Industrial policy and input market access: Evidence from Nigerian fertiliser

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Abstract

Many economies use industrial policy to nurture sectors that produce inputs critical to economic development. While there are theoretical reasons that justify such state interventions, there is limited direct evidence on whether industrial policy in input markets could effectively induce productivity gains for firms that purchase these inputs. In this paper, I make progress on this front by evaluating an import substitution policy in Nigeria that sought to expand domestic production of inorganic fertiliser, a modern input to agriculture. In particular, I focus on assessing two components of the policy: the construction of domestic fertiliser manufacturing plants and a ban on imports of fertilisers. Combining household surveys and geospatial data on plant locations, I estimate the effects of policy-induced changes in access to fertiliser on adoption rates, and crop yields. To deliver credible estimates, I take advantage of the fact that farm-households were differentially exposed to the policy based on their distance to sources of fertiliser. I find that farms closer to sources of fertiliser exhibit higher rates of adoption on both the extensive and intensive margin, as well as greater crop yields. Preliminary evidence also suggests that the observed effect works through retail prices.

JEL codes: F13, O13, O25

Keywords: industrial policy, market access, agricultural productivity

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1 Introduction

One important reason why states deploy industrial policy is to nurture sectors that produce inputs critical to economic development. States have historically protected their domestic steel, chemical, and mineral sectors that produce specialised intermediate goods for manufacturing, infrastructure and other sectors that facilitate industrialisation (Shafaeddin et al. 1998, Rodrik 2006). Today, governments continue to use a combination of trade restrictions and subsidies to improve access to inputs for sectors deemed important to achieving economic or social goals. For example, Indonesia imposed an export ban to develop its nickel sector, the goods of which are inputs to the production of low-carbon technologies such as electric vehicles.[1]

When is industrial policy an appropriate tool to lower input costs for sectors downstream? The standard theory of infant industry protection has a clear answer (Baldwin 1969; Harrison and Rodrìguez-Clare 2010). Protecting a sector via trade barriers and/or subsidies is justified when the country has an unrealised comparative advantage in the sector such that its domestic price (relative to world price) is higher than the true opportunity cost of the good. [2]If protection enables the country to realise this comparative advantage and thereby lower the price of the protected good, then firms in downstream sectors stand to benefit from lower input costs. Otherwise, protection will hurt firms downstream as increases in the output price of the protected sector translate into higher costs for firms that purchase this input.

While theory is well-developed in this regard, there is limited direct evidence on whether industrial policy in input markets could induce productivity gains in sectors downstream. In this paper, I make progress on this front by studying an import substitution policy that sought to expand domestic production of inorganic fertiliser, a labour-saving input to agriculture. The empirical setting is Nigeria whose government implemented a set of policies designed to replace imports of inorganic fertilisers with locally produced ones. In particular, the government subsidised domestic blenders of inorganic fertiliser to spur domestic production while simultaneously banning the imports of these same fertilisers. I evaluate the extent to which these two components were effective in raising productivity in agriculture, a sector whose firms (i.e. farm-households) purchase these inputs.

To provide direct evidence, I estimate the effect of changes in input market access induced by the policy on fertiliser adoption rates and crop yields among farm-households. Using geospatial data on factory and port locations, I first construct two measures that capture changes in input market access brought about by the policy: (1) distance of farm-households to the nearest source of fertiliser along the transport network and (2) a measure of input market access that interacts trade costs and factory production. The two components of the policy exert opposing effects on input market access: factory entry raises market access while the ban on imports lowers it.

Armed with measures of input market access, I then estimate the effect of the policy on two outcomes: (1) fertiliser adoption rates, and (2) crop yields. These outcomes are calculated using a national survey that collects plot-level information on inputs and outputs of a tracked sample of households, enabling comparisons before and after the policy. To deliver causal estimates of the effect

[1] Recent examples in advanced economies include the United States' Creating Helpful Incentives to Produce Semiconductors Act (CHIPS) and the EU's Chips for Europe Initiative. Both policies aim to boost semiconductor manufacturing.

[2] The country may have unrealised comparative advantage because of learning externalities.

of the policy, I take advantage of the fact that households are differentially exposed to sources of fertiliser (i.e. factories and ports) based on their distance to these sources. This exposure changes over time as factories enter and the port ceases to become a viable source of fertiliser.

Literature review and contribution This paper contributes to three strands in the literature: First, I contribute to a large literature on the role of market access in agricultural productivity (Suri 2011, Donaldson 2018, Aggarwal 2018, Porteous 2020, Shamdasani 2021, Aggarwal et al. 2022,Ghose, Fraga, and Fernandes 2023). Most of the papers here connect changes in market access induced by changes in transport infrastructure or trade policy to local outcomes such as labour supply and technology adoption. A central theme among these papers is that high transaction costs in accessing markets (due to poor infrastructure, low density of rural population) can render modern technologies unprofitable for farmers. Among these papers, my work is closest to Ghose, Fraga and Fernandes (2023) who use firm data to study the 2021 import ban on organic fertiliser in Sri Lanka and its effects on crop yields and agricultural exports. I contribute to this literature by looking at an import substitution policy, a policy that has theoretically ambiguous effects on market access due to the size of domestic trade costs and the dispersion of smallholder agriculture across space.

Second, I contribute to a strand of the literature on the effectiveness of industrial policy. This literature studies specific policy episodes in different settings such as steel in the United States (Head 1994); shipbuilding in Britain and United States (Hanlon 2020); textiles in France (Juhász 2018); heavy-chemicals in South Korea (Choi and Levchenko 2021; Lane 2022), and information technology in Romania (Manelici and Pantea 2021).[3] In this area, the most related paper is Blonigen (2016) who studies the consequences of steel-sector industrial policy on downstream manufacturing in a cross-country sample. Similar to Blonigen (2016), I look at how industrial policy targeting production of an input cascades into firms downstream. Differently, I study the effect of an import substitution on smallholder agriculture, a context where productivity is tightly linked to real incomes and welfare. Evaluating the effectiveness of this import substitution policy, while unique to Nigeria, could serve as a litmus test (a paragon or a warning) for similar developing countries that aspire to raise productivity in agriculture.

Lastly, my work speaks to the literature on domestic trade frictions (Atkin and Donaldson 2015, Sotelo 2020). A key finding in this literature is that the gains from trade liberalisation are distributed unevenly across consumers and firms because of domestic frictions. In other words, remoteness insulates consumers from the benefits of globalisation. My analysis demonstrates that large domestic trade costs shapes the consequences of trade and industrial policies on firm and household outcomes.

The remainder of the paper is structured as follows. Section 2 describes the policy episode of interest: the ban on fertiliser imports and the construction of domestic fertiliser plants. In Section 3, I lay out a theoretical framework that generates predictions brought to the data. Section 4 presents the identification strategy and the empirical specifications testing the theoretical predictions. In Section 5, I present the main empirical results on the effects of the policy. I provide evidence on the mechanisms that drive the results in Section 6.

[3]A complementary strand of this literature quantifies the gains from optimal industrial policy using general equilibrium models with scale economies (Bartelme et al. 2019, Lashkaripour and Lugovskyy 2023)

2 Context: Import substitution in the Presidential Fertiliser Initiative

In 2016, the newly elected government of Nigeria launched a programme called the Presidential Fertiliser Initiative (PFI) which sought to expand the country's domestic capacity to produce inorganic fertiliser. The rationale of the program was to ensure food security through the provision of affordable and quality fertiliser to local farmers. But unlike previous reforms which championed input subsidy programmes, the PFI had the explicit goal of boosting the production of domestic inorganic fertiliser while reducing reliance on foreign sources (NSIA 2017). Concerned that previous input subsidy regimes were rife with inefficiency and corruption, the government sought to cut subsidy-driven imports of fertiliser that were putting immense strain on government budgets.

