments to promote agricultural technology adoption. The African Union's 2006 Abuja Declaration on Fertilizer for an African Green Revolution urged member states to improve access to fertilizer through the use of targeted subsidies. By 2011, 10 African countries were spending \$1 billion annually on fertilizer subsidy programs, more than a quarter of their annual budgets for agriculture (Jayne and Rashid 2013). I use my estimated model with endogenous technology adoption to compare the effects of (1) lowering trade costs to an international benchmark without a fertilizer subsidy, (2) implementing a 50% fertilizer subsidy under existing high trade costs, and (3) implementing the same 50% subsidy once trade costs are low. Trade cost reduction by itself decreases average local fertilizer prices by 52.7% (more than the 50% subsidy), but it also lowers average local grain prices substantially since most markets are net grain importers, so the overall increase in fertilizer use is modest (16%). However, there is a substantial shift of production towards the most productive regions. In both of the subsidy simulations, in contrast, fertilizer use nearly doubles without a comparable reallocation of production. Fertilizer subsidies are cheaper and lead to larger increases in both use and production when trade costs are low than when they are high. Average local grain prices fall by 4.5 times more due to the subsidy under high trade costs, which confine extra production to local markets with inelastic demand. While this benefits local consumers, fertilizer subsidies only increase agricultural revenues when trade costs are low. With both low trade costs and fertilizer subsidies, sub-Saharan Africa as a whole switches from a net grain importer to a net grain exporter, with an overall welfare gain equivalent to 3.87% of GDP. Fertilizer subsidies are however very expensive — once their cost is taken into account, subsidies lead to a net welfare loss regardless of the level of trade costs.

This paper contributes to four strands of the existing literature. First, it provides a continent-wide perspective on the incentives for and general equilibrium effects of widespread agricultural technology adoption that complements the extensive existing literature on the microeconomics of agricultural technology adoption (reviewed by Foster and Rosenzweig 2010). Particularly related papers in this literature include Suri (2011), who uses household survey data from Kenya to highlight how the heterogeneous costs of accessing hybrid maize technology due to trade costs contribute to low and uneven adoption, and Aggarwal et al. (2018), who document the substantial additional market-to-farm trade costs for fertilizer and grain in Tanzania and their consequences for adoption. Second, it contributes to the recent literature on trade and the spatial distribution of economic activity along intra-national transportation networks and the effects of trade cost reductions in these networks (Donaldson 2018; Allen and Arkolakis 2014; Faber 2014; Donaldson and Hornbeck 2016). Sotelo (2016) develops a static spatial model of agricultural production and trade between the 194 provinces of Peru and the world market that includes an imported intermediate input (a bundle of fertilizers) for which the local price falls and adoption increases as trade costs fall. I find that this increase in adoption due to lower input prices can be offset by lower output prices in net importing regions, and I contrast the effects of technology adoption promotion policies under high and low trade costs. Third, it provides evidence from counterfactual policy simulations that complements the empirical literature evaluating the effects of fertilizer subsidies in different African countries (e.g. Ricker-Gilbert, Jayne, and Chirwa 2011 on Malawi; Mason, Jayne, and Mofya-Mukuka 2013 on Zambia; Wossen et al. 2017 on Nigeria). Ricker-Gilbert et al. (2013) find that the targeted subsidy programs in Zambia and Malawi have thus far only lowered local maize prices by 1–3%. My simulations of continent-wide, universal fertilizer subsidies are not directly comparable, but they do suggest that price decreases could be more pronounced under existing high trade costs if subsidy programs continue to expand in size and scope and spread to additional countries. Fourth, it speaks to a long-standing literature on the distribution of the gains from agricultural technology adoption dating back at least to the "technological treadmill" of Cochrane (1958). Studies of the impact of the Green Revolution generally conclude that most of the gains from widespread technology adoption accrued to consumers, with gains for farmers from increased output offset by lower prices (Scobie and Posada 1978; Evenson and Gollin 2003). My simulations show that farmers in local markets closed off by high trade costs do lose from lower prices induced by widespread technology adoption, but these results are reversed when lower trade costs provide greater access to the more elastic world market, where African farmers stand to gain by adopting technology already adopted elsewhere.

2 Model

2.1 Intuition

To fix ideas, consider first the case of a single market or country producing a single grain with initial production H_0. Let local demand for this grain have a constant price elasticity $\epsilon < 0$. Figure 2 compares the effective demand functions facing local farmers if this is a closed economy, a small open economy with a world price P_W, or a small open economy with trade costs τ for imports and exports. The value of H_0 shown in figure 2 is such that the market is a net importer when open to trade, which is the case for 160 of the 230 markets (70%) in the baseline Porteous (2017) model.

Now suppose that farmers increase production by adopting a new technology (for simplicity, assume that there are no costs to acquiring or using the new technology). Then the following proposition, which is proved in the appendix, holds:

Proposition 1. *An increase in production increases farmer revenues if $\epsilon < -1$, has no effect on farmer revenues if $\epsilon = -1$, and decreases farmer revenues if $-1 < \epsilon < 0$.*

This simple result is similar to findings by Alston (2018), who uses a two-factor model and finds that $-1 < \epsilon < 0$ is a sufficient condition for expenditure on the farmer-supplied input to decrease under either factor-neutral or farmer-supplied-input-saving technological change. Demand for staple grains is generally considered to be very inelastic: Roberts and Schlenker (2013) estimate an elasticity of -0.066. For a closed economy, then, this means that farmers

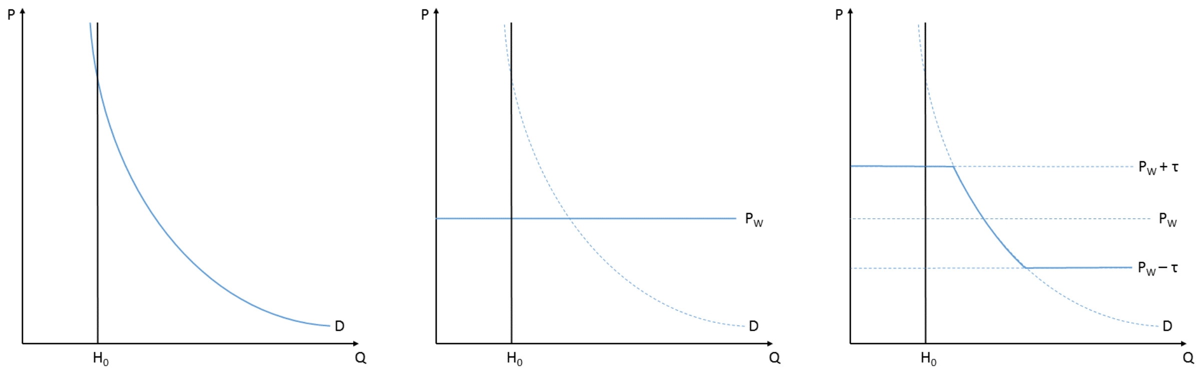

Figure 2: Effective demand functions (solid) for a closed economy (left), a small open economy (center), and a small open economy with trade costs (right)

lose revenue with increased production as the price decrease more than offsets the increase in output. For a small open economy ($\epsilon = -\infty$), farmers gain revenue one-for-one with increased production. For a small open economy with trade costs, the effects on farmer revenues depend on the market's trading position. For an importing market, initial increases in production lead to increases in revenue via import substitution that are equivalent to the small open economy case. Once imports fall to 0, the price begins falling and farmers lose revenue as in the closed economy case. If the price reaches the export parity price, further increases in production are exported, with farmers once again experiencing one-for-one revenue gains.

