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Emission Intensity and Firm Dynamics: Reallocation, Product Mix, and Technology in India

Geoffrey Barrows* and Hélène Ollivier†

June 27, 2016

Abstract

We study how market conditions shape aggregate CO_2 emission intensity from manufacturing. We first develop a multi-product multi-factor model with heterogeneous firms, variable markups, and monopolistic competition in which each product has a specific emission intensity. Competition affects output shares across heterogeneous firms, product-mix across heterogeneous products, and technological choice within firm-product lines. We find that increased competition shifts production to cleaner firms, but has ambiguous effects on within-firm changes in emission intensity via product-mix and technology adoption. Next, using detailed firm-product emission intensity data from India, we find core-competency products tend to be cleaner than non-core products; but since market conditions have induced Indian firms to shift production away from core-competency, product-mix has increased CO_2 emission intensity in India by 49% between 1990-2010. These emission intensity increases are offset by reductions within firm-product lines and by across-firm share shifts, so aggregate emission intensity has actually fallen by 50%.

Keywords: heterogeneous firms; trade and the environment; product mix

JEL codes: F14; F18; Q56

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1 Introduction

A central strategy for slowing the pace of climate change is to reduce the emission intensity of production within countries, industries, and firms. By now, it is widely acknowledged that market incentives should play an important role in bringing about these reductions, but our understanding of how exactly aggregate emission intensity responds to changing market conditions is relatively incomplete. Research indicates that emission intensity of production depends on the composition of firms in the industry (Kreickemeier & Richter, 2013; Forslid et al., 2014), the types of products firms make (Copeland & Taylor, 2003; Shapiro & Walker, 2015), and the technology with which they make them (Antweiler et al., 2001); but how do each of these factors respond to market conditions? And how much do each contribute to aggregate changes in emissions? Answering these questions is critical for understanding future trends in emission intensity and the environmental consequences of market reforms.

In this paper, we study both theoretically and empirically the sources of aggregate emission intensity growth and the ways in which changing market conditions affect these root sources. We first build a micro-based model of the economy to study the across-firms and within-firms channels in general equilibrium. Emissions are a necessary by-product of production, but emission intensity can be modulated by endogenous choices at the firm level. First, heterogeneous firms vary in productivity, as well as in average emission intensity. Changes in market forces change the distribution of market shares across heterogeneous firms, and hence impact aggregate emissions. Second, firms endogenously select the efficiency of the technology they produce with. Changes in market conditions change the incentive to invest in more efficient, and hence cleaner, technologies. Finally, firms endogenously select the type and number of products to produce within the firm. Different products within the firm are produced with different levels of efficiency, so changes in factor allocations across product lines also affect emission intensity. We solve the model and derive testable predictions at the firm and firm-product level. The model also delivers aggregate predictions for the impact of market forces – i.e., competition and trade liberalization – on emission intensity.

Next, we evaluate the predictions and assess the magnitude of each channel in explaining aggregate emissions growth in a single country over a specific period – India between 1990 and 2010. This empirical setting offers two key benefits for our purposes. First, the Indian economy saw a remarkable array of market reforms at this time that dramatically increased the competitiveness of the economy (Goldberg et al., 2010a,b). Second, there exists unusually detailed production data for a large swath of firms over this period with which we can explore the different micro channels laid out in the model. Additionally, India is a major emitter of CO_2 (and other greenhouse gases – GHG) that is expected to contribute significantly to emissions growth over the next century, so the determinants of emission intensity in this country are important in their own right.

Our empirical exercise is based on a novel panel dataset of Indian firms from the Center for Monitoring the Indian Economy (CMIE). The key feature of the data is that we observe both outputs and energy inputs in physical quantities at the *product level*. This degree of specificity is highly unusual in production datasets, and is what allows us to track firm-product CO_2 intensity over time without assuming a specific structure on production or assuming anything at all about pricing behavior. The product-specific output data has attracted attention from researchers precisely because of its specificity in terms of product-line outputs (De Loecker et al., 2012; Goldberg et al., 2010a,b; Chakraborty, 2012; Lipscomb, 2008), but ours is the first paper to merge the output data with the product-specific energy input data, and hence compute efficiency metrics directly from the data.

With these detailed emissions estimates, we first test predictions of the theoretical model. As predicted by the model, we find that bigger firms have lower emission intensity. Furthermore, we find a systematic relationship between the sales rank of products within the firm (i.e., core competency) and the emission intensity of the product. These two facts together imply that if market forces influence the composition of firms in the industry or products within the firm, they should also impact industry-average emission intensity. We also find that there is significant variation in emission intensity of production over time within firm-product line, which indicates that technological change may explain changes in aggregate emission intensity.

We then decompose aggregate emissions in the Indian economy over 1990-2010 into the traditional scale, composition (across industries), and technique (within industries) effects (Antweiler et al., 2001; Levinson, 2009). We find that while scale has nearly quadrupled over the period, emissions only doubled, so economy-wide emission intensity has fallen drastically (50%). We confirm these aggregate results with auxiliary data from the nationally representative Annual Survey of Industries (Figure C.1). Furthermore, we find that industrial composition explains about 56% of the emission intensity reduction, while within-industry effects explain the rest. The fact that output has shifted *away* from emission-intensive industries over the period is perhaps surprising, and runs contrary to the general perception that increased globalization reallocates dirty production to the developing world, where environmental regulation is weak (Copeland & Taylor, 2003; Kellenberg, 2009).

Next, we decompose the within-industry effect into three components – across-firm compositional shifts (reallocation), across-product compositional shifts (product-mix), and within firm-product changes over time (technology). This decomposition is novel to the literature, as ours is the only data in which these three components can be separated. We find that across-firm reallocation explains 58% of the total aggregate reduction. However, these reductions are offset by a significant *increase* in emission intensity due to product-mix adjustments within the firm. That is, continuing firms shift production towards "dirtier" varieties, which increases aggregate emission intensity by 49%. At the firm level, two countervailing forces are at play. While product mix changes make firms dirtier, technology upgrading within-firm-product lines reduces aggregate emission intensity by 35%. Additionally, we find that both the across-firm and across-product effects are driven mostly by intensive margin changes (i.e., continuing firms and continuing products) as opposed to either firm or product entry/exit. These aggregate effects are consistent with predictions from the model, whereby increased competition favors larger, more productive firms, but has an ambiguous effect on reallocations across products within the firm.

Altogether, the results indicate that market forces significantly impact the emission intensity of production, even absent environmental regulation.[1] The process of globalization and market reforms in the developing world significantly influence emission intensity, as firms internalize the global externality via input costs. This point is critically important for discussions of carbon leakage, in which usually only the scale and across-industry effects are considered. By contrast, our results indicate that within-industry impacts of increased foreign demand are quite important as well. Furthermore, as this globalization process is likely to continue, emission intensity is likely to change significantly, even if climate negotiations are ineffective.

Our paper contributes to several strands of literature. First, our work relates to a growing literature regarding the impacts of market forces such as competition and trade liberalization on the emission intensity of production. This literature tends to focus on across-firm reallocations and technological upgrading (Forslid et al., 2014; Cui et al., 2012; Jing Cao & Zhou, 2013; Galdeano-Gómez, 2010; Gutiérrez & Teshima, 2011; Martin, 2012; Cherniwchan, 2013; Holladay, 2015). Ours is the first to introduce formally the product-mix mechanism and provide empirical evidence of the relative magnitudes of the different channels. One paper of particular importance for our work is Shapiro & Walker (2015), which also seeks to explain the root causes of emission intensity reductions in production – emissions of local pollutants in the US, in their case. Shapiro & Walker (2015) find that regulation – not trade/competition – explains the majority of emission intensity reductions in the US over the last 40 years. The main difference between our work and theirs that could account for the difference in findings is that we investigate a different context,

[1]There was no overall regulation of CO_2 in India during the period. To the possibility of co-benefits from regulating related pollutants, Greenstone & Hanna (2014) find that local pollution regulations were relatively inefficient in reducing emissions in India, hence any indirect impact on CO_2 emissions was likely minimal.

in which environmental regulation played almost no role.

Second, our paper contributes both theoretically and empirically to literatures that emphasize the importance of within-firm endogenous choices in explaining industry dynamics (Olley & Pakes, 1996; Verhoogen, 2008; Lileeva & Trefler, 2010; Eckel & Neary, 2010; Bernard et al., 2011; De Loecker, 2011; Bernard et al., 2010; Mayer et al., 2014; Collard-Wexler & De Loecker, 2015; Bloom et al., 2016). On the theory side, our model can be thought of as a generalization of the Mayer et al. (2014) multi-product trade model. The key feature of Mayer et al. (2014) (henceforth MMO) is that multi-product firms endogenously tailor product scope and sales to market conditions, which thus determine firm-average (total factor) productivity. We generalize this framework by adding a second factor of production, and by allowing firms to adopt a productivity-enhancing technology at the firm-product level (similarly to Bustos (2011) and Cui et al. (2012)).[2] Our model is thus the first to treat both technological adoption and product-mix simultaneously, while preserving the parsimony and tractability of the original MMO model.

Finally, our paper contributes to a growing literature that investigates the determinants of productivity growth in India. A few papers merit particular discussion. In an influential paper, Hsieh & Klenow (2009) find a striking degree of inefficiency in the allocation of resources across firms in India. Our finding that increased competition has lead to increased market share for more productive firms is in line with the historical misallocation of resources. Harrison et al. (2014) and Tewari & Wilde (2014) investigate the role of product reservation regulation in thwarting aggregate productivity growth, finding that firms that moved into previously-reserved product categories after the reservation policy ended grew significantly. We find direct support for the claim that product-mix matters for productivity, and thus illuminate the micro-channel posited by these papers. Goldberg et al. (2010b) also studies product-line dynamics in the Indian context (also using data from CMIE). We go further then Goldberg et al. (2010b) by studying both the intensive and extensive margins of product-mix, and by computing efficiency at the firm-product level and relating these metrics to our model of production. Finally, three recent papers study the impacts of regulation and market failures on emission intensity in India (Greenstone & Hanna, 2014; Duflo et al., 2013; Allcott et al., 2014). We see our work as connected to these efforts in that we illuminate the micro channels through which policies/market failures impact firm-level and aggregate emission intensity.

[2]The one-factor model of MMO already explains several chanels of aggregate emission intensity dynamics, if firms' technologies and input shares are fixed. For example, if there is no technological upgrading within firm-product line, and if there is little or no factor substitutions, then all the results on firm-level and aggregate-level cost efficiency from Mayer et al. (2014) cary over directly to emissions efficiency as well.

2 Theoretical Framework

In this section, we present a theoretical model of how emission intensity at the industry, firm, and product level adjust endogenously to changing market conditions. Our goal is to illuminate the mechanisms that contribute to aggregate changes in emission intensity, assess the conditions under which these mechanisms influence emission intensity, derive testable predictions that we can take to the data, and study aggregate impacts in comparative static exercises.

We begin with a closed-economy version of the model in section 2.1. Our model extends the framework of Mayer et al. (2014) to multiple factors and technology adoption. Since the mechanics of this model are presented in detail elsewhere, we move briskly through the preliminaries to focus attention on the novel elements. We prove that the generalized model supports a unique general equilibrium solution. Intermediate results are presented in appendix A.3.

In section 2.2, we derive comparative static impacts of increased market size, hence increased competition, on economic and environmental efficiency at both the firm and industry levels. Most of the analysis is conducted for the closed economy, except for a subsection that discusses open-economy results derived in the appendix. Finally, in section 2.3, we collect the empirical implications of our model for the data.

2.1 Model

2.1.1 Preferences and Demand

We consider a closed economy in which L consumers each supply one unit of labor and have identical preferences over a continuum of differentiated varieties (q_i) and a homogeneous good (q_0). Differentiated varieties are indexed by $i \in \Lambda$. Consumers suffer damages from global externalities that arise from emissions of greenhouse gases (Z^w), generated in production of goods. The homogeneous good is chosen as numeraire.

Similarly to MMO, we assume individual utility is quasi-linear over goods and damages:

$$U = q_0^c + \alpha \int_{i\in\Lambda} q_i^c di - \frac{1}{2}\gamma \int_{i\in\Lambda} (q_i^c)^2 di - \frac{1}{2}\eta \left(\int_{i\in\Lambda} q_i^c di \right)^2 - F\left(Z^w\right). \tag{1}$$

This assumption on preferences rules out income effects. Parameters α, γ, and η are all positive and govern substitutability between goods. An increase in α and a decrease in η both shift out the demand for the differentiated varieties relative to the numeraire, while an increase in γ increases the degree of product differentiation between varieties. In the limit when $\gamma = 0$, varieties are perfect substitutes. The function $F(Z^w)$ determines the relative disutility from environmental damages compared to the utility from consumption.