After abolishing its national input subsidy programme, the government implemented three sets of policies as part of the PFI: First, the government relinquished its procurement and distribution functions to the private sector and instead intervened in the sourcing of raw materials used to produce NPK. As a compound multi-nutrient fertiliser, NPK requires four materials: urea, limestone, diammonium phosphate (DAP), and muriate of potash (MOP). As only urea and limestone are domestically available, Nigeria negotiated discounted contracts for the procurement of DAP with a Moroccan state-owned enterprise, the OCP Group.[4] For each delivery of raw materials, the government pays foreign and local suppliers directly then delivers the materials to the blending plants.

Second, the government subsidised blending plants at a rate of 620 naira (0.75 USD) per bag of fertiliser. Once blenders produce and sell NPK, any revenue from sales are remitted to the government who uses the cash in the subsequent cycles of production.[5]

Third, the government imposed a prohibitive ban on the imports of two specific fertilisers: urea and NPK. To be precise, the Central Bank of Nigeria placed urea in the list of items ineligible for foreign exchange (Argus Media 2020). Items in the list are restricted from accessing foreign exchange from the investor's and exporters' window. The ban on urea was imposed in 2016 and took effect in 2017. The ban on NPK was announced in 2018 and became effective in 2019.

2.1 Facts from trade and factory data

The policy has led to several important changes in Nigeria's fertiliser trade and domestic production. I briefly describe the relevant facts here based on factory and trade data.

Fact 1. The ban on imports of fertiliser was prohibitive.

Nigeria's trade patterns for two majors of fertiliser – urea and NPK – have dramatically shifted over the span of the reform. Figure 1 indicates that before 2015, the country was historically a net importer of urea. Not only did Nigeria halt importing (as a result of the import ban) but Nigeria has become a net exporter of urea from 2017 onwards. For NPK, Figure 2 shows that the ban on NPK was prohibitive but Nigeria has not exported any NPK since the start of the reform.

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[4]To be precise, the government created a special purpose vehicle called the NAIC-NPK Limited managed by its sovereign wealth fund, NSIA.

[5]These blending fees were designed to be temporary. In 2021, blenders would have to recover costs through sales

Fact 2. The number of operational factories has increased over time.

Figure 3 shows that the number of operational factories increased from 21 in 2010 to 55 in 2020. In between the two waves of the household survey relevant to this study (Wave 3-2015 and Wave 4-2018), the number of factories increased from 24 in 2015 to 37 in 2018. Almost all firms that entered in this period produce NPK. These firms are called 'blending plants' as they blend raw materials to product the composite product, NPK.

Over this 10-year period, only two (2) urea factories entered. Before 2010, there was only one urea plant in the country (Notore Chemical Industrial PLC). The production capacity of the urea factory that entered in 2016 (Indorama Fertilizer) is quite substantial at 3 million metric tons per year.

Fact 3. There has been a substantial expansion of domestic capacity to produce fertiliser

Nigeria's total capacity to produce both urea and NPK, in terms of the full-load sustained output of the plant, dramatically increased over this period. Figure 4 shows that the country's capacity to produce NPK increased from 2.7 million MT to 9.3 million MT in 2020. For urea, capacity to produce urea increased from 400,000 MT in 2010 (one plant) to 3.4 million MT in 2016 (two plants) to 6.2 million MT in 2020 (two plants).

In between the two waves of the household survey (Wave 3-2015 and Wave 4-2018), capacity value to produce both NPK and urea increased from 3.4 million MT to 7.8 million MT. All NPK factories have lower production capacity than the three urea factories. The urea factories that entered are billion dollar plants and are owned by multinational manufacturing conglomerates.

Figure 1. Urea - volume of exports and imports, 2006-2020 (Source: CEPII-BACI)

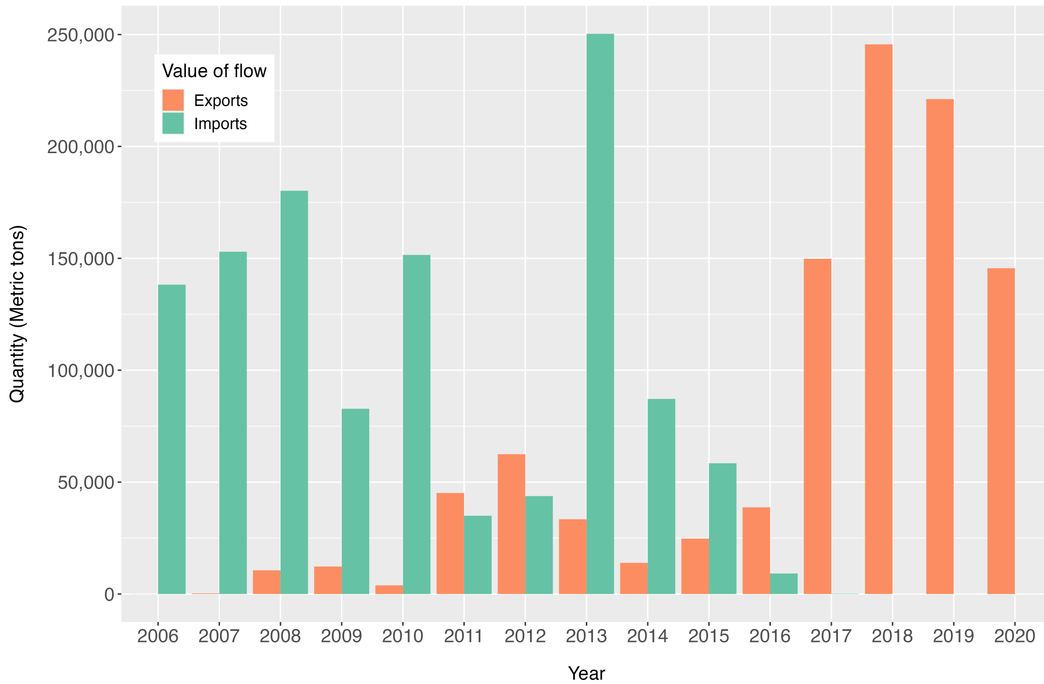


Figure 2. NPK - volume of exports and imports, 2006-2020 (Source: CEPII-BACI)

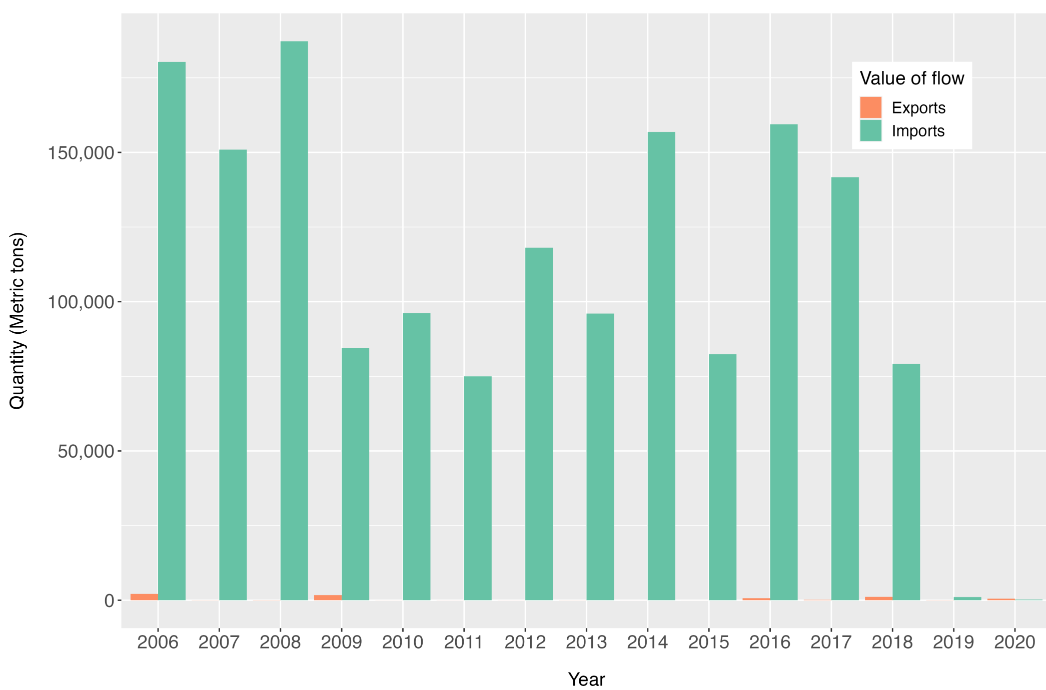


Figure 3. Cumulative number of domestic factories over time (Source: AFO Fertiliser Directory)