In subsequent sections, I model technology adoption across a spatial network of 230 markets with trade costs both along the overland transportation routes connecting them as well as between 30 ports and the world market. Despite this added complexity, the basic intuition developed in this section will continue to be useful in interpreting my simulation results. The higher trade costs are, the closer markets are to the closed economy case, with widespread technology adoption likely leading to lower local prices and decreased farmer income.

2.2 The Baseline Porteous Model

My starting point is the dynamic monthly model of grain storage and trade of Porteous (2017). The model includes the six major staple cereal grains – maize, sorghum, millet, rice, wheat, and teff – which together constitute 97.3% of cereal grain production and 46.3% of caloric intake in sub-Saharan Africa. In this section, I provide a concise summary of the relevant features of the model. Additional detail can be found in Porteous (2017).

In the model, representative competitive traders in each market m decide in each month t how much of available supply of each grain i to sell for local consumption (Q_{imt}), to keep in storage ($S_{imt} \geq 0$), and to trade with other markets indexed n ($T_{imnt} > 0$ for exports and < 0 for imports). Available supply comes from grain harvests (H_{imt}), which occur once or twice a year depending on the local agricultural calendar, and stocks from the prior month ($S_{im,t-1}$). This leads to the following market clearing condition:

$$Q_{imt} = S_{im,t-1} + H_{imt} - S_{imt} - \sum_{n \neq m} T_{imnt} \tag{1}$$

Trade is subject to additive trade costs between markets (τ_{mn}), and storage is subject to per-unit storage costs (k_m) and a monthly interest rate (r_m). Competition ensures that the following spatial and temporal no-arbitrage conditions hold:

$$P_{imt} + \tau_{mn} - P_{int} \geq 0, \ = 0 \text{ if } T_{imnt} > 0 \quad \text{and} \quad P_{int} + \tau_{mn} - P_{imt} \geq 0, \ = 0 \text{ if } T_{imnt} < 0 \tag{2}$$

$$P_{imt} + k_m - \frac{\mathbb{E}_t[P_{im,t+1}]}{1 + r_m} \geq 0, \ = 0 \text{ if } S_{imt} > 0 \tag{3}$$

Representative consumers in each market m have utility quasilinear in a grain composite (Q_{mt}) and an outside good (X_{mt}), specified in such a way that demand for the grain composite has a constant price elasticity of demand ϵ. Estimates by Porteous (2017) of both ϵ and the elasticity of substitution between grains using instrumental variables are weak and imprecise, so values of -0.066 (estimated by Roberts and Schlenker (2013)) and 1 (Cobb-Douglas) are used, both of which are within the 95% confidence intervals of the estimates. Quasilinear utility means that the income elasticity of grain demand is 0, i.e. consumers choose grain consumption based on grain prices and spend all remaining income on the outside numeraire good, which is not subject to trade costs and has price normalized to 1. Welfare depends on the price of the grain composite (P_{mt}) and income (Y_{mt}). Income comes from sales of grains net of storage and trade costs and sales of the production of the numeraire good (Π_{mt}), which is recovered using GDP data. Trade and storage costs are considered to be services that are paid for with the numeraire good.

The Porteous model includes 230 markets in all 42 countries of continental sub-Saharan Africa (figure 3). These are large, competitive regional hub markets where traders collect grain from surrounding farms and peripheral markets for trade with other hub markets (Fafchamps, Gabre-Madhin, and Minten 2005; Myers 2013). Due to data limitations and tractability concerns, the model does not capture trade or trade costs between these hub markets and the different peripheral locations within their catchment areas[1]. Trade in the

[1] Aggarwal et al. (2018) and Bergquist (2017) provide evidence of the sizeable trade costs and different market structure characterizing this hub-periphery trade.

model occurs along the 413 direct overland transportation links connecting the hub markets. Trade with the world market (Bangkok and the US Gulf) occurs through 30 ports and is subject to the same spatial no-arbitrage conditions from equation 2. The model treats the world market price as exogenous, allowing for unlimited imports and exports at the world price (plus or minus link-specific port-to-world-market trade costs). Johannesburg, South Africa, is treated as exogenous in the same way due to its close integration with the world market and South Africa's very large grain production and consumption relative to its neighbors. The model is thus a hybrid between a small open economy model with exogenous world prices and a closed economy model with local prices determined endogenously, as in Sotelo (2016). The small open economy assumption is justified by the fact that the 41 countries excluding South Africa together constitute just 5% of global cereal grain production and 6% of global cereal grain consumption. Removing this assumption would lead to slightly lower world prices and hence some lower local prices in those counterfactual simulations with significant increases in African production.

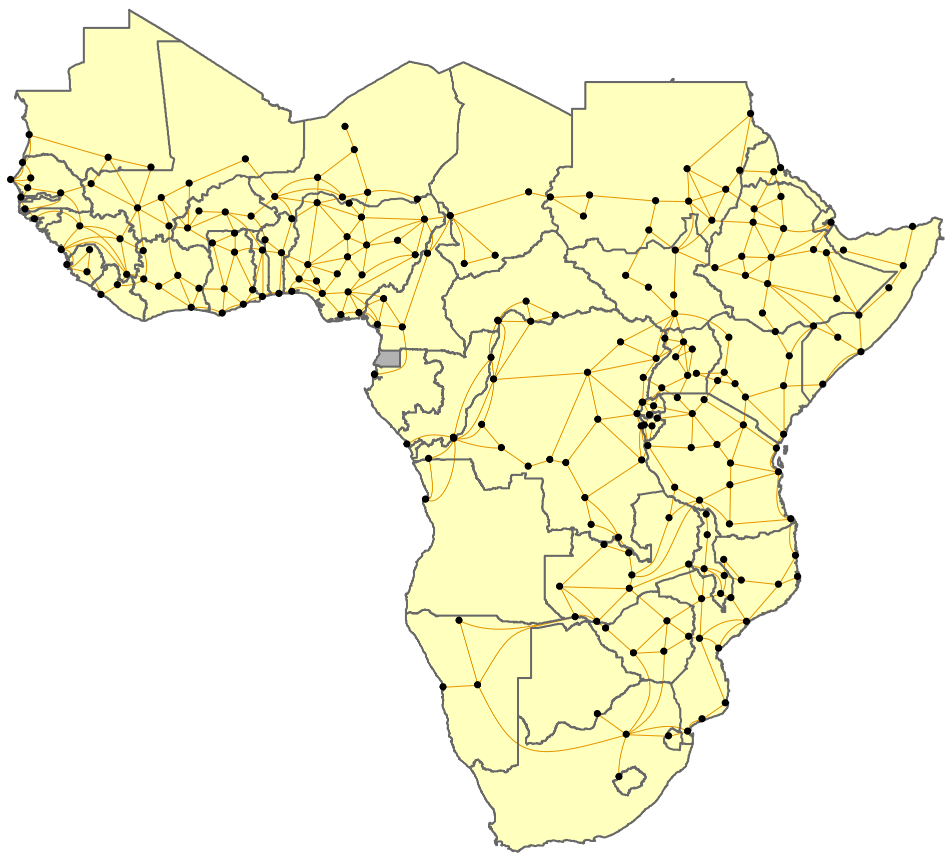

Figure 3: Map of 230 Markets and 413 Direct Links of Porteous (2017) Model

Porteous (2017) estimates local demand parameters, trade costs, and storage costs. In the baseline model, both world prices and harvests (H_{imt}) are treated as exogenous. For tractability, Porteous assumes that traders believe that future harvests will equal a linear prediction using the past 10 harvests and that future world prices will equal current world prices. This assumption leads to some underestimates of equilibrium storage, but Porteous (2017) shows that these are small enough that they do not have a statistically significant effect on the model's simulation results. Simulations are run month-by-month starting in May 2003, with traders updating their expectations and plans after new harvest and world price realizations.