Total demand for each differentiated variety is a function of its own price (p_i) and market fundamentals:

$$q_i \equiv L q_i^c = \frac{\alpha L}{\eta M + \gamma} - p_i \frac{L}{\gamma} + \frac{\eta L \bar{p} M}{\gamma(\eta M + \gamma)}, \tag{2}$$

where M is the measure of consumed varieties and $\bar{p}$ is their average price. While q_i exists for all i, this quantity need not be positive. Define p^{max} as the price at which demand for a variety is driven to zero and the set Λ^* as the largest subset of Λ for which demand is positive. Then we have for all $i \in \Lambda^*$, given $\bar{p} = (1/M) \int_{i \in \Lambda^*} p_i di$,

$$p_i \leq \frac{\alpha\gamma + \eta \bar{p} M}{\eta M + \gamma} \equiv p^{max}. \tag{3}$$

Thus, each varieties' price (p_i) depends on endogenous entry and the average price in the market. With these assumptions on preferences, it can be shown that the price elasticity of demand is not uniquely determined by product differentiation γ (as in the classic monopolistically competitive setup of Dixit & Stiglitz (1977)), but depends on the number of varieties M available. An increase in the number of varieties and a decrease in the average price reduces the price bound p^{max}, resulting in what we will consider "tougher" competition.

2.1.2 Production

The economy is composed of a non-polluting homogeneous good sector and a differentiated variety sector, the latter of which generates emissions as a byproduct of production. Labor is mobile across sectors and is inelastically supplied in a competitive market. The numeraire good is produced under constant returns to scale at unit cost and sold in a competitive market, which implies a unit wage.

The differentiated sector requires both labor and energy inputs. Emissions z are directly proportional to energy consumption, so there is an equivalence between treating emissions as a by-product of production and as an input (Copeland & Taylor, 2003). We assume that the price of emissions τ embodies the price of energy, and an exogenous environmental tax that is fixed by the government.

Entry in the differentiated product sector is costly as each firm incurs product development and production startup costs, which are assumed to be labor costs. Subsequent production exhibits constant returns to scale. After making the irreversible investment f_E required for entry, a firm learns its total factor productivity φ, which was a priori uncertain. We model this as a draw from a common (and known) distribution $G(\varphi)$ with support on $[0, \infty]$. Since the entry cost is sunk, firms that can cover their marginal cost survive and produce.

As in other multi-product models, firms have a “core competency”, which corresponds to their lowest marginal cost variety. This is the product for which firms are most efficient at turning inputs into outputs. In a competitive market, firms would specialize in this core competency; however, with downward sloping variety-specific demand curves, firms may find it profitable to expand production to other varieties. These varieties will be produced at higher marginal cost than core-competency varieties, but as long as their marginal cost lies below the price bound p^{max}, the firm can profitably bring the varieties to market. We index by m the varieties produced by the same firm in increasing order of distance from its core variety $m = 0$.

To formalize this notion, assume each variety within the firm is produced with a different technology, and that the core variety’s technology is the most efficient. Production of a variety m by a firm with total factor productivity φ takes the form:

$$q(\varphi, m) = \varphi[(e^{-\sigma m}\ell)^{\epsilon} + (e^{-\nu m}z)^{\epsilon}]^{1/\epsilon}, \tag{4}$$

where ϵ governs the elasticity of substitution between “effective” inputs, which equal actual inputs l and z scaled by their respective distance functions from the core.[3] Parameters σ and ν govern these distance functions. Production function (4) is quasi-concave if $\epsilon \leq 1$, which is assumed in the rest of the paper. Parameters σ, ν and ϵ are common to all firms and will play critical roles in determining the environmental impacts of competition. Equation (4) nests the single-input production function in MMO, which is recovered by setting $z = 0$.

Given the normalization assumption for the wage rate ($w = 1$), the cost-minimizing firm with productivity φ produces variety m with unit cost

$$\Phi(\varphi, m) = w\ell + \tau z = \frac{1}{\varphi}\left[\tau^{\frac{\epsilon}{\epsilon-1}}e^{\frac{\nu m\epsilon}{\epsilon-1}} + e^{\frac{\sigma m\epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}}. \tag{5}$$

Hence, more-efficient firms (higher φ) have lower unit costs, all else equal. Emission intensity of production is also specific to each variety within the firm and is defined as

$$E(\varphi, m) = \frac{z}{q} = \frac{1}{\varphi}\left[e^{-\nu m\epsilon} + \left(\tau e^{m(\epsilon\nu-\sigma)}\right)^{\frac{\epsilon}{1-\epsilon}}\right]^{-1/\epsilon}. \tag{6}$$

[3]There is no loss in generality in omitting sharing parameters.

Mirroring the correlation between productivity and cost, higher φ is associated with lower $E(\varphi, m)$. Additionally, we have that (for the proof, see Appendix A.1)

Lemma 1. *The unit cost of variety m produced by firm with productivity φ, $\Phi(\varphi, m)$, is increasing in m if $\nu > 0,\ \sigma > 0$.*

and

Lemma 2. *The emission intensity of variety m, $E(\varphi, m)$, is increasing (decreasing) in m if and only if*

$$\epsilon - (1-\epsilon)\left(\tau e^{m(\nu-\sigma)}\right)^{\frac{\epsilon}{\epsilon-1}} < (>) \frac{\sigma}{\nu}.$$

The emission intensity of variety m can be either increasing or decreasing in m only if $\epsilon > 0$ and $\nu > \sigma$.

Lemma 1 ensures that the firm's core competency corresponds to $m = 0$, for which the unit cost of production is the lowest in the firm with productivity φ. Adding a new variety m away from this core competency raises the unit cost of production. The sufficient condition on parameters ν and σ implies that the technology for producing a new variety uses both factors less efficiently.

By contrast, lemma 2 implies that even though core products are cheapest to produce, they need not have the lowest emission intensity. Though input-use efficiency is falling for both inputs as m increases (lemma 1), a high degree of substitutability between the two factors could induce the firm to substitute heavily away from emissions for higher-m products. Under the conditions specified in lemma 2, this flexibility can actually leave core products with higher emission intensity than other (higher-marginal cost) varieties. For the remainder of the paper, we assume the conditions of lemma 2 hold to preserve the possibility that emission intensity and unit cost could be negatively correlated. These conditions imply that labor and emissions exhibit a high-degree of substitutability, and higher-m varieties use even less efficiently emissions than labor.[4]

[4] Note that a more restrictive production function would preclude the possibility of a negative correlation, for example, when the elasticity of substitution between emissions and labor is positive and close to 1 ($\epsilon \to 0$). This corresponds to the standard framework in the literature following Copeland & Taylor (1994) where production is represented by a Cobb-Douglas function with emissions and labor as inputs. To illustrate, consider the production function for variety m: $q(\varphi, m) = \varphi(e^{-\sigma m}\ell)^{\beta}(e^{-\nu m}z)^{1-\beta}$. This technology implies that both the unit cost function and the emission intensity function can be factorized by $e^{m[\beta\sigma+(1-\beta)\nu]}$. Thus these functions are both increasing in m for $\sigma, \nu > 0$.

2.1.3 Technology Adoption

To this point, we have assumed that productivity and emission intensity are fixed for a given variety over time (conditional on input prices and exogenous parameters). However, there is a large literature that finds that firms increase productivity over time in response to changing market conditions (Bustos, 2011; Bloom et al., 2016; De Loecker et al., 2012). Probably the most common explanation of this behavior in the literature is that firms upgrade technology within firm-product line. To allow for this behavior, we now introduce the possibility of variety-specific productivity-augmenting technological upgrading.

Following Bustos (2011), we model endogenous technology as a binary choice between a *low* and a *high* productivity technology. The *high* technology raises the firms efficiency in turning inputs into outputs, dividing marginal cost by ρ, with $\rho > 1$. If we assume that the technological change is Hicks-neutral, then adoption of the high technology also lowers emission intensity. These productivity gains are traded off against a positive fixed cost of adoption f. The firm computes expected profits from producing the variety under each technology, and selects the technology which yields higher profits (assuming that technology l corresponds to (4)). This choice proceeds variety by variety, so firms could choose to adopt the technological "boost" (ρ) for some, all, or none of their varieties. We assume there are no spillover effects of adoption across varieties within the firm (other than general equilibrium effects on competition).[5]

2.1.4 Profit Maximization

Firms that can cover at least the marginal cost of production of their core competency survive and produce. All other firms exit the industry. Surviving firms maximize their profits using the residual demand function (2). In so doing, given the continuum of competitors, a firm takes the average price level $\bar{p}$ and total number of varieties M as given. This describes the monopolistic competition framework.

The profit maximizing price $p(\Phi)$ and output level $q(\Phi)$ of a variety with marginal cost $\Phi(\varphi, m)$ must then satisfy

$$q(\Phi) = \frac{L}{\gamma} \left[p(\Phi) - \Phi(\varphi, m) \right], \tag{7}$$

where $\Phi(\varphi, m)/\rho$ replaces $\Phi(\varphi, m)$ for technology h. The variety is supplied if and only if

[5] We further assume that adopting technology h for some varieties within the firm alters neither the ranking of varieties in terms of their production costs nor their ranking in terms of emission intensity. This last assumption is made for technical reasons that will become clear below.

the maximizing price $p(\Phi)$ is below the price bound p^{max} from (3). Let Φ_D denote the unit cost of the domestic marginal variety achieving zero sales. Its demand level $q(\Phi_D)$ is driven to zero as $p(\Phi_D) = \Phi_D = p^{max}$. This yields the cutoff productivity for firm survival: $\varphi_D = [1 + \tau^{\frac{\epsilon}{\epsilon-1}}]^{\frac{\epsilon-1}{\epsilon}}/\Phi_D$.

For each firm with $\Phi(\varphi, 0) < \Phi_D$, profits can potentially be earned from adding varieties beyond the core. The total number of varieties produced by a firm with productivity φ is

$$m(\varphi) = \max\left\{ m| \left[\tau^{\frac{\epsilon}{\epsilon-1}} e^{\frac{\nu m\epsilon}{\epsilon-1}} + e^{\frac{\sigma m\epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}} /\Phi_D \leq \varphi \right\} + 1 \quad \text{if } \varphi \geq \varphi_D, \tag{8}$$

which is (weakly) increasing for all $\varphi \in [0, \infty]$. Accordingly, the number of varieties produced by a firm with productivity φ is an integer. This number is an increasing step function of the firm productivity.

Let $p(\Phi)$, $\pi(\Phi) = p(\Phi)q(\Phi) - q(\Phi)\Phi$, and $\lambda(\Phi) = p(\Phi) - \Phi$ denote the price, the profit, and the (absolute) markup of a variety with production cost Φ, which can take the value $\Phi(\varphi, m)$ under technology l and $\Phi(\varphi, m)/\rho$ under technology h. All these performance measures can then be written as functions of Φ_D and Φ:

$$p(\Phi) = [\Phi_D + \Phi]/2, \;\; \lambda(\Phi) = [\Phi_D - \Phi]/2, \tag{9}$$

$$q(\Phi) = \frac{L}{2\gamma}[\Phi_D - \Phi], \; r(\Phi) = \frac{L}{4\gamma}[\Phi_D^2 - \Phi^2], \tag{10}$$

$$\pi(\Phi) = \frac{L}{4\gamma}[\Phi_D - \Phi]^2. \tag{11}$$

Thus, lower marginal cost varieties have lower prices and earn higher revenues and profits than varieties with higher marginal costs.

