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Good for Business, Not So Much for the Environment? Entry Into Importing and the Energy Intensity of Indian Plants

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Abstract

The global fragmentation of production has important implications for the environment. As emerging economies increase their participation in trade, scale effects increase environmental impacts worldwide. Yet at the same time, access to international markets might help offset these impacts by increasing the efficiency of production. Existing literature suggests that trading firms tend to be more energy efficient than non-traders. However, this literature does not take into account the effect of firms' product baskets. In this paper, we leverage a rich plant- and product-level database from India to investigate the effects of importing on plant-level-environmental outcomes. We first construct a measure of energy efficiency that is net of effects arising from plants' product baskets. We then use an event study set up to compare outcomes between importers and future importers at the time of their entry into import markets. Our design takes advantage of plants' staggered entry into importing to address issues of selection. Our findings suggest that after they start importing, plants experience increases in their energy intensity. Plants which start importing also grow larger and more productive and diversify their product baskets. Our results suggest that access to international markets leads to gains in scale and productivity, but not in environmental performance. This finding suggests that there is an environmental cost to learning and product diversification.

Keywords

International Trade, Energy Intensity, Product Basket, Event Study
JEL Codes: D22, F10, F14, F18, O11, 033

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1. Introduction

India's economy has grown at a sustained and rapid pace over the past two decades, although discussion continues into the causes and the future of India's growth experience (Kohli, 2006; Basu and Maertens, 2007; Kumar and Subramanian, 2012; Chatterjee and Subramanian, 2020). Economic growth has raised per capita incomes, but it has also turned India into the world's third largest and second fastest-growing emitter of CO2, just behind China and the US (IPCC, 2022). Heavy reliance on coal for electricity generation compounds the problem (Ortega-Ruiz et al., 2020). Shifts in the country's energy mix—away from coal and towards natural gas and renewable energy—and investments in the efficiency of energy generation and use are thus considered important policy priorities for the Indian economy (Wang et al., 2018; Ortega-Ruiz et al., 2020; Hubacek et al., 2021).

Under IMF pressure, India started liberalizing its trade regime in 1991 by gradually lowering tariffs and reforming the import quota system (Kohli, 2006). The country has greatly increased its participation in global trade flows since then, with scholars pointing to productivity gains (Topalova and Khandelwal, 2011) and a sizeable growth in exports (Chatterjee and Subramanian, 2020) as a result of liberalization. In this paper, we ask whether international trade has also improved the energy efficiency of Indian producers. Theory suggests that international trade should affect the environment through effects related to the scale, composition, and efficiency of production (Cherniwchan et al., 2017; Copeland et al., 2021). Insofar as it enables firms to scale up production, international trade directly contributes to increasing energy use and emissions.

A related concern is that following liberalization, polluting industries—which tend to face, on aver- age, lower tariff and non-tariff barriers to trade (Shapiro, 2020)—based in industrialized economies would choose to offshore energy-intensive activities to emerging and developing economies in order to evade strict environmental regulation at home (Cherniwchan et al., 2017)[1]. Yet at the same time, access to international markets can also make production more efficient by pushing less efficient firms out of the market (Melitz, 2003; Bernard et al., 2003; Martin, 2011) or by improving access to new technologies that make local production processes more efficient (Goldberg et al., 2010; Kasahara and Rodrigue, 2008; Imbruno and Ketterer, 2018).

A growing literature leverages micro-level panel data to investigate this last channel. This literature asks whether trading firms are more energy and emission efficient than their non-trading counterparts. The majority of these studies focus on exporters, in both industrialized (Batrakova and Davies, 2012; Cui et al., 2016; Holladay, 2016; Forslid et al., 2018; Dussaux et al., 2020) and developing and emerging economies (Barrows and Ollivier, 2021; Pei et al., 2021; Blyde and Ramirez, 2021). These studies consistently find that exporters are generally less polluting than non-exporters, either because they are more productive and therefore use all inputs, including energy, more efficiently (Martin, 2011) or because their larger size enables them to invest in abatement activities (Forslid et al., 2018).

Evidence on firms' importing behaviour is more limited, with only a handful of studies focusing on the role of imports in driving environmental performance at the micro level (Cherniwchan, 2017; Imbruno and Ketterer, 2018). Yet importing represents a potentially important learning avenue. Access to inputs available on international markets might enable firms to switch to more productive and energy efficient technologies than those available domestically, particularly through access to intermediate inputs (Amiti and Konings, 2007; Goldberg et al., 2010; Abreha, 2019) and capital goods (Mo et al., 2021). With this paper, we provide novel evidence on the effects of imports on the environmental performance of plants in a large emerging economy.

To study the effects of imports on micro-level environmental performance, we leverage data from the Annual Survey of Industries (ASI), an official survey of formal manufacturing plants in India, over the 2000-2016 period. Arguably, ASI data represents the ideal setting to study our question. It provides detailed data on plants' expenditure on electricity and different types of fuel (including petrol and diesel). We also have access to information on plants' domestic and international sourcing behaviour, and on their production activity. Data on trade and production is available at the five- digit product level.

We follow the literature on international trade and the environment and focus on energy intensity as a proxy for plants' environmental performance (Batrakova and Davies, 2012; Imbruno and Ketterer, 2018). We take one step further, however, and

1 There is no evidence in favour of the strong version of the pollution haven hypothesis, which sees offshoring as being driven by environmental regulation. Yet offshoring has certainly brought about a growing disconnect between production- and consumption-based emission accounting methods (Hoekstra et al., 2016; Meng et al., 2018; Dietzenbacher et al., 2020). Lower-income economies have thus become net exporters of emissions embodied in trade, to cater to consumers in higher-income economies (IPCC, 2022).

measure energy intensity net of any effect arising from differences across plants' product baskets. Our measure reflects the distance between a plant's actual energy intensity and that which would be associated with its product basket. Accounting for product mix effects matters because some products require more energy than others.[2] Plants might thus appear to have become relatively cleaner or dirtier by simply changing their product mix.[3] By removing the contribution of a plant's product mix from its energy performance, we are able to isolate the effects which are driven by efficiency improvements—rather than changes in a plant's product basket.