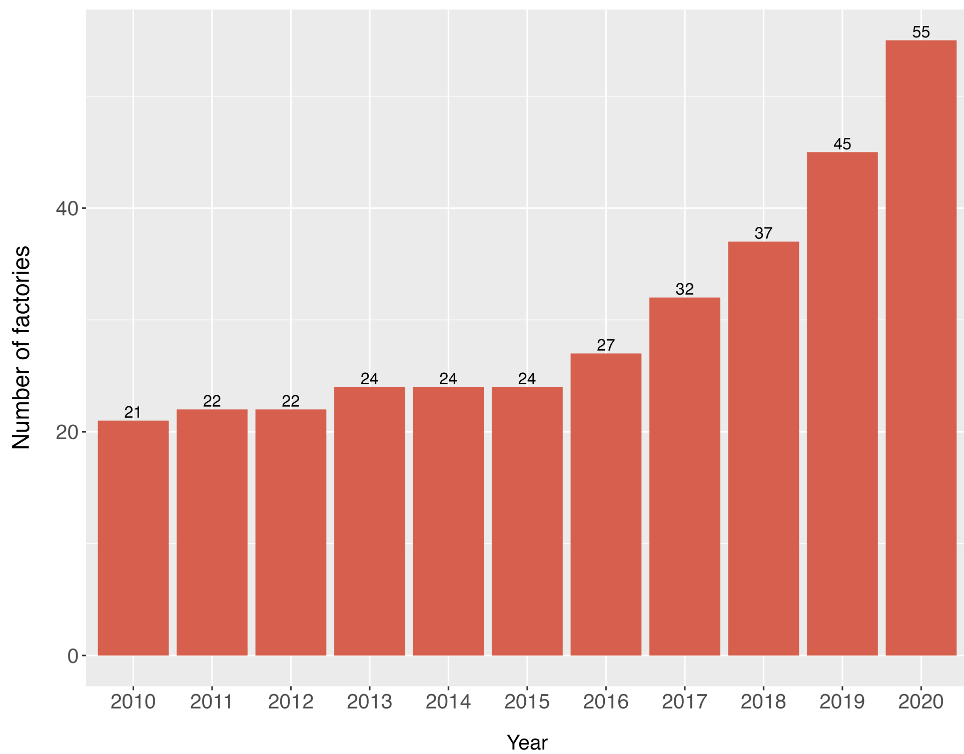
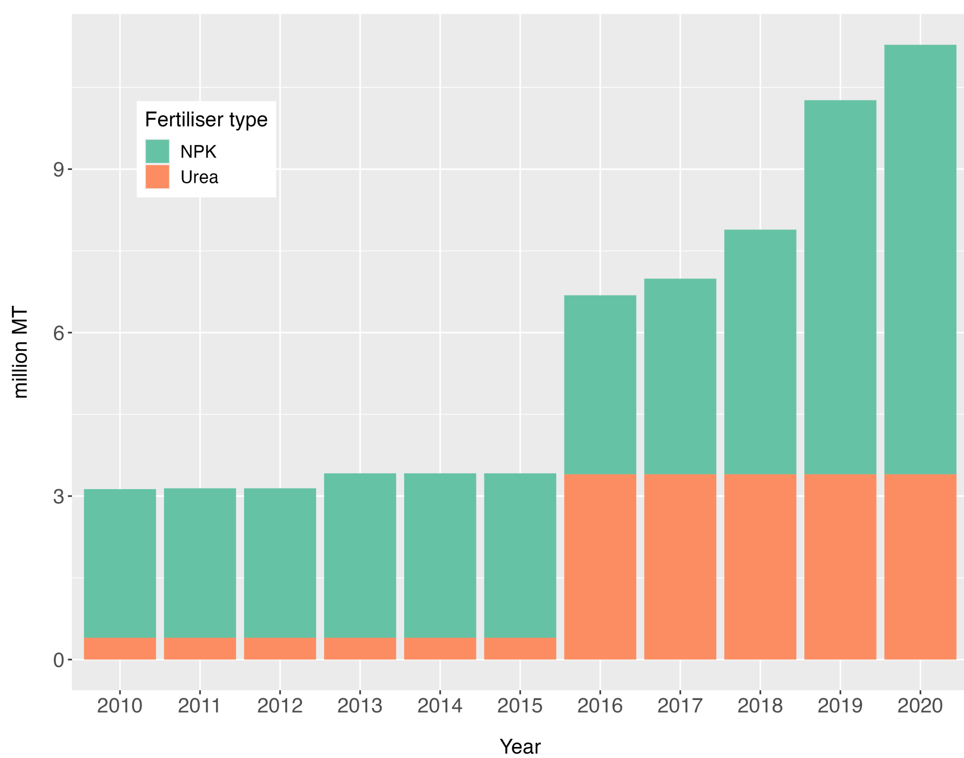


Figure 4. Total production capacity of domestic firms (Source: AFO Fertiliser Directory)



3 Theoretical framework: Model of farm production and input choice

In this section, I write a model linking changes in market access to fertiliser to adoption rates, expenditure shares, and crop yields. The model closely follows Aggarwal et al. (2022).

3.1 Model environment

Farmer f produces output (i.e. crops) using land, labour, and fertiliser bought from source j:

$$Y_{fj} = \theta_f K_{fj}^{\alpha} L_f^{\beta\gamma} M_{fj}^{\beta(1-\gamma)} \qquad \text{(1. Farm's production function)}$$

where

- Y_{fj} is output of farmer f
- θ_f is productivity of farmer f
- K_{fj} is land held by farmer f (fixed)
- L_{fj} is labour employed by farmer f
- M_{fj} is fertiliser purchased by farmer f from source j.
- α, $\beta\gamma$, $\beta(1-\gamma)$ are land, labour and fertiliser shares, respectively.

Farmer f employs labour at prevailing wage w and purchases fertiliser at price r_{fj}:

$$c_{fj} = wL_{fj} + r_{fj}M_{fj} \qquad \text{(2. Farm's variable cost function)}$$

where

- c_{fj} represents variable costs incurred by farmer f
- w is the prevailing wage
- r_{fj} is the price of fertiliser bought by farmer f from source j

3.2 Profit function

Given output prices and wages, farm maximises profits subject to cost c_{fj}:

$$\max_{\{L_{fj}, M_{fj}\}} \Pi_{fj} = pY_{fj} - c_{fj} \qquad \text{(3. Farm's profit function)}$$

Using (1) and (2), solve for optimal demand for labour and fertiliser:

$$L_{fj}^{*} = \left(\frac{\beta\gamma p \theta_f K_{fj}^{\alpha} M_{fj}^{\beta(1-\gamma)}}{w} \right)^{\frac{1}{1-\beta\gamma}} \qquad \text{(4. Optimal labour)}$$

$$M_{fj}^{*} = \left(\frac{\beta(1-\gamma) p \theta_f K_{fj}^{\alpha} L_{fj}^{\beta\gamma}}{r_{fj}} \right)^{\frac{1}{1-\beta(1-\gamma)}} \qquad \text{(5. Optimal fertiliser)}$$

Using optimal demand for inputs, I write profits as:

$$\Pi^*_{fj} = \tilde{\theta}_{fj} p^{\frac{1}{1-\beta}} w^{-\gamma \frac{1}{1-\beta}} r_{fj}^{-\sigma} K_{fj}^{\frac{\alpha}{1-\beta}} \quad \text{(6. Optimal profits)}$$

Equation (6) shows that farm profits are a function of:

- Productivity of farmer f buying from particular source j, $\tilde{\theta}_{fj}$
  - captures benefits to farmer f of purchasing from source j, e.g. suitability of particular fertiliser to soil of farmer, unobserved quality of fertiliser, other inputs or information acquired from source j.
- Output price p and prevailing wage w
- Price of fertiliser paid by farmer f buying from j, r_{fj} **(retail price)**
  - With elasticity $\sigma \equiv \frac{\beta}{1-\beta}(1-\gamma)$
- Land holdings of farmer f, K_{fj}

3.3 Profits when not using fertiliser (outside option)

As farmers have a choice not to adopt, I can write a profit function when farmer chooses not to use fertiliser:

$$\Pi_{f0} = \tilde{\theta}_{f0} p^{\frac{1}{1-\beta}} w^{-\frac{\beta}{1-\beta}} K_{f0}^{\frac{\alpha_0}{1-\beta_0}} \quad \text{(6.1 Optimal profits when not adopting)}$$

3.4 Retail prices and trade costs

Farmers choose whether to purchase fertiliser (adoption choice) and from where to source it (e.g. factory or port). I assume per-unit costs to farmer f buying from source j take iceberg form:

$$r_{fj} = r_j \tau_{fj} \quad \text{(7. Retail price)}$$

where

- r_j is the price of fertiliser set by source j
- τ_{fj} represents iceberg trade costs between farmer f and source j.

Here, trade costs drive a wedge between prices at the factory-gate and prices faced by farms.[6]

3.5 Distribution of farmer-source productivity

Assume the productivity of farmer f when buying from source j, $\tilde{\theta}_{fj}$, is a random variable that follows a Frétchet distribution:

[6]Alternatively, the price farms is equal to the sum of the price set by factories and a trade costs between farms and factories. $p_i = r_j(s, p_m) + \tau_{ij}$

$$\Pr(\tilde{\theta}_{fj} < \theta) = \exp(-T_j \theta^{-\varepsilon}) \tag{8}$$

where

- T_j is the location parameter (scale). A higher T_j means that a farmer is more likely to draw a high productivity for any good.
- ε is the dispersion parameter (shape). A larger ε implies less variability in productivity.

3.6 Unconditional distribution of profits

Using optimal profits (Equation 6), I write the unconditional distribution of profits for farmer f buying fertiliser from source j as:

$$\Pr(\Pi_{fj} < \pi) = \Pr\left(\tilde{\theta}_{fj} p^{\frac{1}{1-\beta}} w^{-\gamma\frac{1}{1-\beta}} r_{fj}^{-\sigma} K_{fj}^{\frac{\alpha}{1-\beta}} < \pi\right) \tag{9.1}$$

Isolating the random variable on the left hand side of the probability:

$$\Pr(\Pi_{fj} < \pi) = \Pr\left(\tilde{\theta}_{fj} < p^{-\frac{1}{1-\beta}} w^{\gamma\frac{1}{1-\beta}} r_{fj}^{\sigma} K_{fj}^{-\frac{\alpha}{1-\beta}} \pi\right) \tag{9.2}$$

Since productivity, $\tilde{\theta}_{fj}$, is distributed à la Frétchet, we can rewrite this as:

$$\Pr(\Pi_{fj} < \pi) = \exp\left(T_j p^{\frac{\varepsilon}{1-\beta}} w^{-\varepsilon\gamma\frac{1}{1-\beta}} r_{fj}^{-\varepsilon\sigma} K_{fj}^{\frac{\varepsilon\alpha}{1-\beta}} \pi^{-\varepsilon}\right) \tag{9.3}$$

I also write the unconditional distribution of profits when farmer f does not purchase fertiliser:

$$\Pr(\Pi_{f0} < \pi) = \exp\left(T_0 p^{\frac{\varepsilon}{1-\beta}} w^{-\varepsilon\gamma\frac{1}{1-\beta}} K_{f0}^{\frac{\varepsilon\alpha}{1-\beta}} \pi^{-\varepsilon}\right) \tag{9.4 When not adopting}$$

3.7 Adoption probabilities

Following Train (2009), the probability that farmer f buys from source j is:

$$\lambda_{fj} = \Pr(\Pi_{fj} > \Pi_{f\ell}) \qquad \forall j \neq \ell \tag{10.1}$$

In other words, farmer f buys from source j when her profits from purchasing fertiliser from source j are higher than sourcing from source ℓ.

Using optimal profits (Equation 6), we can rewrite this probability:

$$\lambda_{fj} = \Pr\left(\tilde{\theta}_{fj} p^{\frac{1}{1-\beta}} w^{-\gamma\frac{1}{1-\beta}} r_{fj}^{-\sigma} K_{fj}^{\frac{\alpha}{1-\beta}} > \tilde{\theta}_{f\ell} p^{\frac{1}{1-\beta}} w^{-\gamma\frac{1}{1-\beta}} r_{f\ell}^{-\sigma} K_{f\ell}^{\frac{\alpha}{1-\beta}}\right) \tag{10.2}$$

We can eliminate terms that do not vary across farmers and sources:

$$\lambda_{fj} = \Pr\left(\tilde{\theta}_{fj} r_{fj}^{-\sigma} K_{fj}^{\frac{\alpha}{1-\beta}} > \tilde{\theta}_{f\ell} r_{f\ell}^{-\sigma} K_{f\ell}^{\frac{\alpha}{1-\beta}}\right) \tag{10.3}$$

We rewrite the probability, flipping the inequality:

$$\lambda_{fj} = \Pr\left(\tilde{\theta}_{f\ell} r_{f\ell}^{-\sigma} K_{f\ell}^{\frac{\alpha}{1-\beta}} < \tilde{\theta}_{fj} r_{fj}^{-\sigma} K_{fj}^{\frac{\alpha}{1-\beta}}\right) \tag{10.4}$$

We place error terms on the left hand side:

$$\lambda_{fj} = \Pr\left(\frac{\tilde{\theta}_{f\ell}}{\tilde{\theta}_{fj}} < \frac{r_{fj}^{-\sigma}}{r_{f\ell}^{-\sigma}} \frac{K_{fj}^{\frac{\alpha}{1-\beta}}}{K_{f\ell}^{\frac{\alpha}{1-\beta}}}\right) \tag{10.5}$$

If the productivity terms are independent, the cumulative distribution over all $j \neq \ell$ is the product of the individual cumulative distributions:[7]:

$$\lambda_{fj} \mid \tilde{\theta}_{fj} = \prod_{j \neq \ell} \exp\left(\left(\frac{T_j}{T_\ell}\right)\left(\frac{r_{fj}}{r_{f\ell}}\right)^{\varepsilon\sigma}\left(\frac{K_{fj}}{K_{f\ell}}\right)^{-\varepsilon\frac{\alpha}{1-\beta}}\right) \tag{10.6}$$

The choice probability is the integral of $\lambda_{fj} \mid \tilde{\theta}_{fj}$ over all values of $\tilde{\theta}_{fj}$ weighted by its density:

$$\lambda_{fj} = \int_{-\infty}^{\infty}\left(\prod_{j \neq \ell} \exp\left(\left(\frac{T_j}{T_\ell}\right)\left(\frac{r_{fj}}{r_{f\ell}}\right)^{\varepsilon\sigma}\left(\frac{K_{fj}}{K_{f\ell}}\right)^{-\varepsilon\frac{\alpha}{1-\beta}}\right)\right) f(\tilde{\theta}_{fj}) d\tilde{\theta}_{fj} \tag{10.7}$$

Simplifying this:

$$\lambda_{fj} = \frac{T_j r_{fj}^{-\sigma\varepsilon} K_{fj}^{\varepsilon\frac{\alpha}{1-\beta}}}{T_0\left(\frac{\pi_0}{\pi}\right)^{\varepsilon} + \sum_\ell T_\ell r_\ell^{-\sigma\varepsilon} K_{f\ell}^{\varepsilon\frac{\alpha}{1-\beta}}} \tag{10.8}$$