To close the discussion of firms' behavior, in equation (11), firms maximize profits for an arbitrary technology (either l or h). Variety by variety, firms compare optimized profits across the two technologies and select the option that yields higher profits. The cost of using technology h is the same for all varieties while the benefit varies with the varieties' initial marginal cost. The marginal variety for which a firm adopts technology h, with initial marginal cost Φ_A, is determined by $\pi^h(\Phi_A/\rho) - f - \pi^l(\Phi_A) = 0$. Using (11), the cutoff for technology adoption can be expressed as a function of the production cost cutoff Φ_D:

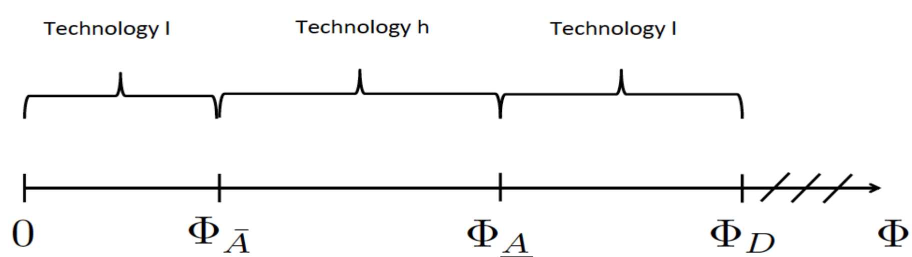
$$\Phi_A^2(1 + \frac{1}{\rho}) - 2\Phi_D\Phi_A + \frac{4\gamma f}{L(1 - 1/\rho)} = 0. \tag{12}$$

This quadratic function finds solutions if and only if $\Phi_D^2 \geq 4(1+\rho)\gamma f/(\rho L - L)$; in which case, we obtain

$$\Phi_{\bar{A}} = \frac{\Phi_D - \sqrt{\Phi_D^2 - \frac{C_1}{L}}}{1+1/\rho}\ , \Phi_{\underline{A}} = \frac{\Phi_D + \sqrt{\Phi_D^2 - \frac{C_1}{L}}}{1+1/\rho} \tag{13}$$

with $C_1 = \frac{4(1+\rho)\gamma f}{L(\rho-1)}$. In the absence of solution, all varieties are produced under technology l. If both solutions are interior, that is $\Phi_{\bar{A}}, \Phi_{\underline{A}} < \Phi_D$, then there is a range of varieties with initial production costs contained in the interval $[\Phi_{\bar{A}}, \Phi_{\underline{A}}]$ for which firms prefer to adopt technology h. The lowest cost varieties, $[0, \Phi_{\bar{A}}]$, and the highest cost varieties, $[\Phi_{\underline{A}}, \Phi_D]$, remain produced under technology l as the gains from technology adoption do not outweigh the fixed cost f. This closes the production plan for the firm.[6] Figure 1 summarizes the technology choice for all varieties depending on their production costs, when both technology cutoffs are lower than Φ_D.

Figure 1: Technological choice for all varieties depending on their production costs



2.1.5 Free Entry and Equilibrium

In the long run equilibrium, the unrestricted entry of new firms drives expected profit to zero. Prior to entry, expected firm profit is given by $\int_{\varphi_D}^{\infty} \Pi(\varphi) dG(\varphi) - f_E$ where

$$\Pi(\varphi) = \sum_{m=0}^{m_{\bar{A}}(\varphi)-1} \pi^l(\Phi(\varphi, m)) + \sum_{m=m_{\bar{A}}(\varphi)}^{m_{\underline{A}}(\varphi)} \pi^h\left(\frac{\Phi(\varphi, m)}{\rho}\right) + \sum_{m=m_{\underline{A}}(\varphi)+1}^{m(\varphi)-1} \pi^l(\Phi(\varphi, m))$$
$$- [m_{\underline{A}}(\varphi) - m_{\bar{A}}(\varphi) - 1]f, \tag{14}$$

[6] Since $\Phi_{\bar{A}} < \Phi_D$, whereas $\Phi_{\underline{A}} < \Phi_D$ if and only if $\Phi_D^2 < 4\gamma\rho^2 f/((\rho-1)^2 L)$, there could also be only one cutoff $\Phi_{\bar{A}}$ above which all varieties adopt technology h. We do not allow firms to create a new variety that would not be profitable under technology l, but would be under technology h. The technology decision is thus posterior to the decision to produce each variety.

if the firm receives a high productivity draw $\varphi \geq \varphi_{\bar{A}}$ where $\varphi_{\bar{A}} \equiv \left[\tau^{\frac{\epsilon}{\epsilon-1}} e^{\frac{\nu m\epsilon}{\epsilon-1}} + e^{\frac{\sigma m\epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}} / \Phi_{\bar{A}} \equiv A(m)/\Phi_{\bar{A}}$. $m_{\bar{A}}(\varphi)$ and $m_{\underline{A}}(\varphi)$ identify the varieties with the lowest and the highest production cost, respectively, produced under technology h, while the firm produces $m(\varphi)$ varieties. When the firm receives a lower productivity draw, its core product may directly use technology h, and only its highest production cost varieties would use technology l. If the productivity draw is very low, $\varphi_D < \varphi < \varphi_{\underline{A}}$, the firm only produces under technology l.

Taking expectations over $G(\varphi)$, the equilibrium free entry condition simplifies to

$$\sum_{m=0}^{\infty}\left[\int_{\frac{A(m)}{\Phi_D}}^{\frac{A(m)}{\Phi_{\underline{A}}}} \pi^l(\Phi(\varphi,m))dG(\varphi) + \int_{\frac{A(m)}{\Phi_{\underline{A}}}}^{\frac{A(m)}{\Phi_{\bar{A}}}} [\pi^h(\Phi(\varphi,m)) - f]dG(\varphi) + \int_{\frac{A(m)}{\Phi_{\bar{A}}}}^{\infty} \pi^l(\Phi(\varphi,m))dG(\varphi)\right] = f_E. \tag{15}$$

To obtain closed form expressions, we follow MMO and assume productivity draws φ follow a Pareto distribution with cumulative distribution function $G(\varphi) = 1 - \varphi^{-k}$, $\varphi \in [0,\infty]$. The shape parameter k indexes the dispersion of productivity draws. The distribution is uniform when $k = 1$, and it becomes more concentrated at lower initial productivity levels when k increases. Any truncation from below will retain the same distribution function, hence the productivity distribution of surviving firms will also be Pareto with shape k.

We can rewrite and simplify the free entry condition (15) using this parametrization as

$$\frac{f_E}{\Omega} = C_2\Phi_D^{k+2} + C_3(\Phi_{\bar{A}}^{k+2} - \Phi_{\underline{A}}^{k+2}) - C_4\Phi_D(\Phi_{\underline{A}}^{k+1} - \Phi_{\bar{A}}^{k+1}) - f(\Phi_{\underline{A}}^{k} - \Phi_{\bar{A}}^{k}), \tag{16}$$

where C_2, C_3 and C_4 are constants[7], and $\Omega \equiv \sum_{m=0}^{\infty} A(m)^{-k}$ is the sequence of the unit cost component that does not depend on firm productivity. We find that this sequence converges if and only if $\epsilon \leq 1$, $\nu > 0$ and $\sigma > 0$, which are assumed in Lemma 1.[8] Substituting the technology cutoffs $\Phi_{\bar{A}}$ and $\Phi_{\underline{A}}$ by their values from (13) implies that (16) has a unique unknown variable, the production cost cutoff Φ_D. In appendix A.2, we prove the existence and unicity of the solution to equation (16).

[7] We have $C_2 = \frac{L}{2\gamma(k+2)(k+1)}$, $C_3 = \frac{Lk(1-1/\rho^2)}{4\gamma(k+2)}$, and $C_4 = \frac{Lk(1-1/\rho)}{2\gamma(k+1)}$.

[8] We have $\left[\tau^{\frac{\epsilon}{\epsilon-1}} e^{\frac{\nu m\epsilon}{\epsilon-1}} + e^{\frac{\sigma m\epsilon}{\epsilon-1}}\right]^{\frac{(1-\epsilon)k}{\epsilon}} \longrightarrow_{m\to\infty} 0$ if and only if $\nu, \sigma > 0$ and $\epsilon \leq 1$. We also know that $d\Omega/d\tau < 0$ as $0 < \epsilon \leq 1$.

2.2 Results

Our interest lies in identifying the role of three channels – firm reallocation, product mix and technology adoption – in determining the emission intensity of manufacturing production. We will proceed sequentially by analyzing first firm reallocation and product mix, and then add the technology adoption decision.

2.2.1 Results on Firm Reallocation and Product Mix

Assuming that the decision to adopt technology h is not profitable for any variety, the free entry condition (16) simplifies greatly (using $\Phi_{\bar{A}} = \Phi_{\underline{A}}$).[9] In this case, the endogenous cost cutoff solves to

$$\Phi_D = \left[\frac{2\gamma(k+1)(k+2)f_E}{L\Omega}\right]^{\frac{1}{k+2}}. \tag{17}$$

An increase in market size L, as well as an decrease in environmental regulation (since $d\Omega/d\tau < 0$), decreases the cost cutoff Φ_D, which translates into a tougher competitive environment. This market with tougher competition then features more product variety M and lower average price $\bar{p}$ because of the combined effect of product selection toward the lowest cost varieties and of lower markups (see Appendix A.3).

What are the economic and environmental impacts of the increase in competition? To answer this question, we compute the aggregate output, total cost, and total pollution level by summing these variables over all varieties produced:

$$Q(\varphi) \equiv \sum_{m=0}^{M(\varphi)-1} q(\Phi(\varphi,m)), C(\varphi) \equiv \sum_{m=0}^{M(\varphi)-1} \Phi(\varphi,m)q(\Phi(\varphi,m)), Z(\varphi) \equiv \sum_{m=0}^{M(\varphi)-1} z(\Phi(\varphi,m)),$$

where, using (6) and (10), we have $z(\Phi(\varphi,m)) = \frac{L}{2\gamma}E(\varphi,m)[\Phi_D - \Phi(\varphi,m)]$. From these aggregates, we construct two efficiency measures: one for economic efficiency, the other for environmental efficiency. Our measure of firm efficiency is simply the inverse of the average cost per product, i.e., $\psi_C(\varphi) \equiv Q(\varphi)/C(\varphi)$. Our measure of firm emission intensity is the average emission level per unit of output, i.e., $\psi_Z(\varphi) \equiv Z(\varphi)/Q(\varphi)$.

As in Mayer et al. (2014), a firm facing increased competition can choose to drop some of its most expensive varieties, but it can also change the relative output share of each variety. There are thus an intensive and an extensive margins of adjustment within firms that are channeled

[9] Recall that this case occurs if and only if $\Phi_D^2 < 4(1+\rho)\gamma f/(\rho L - L)$.

through the product mix. The product mix effect makes firms skew their production toward their core varieties whose relative markups and profits rise. This yields

Proposition 1. *Tougher competition (a decrease in Φ_D) improves firm-level productivity measure, and it reduces (increases) firm-level emission intensity if and only if $E(\varphi, m)$ is increasing (decreasing) in m.*

Proof: see Appendix A.4.

Proposition 1 shows that even though increased competition always raises firm-level economic efficiency, it does not necessarily raise firm-level environmental efficiency. The environmental impact depends on whether core products are cleaner or dirtier than higher-m varieties.

At the industry level, however, the product mix effect is combined with the reallocation effect through which less productive firms exit while more productive firms enter the market and increase their market share. This selection effect that skews aggregate production toward more productive firms improves the average productivity of the sector. Its impact on the average environmental performance depends on two countervailing forces: first, more productive firms use inputs more efficiently, which decreases the average emission intensity; second, more productive firms produce a wider variety of products, which can make these firms dirtier or cleaner depending on the emission intensity of higher-m varieties. We get the industry productivity measure by aggregating over firms:

$$\bar{\psi}_C \equiv \frac{\int_{\varphi_D}^{\infty} Q(\varphi) dG(\varphi)}{\int_{\varphi_D}^{\infty} C(\varphi) dG(\varphi)} = \frac{k+2}{k} \frac{1}{\Phi_D}. \tag{18}$$

Similarly, the industry emission intensity depends on the aggregate emissions level, which is given by

$$\int_{\varphi_D}^{\infty} Z(\varphi) dG(\varphi) \equiv \int_{\varphi_D}^{\infty} \left[\sum_{m=0}^{M(\varphi)-1} z(\Phi(\varphi, m)) \right] dG(\varphi) = \frac{Lk\Phi_D^{k+2}\Gamma}{2\gamma(k+1)(k+2)}, \tag{19}$$

where $\Gamma \equiv \sum_{m=0}^{\infty} \varphi E(\varphi, m) A(m)^{-k-1}$. The sequence Γ is finite under the conditions $\epsilon > 0$ and $\nu > \sigma$, as shown in Appendix A.5. Because these conditions are precisely the sufficient conditions required in Lemma 2 to preserve an ambiguous relationship between $E(\varphi, m)$ and m, and because we are only interested in cases that preserve this possibility, we need no further restriction. The aggregate emission intensity measure is thus given by

$$\bar{\psi}_Z \equiv \frac{\int_{\varphi_D}^{\infty} Z(\varphi)dG(\varphi)}{\int_{\varphi_D}^{\infty} Q(\varphi)dG(\varphi)} = \frac{k\Phi_D\Gamma}{(k+2)\Omega}, \tag{20}$$

and we have

Proposition 2. *Tougher competition (a decrease in Φ_D) implies*

i/ an increase in aggregate productivity;

ii/ a decrease in aggregate emission intensity.