To study the effects of importing on the environmental performance of Indian plants, we use an event study design which takes advantage of the staggered timing of plants' entry into import markets. We compare the outcomes of first-time importers at a given time to those of first-importers who begin importing at a later stage. We opt for this design to address the risk of selection. Consistent with both theory and evidence (Vogel and Wagner, 2010; Foster-McGregor et al., 2014; Abreha, 2019), importing plants in our data tend to be larger and more productive (see Figure C1). These static differences could result from the impact of access to imported goods on the productivity of labour or on employment. Yet it is more likely that they reflect the selection of better-performing plants into import markets.

We find that first-time importers experience a small increase—equivalent to between 1 and 3 percent—in their energy intensity following their entry into importing. While these effects are only significant for the first three years of an importer's tenure, they would indicate that in India, access to import markets does not improve environmental outcomes. This is not to say that imports do not matter for the overall performance of Indian plants. When we estimate our event study specification on other plant-level outcomes including productivity, sales, and product diversification, we find that entry into importing leads to consistent plant-level gains. Importers experience productivity gains of up to 4 percent and increase their sales by between 5 and 10 percent. These effects materialise in the year of entry, and tend to be long-lived.

These results are corroborated by an endogenous switching regression approach—another counter- factual based estimation method—which suggests that, had they not begun to import, importers would have been significantly more energy efficient. Taken together, our findings support the idea that plants in India do learn from importing. More specifically, they become more productive, diversify their product baskets, and reach new markets. Yet these gains do not translate into environmental improvements. Quite the opposite: net of product mix effects, importing is linked to sizeable increases in the intensity of energy use. While our findings stand out relative to parts of the literature (see, for instance, Imbruno and Ketterer 2018), they are not necessarily surprising.

One mechanism which might be driving our results is product diversification.[4] While our measure of energy intensity accounts for static differences between plants, arising from differences in the energy intensities of different product lines, it does not account for dynamic changes in the composition of plants' product baskets over time. To the extent that plants scale up and introduce new products following their first imports—as we observe—their energy intensity also increases. This view is supported by Barrows and Ollivier (2018), who find that the environmental performance of Indian firms worsens when they diversify away from their core product offerings.

Should our line of reasoning be correct, our results would imply that, at least in the case of India and over the short term, there exists an environmental cost to processes of learning and diversification. That a trade-off should exist between these processes and environmental sustainability has important implications for the design of trade and industrial policy in both industrialized and emerging economies. Economic development is, at its core, a process of learning (Kim, 1999; Malerba and Nelson, 2012) and diversification (Dosi et al., 2020; Nomaler and Verspagen, 2021). In a rapidly warming planet, a combination of new-generation trade agreements; industrial policy; and substantial technology transfer from North to South, would be required to decarbonise the energy systems of emerging economies and make sure that the environmental costs of learning processes are minimised.

2 Another concern is that plants in India might also be producing relatively "dirty" products as a result of outsourcing from countries where environmental regulation is stricter.

3Barrows and Ollivier (2018; 2021) have shown that a non-negligible portion of changes in the emission intensity of Indian firms are attributable to changes in their product baskets.

4 Another potential mechanism relates to India's position in global value chains. Importers might be on the receiving end of offshoring from relatively energy intensive industries in industrialised economies. In this case, entry in import markets would, almost by default, be associated with a worsening environmental performance. We are less convinced of this mechanism because our measure of energy intensity already accounts for differences in plants' product baskets.

2. Data

Our data derives from the ASI, a survey of formal manufacturing plants in India conducted by the Central Statistical Office, a division of India's National Statistical Office (NSO) under the Ministry of Statistics and Programme Implementation (MSPI). We use plant-level data from 2000 to 2016. The ASI sampling frame includes all plants registered under Sections 2m(i) and 2m(ii) of the 1948 Factories Act. These include factories that use power for manufacturing activities and employ more than 10 employees; and those manufacturing plants which do not use power, but that employ over 20 workers. The ASI sampling frame includes 'census' and 'sample' plants. Census plants are surveyed each year, whereas sample plants are randomly selected.

2.1 Sample construction

ASI data is subdivided in various 'Blocks', thematic sub-units of data. To construct our sample, we use all non-missing observations from Blocks A (basic information), B (additional information), C (capital and investment), D (finished goods), E (employment), G (receipts), H (inputs, including fuel and electricity), I (imports), and J (production). We restrict our sample to manufacturing plants, i.e., industries 15 to 36 of India's NIC classification, and drop a very small number of observations with unreliable data. We also remove all plants which appear only once in the ASI data.[5] This results in an unbalanced panel containing 56,798 individual plants and 254,912 plant- year observations. Table 1 provides an overview of our data.

Information	All ASI	Our panel
# of products, CPC 7-digit	6220	-
# of products, CPC 5-digit	1449	1449
# of plants	175570	56978
# of multiproduct (mpc) plants	61699	20320
# of single-product plants	113871	36658
average # of products for mpc plants, 5-digit level	3.5	2.7

Table 1: Basic information on the data

Notes: *'All ASI' refers to the universe of plants reported within the ASI's Block J for the years 1999-2016, where we have mapped India's ASICC classification to the Central Product Classification (CPC). 'Our panel' refers to the final plant-level panel we use for the analysis, which contains the sub-set of all non-missing observations from the ASI's Blocks A, B, C, D, E, G, H, I, and J; and excludes plants that appear only once in the survey.*

ASI provides product-level data for all census and sample plants. We know which products plants produce, and which products they source domestically and abroad. Until 2010, products are classified using the Annual Survey of Industries Commodity Classification (ASICC). From 2011 onward, the National Product Classification for Manufacturing Sectors (NPCMS) is used. To harmonize the two classifications, we map ASICC product codes to NPCMS codes using a concordance table provided by the Ministry of Statistics and Programme Implementation.[6] At the 5-digit level, the NPCMS classification maps neatly onto the Central Product Classification (CPC). We therefore aggregate product codes from the 7- to the 5-digit level, resulting in a total of 1449 unique product codes.