2.3 Technology Adoption in the Baseline Model

As a simple first pass to simulating widespread technology adoption, I use the baseline Porteous (2017) model to estimate the effects of doubling agricultural production in sub-Saharan Africa. In other words, what would happen if African governments provided enough free fertilizer to farmers to bring yields up to the levels of South Asia shown in figure 1? Practically speaking, I implement this counterfactual by doubling the harvest (H_{imt}) in all markets and all time periods while keeping all other exogenous variables and parameters the same[2].

Table 1 compares results for key aggregate indicators from different counterfactual scenarios. In the first column are results reported in Porteous (2017) from lowering trade costs to match benchmark levels from elsewhere in the world without changing production. The direction of these aggregate results is explained by the fact that most markets are net grain importers with artificially high prices that fall when trade costs are lowered. In the second and third columns are results from doubling production under existing high trade costs and under counterfactual low trade costs. The fourth column is a combined simulation with both trade cost reduction and doubled production (fourth column = first column + third column). All percentage changes in table 1 are given in terms of the baseline equilibrium with existing high trade costs and observed production. Reported welfare effects are equivalent variation as a percentage of baseline GDP.

Under high trade costs, increased production is largely stuck in local markets with inelastic demand, leading to a collapse of prices and agricultural revenues. Only 39 markets (17.0%) experience an increase in agricultural revenues, 37 of which are net importers for which increased production primarily serves to substitute for imports[3]. In contrast, under

[2]I have also run simulations increasing production by less than 100% (10%, 20%,... 90%) and find that the aggregate effects always have the same sign, with lower percentages just leading to lower magnitudes.

[3]The other 2 markets are net exporters that have relatively cheap access to the world market even under

Table 1: Aggregate Results with Doubled Production

Baseline Counterfactual	High τ Low τ	High τ Double H	Low τ Double H	High τ Both
Average Grain Price Index	–46.4%	–58.6%	–14.2%	–60.2%
Net Agricultural Revenues	–42.1%	–71.4%	+12.4%	–29.7%
Annual Net Grain Exports	–3.2 mill t	+25.4 mill t	+69.7 mill t	+66.5 mill t
Welfare	+2.17%	+2.56%	+2.19%	+4.36%

low trade costs, agricultural revenues increase on aggregate and for 184 individual markets (80.3%), as much more of the increased production can be exported to deficit areas and the world market. The net welfare effect of doubling production is similar in magnitude to the net welfare effect of lowering trade costs[4]. Although lower trade costs and increased production are partial substitutes as both lead to lower prices in most markets, the combined welfare effect of both (4.36%) represents 92% of the sum of the effects of each intervention on its own (4.73%).

2.4 Endogenizing Technology Adoption

In the baseline model of Porteous (2017), the production of both grains and the outside good are treated as exogenous endowments. In an extension, Porteous (2017) introduces a model with endogenous production with supply elasticity η that nests his baseline model when $\eta = 0$. For tractability, the extension assumes that harvest decisions are made in the harvest month and that traders continue to base their expectations of future harvests on past harvests. In this section, I develop this extension further to endogenize both production and technology adoption by introducing a representative competitive farmer for each grain in each market.

As in the Porteous (2017) extension, I suppose that there is a composite factor of production called labor (L). In each time period, each market's labor endowment ($\bar{L}_{mt}$) is used for production of the numeraire good and each grain i:

$$L_{Xmt} + \sum_i L_{imt} = \bar{L}_{mt} \tag{4}$$

Production of the numeraire good is linear in labor ($\Pi_{mt} = B_X L_{Xmt}$).

For simplicity, I assume that each representative farmer uses a fixed amount of land, D_{im}, that is constant over the study period[5]. On this fixed amount of land, there are diminishing

high trade costs.

[4]If policies that reduce agricultural trade costs also reduces trade costs for other sectors, the effect of lowering trade costs would likely be much larger than that of doubling agricultural production.

[5]I use GIS data at the 5 arc-minute level of land cultivated from each crop from 2005 from the GAEZ

returns to labor. The farmer can also choose to increase production by applying fertilizer. Let Z_{imt} be the amount of fertilizer applied per hectare of land and $F(Z_{imt})$ be a yield multiplier with $F(0) = 1$, $F'(Z) > 0$, and $F''(Z) < 0$. I assume that fertilizer use does not require additional labor, which is consistent with some empirical studies from Africa (Duflo, Kremer, and Robinson 2008) but not others (Beaman et al. 2013), a potential issue I account for later when adjusting fertilizer prices. The farmer's production function is:

$$H_{imt} = F(Z_{imt})B_{imt}L_{imt}^{\beta} \tag{5}$$

where $0 \leq \beta < 1$. B_{imt} is a crop-market-time specific productivity shock. Land D_{im} does not appear explicitly in the production function as it is subsumed within B_{imt}.

The representative farmer chooses labor and fertilizer to maximize profits:

$$\max_{L_{imt}, Z_{imt}} F(Z_{imt})B_{imt}L_{imt}^{\beta}P_{imt} - WL_{imt} - P_{Zmt}Z_{imt}D_{im} \tag{6}$$

where W is the wage rate and P_{Zmt} is the local price of fertilizer in market m in month t[6].

Labor is perfectly mobile between sectors. Given that the freely-traded numeraire good is produced everywhere with the same technology, W is equal across locations. Choose units of labor such that $W = 1$. Then taking the first order condition with respect to labor gives:

$$W = 1 = \beta F(Z_{imt})B_{imt}L_{imt}^{\beta-1}P_{imt} \tag{7}$$

Combining equations 5 and 7 leads to the following supply function:

$$H_{imt} = \beta^{\frac{\beta}{1-\beta}}[F(Z_{imt})]^{\frac{1}{1-\beta}}B_{imt}^{\frac{1}{1-\beta}}P_{imt}^{\frac{\beta}{1-\beta}} \tag{8}$$

For $Z_{imt} = 0$, this supply function has a constant price elasticity $\eta = \frac{\beta}{1-\beta}$. This parameter reflects the degree to which the composite factor of production (labor) reallocates between grains and the outside good sector in response to relative price changes. In the baseline model of Porteous (2017), labor does not reallocate ($\eta = 0$), reflective of the short term.