Proof: see Appendix A.5.

Thus, bigger markets (low Φ_D) also have higher aggregate productivity and lower aggregate emission intensity. These aggregate responses combine a firm level response (including product mix effect) with across-firm reallocation effects (including entry and exit). The result on aggregate productivity is consistent with Mayer et al. (2014). Firms skew production towards their better-performing products, and less competitive firms exit the market as competition increases. This reduces the average cost of production at the sector level. Consumers benefit from tougher competition because it lowers average prices ($\bar{p}$), as well as average markups ($\bar{\lambda}$).

The result on aggregate emission intensity is novel. Despite the ambiguity in the firm level response (see Proposition 1), we find that tougher competition reduces aggregate emission intensity at the industry level. This impact is driven by the across-firm reallocation effect. Even though productive firms can adjust their product mix in a way that increases their emission intensity, they remain cleaner than less efficient firms.

2.2.2 Results on Technology Adoption and Product Mix

When the decision to adopt technology h is profitable for some varieties within firms, firms adjust endogenously both their product mix and their technology choice when market conditions vary. Since technology h is more efficient in using all inputs, within-firm-product technical change reduces the emission intensity of the adopting firms. Technology adoption is thus unambiguously good for emission intensity, in isolation. However, the impacts are more complicated when the firm can adjust both technology and product mix at the same time.

When both channels are available to firms, three cutoffs (Φ_D, $\Phi_{\bar{A}}$ and $\Phi_{\underline{A}}$) determine the equilibrium. It is no longer sufficient to consider that a change in Φ_D reflects the change in market conditions, since both technology cutoffs depend on Φ_D and other exogenous variables such as the size of the market L. We obtain

Proposition 3. *An increase in market size implies*

i/ tougher competition (a decrease in Φ_D),

ii/ and an ambiguous impact on technology adoption.

Proof: see Appendix A.6.

Whereas an increase in market size unambiguously implies tougher competition – as in the context when no variety adopts technology h – its impact on technology adoption is ambiguous. In Appendix A.2, we note that for sufficiently large market sizes, more lowest cost varieties would adopt technology h. This results in an increase in technology adoption when the cutoff $\Phi_{\underline{A}}$ is not interior. When the cutoff $\Phi_{\underline{A}}$ is interior, however, this increase in technology adoption can however be counterbalanced by a reduction in technology adoption from the highest cost varieties. We illustrate these different outcomes using numerical simulations in the Appendix. These simulations suggest that more efficient firms will adopt technology h for some of their best products, while higher cost varieties may switch back to being produced under technology l when competition gets tougher.

Next, we consider the interaction effects of the two forces. From Proposition 3, we know that an increase in market size increases competition, and may induce technology adoption for some varieties, especially some of the best performing ones. To isolate the product mix response to competition and the interaction between technology adoption and product mix, consider two varieties m and m' produced by a firm with productivity φ, where $m < m'$. Assuming that both varieties are initially produced under technology l, the ratio of the firm's output of the two varieties is given by

$$\frac{q^l(\Phi(\varphi, m))}{q^l(\Phi(\varphi, m'))} = \frac{\Phi_D - \Phi^l(\varphi, m)}{\Phi_D - \Phi^l(\varphi, m')}. \tag{21}$$

First, assume that the firm will not adopt technology h for any of its products. As competition increases (Φ_D decreases), this ratio (21) increases, implying that the firm skews its production toward its core varieties. This reallocation of output toward better performing products generates the productivity increase within the firm; this describes a pure product mix channel.

By contrast, assume the firm adopts technology h for one of its varieties as competition increases. If the firm selects variety m for technology adoption, then the marginal cost of production of this variety decreases to $\Phi^h(\varphi, m) = \Phi^l(\varphi, m)/\rho$. This translates into higher relative demand and sales for good m as its relative price decreases. Thus, technology adoption for good m exacerbates the output reallocation toward better performing products. Technology adoption reinforces the product mix effect in this case.

If variety m is extremely profitable, however, the firm might decide to adopt technology h for variety m' instead, lowering its marginal cost to $\Phi^h(\varphi, m') = \Phi^l(\varphi, m')/\rho$. In this case, technology adoption decreases the relative price of variety m', and increases its relative demand. This counteracts the product mix effect as variety m' gains market shares due to its lower marginal cost of production. Technology adoption cannot however revert the ranking of varieties in terms of marginal costs, hence $\Phi^l(\varphi, m) < \Phi^h(\varphi, m')$. An increase in competition in this context leads to ambiguous impacts on product mix because of its effect on technology adoption, which reallocates output toward varieties using new technologies.

2.2.3 Impacts of Trade

The expansion of the Indian economy in the last two decades reflects not only an increase in the domestic market size, as Indian consumers gain purchasing power, but also an increase in trade, as Indian firms gain access to foreign markets. The model yields implications about the relationship between trade liberalization and the equilibrium domestic cost cutoff level, denoted by Φ_{jj}. As shown in Appendix A.7, bilateral trade liberalization induces two countervailing effects: a domestic competitive effect (i.e., a decrease in Φ_{jj} as described above) and an increased export market access effect (i.e., an increase in the export cost cutoff Φ_{jf}). The latter effect is such that, as it becomes less costly to ship goods to the trading partner, more firms start to export and more varieties are shipped. Therefore, the impacts described in Propositions 1 and 2 are reversed for the export market access effect. This implies that depending on the relative strength of these countervailing effects, Indian manufacturing emission intensity can increase or decrease over time. We provide details about the impacts of trade liberalization in Appendix A.7.

2.3 Empirical Implications

Our framework implies three empirical predictions that we can test in the data:

Prediction 1. *Bigger firms have lower emission intensity.*

Prediction 2. *Emission intensity is either systematically increasing or decreasing in sales across varieties within the firm.*

Prediction 3. *The probability of entry and exit is increasing in* m.

Prediction 1 follows from Proposition 2. Since tougher competition reallocates market shares to more productive firms and reduces the industry-level emission intensity, it implies that firm average emission intensity is falling in firm size.

Prediction 2 follows directly from (10) and lemma 2: higher-m varieties generate lower sales, and either have higher or lower emission intensity, depending on the parameters σ, ν, and ϵ. As these parameters are assumed constant across firms and products within an industry, the sign of the correlation should be constant at the industry level, but it could vary between industries.[10]

Prediction 3 follows from (10), (11) and Proposition 1: higher-m varieties are produced at low quantities and earn low profits. Hence, when market conditions change, these varieties will become either newly profitable (in the case that Φ_D increases) or newly unprofitable (in the case that Φ_D falls). This generates either entry or exit.

Our model also illuminates several points about our channels that we can bring to the data. First, the product mix effect depends on whether core products are cleaner or dirtier than higher-m varieties. Second, even though the product mix effect makes firms dirtier when core products are dirtier, reallocating resources to more efficient firms makes the industry cleaner. Third, technology adoption makes firms cleaner, but the impact of an increase in market size on adoption and product mix is ambiguous.

3 Data and Background

We test the implications of our model using detailed production for the Indian economy between 1990-2010. This empirical setting offers two key benefits for our purpose. First, the Indian economy saw a remarkable array of market reforms over this period that dramatically increased the competitiveness of the economy (Goldberg et al., 2010a,b). Second, there exists unusually detailed production data for a large swath of firms over this period with which we can explore the different micro channels laid out in the model. Additionally, India is a major emitter of GHGs that is expected to contribute significantly to emission growth over the next century, so the determinants of emission intensity in this country are important in their own right. In this section, we describe the institutional background, discuss issues in calculating the different components of emission intensity, and then present the data.

[10] Even though our theoretical framework considers only one differentiated sector, we consider several industries in the empirical part of the paper.

3.1 Institutional Context

In India, sweeping market reforms have been implemented in recent years, including the trade liberalization of the early 1990s and a stepped-up dismantling of the license raj. These reforms have had pro-competitive effects on industry and firm productivities. Market conditions have also changed due to the increased domestic demand of a fast-growing economy and greater access to foreign markets after the removal of export tariffs in the early 1990s. These changes could lower competition among firms and products. We successively present the reforms with pro-competitive impacts and the changes in market conditions that lowered competition in India.

Significant reforms were introduced in 1991 that transitioned India from a closed, highly regulated economy to a more open, free-market oriented system. The proximate cause for the reforms was a severe balance of payments crisis in 1991. Financial assistance was granted by the International Monetary Fund to support India's adjustment program, which included major structural reforms. One big reform was the extensive liberalization of licensing requirements for establishing and expanding capacity (a system called the "license raj"). India started dismantling its license system during the 1980s and stepped up this process in 1991. By 1997, roughly 90 percent of industries (and output) were delicensed (Aghion et al., 2008). Other pro-competitive reforms initiated in 1991 included the trade liberalization of imports and exports, and the removal of restrictions on foreign direct investments. These reforms have had the expected pro-competitive effects on Indian industries. Lower output tariffs induce productivity gains (Krishna & Mitra, 1998; Sivadasan, 2009; Topalova & Khandelwal, 2011). More precisely, Topalova & Khandelwal (2011) find that trade liberalization lead to higher levels of productivity only for private companies.

Since 1997, there have been further adjustments to import tariffs, and other sweeping reforms have also been undertaken, some under the influence of standard political economy pressures (Topalova & Khandelwal, 2011). For instance, the progressive dismantling of the "reservation" system, under which certain industrial products would be reserved for exclusive manufacture by small-scale enterprises, started in 1997 and ended in 2010. After the removal of these product market restrictions, product churning and productivity rose (Tewari & Wilde, 2014; Harrison et al., 2014).

In a fast-growing economy with a population characterized by huge wealth disparities, it is possible that the expansion of the domestic market lead to little product churning since there is always a demand for older products while new products are adopted by the wealthy (Goldberg et al., 2010b). This evidence indicates that pro-competitive forces are not the only ones affecting market conditions. An increase in foreign demand for Indian products also lower competition among exporters and allow firms to export less profitable varieties (Chakraborty, 2012; Barrows & Ollivier, 2015).

3.2 Data Preliminaries

Our theoretical model indicates that market liberalization lowers aggregate emission intensity through reallocating production across heterogeneous firms over time and through technological adoption within product lines, but could be offset by reallocations across products within firms (depending on the correlation between unit cost and emission intensity). We aim at shedding new light on these channels, but in doing so we face some well-known empirical challenges.

First, measuring pollution as a byproduct of production can be quite difficult. The generation of most air pollutants (e.g., SO2, NOx, VOC) depends on production and abatement technologies, which means that they are only measurable end-of-pipe. In order to measure these pollutants, firms must install monitoring technology on site, run them constantly during production periods, and continuously record the readings. Furthermore, firms must truthfully reveal their pollution rates, which research indicates firms tend not to do when external auditing efforts are low (Duflo et al., 2013)

Second, most firms-level datasets only report outputs in terms of total revenue. This means that "productivity" estimates are usually contaminated by endogenous firm-specific pricing decisions and product-mix effects. Additionally, product-mix effects are not separately identifiable from within-product line technological change (since output is not broken down by product-line within the firm). Thus, even if measured productivity responds to competition shocks, it is not clear which mechanism explains the results. One approach to addressing these sources of biases is to assume specific functional forms for production technologies; yet, these assumptions are restrictive and untestable in most cases (De Loecker et al., 2012). As a result, previous research has been unable to credibly identify the micro determinants of emission intensity.

To surmount these measurement problems, we employ a novel production dataset that allows us to compute emission intensity at the firm-product level directly from the data, without imposing any functional form assumptions at all.[11] As mentioned above, these calculations are made possible due to an unusually detailed reporting requirement from the Indian government. By the Indian Companies Act of 1956, Indian firms are required to issue annual reports of economic activity over the period, including outputs in *physical quantities by product line*. This requirement is rare among firm-level dataset and allows us to address both endogeneity of pricing and

[11] That is, we need not impose any assumptions on the production function. We still assume that GHG emissions are directly proportional to energy consumption, as we discuss below.

product-mix.[12] Additionally, while most known production datasets report only at the firm level, the 1988 amendments to the Companies Act also requires firms to breakdown *energy inputs by product* as well. That is, firms are required to report energy intensity of production by both energy source (e.g., coal, diesel, electricity) and product line, each year.[13] This feature of the data is not only rare, it is – to our knowledge – unique among production datasets, and it is what allows us to compute energy input intensity without assuming a specific structure on production.