We classify plants as being multi-product (mpc) when they produce more than one 5-digit product in a given year. Mpc plants represent approximately 35 percent of our sample. The average number of products per plant in our data is 2.7 (Table 1). Tables B1 and B2 in the Annexes provide additional details on our sample, by plant size and by industry. We collect information on

5 We therefore keep plants for which we have at least two (not necessarily consecutive) years of data. We can follow plants for an average of six (not necessarily consecutive) years over the 2000-16 period.

6 The concordance table is available, in PDFformat, at the following link: http://www.csoisw.gov.in/cms/cms/Files/181.pdf.

plants' environmental performance from Block H, which reports plants' expenditure on electricity and different fuel sources, i.e., coal, petrol, gas, and other types of fuel. Electricity from the grid accounts for over 40 percent of energy use by plants in our panel, followed by coal (18 percent) and petrol (16 percent) (see Table 2).

Energy source	Total energy use, %
Electricity	42.6
Coal	18.2
Petrol	16.4
Other fuel	12.4
Gas	10.4
Total	100

Table 2: Sources of energy consumption

2.2 Measuring environmental performance

To measure plants' environmental performance, we depart from a measure of energy intensity. More specifically, we use data on energy consumption and sales to construct plant-level indices of energy intensity. In keeping with the literature (see, for instance, Batrakova and Davies 2012, Imbruno and Ketterer 2018, Barrows and Ollivier 2021), we start by defining energy intensity at the plant level as the sum of a plant's observed energy expenditure over its sales—with both of these measures defined in real terms. To calculate these—and all other variables—in real terms, we use 2-digit industry- level deflators. We clean our measure of plant-level energy intensity by removing observations for those plants whose expenditure on energy is more than double their sales. This results in a loss of 7877 unique plants, which is equivalent to 0.06 percent of our sample.

Our measure of energy intensity is a monetary, rather than a physical measure. In principle, Block H of the ASI database reports energy consumption in physical units. These can be used to observe energy use and emissions net of price effects (Martin, 2011; Barrows and Ollivier, 2018). We decide to focus on monetary measures of energy use rather than on physical measures for two reasons. First, the data is not entirely reliable: petrol, for instance, can be denominated in "bags" rather than in "barrels". These instances make it difficult to assign emission factors. Secondly, we lack information on plants' location. India's electricity system is decentralized, and emission factors differ substantially between locations (Martin, 2011). Since electricity accounts for almost half of plants' energy use, estimations would risk being biased for a large portion of our data.

The energy intensity indices described so far, however, do not account for across-plant differences in the product mix. We therefore leverage product-level information from the ASI data to con- struct a product-level measure of environmental performance. Our motivation here stems from our interest in isolating effects arising from improvements in efficiency from those arising from changes in plants' product baskets. To the extent that different products are associated with different lev- els of energy intensity, differences in across-plant environmental performance might simply reflect plants' engagement in the production of more energy-intensive products, rather than improvements in efficiency (Barrows and Ollivier, 2018). A unique feature of our data is that we have information on what plants produce.

This feature allows us to compute energy intensity measures at the product level. To do so, we focus on single-product plants. We have 132,469 single product plants plants, producing 1259 products.[7] We use data on all single-product plants in the entire sample to calculate, for each year of data, the average energy intensity (i.e., real energy expenditure over real sales) of these 5-digit products.[8] We choose to focus only on those products which are produced by at least 10 plants. Excluding products produced by fewer than 10 plants means that we exclude a further 332 products, leaving us with product-level indices for 981 products. Table C1 provide a ranking of products in terms of how much energy it costs to produce them.

7 There are 190 unique products which are only produced by multiproduct plants—an attrition rate of 7.6 percent.

8 We have also computed these measures using median values. There is a very correlation between the two measures, and results are unaffected.

Our data, however, also include plants that produce more than one product. For these plants, we use the average of their product-level indices, weighted by product sales. When aggregated to the plant-level, this measure gives us an understanding of a plant's 'expected' energy intensity based on its product mix. What we observe is that there is substantial variation across plants, both in terms of their observed and their expected energy intensity (Panels A and B, respectively, in Figure 1). The distributions of both plant- and product-level energy intensities are similar—they are both right-skewed and long-tailed. In addition, breaking down the distribution of plant-level energy intensity by industry reveals a degree of across-industry heterogeneity (see Figure C2).

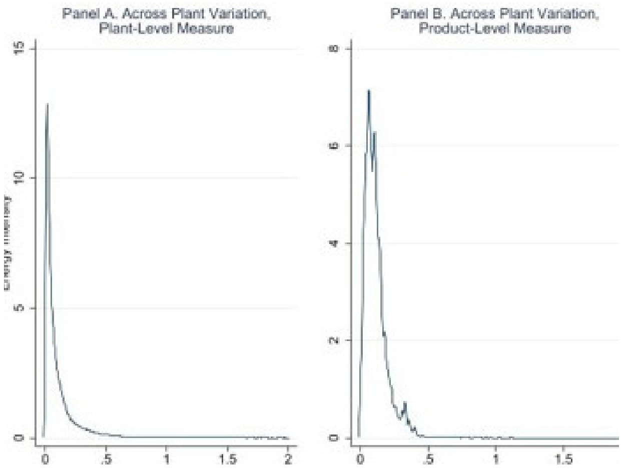

Figure 1: The distribution of energy intensity across plants

Plants in our sample are heterogeneous not only because of differences in productivity, size, and exposure to trade; they are also heterogeneous because of differences in their product mix. We observe heterogeneity both within and between industries. To account for these observations, we normalise our energy intensity measure. We take the difference between a plant's observed energy intensity and the energy intensity one would expect judging from its product basket for each plant- year combination in our data. We are, in essence, focusing on the distance between a plant's measured energy intensity and the energy intensity associated with its products. Figure 2 below shows the result of this normalisation, and Figure C3 shows a breakdown by industry.