Summing across j to obtain probability of adoption by farmer f from any source:

$$\mu_f = \frac{\sum_j T_j r_{fj}^{-\sigma\varepsilon} K_{fj}^{\varepsilon\frac{\alpha}{1-\beta}}}{T_0\left(\frac{\pi_0}{\pi}\right)^{\varepsilon} + \sum_\ell T_\ell r_\ell^{-\sigma\varepsilon} K_{f\ell}^{\varepsilon\frac{\alpha}{1-\beta}}} \tag{11}$$

3.8 Defining market access

I define farmer f's market access to fertiliser as:

$$\text{MA}_f \equiv \sum_j T_j r_{fj}^{-\sigma\varepsilon} \tag{12.1}$$

[7]We also know the product of two random variables distributed à la Frétchet also follows a Fretchet distribution

Using the definition of the retail price (Equation 7):

$$\text{MA}_f \equiv \sum_j T_j \left(r_j \tau_{fj}\right)^{-\sigma\varepsilon} \tag{12.2}$$

This term is a function of:

- Trade costs between farmer f and source j, τ_{fj}
- Retail prices r_j

This market access term captures the two effects of the import substitution policy: the effect on prices set by sources (factories and port) and the trade costs between farmers and sources. In other words, import substitution exerts an effect on the probability of adoption via changes in retail prices and trade costs.

3.9 Connecting market access and adoption rates

Using (12.2), I rewrite the probability of adopting fertiliser as:

$$\mu_f = \frac{\text{MA}_f K_{fj}^{\varepsilon \frac{\alpha}{1-\beta}}}{T_0 \left(\frac{\pi_0}{\pi}\right)^{\varepsilon} + \text{MA}_f K_{f\ell}^{\varepsilon \frac{\alpha}{1-\beta}}} \tag{13}$$

This equation connects changes in market access and the probability of adopting fertiliser. The probability that a particular farm i adopts fertiliser sourced from factory j depends on the price of fertiliser set by factory j and the trade costs between the farm i and factory j.

This equation can be directly taken to the data by estimating a binary model, i.e. regressing the probability of adoption (0/1).

To see this another way, I define value of variable after the policy as x', I take the log changes of both sides:

$$\log\left(\frac{\mu'_f}{\mu_f}\right) = \log\left(\frac{\text{MA}'_f}{\text{MA}_f}\right) - \log\left(1 + \mu_f \left(\frac{\text{MA}'_f}{\text{MA}_f} - 1\right)\right) \tag{14}$$

This equation shows how log changes in adoption is a function of:

- log changes in market access (first term)
- a non-linear function of the interaction between percent change in market access, $\left(\frac{\text{MA}'_f}{\text{MA}_f} - 1\right)$, and baseline adoption probability μ_f (second term)

4 Testable predictions

In line with the framework above, I make two predictions:

Proposition 1. Input market access and fertiliser adoption rates.: *Farms that have greater market access to fertiliser sources have higher adoption rates, on both the extensive and intensive margin.* This second prediction tests whether farms with greater access to fertiliser sources adopt fertiliser at higher rates. I define adoption in two ways: whether or not a farm applies inorganic fertiliser to a particular plot (extensive margin of adoption) and the quantity of fertiliser applied to a plot (intensive margin of adoption). The relevant hypothesis is:

$$\uparrow \text{Market access to fertiliser} \Rightarrow \uparrow \text{Fertiliser adoption rates (intensive and extensive margin)}$$

Proposition 2. Input market access and crop yields.: *Crop yields are higher among farms with greater access to sources of fertiliser relative to farms with weaker access.* This is the key prediction of the paper. Here, I compare the value of crop yields of households that enjoy greater access to fertiliser to those with weaker access. The hypothesised relationship is:

$$\uparrow \text{Market access to fertiliser} \Rightarrow \uparrow \text{Value of crop yields}$$

I now bring these propositions to data in the remaining sections.

5 Data sources and variable construction

5.1 Household data

To construct measures of fertiliser adoption and agricultural productivity, I use data from the panel sample of households from Nigeria's General Household Survey (GHS).[8] The GHS is representative of households at the national level and at the level of Nigeria's six geopolitical zones. I use data from four waves of the survey: 2010/11 (Wave 1), 2012/13 (Wave 2), 2015/16 (Wave 3) and 2018/19 (Wave 4). In each wave, households are visited after the planting season (between July and September) and after the harvest season (between January and February). Information on plot preparation and inputs used for planting is collected after planting season while information on crops harvested is collected after harvest season.

Data from the household survey serves three purposes: First, it provides detailed measures of farm inputs and outputs which allows me to construct physical measures of factor inputs and outputs at the plot-level. Second, as the survey tracks a sample of households across four waves, I can identify which households experienced greater changes in input market access and observe corresponding changes in their input expenditures, productivity and other relevant outcomes. Finally, I use information on crop production shares in the survey to construct the initial distribution of crop production.

5.2 Factory and port data

I obtain data on the location of fertiliser plants from a directory of fertiliser plants compiled by AfricaFertilizer (AFO), a project of the International Fertiliser Development Centre (IFDC). The directory identifies the locations of operational manufacturing and processing plants across Sub-Saharan Africa (Link here).

[8] The GHS belongs to a series of surveys implemented with the World Bank Living Standards Measurement Study - Integrated Surveys on Agriculture program (LSMS-ISA). A detailed description of the survey can be found in Dillon et al. 2021.

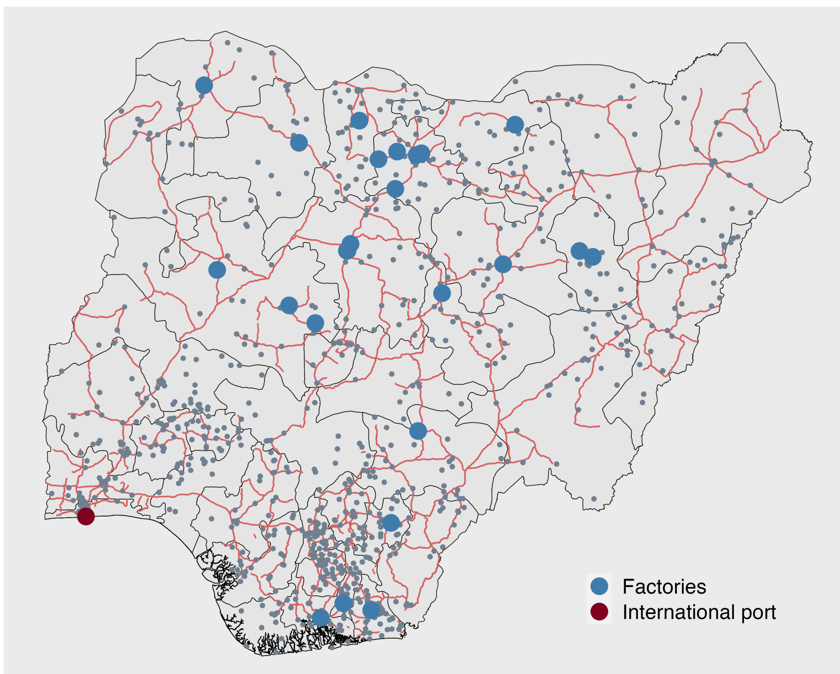
The dataset also provides the production capacity of the factory, the year the factory began operations, and the type of fertiliser blend produced.

To identify the coordinates of the international port of entry, I geocode the address of the port available on the records of the Nigerian customs authority (Nigeria Customs Service 2023). Figure 5 plots the coordinates of factories and the port. While farms are widely dispersed across space (farms represented by the gray points), factories tend to locate in similar locations.

5.3 Distance data and the road network

I use two measures of distance, the first based on simple geographic distance along Nigeria's road network as calculated by Open Street Map (OSM). OSM collects the network of primary and secondary highways in the country. To capture the quality of the road network, I rely on a second measure of distance based on travel times. OSM calculates the duration between origins and destinations based on the travel speeds.