Taking the first order condition for equation 6 with respect to fertilizer gives:

$$P_{Zmt}D_{im} = F'(Z_{imt})B_{imt}L_{imt}^{\beta}P_{imt} \tag{9}$$

Combining with equation 7 gives:

$$P_{Zmt}D_{im} = F'(Z_{imt})\beta^{\frac{\beta}{1-\beta}}[F(Z_{imt})]^{\frac{\beta}{1-\beta}}B_{imt}^{\frac{1}{1-\beta}}P_{imt}^{\frac{1}{1-\beta}} \tag{10}$$

project of FAO and IIASA and the HarvestChoice project of IFPRI and the University of Minnesota together with the market catchment areas of Porteous (2017) to obtain D_{im} for each crop-market pair in hectares.

[6] Since fertilizer is purchased and applied before the actual harvest, I use an average of P_{Zmt} over the six months prior to and including the harvest month instead of just the P_{Zmt} of the harvest month when implementing the model.

I can solve equations 8 and 10 for the implied productivity shocks B_{imt} and the implied local fertilizer use rates Z_{imt} — both of which are unobserved — if the other variables are known. I use data for H_{imt} and D_{im} and baseline equilibrium grain prices for P_{imt}. I calibrate η to 0.6, the estimate of the annual price elasticity of supply for individual staple crops reported by Magrini, Balié, and Morales-Opazo (2018) using data from 10 of my 42 countries of interest from 2005–2013 . In the next section, I describe how I obtain data on local fertilizer prices P_{Zmt} and how I estimate the yield response function $F(Z)$.

Once I solve equations 8 and 10 for B_{imt} and Z_{imt}, I can use these values with equations 4 and 5 to obtain implied L_{imt} and $\bar{L}_{mt}$ given that $L_{Xmt} = \frac{\Pi_{mt}}{B_X} = \frac{\Pi_{mt}}{W} = \Pi_{mt}$. I can then endogenize both H_{imt} and Z_{imt} in my counterfactuals by adding equations 8 and 10 to the core equilibrium conditions in the baseline model (equations 1, 2, 3, and the consumer demand functions). Once counterfactual S_{imt}, T_{imnt}, Q_{imt}, P_{imt}, H_{imt}, and Z_{imt} have been found, counterfactual production of the numeraire good can be obtained by subtracting the implied counterfactual L_{imt} from equation 5 from $\bar{L}_{mt}$.

3 Data and Estimation

Inorganic fertilizer provides crops with additional nutrients (primarily nitrogen, phosphorus, and potassium) to enhance plant growth. In 2010, the 41 countries in the Porteous (2017) model excluding South Africa imported 93% of their fertilizer (FAO-STAT). For the 37 countries with national trade statistics available from CEPII's BACI project (Gaulier and Zignago 2010), fertilizer imports averaged \$1.77 billion per year from 2003–2012.

For simplicity, I focus exclusively on the most common type of fertilizer used in sub-Saharan Africa: urea. Urea has the highest nitrogen content by weight (46%) of inorganic fertilizers (an advantage in contexts with high trade costs). It does not contain phosphorus, potassium, or other nutrients. Urea accounts for 26% of African fertilizer imports by value in the CEPII BACI trade data. Ukraine and Russia are the largest sources, together accounting for 40% of these imports.

Given the very high share of imports in domestic consumption, I treat local urea prices P_{Zmt} as exogenous and equal to the world price of urea plus trade costs from the world market to the local market. To obtain these prices, I start with the Black Sea price, which is widely used as the reference world price for urea. For each market m, I then add trade costs along the least-cost path from the world market, under the assumption that per-kilogram trade costs for urea and grain are the same[7]. For trade costs between the world market and

[7]In sub-Saharan Africa, urea, like grain, is generally transported and sold in bags of 50 kilograms. Handling and transport technology is essentially the same as that for grain.

African ports, I use the estimated grain trade costs between each port and Bangkok (for those ports trading rice), the US Gulf (for those ports trading other grains), or an average of the two (for those ports trading both). The Black Sea price of urea averaged \$0.301/kg over the ten-year study period, while trade costs for the least cost path from the world market all the way to local African markets averaged \$0.526/kg, meaning that the average local price of urea I estimate (\$0.827/kg) is 2.75 times larger than the world price.

Before proceeding, I compare these calculated local fertilizer prices to available local fertilizer price data from the AfricaFertilizer.org project. Local monthly urea price observations are available for 2010–2017 for 69 of the markets from the Porteous (2017) model in 16 countries[8]. For these 69 markets, the average price difference with the Black Sea price during this period was \$0.415, while the average trade cost along the least-cost path estimated above is \$0.540. Of the 69 markets, trade costs are larger than observed average price differences for 65% and smaller for 35%. These comparisons suggests that my estimated local fertilizer prices are of similar magnitude — but perhaps slightly higher — than actual prices[9].

The final element I need before being able to back out the implied productivity shocks and local fertilizer use rates is the yield response function, $F(Z)$. Due to data limitations, I assume that this function is constant across locations and grains. To estimate it, I pool data from 9 agronomic and economic field experiments evaluating the yield response of maize, millet, sorghum, and rice to nitrogen in Ethiopia, Ghana, Kenya, Malawi, Niger, Nigeria, and Uganda[10] (Akinnifesi et al. 2007; Bationo and Ntare 2000; Buah and Mwinkaara 2009; Duflo, Kremer, and Robinson 2008; Kaizzi et al. 2012; Kamara et al. 2008; Kamara et al. 2011; Onasanya et al. 2009; Teklay, Nyberg, and Malmer 2006). Each study typically reports average yield responses for several different levels of nitrogen application (ranging from 15 to 120 kilograms per hectare), giving me 22 observations. All of the individual studies support yield response being an increasing and concave function of nitrogen. I estimate the function across studies using a simple quadratic regression of the percentage increase in yield on the application rate per hectare.

Table 2 shows the estimated coefficients from the quadratic regression using either nitrogen per hectare (column 1) or urea per hectare (column 2) as the units for Z. Figure 4 shows the estimated yield response function along with the 22 observations from the reviewed studies[11]. Figure 4 also includes 40 alternate estimated functions obtained by resampling the 22

[8] These fertilizer price series are mostly incomplete. There are a total of 869 observations from the 69 markets (12.6 per market).

[9] Trade costs might be slightly lower for fertilizer due to lower search and information costs or lower taxes and tariffs.

[10] For those studies reporting yield response to a nitrogen fertilizer like urea rather than nitrogen itself, I convert the amount of fertilizer applied to its associated nitrogen content.

[11] The function is $F(Z) = 1 + \alpha_1 Z + \alpha_2 Z^2$, where α_1 and α_2 are the estimated coefficients from table 2.

Table 2: Coefficient Estimates for Yield Response Function

	(1)	(2)
Z	0.0190	0.00873
	(0.00417)	(0.00192)
Z^2	-0.0000869	-0.0000184
	(0.0000421)	(8.91E-06)
Units of Z	kg N/Ha	kg urea/Ha
Observations	22	22

observations with replacement, with all graphed functions truncated at their maxima. The estimated function results in an increase of yield by 50% with application of 30.6 kg N/Ha (66.6 kg urea/Ha) and an increase of yield by 100% with 88.3 kg N/Ha (193.3 kg urea/Ha), with a maximum increase of 107.7% reached with 109.3 kg N/Ha (237.2 kg urea/Ha)[12]. I use the estimated function for urea (column 2 of table 2) when incorporating $F(Z)$ into my model since the local fertilizer prices P_{Zmt} I use are also for urea.