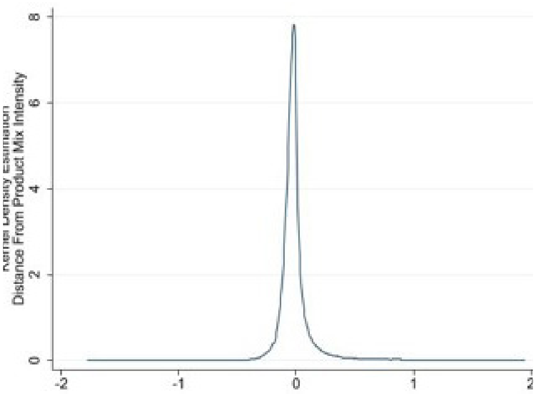

Figure 2: The distribution of distances from product mix intensity

Negative distances imply that a plant is more energy efficient than one would expect; positive distances imply that a plant is more energy intensive than its product mix would imply. In essence, this normalisation reflects a measure of energy intensity which is weighted based on the average energy intensity of each product; and on the shares of each product within a firm's product basket. The normalisation thus allows us to remove across-plant heterogeneity arising from differences in plants' production activities from the analysis. Our measure also varies over time. In what follows, we focus on the effects of international trade on our distance-based measure of energy intensity.[9]

3. International trade and environmental performance

3.1 Event study

3.1.1 Entry into importing and energy intensity

Our point of departure is an event study strategy which focuses on comparing plants which transition into importing during the 2000-2016 period to future first-time importers. Between 2000 and 2016, we observe 5539 plants which start importing and which remain importers.[10] In what follows, we focus on a sub-sample including only these first-time, persistent importers. With this sample, we compare outcomes for first-time importers to the outcomes of future first-time importers in the year prior to their entry into importing (that is, at time −1 relative to entry).[11] We are interested in plants in the former group, and use plants in the latter group as a counterfactual.

Our sample excludes plants which are always and never observed importing. We exclude the former because we are interested in the effects of entry into import markets, which we cannot study for plants which are registered as importers in our data from the very beginning. As for never-importers, we exclude them because they may be structurally different from importers, which would not make them a good counterfactual for our analysis. Having restricted our sample to first-time importers only, any plant-level outcome we might observe arising from entry into import markets would be explained by the staggered timing of plants' first imports, rather than by differences with plants which always or never import (Alfaro-Uren˜a et al., 2022).

At this stage, a note of caution is warranted. For our estimates to reflect a causal relationship between importing and plant-level environmental performance, we would need a counterfactual in which the plants we observe importing would not enter import markets and also not experience any change in their environmental performance. This is similar to the parallel trends assumption which supports difference-in-differences set-ups. While this assumption cannot be tested directly, we will observe whether specific trends can be detected in our outcome variables prior to entry into importing. Lack of pre-trends would increase the likelihood that results are indeed driven by the staggered timing of plants' entry into importing (Alfaro-Uren˜a et al., 2022; Domini et al., 2022).

At the same time, however, since the decision to import cannot be treated as being randomly distributed across plants, we will refrain from attributing causality to our results. We follow Domini et al.'s (2022) line of reasoning in thinking that our estimates are best understood as providing descriptive, rather than causal evidence on the relationship between importing and plant-level performance around the time of entry into import markets.

More specifically, we estimate the following empirical specification:

$$y_{ijt} = \alpha_i + \alpha_{jt} + \beta_1 X_{ijt} + \sum_{T=-6,\, T\neq -1}^{5} \beta_k D^k_{it} + \epsilon_{it}, \tag{1}$$

9 Our measure stands out relative to the rest of the literature. Even works which do have some product-level information tend to focus on the plant- or, more often, the firm-level. The exception here is Barrows and Ollivier (2018), who calculate carbon intensity indices at the product level using data from the ASI and Prowess databases. Prowess provides information on firms' energy expenditure by final product. Barrows and Ollivier (2018) match this information to product-level sales data, so that for each firm, they are able to rank products according to their share of total sales and their share of total emissions. They report that higher-ranked products in terms of sales tend to be cleaner, and that emissions increase approximately linearly in sales rank. An issue with Barrows and Ollivier's Barrows and Ollivier (2018) approach is that it seems to lead to significant data losses (between 70 and 90% of the data gets discarded), largely due to mismatches between ASI

10 Similarly to Imbruno and Ketterer (2018), we focus on persistent importers, that is, plants which enter into importing and remain importers.

11 Our strategy is similar to that of Alfaro-Urenã et al. (2022), with the difference that they start from a sample which includes both first-time suppliers and never suppliers.

where y captures our measure of environmental performance explored above, for plant *i* in year *t*; the α terms capture plant and industry-year fixed effects; and *X* is a vector of plant-level characteristics including labour productivity, capital intensity, sales, location (whether a plant is urban or rural), and whether a plant is publicly listed. We define event dummies *D* as falling between T = -6 and T = 5. Standard errors are clustered at the industry level, to account for correlations between plants active in the same 5-digit industry. With this specification, we are comparing the evolution of energy intensity for plants in the first year of entry into importing to that of plants in the year prior to entry. In other words, we compare outcomes between first-time and future importers.