Figure 5. Coordinates of factories, farms and the port (Source: AFO, LSMS-ISA, Nigeria Customs



5.4 Constructing crop yields and prices from farm output and input variables

In order to capture productivity at the household level, I construct a measure of crop yields based on the reported data on gross output. One measurement challenge here is that households report nominal values for outputs (revenue). Because the measures must be comparable across households and over time, variables must be expressed in terms of their real value. I briefly describe its construction here.

Value of crop yields. Households report the quantity of the crops they produce and sell (in kilograms) and the value at which they sell these crops (in local currency). To obtain a measure of real gross output, I must ensure that values are comparable across households and over time by removing regional and year variations in prices. To this end, I first construct a household-level price defined as value divided by quantity for every crop in a given year. I then take the crop-specific median price across all farms in a given year. I then use this quantity-weighted median price across all years as a common price to value crop quantities for each household.

Finally, as households may operate several plots of land and produce more than one type of crop, I aggregate output at the household level.

Retail prices. Households report the quantity of fertiliser bought from commercial sources (kg) and total amount paid for fertiliser from commercial sources (in local currency). I calculate retail price as total amount paid for fertiliser divided by quantity of fertiliser bought. To ensure prices are market-based, I only consider fertiliser bought from commercial sources and not from informal networks in the village (e.g. family, friends, community). An important note here is that prices are not observed for households that did not use fertiliser. Therefore, there are systematically fewer price observations in areas where fewer households bought fertiliser.

6 Empirical framework

6.1 Measuring input market access

To capture changes in input market access brought about by the policy, I construct two measures of input market access motivated by the literature. The measures should reflect changes in both trade costs and domestic supply as more fertiliser factories enter the market while imports become prohibited at the port in Nigeria's capital, Lagos.

6.1.1 Measure 1: Inverse of distance to nearest fertiliser source

The first measure corresponds to a simple notion of geographic distance between farms and input sources. I compute each farm i's distance to the nearest source of fertiliser at time t along Nigeria's transportation network. Sources of fertiliser refer to either domestic factories that produce fertiliser or the international port of entry.

$$MA_{it} = 1/\min\left\{d_{ijt}, ...d_{iJt}\right\}$$

where d_{ijt} is the distance of household i to source j at time t.

Figure 6 shows that the mean distance to the nearest NPK source across all households has fallen over time. This means that overall, sources of fertiliser are now closer to farms. The sharp decrease in the distance between 2016 and 2017 is consistent with the fact that five (5) factories entered the market (See Fact 2 in Section 2). In contrast, Figure 7 shows that for urea sources, the mean distance to the nearest urea source rose in 2017 (as a result of the import ban on urea) and fell in 2021 when another factory entered the market.

6.1.2 Measure 2: Distance-weighted production capacity

Second, I construct a measure of market access that captures changes in the production capacity of domestic fertiliser producers. To construct the measure for each household i, I weight the production capacity of each fertiliser source by the distance from the household to the source.

$$MA_{it} = \sum_{j} \left(\tau_{ij}\right)^{-1} Y_j$$

where τ_{ij} is the distance from household i to source j while the term Y_j represents the total production capacity of source j.

Note that the port also serves as a source of fertiliser before the import ban. As a proxy for the production capacity of the port, I use the mean volume (MT) of urea and NPK imports across the previous five years before the ban. In other words, I assume that the size of Nigeria's imports of fertiliser before the ban corresponds to the loss in production capacity after the ban.[9]

Household i has greater market access when (1) it is cheaper to travel to source j and (2) if source j enjoys greater fertiliser production. Changes in this measure summarise how changes in domestic fertiliser production, due to the industrial policy, affect districts. This measure is an analogue of Harris' (1954) index where potential for goods in any one location depends on the distance-weighted GDP of all locations. [10] Empirically, we can interpret the distances from farms to sources as shares that capture differentially exposure to expansion in fertiliser production (a shock).

In Figure 8, we can clearly see that market access to NPK sources has been increasing over time. The upward trend post 2016 reflects the entry of NPK producers. For urea, Figure 9 shows market access rises when a large factory enters in 2016 and falls slightly when the import ban takes place in 2017. Market access increases again when another factory enters in 2021.

[9] Sourced from CEPII-BACI trade data: around 300,000 MT for NPK and 250,000 MT for urea

[10] Donaldson and Hornbeck (2016) show a similar measure can be derived from workhorse GE trade models (Eaton and Kortum 2002).

Figure 7. Mean distance of households to nearest NPK source (Source: Author's own calculations)

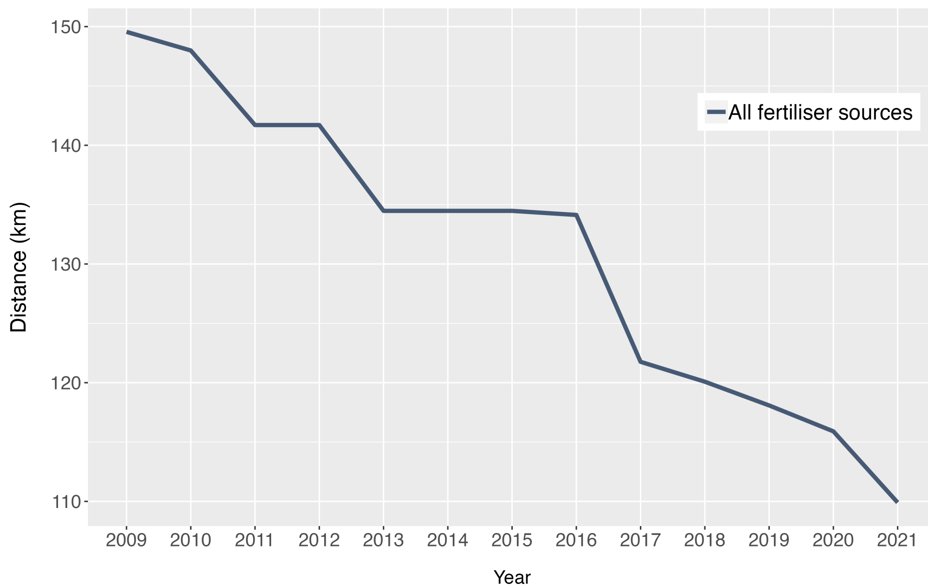


Figure 8. Mean distance of households to nearest Urea source (Source: Author's own calculations)

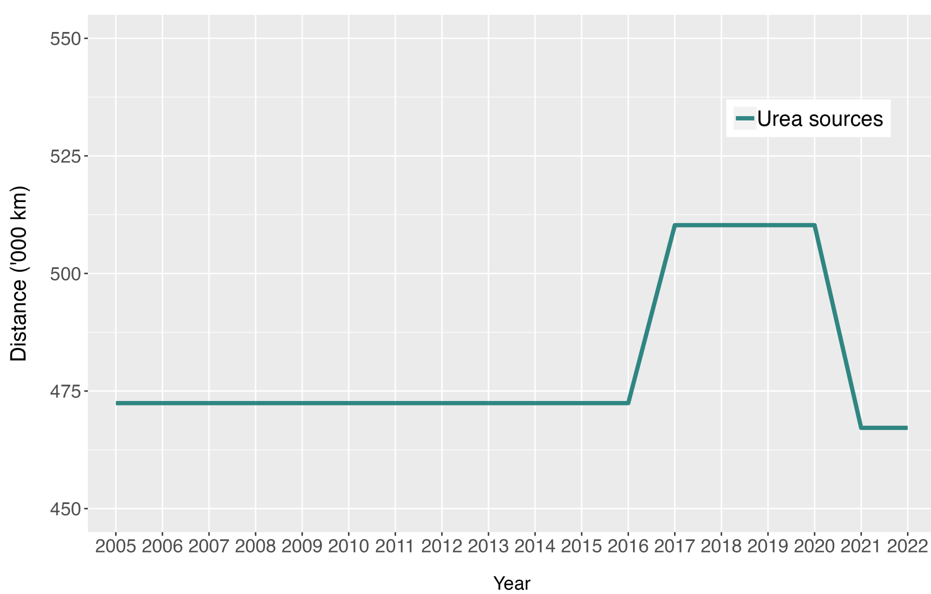


Figure 9. Market access to NPK sources (Source: Author's own calculations)