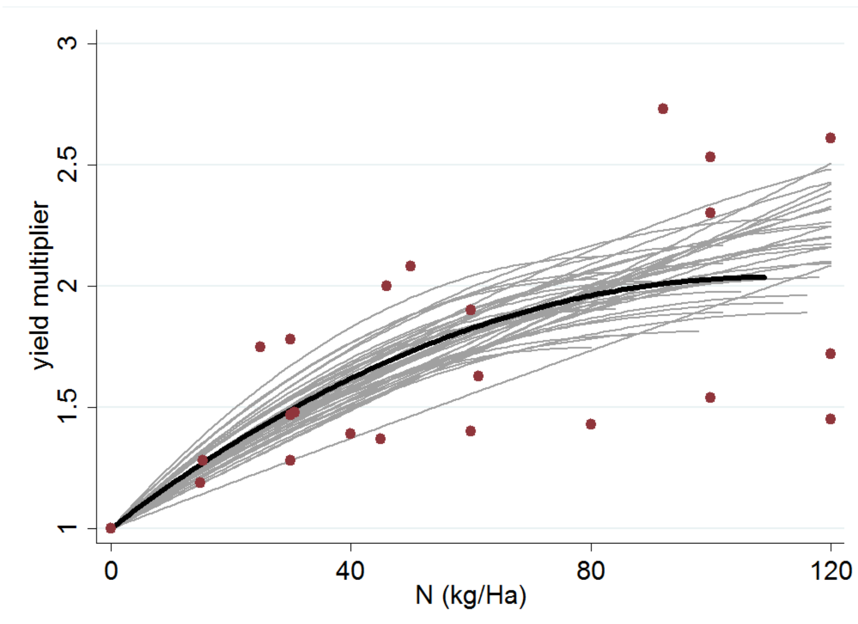

Figure 4: Estimated yield response function

With local urea prices P_{Zmt} and the yield response function $F(Z)$ in hand, I proceed to

[12]Back-of-the-envelope calculations suggest this estimated yield response function is in line with Jayne and Rashid (2013), who review 10 recent studies using farm panel survey data from different African countries and report average response rates of 8-24 kg maize/kg N, with most results in the 8-15 kg maize/kg N range. An average cereal grain yield of 1260 kg/Ha during the study period (figure 1) and an average fertilizer use rate of 26.0 kg N/Ha (Sheahan and Barrett 2017) implies a zero-fertilizer yield of 878 kg/Ha and average response rates of 14.7, 12.9, 11.0, and 9.1 kg grain/kg N for the first 25, 50, 75, and 100 kg N applied.

use equations 8 and 10 to solve for the implied crop-market-time specific productivity shocks B_{imt} and the implied local fertilizer use rates Z_{imt} for each harvest of each grain in each market during my period of interest (May 2003 – April 2013). Implied fertilizer use is 38.8 kg N/Ha (84.3 kg urea/Ha) for all hectares of land cultivated during the study period, while the average implied market-level use rate is 44.4 kg N/Ha (96.5 kg urea/Ha). Despite high prices, it appears to still be optimal for farmers to use significant amounts of fertilizer.

These initial fertilizer use rates are substantially higher than reported use rates in the literature, despite my earlier finding that my estimated local fertilizer prices are if anything slightly higher than actual prices. Minot and Benson (2009) use FAO-STAT data to calculate that farmers in sub-Saharan Africa use 13 kilograms of inorganic fertilizer nutrients per hectare of arable land. Sheahan and Barrett (2017) use data from the World Bank's nationally representative LSMS-ISA household surveys in Ethiopia, Malawi, Niger, Nigeria, Tanzania, and Uganda to show that fertilizer use is actually higher than previously thought. They report an average country-level use rate of 26.0 kilograms of nutrients per hectare. This is still substantially lower than my estimated average market-level use rate of 44.4 kg/Ha. The lower bound of a 95% confidence interval for the average market-level use rate constructed using the 40 bootstrapped functions from figure 4 is 36.6 kg N/Ha.

The most likely explanation for the discrepancy between my estimated fertilizer use rates and the use rates reported in the literature is the presence of additional costs for fertilizer use not captured by my model. These additional costs can be grouped into four major categories. First, "last-mile" trade costs between the hub market and the farm may substantially increase the effective price of fertilizer. Minten, Koru, and Stifel (2013) document effective price increases for fertilizer of 20-50% from the input distribution center to the farm in one locality in Ethiopia, while Aggarwal et al. (2018) report implied market-to-farm trade costs of 30% for the average fertilizer purchase in the Kilimanjaro region of Tanzania. Second, fertilizer must be purchased months in advance of the receipt of harvest revenues, so both the cost of credit and the risk premium associated with uncertain rain-contingent harvests are likely significant. Beaman et al. (2015) evaluate a seasonal loan for agricultural inputs offered by a microcredit organization in Mali with an interest rate of 25%. Dercon and Christiaensen (2011) find that 71% of households purchasing fertilizer in Ethiopia use formal seasonal credit — with an implicit median annual interest rate of 57% — and that lower conditional expectations of consumption during droughts have a significant negative effect on fertilizer use. Third, fertilizer use may require increased use of costly complementary inputs, including labor to apply it and to harvest the increased output. Beaman et al. (2013) find that the distribution of free fertilizer in Mali led to a statistically significant increase in expenditure on hired labor and herbicides, corresponding to 40% of the value of the additional fertilizer actually applied[13]. Fourth, fertilizer sold in local markets may be adulterated. Bold et al. (2017) find that urea sold in retail markets in Uganda contains an average of 31.8% nitrogen per kilogram instead of 46%, suggesting that farmers would have to purchase 45% more urea to obtain a given quantity of nitrogen with its associated yield response. Michelson et al. (2018) find no significant evidence of adulteration in the Morogoro region of Tanzania (average nitrogen content of 45.9%) but report that farmers' willingness to pay for urea increases by 48% after receiving laboratory test results confirming its nitrogen content, suggesting that concerns about adulteration lower fertilizer use even when the fertilizer being sold is of good quality.

How much higher would local fertilizer prices P_{Zmt} need to be to generate implied fertilizer use rates Z_{imt} consistent with household survey data? I find that when I double my estimated local hub market prices, implied fertilizer use falls to 20.2 kg N/Ha for all hectares of land cultivated, with an average implied market-level use rate of 26.0 kg N/Ha, which exactly matches the average country-level use rate from the LSMS-ISA data reported by Sheahan and Barrett (2017). This 100% increase in price is of similar magnitude to the combination of the additional costs of last-mile trade, credit and risk, complementary inputs, and adulteration documented in the papers cited above[14]. I proceed to use these doubled prices and the associated implied productivity shocks B_{imt} for the baseline simulation of the model, which I will compare to counterfactual simulations in the next section.