Figures 3 reports the event study coefficients for our measure of energy intensity. When we measure energy intensity net of product mix effects, first-time importers tend to experience an increase in energy intensity of between 1 and 2 percent following their entry into importing. These effects are relatively precisely estimated, and statistically significant at the 1 percent level. The effects of importing, however, are not necessarily long-lived: after an initial burst, the increase in energy intensity appears to peter out starting in the third year following entry into importing. Reassuringly, we do not observe pre-trends in the years leading up to entry. Table (A1) reports all coefficients for our estimation.[12]

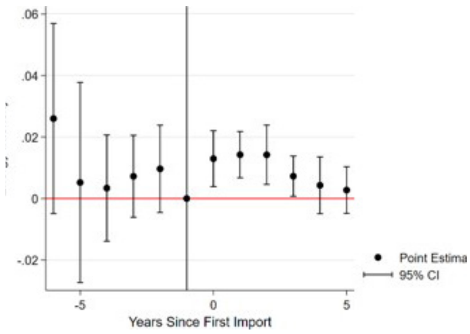

Figure 3: Entry into importing is linked with an increase in energy intensity

3.1.2 Entry into importing: productivity, scale, and diversification

Entry into import markets has been associated with firm-level gains in terms of productivity and scale in different emerging market economies (Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Goldberg et al., 2010; Mo et al., 2021). Import markets expand the availability of foreign intermediates, reducing the cost of inputs but also granting access to embodied technology, as well as superior quality and increased variety of imported intermediates and capital goods (Kasahara and Rodrigue, 2008; Topalova and Khandelwal, 2011; Torres Mazzi and Foster-McGregor, 2021). Recent studies link these effects to improvements in environmental performance, with two potential mechanisms being at play. First is the idea that imported technology enables the more efficient use of resources (Imbruno and Ketterer, 2018) Another possibility is that larger firms are better able to invest in abatement activities (Cui et al., 2016; Forslid et al., 2018).

In what follows, we ask whether Indian plants which enter import markets for the first time also experience similar gains—and whether these effects can help explain the lack of evidence we find on the impact of trade on environmental performance. To this end, we implement specification (1) but focus on different measures of productivity and scale as our dependent variables. We focus, in particular, on the following outcomes: labour productivity; sales; firm size, proxied by the number of workers; and product diversification. The time interval we are interested in remains unchanged, and so does our vector of control variables.[13] We include firm, industry, year, and industry-year fixed effects. Standard errors are, again, clustered at the industry level. Figures 4 and 5 plot event study coefficients for plant-level outcomes.

12 We cannot exclude that importing leads to improvements in energy efficiency over the longer-run, i.e. after the 5 year window we are focusing on. Given that we have, on average, fewer than ten plant-level observations per year, we cannot follow plants for a very extended period of time.

13 13Naturally, as we move between estimations, we drop the dependent variable from this vector.

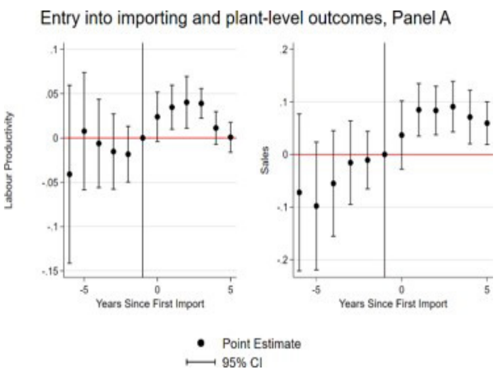

Figure 4: Entry into importing is linked with increases in plants' productivity and sales

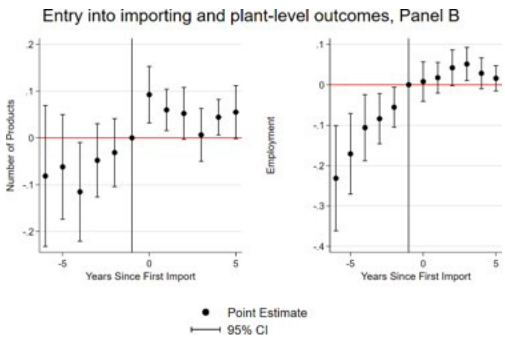

Figure 5: Entry into importing is linked with increases in plants' scale and product diversification

For all outcome variables, we do not find evidence of selection into importing based on past performance. The clear exception is employment, suggesting that there may be a rise in employment leading up to entry into import markets.[14] Employment is also the outcome on which plants' entry into import markets does not seem to have a clear-cut impact (Figure 5). For the other outcomes, plants start growing after they start importing. We observe first-time importers experiencing size-able and lasting gains in productivity, sales, and in the number of products they produce. Labour productivity increases by between 3 and 5 percent. Sales increase by between 8 and 10 percent following entry, and the effect is long-lived. Plants are also significantly more likely to introduce new products as a result of entry into importing. The magnitude of these effects is similar, if somewhat smaller than that reported in Imbruno and Ketter (2018) in Indonesia, who find impacts on productivity and employment upwards of 25 percent following entry into import markets.

3.2 Robustness check: An endogenous switching regression approach

In what follows, we test the robustness of our results with an endogenous switching regression approach (Maddala, 1986; Lokshin and Sajaia, 2004). Our motivation to do so is two-fold. Endogenous switching models also represent a way to deal with selection bias (Coad et al., 2020). Moreover, they allow for the explicit treatment of different counterfactual scenarios. In our event study, the counterfactual remained, at all times, implicit. With an endogenous switching approach, we estimate the effects of importing on plants that actually do so (equivalent to the average effect of treatment on the treated, the ATT); and those on firms that do not import from abroad (the average effect of treatment on the untreated, the ATU) (Coad et al., 2020).[15]

14 In a recent paper, Kurz and Senses (2016) find that importers tend to experience greater employment volatility than exporters and non-traders.

15 Our use of terms such as "treatment effect" here does not imply random assignment, nor causality. We are still focusing on a non-randomly distributed event—importing—and we are still interested in providing descriptive evidence into the relationship between importing and energy intensity.