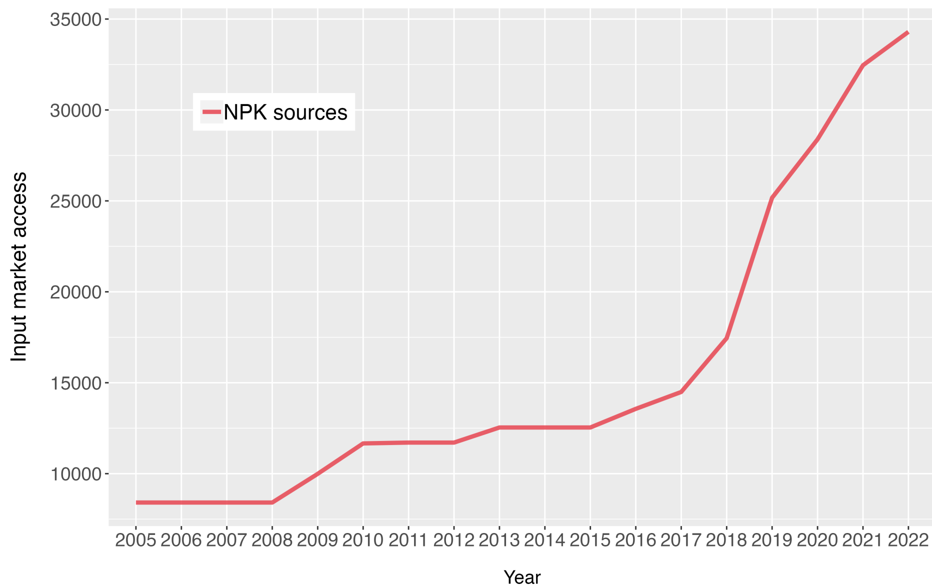
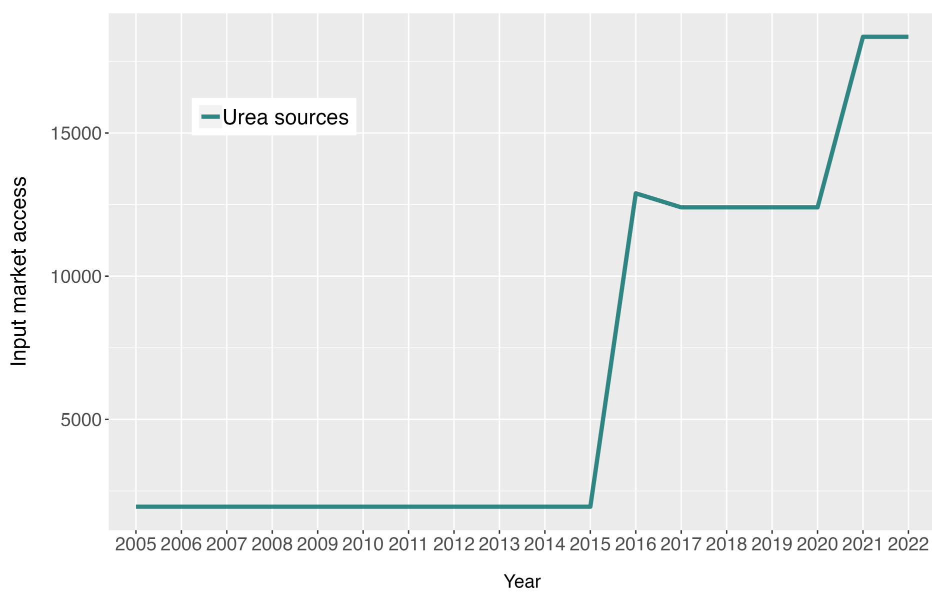


Figure 10. Market access to Urea sources (Source: Author's own calculations)



6.2 Estimating equations

6.2.1 Proposition 1: Fertiliser adoption

I first compare fertiliser adoption among households more exposed to the policy to those less exposed by estimating the following equation:

$$y_{mit} = \beta\, \mathrm{MA}_{it} + \gamma_i + \mu_t + \varepsilon_{mit} \tag{1}$$

where y_{mit} is measure of fertiliser adoption for plot m owned by household i at time t. I measure adoption in two ways:

- Extensive margin: Whether fertiliser is applied to plot (1/0)
- Intensive margin: Quantity of fertiliser applied to plot per unit of cultivated land (kg / ha)

Recall MA_{it} is the measure of market access to fertiliser for household i at time t. Household fixed effects, represented by the term γ_i, control for time-invariant heterogeneity across households (i.e. land quality). The term μ_t represents year fixed effects which account for any shocks at the national level coinciding with the policy (time-varying unobservables that vary across households). Finally, ϵ_{mit} is an idiosyncratic error term.

The key parameter of interest here is the coefficient on the market access term, β. If $\beta > 0$, then greater market access is associated with a higher probability of adoption. When the outcome of interest is adoption at the extensive margin (binary outcome), I estimate Equation 1 using a linear probability model (LPM). For the intensive margin, I use a Poisson estimator as the zeros are meaningful. I cluster standard errors at the household level.

6.2.2 Proposition 2: Agricultural productivity

To compare the productivity of farms with high market access to farms with low market access, I estimate the following equation:

$$\mathrm{yields}_{it} = \beta\, \mathrm{MA}_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{4}$$

where yields_{it} is the crop yield of farm i at time t. The terms γ_i and μ_t represent household and year fixed effects, respectively. Finally, ϵ_{it} is an idiosyncratic error term.

Again, I am interested in estimating coefficient on the market access term, β. When $\beta > 0$, households with greater market access to fertiliser enjoy higher crop yields.

7 Main results

I now present the main estimates. The goal of this analysis is to estimate the effects of change in market access to fertiliser on adoption rates (Proposition 1) and crop yields (Proposition 2).

7.1 Effects of changes in input market access on adoption rates

I then look at whether the import substitution policy led farms to adopt inorganic fertiliser. As described in Section 6, this exercise looks at both the extensive margin of adoption – whether a farm applies fertiliser to a particular plot – and the intensive margin of adoption – the quantity of fertiliser a farmer applies to her plots.

7.1.1 Measure 1: Inverse distance

Table 1 reports the estimates of the effect of inverse distance to the nearest source of fertiliser on the extensive margin of adoption. Each column indicates a specification where adoption of a specific type of fertiliser is regressed on inverse distance (including farm-household and year fixed effects). As Proposition 1 indicates, I expect greater adoption rates among households closer to fertiliser sources.

Estimates in Column (1) of Table 1 indicate that farms closer to sources of NPK are more likely to apply NPK fertiliser to their plots. In particular, a one unit increase in the inverse distance raises the likelihood a farm adopts NPK by 0.4 percentage points. Similarly, a one unit increase in inverse distance to a urea source raises the probability of adopting urea by 1.6 percentage points. This means that that policy induced adoption of both types of fertiliser along the extensive margin.

In Columns (3) and (4) of Table 1, I run a placebo test regressing the extensive margin of adoption – whether or not a farmer applied organic fertiliser – on inverse distance. The results indicate that distance to the nearest source of NPK or urea is unrelated to the probability of applying organic fertiliser to a particular plot.

Table 2 now reports estimates of the effect of inverse distance on the intensive margin of adoption. I find that access to sources of NPK matter for the intensive margin of adoption. Column (2) indicates that the closer a particular plot is to a source of urea, the greater the intensity of urea applied to this plot. In Column (1), I find that the sign of the estimates of the effect on the application rate of NPK is consistent with what theory predicts (positive sign), but the coefficients are not precisely estimated.[11]

In Columns (3) and (4) of Table 2, I run another placebo test regressing application rates of organic fertiliser on inverse distance measures. Similarly, application intensity rates of organic fertiliser are unrelated to distance to sources of NPK or urea.