To fulfill the Companies Act requirement, Indian firms must monitor their energy use with great scrutiny. When a firm produces only one product, or one product per establishment, the energy intensity is easily computed by divided the amount of energy consumed by the quantity produced. When a firm produces multiple products in one establishment, computations become more complex unless the different production lines occur at different times. Energy management softwares (e.g., CMS Computers' energy management solutions – see cms.co.in – or Infotronics Integrators India Pvt Ltd's software – see infotronicsindia.com) have been developed in India to help firms report their energy efficiency adequately. In Appendix B.4, we show that firms do not simply attribute energy use to their products in proportion to sales or production levels, thereby invalidating the main hypothesis for an uninformative rule of thumb calculation.

Of course, energy-use efficiency is not the same thing as pollution intensity. As mentioned above, the emissions of many air pollutants are modulated by end-of-pipe abatement technologies. However, for the case of CO_2, we can exploit the fact that end-of-pipe technologies (e.g., carbon capture and storage) are rarely used, especially in developing countries; hence, emissions *do* scale proportionally with energy use. This equivalence allows us to compute CO_2 emission intensity from quantities of energy used along with embodied CO_2 levels per physical quantity of energy type.

3.3 Data Description

Our production data come from the Center for Monitoring the Indian economy (CMIE), which compiles each year a large set of Indian firms' annual reports into the database called Prowess. In total, CMIE has collected reports from over 10,000 firms, detailing production of more than 40,000 products over the period 1987-2012. The database is not a census, so does not cover all firms, but the database covers every sector of the economy. Also, since Prowess is skewed towards larger firms, it covers a significant portion of output and emissions in the Indian economy

[12] For other datasets with firm-product outputs denominated in quantities, see also Bernard et al. (2011) and Mayer et al. (2014), among others. Note that none of these datasets break down *inputs* by product-line as well.

[13] We refer to 1988 amendment to Section 217(1)(e) of the Indian Companies act of 1956

over the period. Finally, though CMIE does not explicitly assign unique firm and product codes, both firm and product string names are fairly consistent over time, so the data can be linked over time as an unbalanced panel.

CMIE stores different components of the data in different modules. In the output module, a unit of observation is a firm-product-year. For each observation, we have the firm name, product name (i.e., a string variable supplied by the firm to identify the product), the year, the physical quantity of production, the physical unit of production (i.e., denomination of output), and the sales value. In this module, we have a total of 260,295 observations representing 9,715 firms and 36,935 firm-products.

Product-specific energy data is stored in a different module. Here, again, we have the firm name, product name, year, and denomination of physical output (i.e., unit of production). In addition, we also have energy sources used to make 1 unit of output along with the unit rate of consumption of these energy sources. In total, firms report consuming energy in 140 different forms, sometimes consuming multiple types of energy to produce a single product in a given year. To give an example, we see that one firm used 730 Kwh of electricity and .05 tonnes of furnace oil each to produce 1 tonne of "Polyester staple fibre" in 1999. Multiplying each energy source by a specific CO_2 emission rates per unit of energy source from the EPA and summing over energy sources, we compute a firm-product-year CO_2 emission intensity of production (see appendix B for details). This process yields 47,530 firm-product-year observations, representing 3,328 firms and 5,554 firm-products between the years 1987-2012.

Unfortunately, as mentioned above, CMIE assigns neither firms nor products unique identifying codes. Hence, merging input to output data is not straightforward. Since we have string names of both firms and products, a candidate procedure would be to merge on exact string matches, but in many cases matches are not exact. Luckily, in most cases, it is fairly straightforward to merge the two datasets by hand (see appendix B for details). The final dataset contains 31,531 observations (with both output and input values) across 2,746 firms and 4,191 firm-products (restricted to the years 1990-2010, for which we have significant coverage). In Table 1, we breakdown the number of firms by industry and by total number of distinct products manufactured over the period.[14] We find significant coverage across all sub-sectors of manufacturing, and we find a high proportion of multi-product firms.

Descriptive statistics are reported in Table 2. We aggregate across products within the year,

[14]Industries are based on India's National Industrial Classification (NIC). In order to have sufficient coverage in each industry each year, we have aggregated multiple 2-digit NIC codes into the six aggregate industries listed in Table 1. These will also be the industrial classifications we use to calculate the contribution of across-industry reallocations to changes in aggregate emission intensity over time.

Table 1: Number of single and multi-product firms by Industry

Industry	(1) # Firms	(2) 1-Prod	(3) 2-Prod	(4) 3-Prod	(5) >3-Prod
Chemicals, rubber and plastics	735	492	115	56	72
Food, beverage, and tobacco	539	404	85	32	18
Basic/fabricated metal products	529	395	80	29	25
N.metallic min., coke/petroleum	179	128	36	7	8
Textile, apparel, and leather	602	445	105	32	20
Wood and paper	162	132	24	4	2
Total	2746	1996	445	160	145

Notes: Data based on full sample (i.e., outputs denominated in various units). Column (1) reports number of firms by industry. Column (2) reports number of firms that make only 1 product throughout the period. Column (3) reports number of firms that make at least two product throughout the period, and so on. Industries are based on NIC2 classification and are aggregated as follows: Chemicals, rubber and plastics (NIC 20-22), Food, beverage, and tobacco (NIC 10-12), Manufacture of basic metals and fabricated metal products (NIC 24,25), Nonmetallic minerals and coke and petroleum (NIC 23,19), Textile, Apparel, and leather (NIC 13-15), Wood and Paper (NIC 16,17). Columns 2-5 sum to column 1 and industry aggregates sum to total in each column.

so the unit of observation is a firm-year. Panel A reports descriptive statistics for the entire dataset, while Panel B restricts the sample to the set of firms that report output in tonnes.[15] We also split the sample into single-product firms and multi-product firms. A single product firm produces only 1 product throughout the entire period, while a multi-product firm reports making at least two distinct products at some point between 1990-2010. For each set of firms (single-product, all output; multi-product, all output; single-product, only tonnes; multi-product, only tonnes), we report mean, standard deviation, minimum, and maximum of output (i.e. physical production), sales, CO_2, CO_2/value, and number of products (per year) for firm-year observations in the corresponding sample.

As expected, multi-product firms generate more output and emissions, but also have lower emission *intensity* in both value and quantity of output. The average single-product firm in the sample generates 1.817 billion Rs. of sales each year (roughly 40 million USD) and 55.18 kt of CO_2, compared to 1.954 billion Rs and 144.7 kt of CO_2 for multi-product firms. By comparison, the average firm in the nationally representative Indian Annual Survey of Industries generates 0.43 billion Rs in sales and 4.82 kt of CO_2 emissions.[16] So clearly, Prowess firms are much

[15]For some analyses, we will make use of the data in Panel A; but for many of the calculations, it will be necessary to denominate output in a constant physical unit (for example, when comparing emission intensity across firms). In the latter case, we focus on the subsample (Panel B). We note that about 85% of all output observations are denominated in tonnes, so the restriction does not drop much of the data.

[16]These are the authors' own calculations based on ASI microdata, years 2001-2010

Table 2: Descriptive Statistics by Firm-Year Observation

	Single-Product Firms				Multi-Product Firms			
	Mean	SD	Min	Max	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Output Units	*# Firms =1,996*				*# Firms =750*			
Production (various units)	161.6	2488	0.000	93316	5541	130292	0.000	4448870
Sales Value (Bills Rs.)	1.817	25.81	0.000	1293	1.954	6.812	0.000	221
CO_2 (kt)	55.18	282.3	0.000	7424	144.7	484.4	0.000	8149
CO_2/Value (t/Mills Rs.)	411.3	12824	0.000	1365593	261.8	4170	0.000	273598
Number of Products	1	-	1	1	1.874	1.349	1	14
Panel B: Only Tonnes	*# Firms =1,700*				*# Firms =704*			
Production (kt)	98.34	738.2	0.000	15358	219.6	1028	0.000	22633
Sales Value (Bills Rs.)	1.899	27.29	0.000	1293	1.976	7.079	0.000	221
CO_2 (kt)	58.85	285.6	0.000	7158	138.6	470.5	0.000	8149
CO_2/Value (t/Mills Rs.)	241.4	3757	0.000	287169	227.8	4098	0.000	273598
CO_2/Production (t/kt)	11.44	240.5	0.000	12631	2.327	4.661	0.000	149
Number of Products	1	-	1	1	1.786	1.355	1	13

Notes: Data covers 1990-2010. An observation is a firm-year. Inputs and outputs have been aggregated across multiple products in the case of multi-product firms. Panel B restricts the sample to observations with all outputs denominated in tonnes. Entries marked zero in columns 3 and 7 are due to rounding (not true zeros).

larger than the national average. This is due to the reporting threshold for inclusion in Prowess.

4 Empirical Evidence of Mechanisms

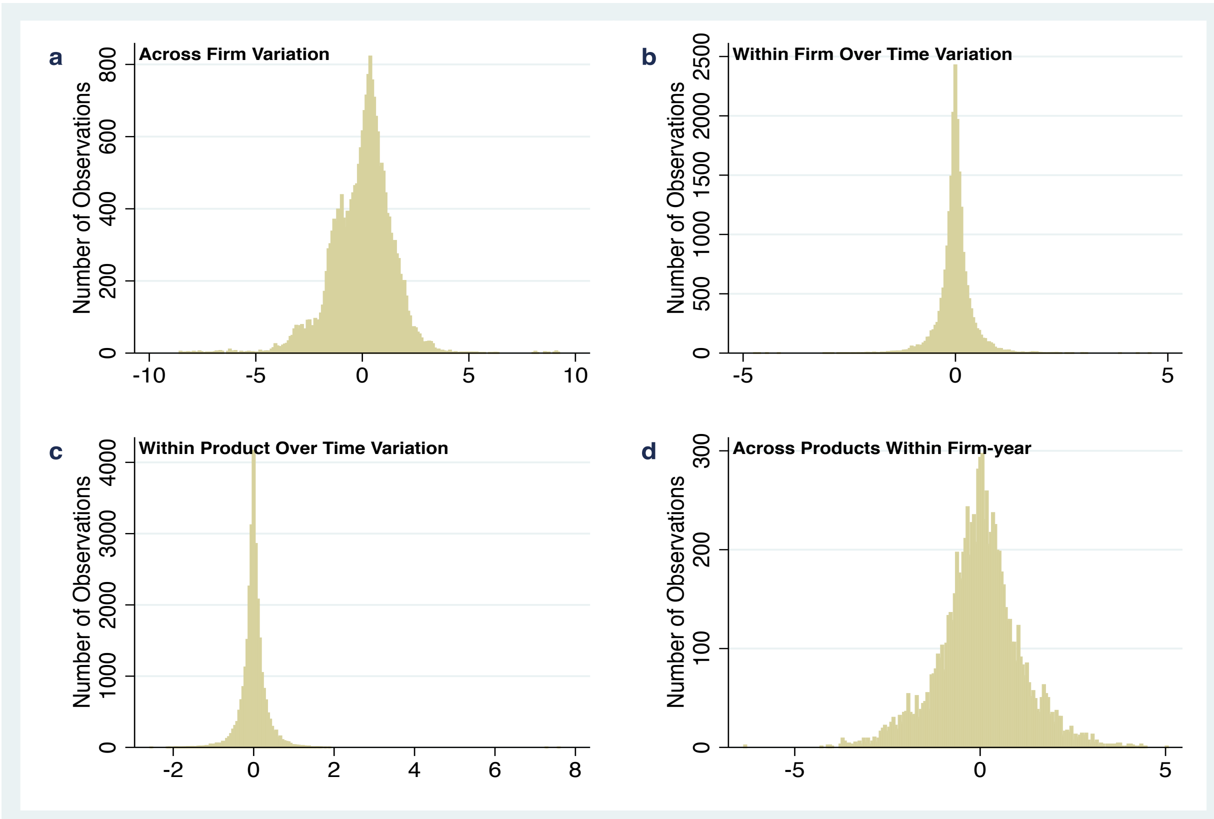
In this section, we bring our detailed production data to bear on the model. The motivation for the model was that firms operate with different levels of productivity over time and across products, and that these productivity differences translate into differences in emission intensity. We begin by checking that these quantities in fact vary (either across units, or within units over time) in the data, and then conduct formal tests of the predictions.