Endogenous switching models use a selection equation, which in our case determines which plants decide to enter import markets, as well as two equations representing different regimes—one for importers, and one for non-importers. For our selection equation, we use the share of importers active in a plant's own 5-digit industry as our exclusion restriction. This is because the exclusion restriction needs to affect the selection equation but not plant-level outcomes—if not through the decision to import (Puhani, 2000). The status of plants in a given industry is a commonly-used restriction, as if other plants are importers it is more likely that the plant under consideration may be an importer too (Coad et al., 2020). The equations are as follows:

$$IMP_{it} = \begin{cases} 0 & \text{if } \gamma Z_{it} + \mu_{it} > 0 \\ 1 & \text{if } \gamma Z_{it} + \mu_{it} \leq 1 \end{cases}$$

$$\text{Regime 1}: \; y_{1it} = \beta_{11it} + \epsilon_{1it}, \; ifIMP_{it} = 1$$

$$\text{Regime 2}: \; y_{2it} = \beta_{22it} + \epsilon_{2it}, \; ifIMP_{it} = 0$$

In this setting, our plants face two regimes, depending on whether or not they import (IMP). Correlations between importing behaviour and any effect of importing on plants' environmental performance are allowed in this set-up. In addition, plants may switch between regimes, depending on the vector of explanatory variables *Z*. In *Z*, we include the same set of variables used in equation (1). Dependent variables *y1* and *y2* capture plants' energy intensity under the two different regimes. γ, $\beta 1$, and $\beta 2$ are vectors of parameters which are jointly estimated using a full information maximum likelihood approach. We can then compute counterfactual scenarios to derive the ATT and the ATU.

More specifically, we estimate the relationship between importing and energy intensity using the regression output, by looking at the counterfactual scenarios in which an importer is compared to other importers, and a non-importer to other non-importers. As a result, we estimate two different coefficients. The first, the ATT, is reported in the penultimate row in Table (3). It reflects the average change in the energy intensity of an importing plant, with respect to the hypothetical scenario where the plant had not entered import markets. The second, the ATU, captures the effects of importing on the energy intensity of a plant which does not import, relative to the scenario in which it had decided to import. The ATU is reported in the last row of Table (3).

	F. Energy Intensity	**F. Energy Intensity**	**Selection**
	Importers	**Non-importers**	
mpc plant	-0.0025 (0.0053)	0.0051*** (0.0019)	0.0188 (0.0230)
labour productivity	-0.0226*** (0.0043)	-0.0079*** (0.0016)	0.1033*** (0.0193)
size (no. employees)	-0.0261*** (0.0037)	-0.0025** (0.0012)	0.1552*** (0.0138)
working capital	-0.0008 (0.0022)	0.0071*** (0.0009)	1.30e-06 (0.0101)
exporter	-0.0223*** (0.0057)	-0.0014 (0.0018)	0.1356*** (0.0240)
share of importing plants			0.6547*** (0.0679)
Rho	-2.059*** (0.0911)	-0.0530*** (0.0087)	
Obs	21316	21316	21316
Industry FE	Yes	Yes	Yes

Year FE	Yes	Yes	Yes
ATT	0.3700*** (0.7508)		
ATU		-0.0083 (0.0536)	

Table 3: Importing and energy intensity, endogenous switching results

*Notes: Standard errors in parentheses. The tables also include controls for plants' legal status and geographical location * p < 0.10, ** p < 0.05, *** p < 0.01*

Table (3) above reports results from our endogenous switching model. The first two columns report results on plants' energy intensity. These correspond to the two separate regime equations sketched above. The third columns reports results from the selection equation. Our results corroborate findings from the event study specifications: importing is linked with a worsening of environmental performance. More specifically, we find that those plants which did decide to import from abroad appear to be over 35 percent more energy intensive than they would have been had they decided not to import. However, we fail to detect any effect on plants that do not import.

4. Discussion

This paper relates to micro-econometric literature studying the energy and emission efficiency of firms and plants who take part in international trade. This tends to find that traders are more energy and emission efficient than their domestically-oriented counterparts (Batrakova and Davies, 2012; Cui et al., 2016; Holladay, 2016; Brucal et al., 2019).[16] Our findings, however, go in a different direction. Using an event study methodology, we find that access to import markets is linked to an decrease in plant-level energy efficiency, at least over the short-term. This is a finding which also appeared throughout different preliminary analyses we conducted.[17] Our results suggest that a degree of caution is warranted when considering the environmental benefits of international trade. Results may be contextual, and dependent on the measure of efficiency chosen by researchers as well as on the choice of counterfactual (Delera, 2022)—which is why we chose to focus on the staggered timing of entry for importers only.

Our findings can be explained in at least two ways. The first is linked to work using MRIO tables. Indian importers might be on the receiving end of offshoring from relatively energy intensive industries in industrialized economies. Our measure of energy intensity, however, is net of effects arising from differences in the energy intensity of different product lines, suggesting that this channel may not be the primary driver behind our results. Another, complementary mechanism relates to the work of Barrows and Olliver (2018), who find that Indian firms tend to become more energy and emission intensive as they diversify into new products and move away from their core product offering.

Our findings indicate that, following entry in import markets, plants grow more productive, expand their sales, and diversify into new products (Figures 4 and 5). While we cannot establish whether importing has a causal effect on these plant-level outcomes, the absence of specific trends prior to entry into import markets does suggest that plants learn from importing (Kasahara and Rodrigue, 2008; Abreha, 2019)—pushing them to diversify. To the extent that learning processes take place, our results, together with those reported in Barrows and Ollivier (2018), would suggest that there is an environmental cost associated with learning.

Our findings could then be interpreted in terms of a trade-off between firm-level learning and environmental sustainability. In aggregate-level and descriptive studies, economic development has long been linked to innovation (Kim, 1999; Malerba and Nelson, 2012; Pietrobelli and Staritz, 2018) and export diversification (Nomaler and Verspagen, 2021; Dosi et al., 2022).

16 This stands in contrast with work using multi-regional input-output (MRIO) tables, which consistently finds that, in its current configuration, international trade contributes to displace environmental impacts from industrialised to emerging economies (see, for instance, Meng et al. 2018). Differences are partly due to different methodological choices, but also, importantly, to the effect of scale—firm-level efficiency may improve, but as the scale of production increases, aggregate emissions also increase.

17 We consistently find a positive relationship between importing and energy intensity across different specifications, including simple OLS, fixed-effects panel data specifications and an endogenous switching regression approach. We decided to show only the latter here, for the sake of brevity.

The underlying micro- level mechanism is one of learning-by-doing, including by experimenting with the introduction of new products. Empirical work on emerging economies, including India, corroborates these ideas (Dosi et al., 2020; Grazzi et al., 2021). Yet at the firm level, product diversification may come at a cost in terms of energy efficiency and, therefore, emissions.