7.1.2 Measure 2: Distance-weighted production capacity

I now use another measure of input market access: each household's exposure to fertiliser production weighted by distance. Table 3 shows the estimates of this measure on the extensive margin of adoption. From Column (1), I find that the greater a household's access to a source of NPK fertiliser, the higher the probability that the farmer applies NPK fertiliser to a particular plot. Similarly, Column (2) indicates that access to urea sources has a positive effect on urea adoption.

Finally, Table 4 shows the estimates of distance-weighted production capacity on the intensive margin of adoption. Consistent with the estimates with inverse distance as measure of market access, the greater the household's access to a source of NPK, the greater the intensity of NPK applied to a particular plot. In contrast, estimates of urea intensity rates are imprecisely estimated but the sign is

[11] Standard errors rise after clustering at the household level.

consistent with theoretical predictions.

Placebo tests in Columns (3) and (4) in Tables 3 and 4 show that measures of market access to either NPK or Urea sources are unrelated to the extensive and intensive margin of adoption.

7.2 Effects of changes in input market access on crop yields

I now turn to the effect of the policy on crop yields. Table 5 reports estimates of the effect of input market access on crop yields using inverse distance while Table 6 shows the same estimates but with distance-weighted production capacity as a measure of market access. Both measures indicate that farms with greater access to NPK sources have higher yields. In contrast, both measures of access to urea sources are unrelated to crop yields.

Table 1. Effect of inverse distance on the extensive margin – whether fertiliser is applied to plot (1/0)

	NPK	Urea	Organic	
	(1)	(2)	(3)	(4)
Inverse distance to nearest NPK source	0.004**		-0.001	
	(0.002)		(0.001)	
Inverse distance to nearest Urea source		0.016***		0.0003
		(0.004)		(0.002)
Household FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
N	4,014	4,014	4,014	4,014
R^2	0.498	0.457	0.616	0.616
Adjusted R^2	0.359	0.307	0.510	0.510
Residual Std. Error (df = 3145)	0.347	0.308	0.285	0.285
F Statistic (df = 868; 3145)	3.592***	3.045***	5.807***	5.804***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 2. Effect of inverse distance on the intensive margin – quantity applied to plot (kg per hectare)

	NPK	Urea	Organic	
	(1)	(2)	(3)	(4)
Inverse distance to nearest NPK source	0.002		0.009	
	(0.008)		(0.009)	
Inverse distance to nearest Urea source		2.989***		0.653
		(0.600)		(1.121)
Household FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
N	4,014	4,014	4,014	4,014

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 3. Effect of distance-weighted production capacity on extensive margin – whether fertiliser is applied to plot (1/0)

	NPK	Urea	Organic	
	(1)	(2)	(3)	(4)
NPK sources	0.290***		0.104	
	(0.099)		(0.091)	
Urea sources		0.050*		-0.017
		(0.030)		(0.032)
Household FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
N	4,014	4,014	4,014	4,014
R^2	0.498	0.456	0.616	0.616
Adjusted R^2	0.360	0.306	0.510	0.510
Residual Std. Error (df = 3145)	0.347	0.308	0.285	0.285
F Statistic (df = 868; 3145)	3.601***	3.042***	5.811***	5.805***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 4. Effect of distance-weighted production capacity on intensive margin – quantity applied to plot (kg per ha)

	NPK	Urea	Organic	
	(1)	(2)	(3)	(4)
NPK sources	1.242*		2,555	
	(0.638)		(9,379)	
Urea sources		0.372		-144.524
		(1.185)		(11,844)
Household FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
N	1,004	654	843	843
R^2	0.666	0.688	0.497	0.497
Adjusted R^2	0.420	0.405	0.170	0.170
Residual Std. Error	1.088 (df = 578)	1.030 (df = 342)	12,637 (df = 510)	12,638 (df = 510)
F Statistic	2.711***	2.429***	1.520***	1.520***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 5. Effect of inverse distance on crop yields – gross output per unit of cultivated land

	Crop yields	
	(1)	(2)
Inverse distance to nearest NPK source	1.152***	
	(0.279)	
Inverse distance to nearest Urea source		0.223
		(0.666)
Household FEs	Yes	Yes
Time FEs	Yes	Yes
N	1,682	1,682
Notes:	***Significant at the 1 percent level.	
	**Significant at the 5 percent level.	
	*Significant at the 10 percent level.	

Table 6. Effect of distance-weighted production capacity on crop yields – gross output per unit of cultivated land

	Crop yields	
	(1)	(2)
NPK sources	1.696***	
	(0.466)	
Urea sources		0.077
		(0.442)
Household FEs	Yes	Yes
Time FEs	Yes	Yes
N	1,596	1,596
R^2	0.625	0.619
Adjusted R^2	0.191	0.178
Residual Std. Error (df = 739)	1.270	1.280
F Statistic (df = 856; 739)	1.441***	1.403***
Notes:	***Significant at the 1 percent level.	
	**Significant at the 5 percent level.	
	*Significant at the 10 percent level.	

8 Mechanisms

8.1 Mechanisms: Effects of changes in input market access on fertiliser retail prices

What channel is driving the effect of market access on fertiliser adoption and yields? I begin with retail prices. Theory tells that market access lowers retail prices. Empirically, I test whether changes in market access had an effect on the prices of fertiliser household paid. Retail prices of a particular type of fertiliser are constructed by dividing the household's expenditure on fertiliser by the quantity of fertiliser purchased from commercial sources.[12]

Note that I cannot observe expenditures and quantities purchased for households that do not use inorganic fertiliser. In one specification, I restrict the sample to only farms who purchased fertiliser to exclude zero purchases of fertiliser in the regression. In another specification, I construct a proxy price for zero purchases equal to the maximum price plus one standard deviation. Here, I assume that households that do not purchase fertiliser face prohibitive retail prices.

Table 7 reports estimates of the effect of inverse distance on log retail prices by type of fertiliser. Estimates in Columns (2) and (4) suggest that the closer a household is to nearest source of NPK, the lower the retail price of NPK faced by the household. A similar result holds for urea. While I do not obtain a precise estimate of the coefficient when I exclude zero purchases, the sign of the estimate is consistent with theory.

Now, Table 8 reports estimates of the effect of input market access on log retail prices by type of fertiliser. Estimates in Columns (2) and (4) suggest that the closer a household is to nearest source of NPK, the lower the retail price of NPK faced by the household. A similar result holds for urea. While I do not obtain a precise estimate of the coefficient when I exclude zero purchases, the sign of the estimate is consistent with theory.

[12] This definition excludes fertiliser obtained informally through family/friends/community or via government input subsidy programmes.

Table 7. Effect of inverse distance on retail prices

	NPK exc. 0 purchases	NPK proxy price	Urea exc. 0 purchases	Urea proxy price
	(1)	(2)	(3)	(4)
Inverse distance to NPK sources	-0.021	-0.161^{***}		
	(0.037)	(0.036)		
Inverse dist to Urea sources			-0.162	-0.256^{***}
			(0.295)	(0.049)
State FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
N	1,940	6,785	1,289	6,785
R^2	0.083	0.212	0.103	0.210
Adjusted R^2	0.065	0.207	0.082	0.205
Residual Std. Error	1.043	1.736	1.161	1.481
F Statistic	4.627^{***}	47.695^{***}	4.818^{***}	47.087^{***}

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 8. Effect of distance-weighted production capacity on retail prices

	NPK exc. 0 purchases	NPK proxy price	Urea exc. 0 purchases	Urea proxy price
	(1)	(2)	(3)	(4)
Market access to NPK sources	0.144	-0.532^{***}		
	(0.079)	(0.091)		
Market access to Urea sources			0.002	-0.134^{**}
			(0.343)	(0.056)
State FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
N	1,940	6,785	1,289	6,785
R^2	0.084	0.214	0.103	0.209
Adjusted R^2	0.066	0.209	0.081	0.204
Residual Std. Error	1.042	1.733	1.161	1.482
F Statistic	4.692^{***}	48.280^{***}	4.807^{***}	46.780^{***}

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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