Figure 5 shows scatter plots of implied market-level use rates of fertilizer against local urea prices using both original and doubled urea prices. While higher urea prices are clearly negatively correlated with fertilizer use rates, much of the variation in use rates appears to be driven by other factors (output prices P_{imt} and productivity B_{imt}). The counterfactual simulations in the next section explore how usage changes as technology adoption policies and falling trade costs change both input and output prices.

4 Counterfactual Results

I use my estimated model with endogenous production and technology adoption to simulate the effects of fertilizer subsidies — the most widely used technology adoption promotion policy — under existing high trade costs and counterfactual low trade costs. I choose a

[13]This increased expenditure on complementary inputs is likely due both to the increased optimal use of other inputs ($\frac{dL}{dZ} > 0$ in the first order condition in equation 7) and to the uncaptured costs of other inputs needed to actually use the fertilizer. The fact that Beaman et al. (2013) find no statistically detectable effect on profits from the distribution and use of free fertilizer suggests that the latter component is significant.

[14]This result has an interesting parallel in the agronomic literature on technology adoption, where a rule of thumb often used is that a technology needs a rate of return of at least 100% (a "2 to 1 return") to be adopted due to a combination of factors including learning costs, capital costs, and risk (CIMMYT 1988).

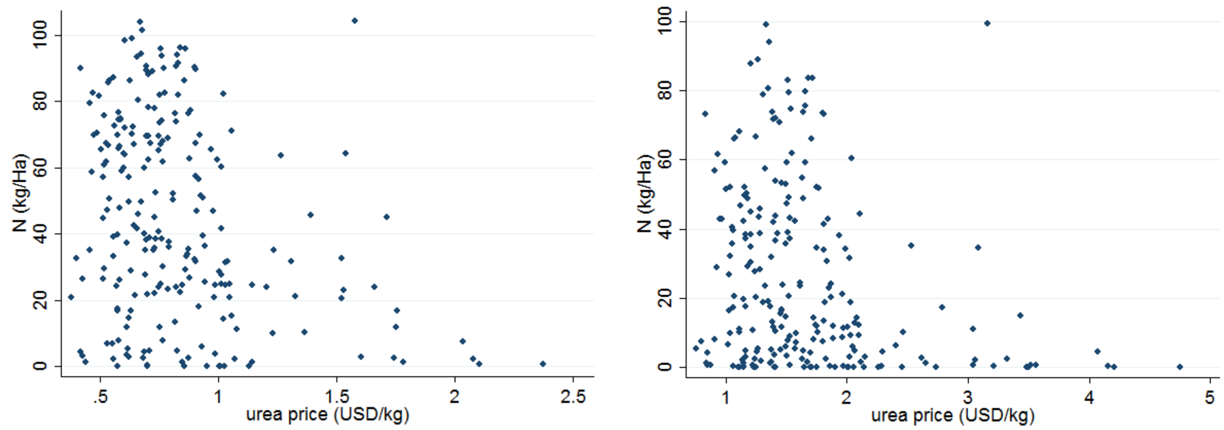

Figure 5: Estimated baseline fertilizer use with original (left) and doubled (right) urea prices

subsidy level of 50%, which is of similar magnitude to that of fertilizer subsidy programs implemented by African countries over the last decade[15]. However, unlike existing subsidy programs, which typically provide subsidized fertilizer in limited amounts only to targeted or registered farmers in individual countries, my simulated subsidies are universal subsidies on unlimited amounts of fertilizer for all farmers in all of the countries in the model[16]. Since I had to double local fertilizer prices to generate fertilizer use rates consistent with the literature, the 50% subsidy reduces effective prices back to my initial estimated levels. Given that the pre-subsidy effective prices included both the hub-market price as well as the additional costs of last-mile trade, credit and risk, complementary inputs, and adulteration, there could be a variety of policy combinations beyond simple point-of-sale subsidies in hub markets that could achieve the 50% reduction in effective fertilizer prices simulated here.

Table 3 reports results from counterfactual simulations using my estimated model with endogenous production and technology adoption, which are analogous to the counterfactuals using the baseline model with exogenous production from table 1. In the first column, I lower trade costs to match the benchmark levels from elsewhere in the world used by Porteous (2017), which leads to lower local prices for imported fertilizer without subsidies. In the second and third columns, I simulate the implementation of a 50% fertilizer subsidy under existing high and counterfactual low trade costs. The fourth column is then a combined

[15]For example, Ricker-Gilbert, Jayne, and Chirwa (2011) report subsidies of 75% in Malawi, Mason, Jayne, and Mofya-Mukuka (2013) report subsidies of 50–80% in Zambia, and Wossen et al. (2017) report subsidies of 50% in Nigeria.

[16]Wossen et al. (2017), for instance, report that Nigeria's subsidy program provides a 50% subsidy on up to 100 kg of fertilizer to registered, full-time, non-commercial farmers. They find that 42% of their nationally-representative sample of farming households report being registered for the program, and only 32% actually received the electronic voucher for the subsidy.

simulation with trade cost reduction and fertilizer subsidies. As in table 1, all percentage changes are given in terms of the baseline equilibrium with high trade costs and no subsidy, and welfare effects are calculated as equivalent variation as a percentage of baseline GDP.

Table 3: Aggregate Results from Counterfactual Simulations

Baseline Counterfactual	High τ Low τ	High τ Subsidy	Low τ Subsidy	High τ Both
Average Fertilizer Price	-52.7%	-50.0%	-23.7%	-76.4%
Average Grain Price Index	-44.4%	-11.2%	-2.4%	-46.8%
Fertilizer Use	+16.4%	+81.2%	+92.5%	+108.9%
Expenditure on Fertilizer	-39.4%	-6.7%	-6.5%	-45.9%
Grain Production	+20.7%	+9.8%	+15.5%	+36.2%
Net Agricultural Revenues	-25.9%	-8.2%	+6.4%	-19.5%
Annual Net Grain Exports	+13.6 mill t	+6.1 mill t	+12.1 mill t	+25.7 mill t
Expenditure on Grains	-40.7%	-10.5%	-2.9%	-43.6%
Welfare (No Subsidy Cost)	+3.39%	+0.79%	+0.48%	+3.87%
Annual Subsidy Cost	$0	$5.1 billion	$2.9 billion	$2.9 billion
Welfare (With Subsidy Cost)	+3.39%	-0.09%	-0.03%	+3.36%

For a given yield response function and local productivity shock, the incentives for technology adoption depend on input and output prices. When trade costs are lowered, the average local fertilizer price falls by 52.7% (more than the 50% subsidy), but fertilizer use rates increase by only 16.4%. This is due to the 44.4% drop in the average grain price index, as lower trade costs lower grain prices in net importing markets. Subsidies, in contrast, lower fertilizer prices while only affecting grain prices indirectly through increased production. Fertilizer use rates increase by 81.2% with a 50% subsidy under high trade costs. When trade costs are low, the same percentage subsidy increases use rates by even more (92.5%), despite the fact that the absolute subsidy is 43% cheaper due to the lower trade costs. Trade facilitation and technology adoption promotion policies are thus complements in terms of adoption itself[17].