As importers move into new product lines, they may have to make adjustments to their machinery, internal routines, and production schedules. New skills may have to be sourced on labour markets. Diversifying away from one's core product lists is therefore likely to have costs in terms of energy efficiency—a cost which we think is reflected in our results. Indeed, while our measure of energy intensity accounts for static across-plant differences arising from the heterogeneity in product-level energy intensity, it does not control for dynamic changes in the product mix. Our results are thus likely to reflect additions and removals from plants' product baskets over time.

Should future research support the idea that learning comes at an environmental cost, there would be important implications for policy in both emerging and industrialised economies. Concerns over the environmental impacts of international trade are growing. Industrialised economies and international organisations are increasingly calling for the inclusion of sustainability clauses in regional trade agreements (RTAs). Clauses in RTAs are certainly a step in the right direction (Brandi et al., 2020), but the degree to which they can actually "bite" remains to be seen. If economic development is to be pursued at no environmental cost, the rapid decarbonisation of energy systems in emerging economies would appear to be the main, if not the only avenue. Trade agreements would then need to be designed with technology transfer in mind (Kirchherr and Urban, 2018), and to be accompanied by substantial government intervention (Rodrik, 2014; Lema et al., 2020).

5. Conclusion

In this paper, we leverage plant- and product-level information from India's ASI database to study the environmental and economic impacts associated with entry into import markets. A novel aspect of our work concerns our measure of plant-level energy intensity. We take advantage of data on the product baskets of single-product plants to construct a measure which is net of effects arising from across-plant differences in production activities. Facing a high risk of selection bias, we opt for an event study methodology which compares first-time importers at different points in time. By way of testing the robustness of our results, we also implement an endogenous switching regression approach.

Overall, our findings suggest that access to import markets is linked to a substantial learning premium. Around the time of their entry into importing, plants become more productive, sell more, and introduce new products. While the non-randomness of importing decisions means that we are not able to establish whether these relationships are causal, they are certainly indicative of a positive effect of importing on plant-level outcomes. These, however, do not translate into energy efficiency gains. To the contrary, we find that first-time importers experience a decrease in the efficiency of energy use—albeit a small, and non-permanent one.

To the extent that our findings highlight a process of learning, they also suggest that learning comes at a cost for the environment. While this idea is to some extent the fruit of speculation, it is also directly supported by Barrows and Olliver (2018), who use a very similar set of data on Indian firms to show that product diversification is linked to a worsening environmental performance at the micro-level. Where we differ is in thinking about the implications of this idea. Diversification is a crucial aspect of development, and pushing firms away from it is hardly a recipe for catching up to industrialised economies. Yet naturally, without large and rapid investments in decarbonisation, the very idea of development begins to take a worrying turn.

Research on the relationship between access to import markets and micro-level environmental performance is incipient. To the best of our knowledge, the only closely related study is Imbruno and Ketterer (2018). They study the case of Indonesian firms, covering a shorter span of time, and reach opposite conclusions. More research in different emerging economies, and focusing on a larger set of pollutants, would be needed to start building a body of evidence on the micro-level effects of importing on the environment. Our hope with this paper is to have contributed to accumulating that evidence.

6. Annexes

6.1 Annex I: Full event study results

	(1) Energy Intensity	(2) Productivity	(3) Sales	(4) No. Products
labour productivity	0.0454*** (0.00546)		0.357*** (0.0348)	-0.0324* (0.0171)
working capital	0.0383*** (0.00447)	0.144*** (0.0100)	0.243*** (0.0119)	0.0145 (0.0165)
no. employees	0.0528*** (0.00554)	-0.281*** (0.0227)	0.386*** (0.0187)	0.0205 (0.0143)
sales	-0.151*** (0.0103)	0.0954*** (0.0132)		0.146*** (0.0129)
urban	-0.00222 (0.00621)	-0.00115 (0.0142)	0.00292 (0.0192)	-0.0000322 (0.0306)
listed	0.00288 (0.00333)	0.0262 (0.0190)	-0.0120 (0.0213)	0.0361 (0.0359)
6 years prior	0.0260* (0.0151)	-0.0409 (0.0489)	-0.0723 (0.0728)	-0.0816 (0.0735)
5 years prior	0.00521 (0.0159)	0.00762 (0.0322)	-0.0981 (0.0592)	-0.0621 (0.0545)
4 years prior	0.00339 (0.00842)	-0.00618 (0.0243)	-0.0552 (0.0489)	-0.115** (0.0514)
3 years prior	0.00722 (0.00651)	-0.0153 (0.0207)	-0.0157 (0.0388)	-0.0481 (0.0382)
2 years prior	0.00966 (0.00692)	-0.0184 (0.0154)	-0.0107 (0.0267)	-0.0315 (0.0354)
Entry	0.0130*** (0.00443)	0.0238* (0.0136)	0.0368 (0.0316)	0.0924*** (0.0295)
1 year after	0.0143*** (0.00367)	0.0346*** (0.0122)	0.0848*** (0.0243)	0.0597** (0.0216)
2 years after	0.0142*** (0.00470)	0.0401*** (0.0142)	0.0835*** (0.0225)	0.0522* (0.0271)
3 years after	0.00726** (0.00318)	0.0389*** (0.00813)	0.0908*** (0.0234)	0.00634 (0.0276)
4 years after	0.00430 (0.00450)	0.0112 (0.00900)	0.0711*** (0.0249)	0.0441* (0.0186)
5 years after	0.00274 (0.00370)	0.000780 (0.00822)	0.0595*** (0.0198)	0.0549* (0.0277)
Obs	26172	26172	26172	26172
R^2	0.654	0.881	0.865	0.696

Table A1: Entry into importing and plant-level outcomes, event study results

Notes: *Robust standard errors in parentheses, clustered at the industry level*
**p < 0.10, ** p < 0.05, *** p < 0.01*