4.1 Analysis of Variation

We begin by assessing variation in emission intensity across firms. In Panel A of Figure 2, we aggregate outputs (in tonnes) and CO_2 to the firm level, regress log emission intensity on year and industry dummies, and plot a histogram of the residuals. Thus, we have only variation across firms within the same industry and year in this panel. Not surprisingly, we find an enormous amount of variation in emission intensity across firms: the standard deviation of log CO_2 per tonne of production in this sample is equal to 1.41. If we assume that log emission intensity is approximately normally distributed, this standard deviation implies that intensities at the 90th percentile are a factor of 37 higher than intensities at the 10th percentile. This is a striking amount of variation in pollution across firms and echoes similar findings with respect to total factor productivity found in other samples (Bernard & Bradford Jensen, 1999; Hsieh & Klenow, 2009).

Moving to panel B of Figure 2, we assess the variation in emission intensity over time within firms. In the model, firm-average emission intensity changes over time both through across-product compositional shifts and within product-line technological change. Here, we study the net effect. We aggregate to the firm-year level, project log emission intensity on firm and year dummies, and plot the residuals. Hence, variation in panel B comes only from within-firm changes over time. As in panel A, we find that emission intensity within firm over time also changes, but that the variation is significantly less than the across-firm variation. With a standard deviation of 0.37 in panel B, emission intensities at the 90th percentile are 3 times higher than intensities at the 10th percentile. Clearly, the variation is much greater across firms, but there is still substantial movement within firms over time. In fact, approximately 60% of firms see their emission intensity fall by at least half over the period (relative to the highest emission intensity for the firm).

Figure 2: Variation in Log Emission Intensity (Tonnes of CO_2/Tonne of Output)



Notes: Each panel plots the distribution of log emission intensity (CO_2/tonne of production) , controlling for different fixed effects. In panel A, industry and year effects have been controlled for. In Panel B, firm and year effect have been controlled for. In both these panels, data has been aggregated across products within the firm, in the case of multi-product firm-years. In panel C, firm-product and year effects are controlled for. In panel D, data is de-meaned by firm-year. Only multi-product firm-years are considered.

Next, we decompose the within-firm variation into its two components – changes in emission intensity within firm-product lines ("technology"), and changes to output shares across heterogeneous products ("product mix"). In panel C, we project log emission intensity at the firm-product level on firm-product and year fixed effects, plot the residuals, and find a standard deviation of = 0.305. This implies a 90-10 split of about 2 for within firm-product lines over time (i.e. technological change).

Finally, in panel D, using only multi-product firm-years, we project log emission intensity at the firm-product level on firm-year fixed effects, plot the residuals, and find standard deviation of 1.108. Hence, using only across-product variation within firm-year, we find a 90-10 split of 17. Thus, emission intensity varies much more across products within the firm than within firm-product over time.

The across product variation can be seen more clearly in Table 3. Here, we report the different deciles of the distribution of ratios in emission intensities between a given firm-product-year and the cleanest firm-product in the same year. That is, within each firm-year, we compare each product to the cleanest firm-product in the year, and then summarize the distribution of this ratio in Table 3. Only multi-product firm-years are considered. In Table 3, we find that the median non-cleanest product has between 1.79 and 5.34 times higher emission intensity than the cleanest product, depending on the industry. For the case of "Chemicals, rubber and plastics" (NIC 20-22), almost 80% of these ratios are more than double the emissions rates of their respective cleanest products. Other industries reveal similarly high degrees of variation.

In summary, we find a striking amount of variation in the data across firms, across products within firms, and within firm-products over time. This degree of variation suggests that the reallocation and technological upgrade mechanisms posited by the model have the potential to play important roles in influencing aggregate emission intensity. We next study the pattern of this variation as it pertains to the predictions of the model.

4.2 Prediction 1: Bigger firms are less emission intensive

Moving to formal tests of the model, we evaluate each of our three empirical predictions in turn. We first present evidence that bigger firms have lower emission intensity. This correlation speaks to the role of across-firm reallocation in determining aggregate emission intensity. While versions of this prediction have been evaluated elsewhere (Holladay, 2015; Galdeano-Gómez, 2010), previous research only observes emission intensity in value of production, whereas we observe physical quantities of production. This allows us to isolate productivity effects from pricing decisions.

Taking firm size (total output) as a proxy for productivity, we split the sample of firms into deciles of productivity each year and estimate the following flexible specification:

$$e_{fy} = \sum_{j=1}^{9} \delta_j * D_{jfy} + \alpha_s + \epsilon_{fy}, \tag{22}$$

where e_{fy} is log CO2 emission intensity of firm f in year y, D_{jfy} is the dummy variable indicating that firm f is part of decile j in year y, α_s controls for sector category, and ϵ_{fy} is an error term. We omit the dummy variable associated with the biggest firms $(j = 10)$, so firm emission

Table 3: Comparison of Emission Intensity Across Products Within Firm-Year

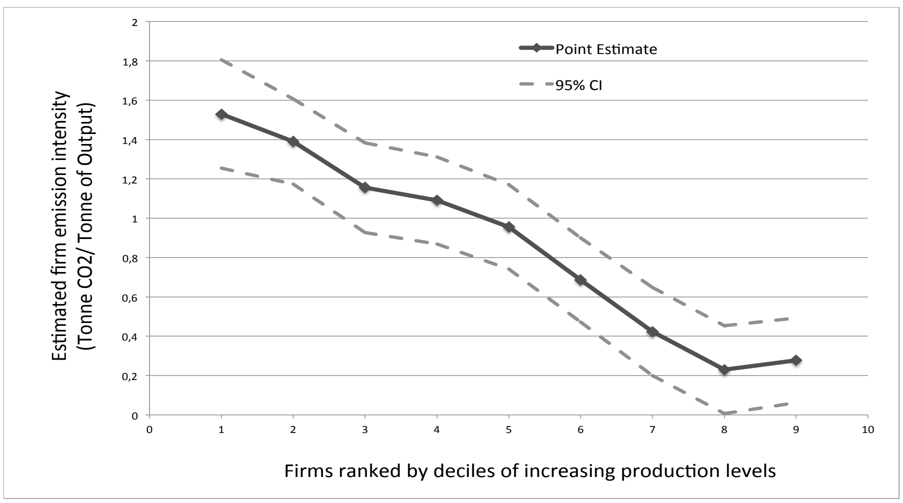
	Ratio of Emission Intensity to cleanest product at Decile										
Industry	10	20	30	40	50	60	70	80	90	Max	Obs
Chemicals, rubber and plastics	1.38	1.96	2.54	3.61	5.34	8.72	16.09	29.09	59.16	1500.38	3131
Food, beverage, and tobacco	1.39	1.68	2.12	2.81	4.04	6.69	11.55	23.54	108.93	5230.52	872
Basic/fabricated metal products	1.28	1.60	1.89	2.16	2.73	3.30	4.16	5.75	9.24	3399.85	717
N.metallic min., coke/petroleum	1.37	1.73	2.28	2.93	3.82	5.25	11.38	27.29	84.65	368.03	531
Textile, apparel, and leather	1.22	1.43	1.67	2.10	2.98	3.85	5.20	7.09	12.59	165.29	511
Wood and paper	1.12	1.21	1.36	1.57	1.79	2.15	2.81	7.61	16.97	71.00	231

Notes: Sample includes only multi-product firm-years. Emission intensity for a given firm-product-year is compared to the lowest emission intensity within the firm-year and summarized by decile.

intensity are relative to the top decile. The coefficients of interest are δ_j, which indicate how firm emission intensity varies with distance from the biggest firms.

Figure 3 reports the regression results graphically. As expected, we find that the less productive firms have higher emission intensity. For the bottom decile, we estimate that firms are approximately 4.5 times dirtier than firms in the top decile.[17]. We see that the point estimates decline approximately linearly with firm size. At the middle decile, firms are about 2.5 times dirtier than firms in the top decile. We plot 95% confidence intervals with dashed lines, and find that all point estimates are statistically significant at the 5% level. These estimates confirm Prediction 1 and indicate that reallocating market shares towards the most efficient firms has the potential to reduce the average emission intensity of the Indian manufacturing sector significantly.

Figure 3: Estimated firm emission intensity as a function of firm size



Notes: Figure plots point estimates and 95% confidence intervals of firm decile impacts on emission intensity derived from projecting log firm emission intensity in tonnes of CO_2 per tonne of output on sector fixed effects and fixed effects for firm deciles. Horizontal axis corresponds to the deciles firms belong to. Regression includes 21,217 firm-year observations, and data span 1990-2010. Standard errors are clustered at the firm level.

4.3 Prediction 2: Emission intensity is either increasing/decreasing in m

Next, we test for systematic variation in emission intensity across varieties within the firm. The basic mechanism at the heart of the model is that firms produce different outputs with different technologies. In particular, firms have a core-competency variety that they are "best" at producing, and all subsequent varieties are produced at lower volumes and higher unit costs. Prediction 2 states that emission intensity may either follow the same pattern as unit cost (increasing in m),

[17] $\delta_1 = 1.5 \Longrightarrow$ firms in the 10th decile are $e^{1.5} = 4.5$ times dirtier than firms in the top decile (omitted category)

or the opposite pattern (decreasing in m). The fact that efficiency decays away from the core pushes emission intensity up as m rises, but the possibility of substitution away from energy towards labor could push emission intensity down. Absent a knife-edge case, one of these effects will dominate, in which case emission intensity should be systematically related to "distance" from the core product.

We first compute output share by product within a firm-year and then order by share, taking output rank as a proxy for unit cost.[18] Denote by m the output rank within the firm, so the core product in a year is coded "$m = 1$" while the product with the second highest output share is coded "$m = 2$," and so on. To test for systematic variations of emission intensity within the firm, we estimate

$$e_{fpy} = \sum_m \delta_m * m_{fpy} + \alpha_{fy} + \alpha_{\bar{p}} + \epsilon_{fpy} \tag{23}$$

where e_{fpy} is log CO_2 emission intensity of product p produced by firm f in year y, m_{fpy} is the output rank of the product within the firm-year, α_{fy} correspond to firm-year fixed effects, $\alpha_{\bar{p}}$ controls for product category, and ϵ_{fpy} is an error term. In equation (23), we flexibly estimate the relationship between the product rank and emission intensity. The coefficients of interest are δ_m, which indicate how emission intensity varies with distance ($m \geq 2$) from the core. If $\delta_m > 0$, core products are cleaner than higher rank-m products whereas if $\delta_m < 0$, core products are dirtier.

Figure 4 presents regression results graphically using the entire firm-product level dataset (Panel A) and tonnes only (Panel B).[19] In Panel A, we find that emission intensity is generally increasing in m, and that this increase is approximately linear. That is, products with $m = 2$ are dirtier than core products, and products with $m = 3$ are dirtier than products with $m = 2$, and so on. We plot 95% confidence intervals with dashed lines and find that these point estimates are statistically significant at the 5% level, up until $m = 9$, at which point precision falls off. To interpret the magnitude of these coefficients, an estimate of δ_2 equal to 0.28 indicates that the first follow-on product is about 33% higher than the core product, while δ_3 equal to 0.65 indicates that the second follow-on product is almost twice as dirty as the core product. Products with m above 5 have emission intensities between 2 and 7 times dirtier than the core, though these effects are less precisely estimated. Coefficients are even larger in Panel B, where we condition output to be denominated in the constant unit tonne.

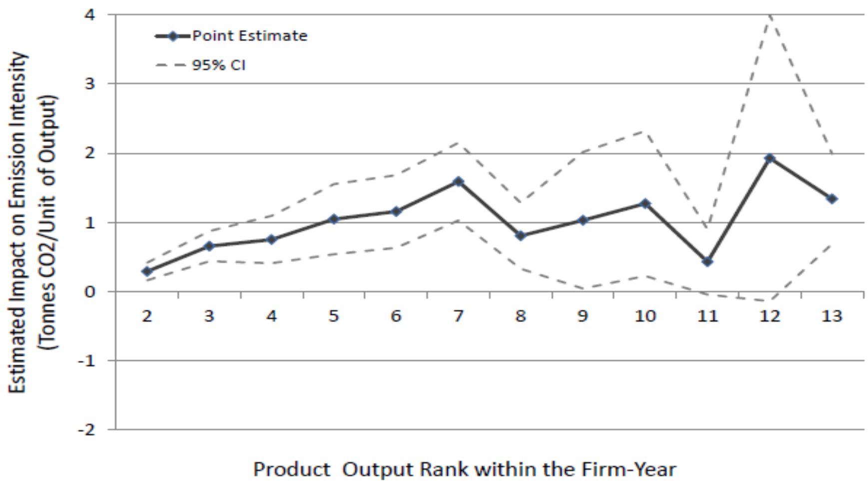
The estimates in Figure 4 represent the first direct evidence that productivity varies systemat-

[18] In the model, the lowest cost product also generates the highest sales, is produced in greater quantity, and represents the firm's core competency.