The effects of technology adoption promotion policies on farmers depend crucially on the level of trade costs. Under existing high trade costs, the average grain price index falls by 11.2% due to fertilizer subsidies, nearly 5 times more than the 2.4% drop when trade costs are low. This is despite the fact that subsidies increase grain production more under low trade costs (15.5%) than under high trade costs (9.8%). Taken together, these price and production changes end up leading to a nearly symmetric loss in net agricultural revenues due to fertilizer subsidies under existing high trade costs (–8.2%) and gain in net agricultural

[17]I consider the policies to be complements if their effect when implemented together (fourth column of table 3) is larger than the sum of their effects when implemented separately (first and second columns), or equivalently if the effect of the subsidy is larger under low trade costs (third column) than under existing high trade costs (second column).

revenues due to fertilizer subsidies under low trade costs (+6.4%).

Lowering trade costs without subsidies increases total production by more than either of the subsidy simulations, despite a much larger fall in the average grain price index. This aggregate result is due to a reallocation of production towards the most productive regions. Only 67 markets (29%) experience increased production with lower trade costs — but with an average increase of 148% — while the remaining markets experience an average decrease in production of 35%. As shown in the left panel of figure 6, the largest increases in production occur in the most productive crop-market-months (those with the largest productivity shocks B_{imt}). The coefficient estimate from a regression of output H_{imt} on productivity B_{imt} with a constant more than doubles when trade costs are lowered. In contrast, fertilizer subsidies (right panel of figure 6) lead to smaller but more widespread production increases that are unrelated to productivity, with no statistically significant change in the coefficient estimate of this regression[18]. Trade facilitation and technology adoption promotion policies are complements in terms of production: the total production increase with both lower trade costs and fertilizer subsidies (36.2%) is 19% larger than the sum of the increase when the two policies are implemented separately (30.5%). With both lower trade costs and fertilizer subsidies, the 41 modeled countries together shift from net grain importers (of 18.3 million tonnes annually) to net grain exporters (of 7.3 million tonnes annually).

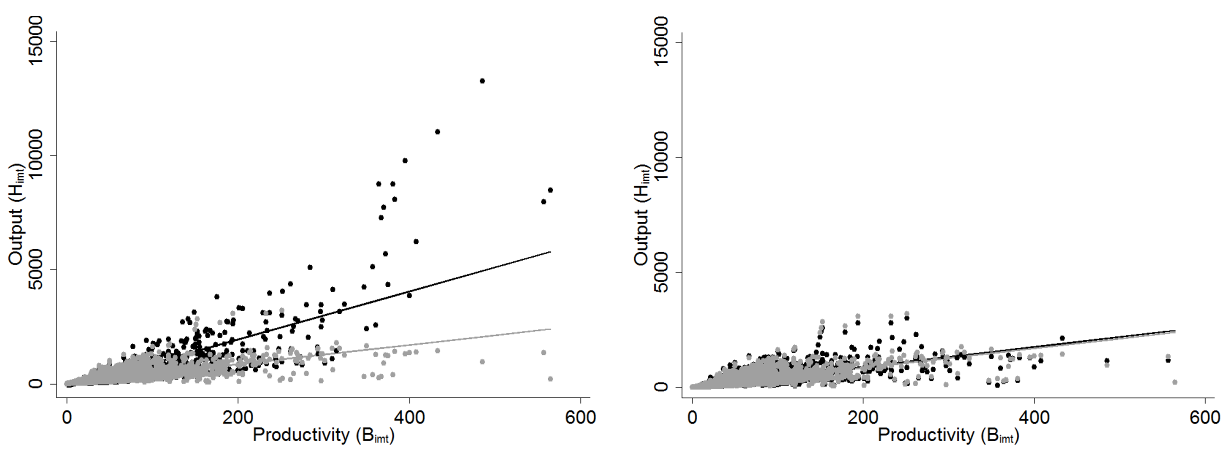

Figure 6: Relationship between productivity (B_{imt}) and output (H_{imt}) at baseline (grey), with trade cost reduction (black, left panel), and with fertilizer subsidies (black, right panel)

Agricultural technology promotion policies like fertilizer subsidies have important effects beyond those on input use, agricultural production, and farmer revenues. In a context where 44% of consumer expenditure is on food, the potential reduction in food prices and

[18] Coefficient estimates for B_{imt} (robust standard errors clustered at the market level) are 4.21 (0.38) at baseline, 10.51 (1.37) with trade cost reduction, and 4.35 (0.41) with fertilizer subsidies.

expenditure on food can be an important source of indirect benefits and a major motivation behind policy implementation (Ricker-Gilbert et al. 2013). Welfare calculations in the Porteous (2017) model incorporate the effects of changes in both agricultural income and consumer food prices. The reduction in consumer expenditure on food due to fertilizer subsidies is 3.5 times larger under existing high trade costs than under lower trade costs due to the larger drop in local grain prices. This offsets the income effects, resulting in a larger overall welfare gain due to fertilizer subsidies under high trade costs (0.79%) than under low trade costs (0.48%) before taking into account the subsidy costs.

Lowering trade costs without fertilizer subsidies leads to an aggregate welfare gain equivalent to 3.39% of GDP. This figure is over 50% higher than the 2.17% reported in Porteous (2017) (table 1). The endogenous supply response accounts for part of this difference — Porteous (2017) reports gains of 2.42% and 2.51% with price elasticities of supply η of 0.5 and 1. The remaining, larger part of this difference is due to the role of fertilizer, which is not accounted for by Porteous (2017). Lower trade costs mean lower local fertilizer prices, increasing fertilizer use and grain production while decreasing expenditure on fertilizer. When fertilizer subsidies lower fertilizer prices even further, the aggregate welfare gain reaches 3.87% of GDP.

Although some fertilizer subsidy programs in sub-Saharan Africa are funded in part through external aid, most funding has come directly from African governments (Dorward and Chirwa 2011; Mason, Jayne, and Mofya-Mukuka 2013). Once the cost of the subsidy is accounted for, the overall welfare effect of subsidies changes from positive to negative, regardless of trade costs[19]. Fertilizer subsidies that lower effective local prices by 50% are substantially more expensive when trade costs are high, since those local prices are much higher. This difference more than offsets the larger initial welfare gain of the subsidies under high trade costs, resulting in a larger loss than under low trade costs. Trade cost reduction and fertilizer subsidies were slight substitutes in terms of welfare before accounting for subsidy costs, but the lower cost of subsidies under low trade costs now makes them very slight complements ($3.36\% > 3.39\% - 0.09\%$)[20].

In table 4, I explore the sensitivity of my results to the price elasticity of supply, η. I calibrated this parameter to 0.6 based on estimates of annual elasticities for individual staple crops, which is the role η plays in my model. A more conservative approach would be to use the annual price elasticity of supply for staple calories rather than individual grains,

[19] The subsidy costs reported in Table 3 are the direct costs of the subsidy ($\sum_t \sum_m \sum_i 0.5 P_{Zmt} Z_{imt}$). Total costs including implementation and administrative costs are likely higher.

[20] Table 3 does not include the costs of trade cost reduction, which cannot be obtained directly from the variables within the model. While these costs are likely significant, they are not affected by fertilizer subsidies, so they would not affect these results on complementarity.

which Roberts and Schlenker (2013) estimate at 0.097. Using a value of $\eta = 0.1$ to match this estimate, I re-estimate the implied productivity shocks B_{imt} and then re-run both the baseline simulation and the counterfactual simulations[21].