6.2 Annex II: Additional information on the sample

Plant size	Plants, %	Output, %	Energy use, %
Micro (fewer than 10 employees)	18.4	1.7	1.5
Small (between 10 and 50 employees)	34.4	9.5	8.1
Medium (between 50 and 250 employees)	32.1	26.4	24.6
Large (over 250 employees)	15.1	62.4	65.8
Total	100	100	100

Table B1: Distribution of output and energy use by plant size

Sector	Plants, %	Output, %	Energy, %	Emp., %
Basic metals	9.5	14.4	23.8	9.8
Chemicals and chemical products	4.3	5.8	7.9	1.9
Coke and refined petroleum	1.5	12	3.4	1.8
Computer, Electronic, and Optical products	4.7	2.9	6.7	4.7
Electrical equipment	6.2	7.5	13.5	9
Fabricated metals	4.9	2.4	1.7	3.2
Food, beverages, and tobacco	10.2	8.5	4	3.6
Furniture	2.4	0.9	0.5	2.5
Machinery and equipment	5.1	3.5	1.5	4
Motor vehicles and transport equipment	6.3	10	3.4	6.3
Other manufacturing	2.8	4	1.7	4.7
Other non-metallic products	4.5	7.8	11	2
Pharmaceutical products	3.5	2.7	2.8	4
Rubber and plastics products	3.2	2.3	1.7	1.2
Textiles, apparel, and leather	18.7	9.3	8.6	15.3

Utilities	2.0	1.5	0.7	2.8
Wood, paper, and printing	10.3	4.5	7.1	23.2
Total	100	100	100	100

Table B2: Distribution of output, energy use, and employment by industry

6.3 Annex III: Additional descriptive evidence

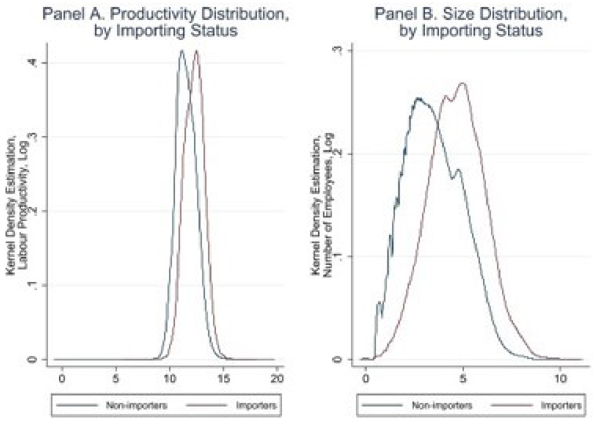

Figure C1: Differences between importing and non-importing plants

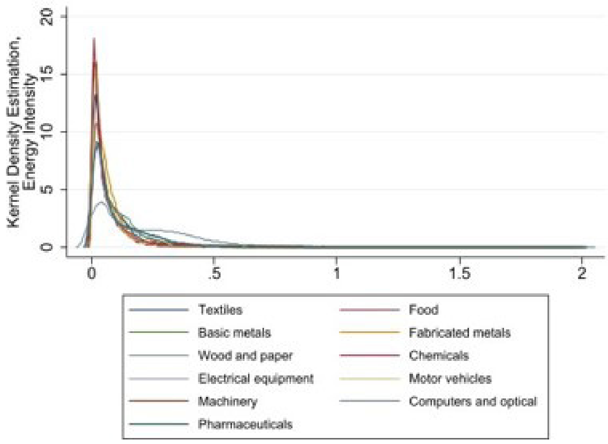

Figure C2: Energy intensity distribution across industries

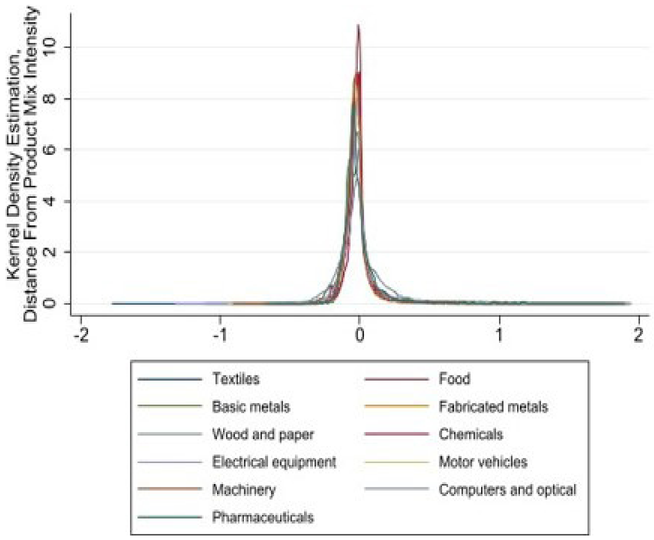

Figure C3: The distribution of distances across industries

Panel A. Top 10 products by energy intensity	
CPC code	**Description**
39215	Other cotton waste; garnetted stock
39240	Waste and scrap of paper or paperboard
17400	Ice and snow
41330	Platinum, unwrought, semi-manufactured, or powder
39361	Waste and scrap of copper
39340	Ferrous waste and scrap
39363	Waste and scrap of aluminium
34280	Hydrogen peroxide; phosphides; carbides; hydrides, etc.
39310	Waste from the manufacture of iron or steel
41117	Granules and powders, of pig iron or steel
Panel B. Top 10 products by total energy use	
CPC code	**Description**
34611	Urea
41211	Flat-rolled products of non-alloy steel (>600mm width)
41212	Flat-rolled products of non-alloy steel (600mm< width)
34644	Fertilizers containing nitrogen and phosphorus
41113	Ferro-chromium

32111	Chemical wood pulp, dissolving grades
49113	Motor cars and other motor vehicles
41112	Ferro-manganese
16110	Natural (aluminium) calcium phosphates and phosphatic chalk
37440	Hydraulic cements, except in the form of clinkers

Table C1: Ranking of 5-digit products, based on energy intensity and energy use

Notes: This ranking is based on product-level measures of energy intensity (i.e. energy use over output) and energy use. Product-level measures are calculated on a sample of 132,469 plants and 981 products over the 2000-2016 period.

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