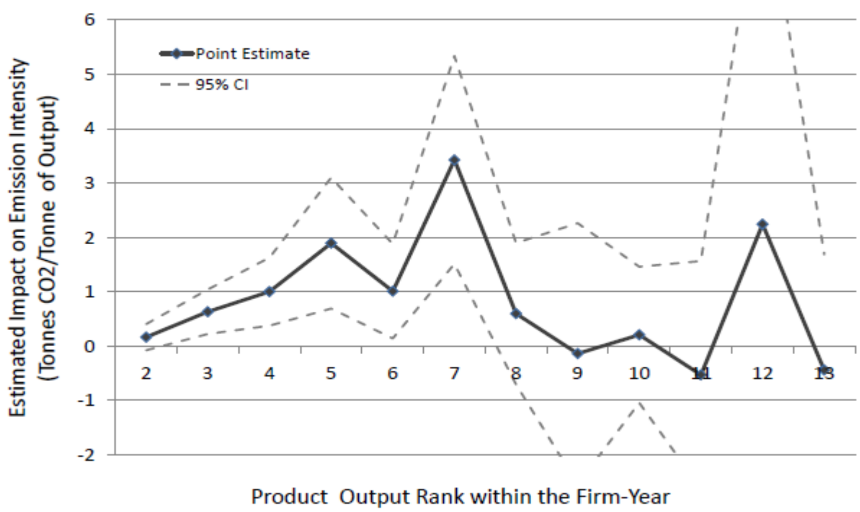
[19] We however impose that all products within a firm have the same unit.

Figure 4: Estimated CO_2 Intensity by Product Rank Relative to Core Product

A) All Units



B) Tonnes Only



Notes: Figure plots point estimates and 95% confidence intervals of product-rank impacts on emission intensity derived from projecting log firm-product emission intensity in tonnes of CO_2 per unit of output on firm-year fixed effects, product category fixed effects (P2-level) and fixed effects for (output-based) product rank within the firm-year. Horizontal axis corresponds to the product rank within the firm-year. Panel A includes 9,012 firm-product observations comprising 3,245 firm-years. Regressions exclude the top and bottom 1% of emission intensities. Output units are restricted to be the same within firm-year. Standard errors are clustered at the firm level. Panel B includes 8,650 firm-product observations comprising 3,091 firm-years. Regressions exclude the top and bottom 1% of emission intensities. Standard errors are clustered at the firm level. Average emission intensity for all products and core-products is 1.83 and 1.40 tonnes of CO_2 per tonne of output, respectively.

ically across products within the firm in the literature and they strongly support the product-mix mechanism posited by the model. Not only is the relationship statistically significant, the magnitudes are striking. To put the size of these coefficients in context, consider that reallocating 1 unit of output from a firm's 5th product to its core product lowers aggregate emission intensity as much as moving 1 unit of production away from a firm at the median decile and reassigning it to a firm in the top (most productive) decile. This finding indicates that across-product reallocations within the firm has the potential to influence aggregate efficiency as much as the well-known across-firm effect of Melitz (2003).

Table 4: Emission Intensity of products by rank within the firm, disaggregated by Industry

Dep Var:	Log(E/Q)					
	Food	Textile	Wood	Chem	Nonmetal	Metal
	(1)	(2)	(3)	(4)	(5)	(6)
Product Rank	0.19*	-0.14	0.39	0.26***	0.38***	0.14
	(0.10)	(0.11)	(0.28)	(0.05)	(0.09)	(0.09)
Firm-Year FE	Y	Y	Y	Y	Y	Y
Product Category FE	Y	Y	Y	Y	Y	Y
Num of Obs	1282	698	414	4353	824	1441
R squared	0.36	0.43	0.51	0.17	0.52	0.12
Mean Dep. Var	-1.04	0.30	0.51	-0.83	-0.41	-1.32

Notes: Each columns tests for product-rank impacts on log emissions intensity in a different industry. Dependent variable is log CO_2 intensity in units of output, where units are restricted to be the same within the firm-year observation. "Product Rank" reflects the real output share of the product within the firm-year (e.g., 1 = highest output share, 2 = second highest output share, etc...) All regressions include only multi-product firm-year observations for the years 1990-2012. The top and bottom 1% of economy-wide emission intensities have been dropped. Standard errors are clustered at the firm level (reported in parentheses). Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Additionally, the estimates in Figure 4 indicate that the direct effect of efficiency decay outweighs any factor substitution effects away from energy. This is an interesting empirical finding, but not at all obvious *a priori*. The model is general enough to allow that either effect could have dominated, it just turns out that we find that the former dominates. This result indicates either that labor and energy are not highly substitutable, or that perhaps labor efficiency decays quicker than energy efficiency as m increases. In any event, the positive correlation between m and emission intensity indicates that increased concentration on core products should lower firm-average emission intensity, while increasing production away from the core will increase emission intensity.

Finally, we test for heterogeneous impacts by industry. In theory, the correlation between emission intensity and m depends on the parameters σ, ν, and ϵ, which could vary by industry. Hence, the correlation could also vary by industry. We investigate this possibility in Table 4, where we impose linearity and estimate (23) industry by industry. While it is theoretically possible that the correlation varies by industry, we find only weak evidence of heterogeneous effects. In Table 4, we estimate a statistically significant and positive δ for the food, chemicals, and nonmetallic industries, and statistically insignificant and negative for textile industries. This indicates that for all industries, with the potential exception of textiles, reallocation towards the core product should lower emission intensity.

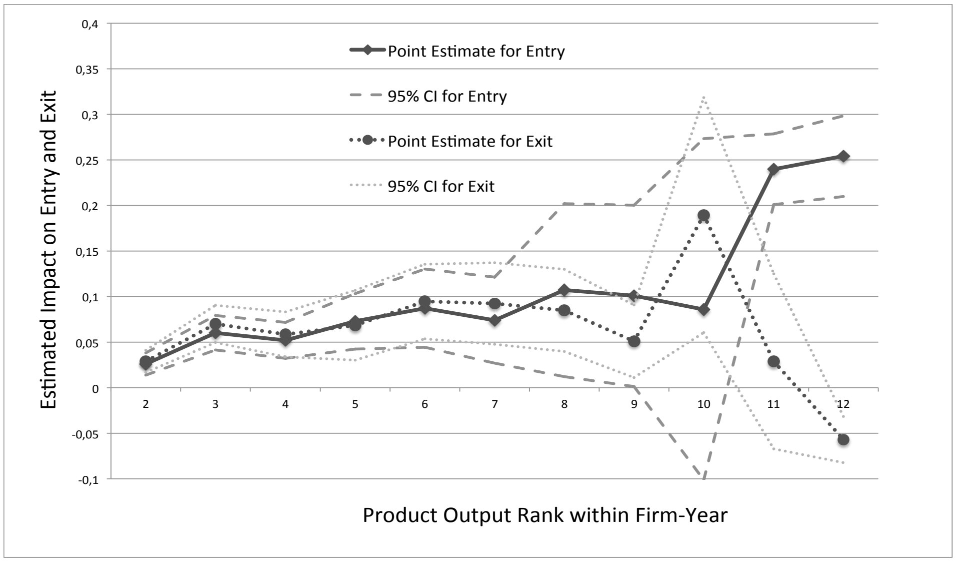
4.4 Prediction 3: Entry and exit are increasing in m

Finally, we consider the relationship between product entry/exit and product rank within the firm. In the model, product-mix effects result from both reallocation across existing products (intensive margin) and entry or exit of products (extensive margin). Furthermore, the model implies that product churn happens away from the core (i.e. at higher m values). We can test this implication directly in the data, and thus provide further evidence of the micro-channels of adjustment.

Defining the rank of each product within a firm-year as above, we estimate equation (23) again, replacing emission intensity on the left hand side with a dummy for entry and a dummy for exit at the firm-product level. An entering product is defined as a product that was not reported in the previous year, but is reported in the current year, given that the firm produces some output in both years. Exit is defined conversely. If product churn occurs away from the core competency of the firm, we should find $\delta_j > 0$, and do, in fact, in Figure 5. Figure 5 displays graphically the point estimates and 95% confidence intervals from these regressions. We find that entry and exist are increasing in distance from the core – firms are between 7% and 25% more likely to add or drop products with $m > 1$ – and that point estimates are significant at the 5% level for ranks below $m = 9$, supporting Prediction 3.

Together with the results in Figure 4, Figure 5 indicates that entering and exiting products should have higher emission intensity than core products. We also find empirical support for this implication in Table 5. First, we regress log emission intensity on firm-year fixed effects and indicators entry and exit (continuing products represent the omitted category). Surprisingly, here, we find that entering and exiting products are both *cleaner* than continuing products (column 1). However, we also find that firms sometimes either drop or add products that are also core products, and hence, cleaner. To account for the two effects separately, we interact non-core status with entering, exiting and continuing products and estimate the model again in column 2.

Figure 5: Estimated Probability of Entry and Exit by Product Rank Relative to Core Product



Notes: Figure plots point estimates and 95% confidence intervals of product-rank impacts on the probability of entry and exit of a product derived from projecting entry and exit dummies on firm-year fixed effects, product category fixed effects (P2-level) and fixed effects for (output-based) product rank within the firm-year. Horizontal axis corresponds to the product rank within the firm-year. Regression includes 8,802 firm-product observations for the period 1990-2010. Regressions exclude the top and bottom 1% of emission intensities. Standard errors are clustered at the firm level.

Here, we compare non-core entering and exiting products to core products. In this comparison, we see that entering and exiting products have higher emission intensity. We also find that other continuing non-core varieties are dirtier than core products, and even more so than entering and exiting products. This reveals that entry and exit can happen for varieties that are of intermediate emission intensity: they are dirtier than core products but cleaner than other continuing varieties within firms.

5 Aggregate Implications

In this section, we gauge the importance of our findings by decomposing the changes in aggregate emission intensity in Indian manufacturing over the period 1990-2010 into component micro channels. We begin with a discussion of the methodology, and then present the results from two different decompositions.

Table 5: Emission Intensity of Entering and Exiting Products

Dep Var:	Log(E/Q)	
	(1)	(2)
Entering Products	-0.11	
	(0.07)	
Exiting Products	-0.10	
	(0.06)	
Non-core Entering		0.21**
		(0.09)
Non-core Exiting		0.25***
		(0.08)
Non-core Continuing		0.44***
		(0.07)
Firm-Year FE	Y	Y
Sector FE	Y	Y
Num of Obs	28116	8802
R squared	0.15	0.18
Mean Dep. Var	-0.56	-0.75

Notes: This table compares the log emission intensity of products within firms. Column 1 compares its levels for entering and exiting products relative to continuing products. Column 2 compares its levels for non-core entering, exiting and continuing products relative to core continuing products. Output units are restricted to be the same within firm. Regressions include only multi-product firm-year observations for the years 1990-2010. The top and bottom 1% of economy-wide emission intensities have been dropped. Standard errors are clustered at the firm level (reported in parentheses). Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

5.1 Preliminaries

In the previous section, we found strong evidence in support of the micro channels posited by the model: emission intensity varies systematically with productivity across firms, with unit cost across products within the firm, within firm-product lines over time, and by entry/exit status. The pattern of the variation is consistent with the model and indicates that industry-level emission intensity should fall with increased allocation towards more-productive firms and lower-cost products within the firm. But how important are these channels in aggregate? In order to answer this question, we need to (1) observe a period over which market conditions changed dramatically, and (2) measure the impacts of component channels on aggregate emission intensities. The massive market reforms in India in the 1990s and 2000s provides an excellent setting in which to study these impacts. The increase in competition that resulted from these reforms should precipitate the kinds of endogenous behaviors predicted by the model, and hence lead to large changes in emission intensity.