Results in table 4 with $\eta = 0.1$ are largely similar to my initial results in table 3 with $\eta = 0.6$. Fertilizer prices are unchanged as they are determined by world prices, trade costs, and subsidies. The aggregate increase in production due to lower trade costs is much smaller that before, as the markets where production expands experience an average increase of 35% instead of 148%. In both of the two subsidy simulations, fertilizer use increases slightly less, expenditure on fertilizer falls slightly more (due to less usage), and production increases slightly more[22]. Across all simulations, the average grain price index falls by more than before, resulting in lower net agricultural revenues and expenditure on grains. These two roughly balance each other out for the subsidy counterfactuals, resulting in welfare effects very close to those with $\eta = 0.6$, although trade cost reduction and fertilizer subsidies are now very slight substitutes when accounting for the cost of the subsidies. The welfare effects for the trade cost counterfactuals are smaller than with $\eta = 0.6$ due to the more muted production response, which is no longer enough for sub-Saharan Africa to become a net grain exporter. I conclude that while the magnitudes of my results change in expected ways with a different price elasticity of supply, my key qualitative findings remain the same.

Table 4: Aggregate Results with $\eta = 0.1$

Baseline Counterfactual	High τ Low τ	High τ Subsidy	Low τ Subsidy	High τ Both
Average Fertilizer Price	-52.7%	-50.0%	-23.7%	-76.4%
Average Grain Price Index	-46.3%	-12.9%	-3.4%	-49.7%
Fertilizer Use	+16.7%	+69.8%	+90.7%	+107.4%
Expenditure on Fertilizer	-39.2%	-12.8%	-6.8%	-46.0%
Grain Production	+5.6%	+10.1%	+16.0%	+21.6%
Net Agricultural Revenues	-38.6%	-11.6%	+2.4%	-36.2%
Annual Net Grain Exports	+1.3 mill t	+5.9 mill t	+11.9 mill t	+13.2 mill t
Expenditure on Grains	-43.7%	-12.8%	-3.8%	-47.5%
Welfare (No Subsidy Cost)	+2.83%	+0.79%	+0.46%	+3.29%
Annual Subsidy Cost	$0	$4.7 billion	$2.9 billion	$2.9 billion
Welfare (With Subsidy Cost)	+2.83%	-0.03%	-0.05%	+2.78%

Taken together, my results highlight both the ways in which trade costs alter the incidence of technology adoption promotion policies as well as the complementarities between these policies and trade cost reduction. Under high trade costs, fertilizer subsidies lower local

[21] Note that the implied baseline local fertilizer use rates Z_{imt} are not affected by the change in η. Combining equations 5 and 9 gives $P_{Zmt}D_{im} = [F'(Z_{imt})/F(Z_{imt})]\, H_{imt}P_{imt}$.

[22] The smaller negative effect on production due to the decrease in price outweighs the smaller positive effect on production due to the increase in fertilizer use.

grain prices, benefiting local consumers but harming local producers by lowering revenues despite increased production. Under low trade costs, fertilizer subsidies have minimal effects on local grain prices, benefiting local producers through increased revenue from increased production. The same percentage subsidy is cheaper, increases fertilizer use rates by more, and increases agricultural production by more when trade costs are low.

5 Conclusion

I have used a spatially explicit model of agricultural production, storage, and trade in sub-Saharan Africa to evaluate how trade costs alter the incentives for agricultural technology adoption and the effects of technology adoption promotion policies. My model was based on the Porteous (2017) dynamic model of storage and trade of the six major staple cereal grains between 230 large hub markets in all 42 countries of continental sub-Saharan Africa and the world market. Initial simulations in which I doubled production in the baseline Porteous (2017) model led to large price and revenue collapses in local markets under existing high trade costs but small price effects and significant revenue gains with lower trade costs. I subsequently extended the model by adding representative competitive farmers who decide how much grain to produce and how much imported fertilizer to use based on local grain prices, local fertilizer prices, and crop-market-time specific productivity shocks. I estimated local fertilizer prices using world prices plus trade costs along the least-cost path from the world market, and I estimated the yield response function to fertilizer using data points taken from a review of the relevant agronomic and economic literature. I found that I had to double my estimated local fertilizer prices in hub markets to account for additional costs of fertilizer use and obtain implied fertilizer use rates that match household survey data.

My simulation results shed light on the ways in which trade cost reduction and technology adoption promotion policies like fertilizer subsidies have different, complementary effects. Falling trade costs lead to substantial increases in overall grain production that are primarily due to a reallocation and concentration of production in the most productive regions rather than an increase in overall fertilizer use. Fertilizer subsidies lead to a larger increase in fertilizer use and more widespread increases in production. The main effect of this extra output under high trade costs is to decrease local grain prices (helping consumers while hurting farmers), whereas under low trade costs it is to increase farmer incomes. Trade cost reduction and fertilizer subsidies are complements in terms of fertilizer use and agricultural production, with the combined policies enabling sub-Saharan Africa to achieve self-sufficiency in grain production and begin exporting to the rest of the world while realizing a welfare gain equivalent to 3.87% of GDP before accounting for the subsidy costs. Once these costs are included, however, fertilizer subsidies lead to a welfare loss at all levels of trade costs.

African governments are increasingly pursuing technology adoption promotion policies like fertilizer subsidies in an effort to spark a Green Revolution. My findings highlight the essential role that trade costs in input and output markets play in determining both the incentives for adoption and the effects of adoption promotion policies. In the presence of high trade costs, the spread of subsidy programs is likely to put increasing downward pressure on local agricultural prices, benefiting local consumers while hurting local farmers despite increased production. A different outcome can emerge if adoption promotion policies are linked to ongoing and planned trade cost reduction initiatives — including infrastructure investment and regional trade integration. As trade costs fall, agricultural production will become more concentrated in high-productivity areas with ready access to cheap inputs and elastic output markets, and technology adoption promotion policies will then lead to greater production increases and smaller price effects, boosting farmer incomes. Evaluating the impact of specific trade and technology policies as they are implemented separately and in combination is an important topic for future research.

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Appendix: Proofs of Propositions

Proof of Proposition 1. Let $R = PH$ denote farmer revenues. Taking the total derivative of revenues with respect to quantity gives:

$$\frac{dR}{dH} = \frac{\partial R}{\partial H} + \frac{\partial R}{\partial P}\frac{dP}{dH} = P + H\frac{dP}{dH} \tag{11}$$

By the definition of elasticity, $\frac{dP}{dH} = \frac{1}{\epsilon}\left(\frac{P}{H}\right)$, so the total derivative becomes:

$$\frac{dR}{dH} = P + \frac{H}{\epsilon}\left(\frac{P}{H}\right) = (1 + \frac{1}{\epsilon})P \tag{12}$$

If $\epsilon < -1$, then $-1 < \frac{1}{\epsilon}$ so $\frac{dR}{dH} > 0$ (an increase in production increases farmer revenues). If $\epsilon = -1$, then $\frac{dR}{dH} = 0$ (an increase in production has no effect on farmer revenues). If $-1 < \epsilon < 0$, then $\frac{1}{\epsilon} < -1$ so $\frac{dR}{dH} < 0$ (an increase in production decreases farmer revenues).