To assess the importance of each channel, we perform a statistical decomposition of aggregate emission intensity over the period. Statistical decompositions are common in the literature and have proven useful for understanding the sources of productivity growth over time. The novelty of our work is that (1) we abstract from all price effects, since we observe firm-product outputs in quantity, (2) we can separately identify technological upgrading within firm-product line from across product reallocations (product-mix). Additionally, we can distinguish product churn effects (extensive margin) from reallocation across existing products (intensive margin). This level of detail allow us to uncover new facts about the drivers of aggregate emissions growth; however, since our data are more detailed than what are usually available, we must make some small adjustments to the standard decomposition methodologies.

There are two broad approaches to statistical decompositions of productivity or emissions in the literature. First, researchers decompose changes in overall emissions *levels* into scale, composition, and technique effects (Antweiler et al., 2001; Levinson, 2009). "Scale" captures the impact of overall changes in total output of the economy, "composition" captures changes in output shares across industries, and "technique" captures changes to emission intensity within industries.[20] In industry-level analyses, reallocations across firms within an industry, reallocations across products within the firm, and changes to technology within firm-product over time are all lumped together under the heading "technique." In our context, we can separately estimate these different margins.

Second, researchers decompose changes in aggregate *intensity* into within vs across unit changes (Foster et al., 2008). The unit of observation is usually the firm, so "within-unit" changes encompass both product-mix effects as well as technological adoption. The specific focus on productivity misses the scale and across-industry effects, but is better suited to studying differences between the intensive and extensive margin (e.g., firm churn). In our case, we can evaluate both the across-firm channel, and decompose the within-firm channel into across-products (both intensive and extensive margins) and within-products over time.

As we are interested in all components of the decomposition (from industry-level scale and composition, to firm-product intensive vs extensive margins) we will utilize both approaches. We first present the economy-wide decomposition (à la Antweiler et al. & Levinson), and then delve deeper into the different channels of compositional adjustment with the productivity approach of

[20]In many environmental applications, a representative firm is assumed for each industry, and the entire "technique" effect is attributed to within-firm technological change. By contrast, in our modeling framework, changes in competition could trigger different forms of reallocation across units within an industry without inducing any technological adoption at all. With our detailed decomposition, we can assess the importance of these reallocation channels and give a much more precise estimation of the role of within-unit technological growth.

Foster et al. (2008).

5.2 Decomposition of Levels

Consider the economy-wide decomposition of Levinson (2009) (in vector notation):

$$\Delta Z = \underbrace{\theta' z dQ}_{scale} + \underbrace{Qz' d\theta}_{composition} + \underbrace{Q\theta' dz}_{technique} \tag{24}$$

where Z indicates total emissions, θ is the vector of industry output shares, z is the vector of industry emission intensities, and Q is total output in the economy. Equation (24) is an accounting identity, and hence holds with equality. With aggregate data, computing the three components of total emissions is fairly straight-forward, but with disaggregated data (such as firm or firm-product), entry and exit present identification challenges.[21]

We proceed as follows. First, for a given level of aggregation (either industry, firm, or firm-product), we compute total observed change in emission *intensity* from within units as

$$\Delta z_t = \sum_{j \in C_j} \theta_{j,t-1} \frac{(z_{j,t} - z_{j,t-1})}{z_{t-1}} \tag{25}$$

where j indexes unit (either industry, firm, or firm-product), C_j indicates the set of continuing units (producing in both t and $t-1$), $\theta_{j,t-1}$ indicates the output share of unit j in total output in the previous year ($t-1$), $z_{j,t}$ and $z_{j,t-1}$ indicate emission intensity in current and previous years, and z_{t-1} indicates aggregate emission intensity in the previous year. That is, we compute weighted average change in emission intensity year-to-year from within-unit changes. Computing changes in this way allows within-unit changes for units that previously entered (prior to $t-1$) to be accounted for. I.e., we can accommodate technological change from entering units. Additionally, by conditioning on continuing units, the effect of exit on emissions is correctly attributed to

[21] To see this, consider the case in which a firm enters production in the middle of the period. Computing the counterfactual emissions requires holding composition fixed at base-year levels; but if a firm enters production after the base year, then its counterfactual share will be stuck at zero for the entire period. As long as the firm does not change its emission intensity, this is no problem for the standard methodology. But if the firm changes its emission intensity, these changes will not be taken into account in the calculation of counterfactual emissions, because the counterfactual output share of the firm is always held at zero. All changes to emission intensity from entering firms will be incorrectly attributed to compositional shifts. Additionally, firm exit poses a problem for the standard methodology too. When a firm exits, its emission intensity is missing. If the firm produced in the base year, then it will have a positive share for the entire period, but with a missing emission intensity in the year it exits (and all subsequent years). If the emission intensity is mistakenly set to zero, the decomposition would treat the firm as though it become emission free, which is not true.

compositional shift.

Next, we compute counterfactual emission *levels* as:

$$\widetilde{Z}_t = (1 + \Delta Q_t) * (1 + \Delta z_t) * \widetilde{Z_{t-1}}. \tag{26}$$

where ΔQ_t denotes observed output growth and Δz_t is computed as above. $\widetilde{Z}_t$ constitutes the analogue to counterfactual emissions as computed by a standard Levinson (2009) approach, but takes entry and exit into account. Thus, the difference between $\widetilde{Z}_t$ and the raw output data indicates the contribution of within-unit technological changes to aggregate emissions growth, while the difference between $\widetilde{Z}_t$ and actual emissions captures the compositional effect.

We compute $\widetilde{Z}_t$ separately taking the industry, firm, and firm-product as the unit j and plot results graphically in Figure 6 along with output and emissions indices. The scale effect is represented by the red curve, which plots observed total physical output (measured in tonnes) over the period 1990-2010. Tonnes of production quadrupled over the period, implying a strong scale effect. By contrast, total emissions (drawn in black) only doubled by 2010, indicating a large reduction in emission intensity. These reductions are confirmed by auxiliary data from the nationally representative Indian Annual Survey of Industries (ASI) (see Figure C.1).[22]

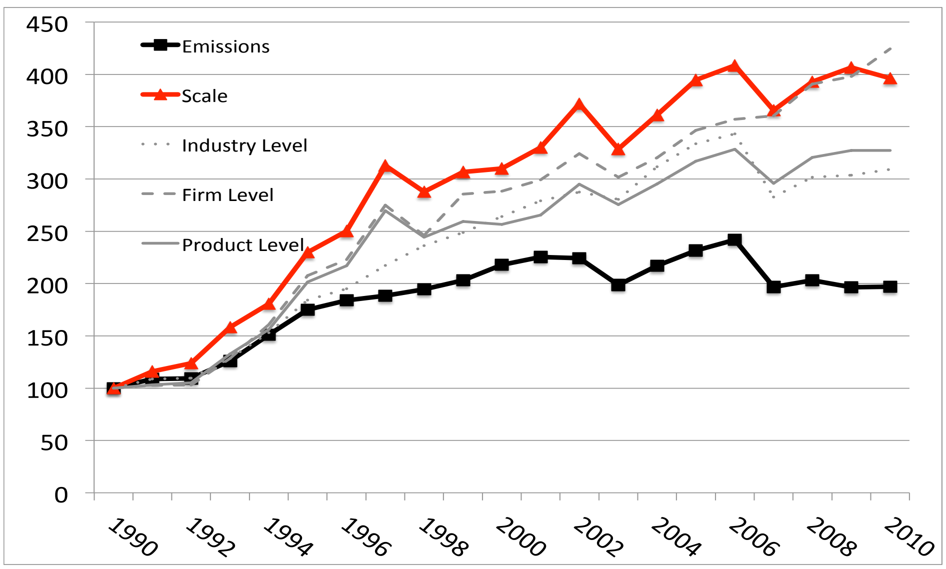
The three grey lines decompose the reduction in emission intensity into technique and compositional effects at different levels of aggregation. First, we plot counterfactual emissions taking the industry as the unit j with the dotted line in Figure 6. The "technique" effect is measured by the distance between the red line and the dotted line. In this case, it represents across-firm reallocations, across-product reallocations, and within product line technological adoption. The compositional effect is measured by the distance between the dotted line and the black line. In this case, it represents output share changes across industries. In Figure 6, we find that the industry-level technique effect contributes to a little under half of the reduction in emission intensity (44%), with across-industry composition accounting for the rest (56%). This suggests that Indian manufacturing production shifted toward *cleaner* industries, while changes at the industry level contributed to the decrease in aggregate emission intensity as well. The strong negative effect of industrial composition is quite striking. The fact that India has shifted production *away* from dirtier industries is evidence against the well-known "pollution haven" result, in which poor countries attract dirty industries as they open to trade.

Next, we compute counterfactual emissions taking the firm as the unit of observation, and plot with the gray dashed line in Figure 6. At this level of aggregation, the technique effect – measured

[22]In Figure C.1, we restrict attention to the period 2001-2009 due to data limitations in the ASI. For these years, we find that real sales growth and emissions growth both track very well between the ASI and Prowess.

by the distance between the red line and this gray dashed line – includes only those channels that affect firm-level emission intensity. Across-firm reallocations are now counted as part of the compositional effect. At this level of aggregation, it appears as though composition explains virtually *all* of the reduction in emission intensity (almost no distance between dashed line and red line). The big change in the evaluation of the composition effect comes from across-firm reallocations: we find that more-efficient firms capture larger market shares over time, lowering industry-level emissions intensity by 58%. This is exactly what one would expect, given the dramatic increase in the competitive environment (see Proposition 2).

Figure 6: Scale, Technique, and Composition Effects at Different Levels of Aggregation



Notes: Figure plots total output index ("scale"), total CO_2 emissions ("Emissions") and counterfactual emissions at the industry, firm, and product levels. Only data denominated in tonnes are used. Industry definitions are the same as in Table 1.

An implication of the previous result is that firm-level emission intensity must not have changed very much over the period, since across-firm reallocations explains virtually all of the industry-level "technique" effect. This is perhaps surprising, given the large degree of variation over time across products and within product lines discovered in section 3. However, when we disaggregate further, we find that two equally strong forces are at work within the firm, each pushing emission intensity in different directions. When we plot counterfactual emissions at the firm-product level in solid gray line in Figure 6, we find that technological adoption within firm-product (reflected by the difference between the solid red and gray lines) reduced emission intensity by 34%, whereas product mix (measured by the difference between the solid gray line and the dashed gray line) *increased* emission intensity by 49%. This means that firms both adopted more efficient technologies and reallocated production towards dirtier products. According to the previous section, the latter would imply reallocation away from core products. These two behaviors make sense in the context of increased competition, given the ambiguous impact of the interaction effect of technology and product mix (Proposition 3).

We investigate these results further in Figures C.2 and C.3, where we present decompositions broken down by heavy-weight vs light-weight industries, and single-product vs multi-product firms, respectively. In Panel A of Figure C.2, we present results for light industries (e.g., Food & Beverages manufacturing, Textile & Leather, Wood and Paper production), while Panel B reports the same for heavy industries (e.g., Chemicals, Plastics, Nonmetallic & Equipment manufacturing, Metals). Comparing the different panels of Figure C.2 reveals a sharp contrast: while there is almost no evidence of a decrease in emission intensity for light industries, heavy industries contributed strongly to the overall decrease in emission intensity. Being more emission intensive, these industries have more opportunities to improve on their environmental performance. Additionally, firm-level counterfactual emissions for light industries are even higher than the scale effect after 1994, which implies that technological investments make firms dirtier. This could happen if new technologies are more energy-intensive than old ones.

Next, in Figure C.3, we find that across-sector reallocations play an important role for single-product firms after 2002, while they play a minor role for multi-product firms. By contrast, reallocations across firms explain a large part of the cleanup among multi-product firms, but not single-product firms. Additionally, single-product firms adopt few cleaner technologies whereas multi-product firms adopt them more intensely but they also change their product mix in a way that cancel out the environmental gain from technology adoption.

5.3 Decompositions of Intensity

The decompositions above reveal that reallocations across firms, reallocation across products within firms, and technological adoption within firm-products all contribute significantly to changes in aggregate emission intensity. We now investigate the role of intensive vs extensive margins both across firms and within firms in explaining these effects with our second decomposition. This distinction between intensive and extensive margins can have important policy implications: Should the government encourage new firms/products to enter in the market to reduce aggregate emission intensity? Should the government encourage firms to expand their product lines and upgrade their technologies on existing or new products? These questions could find a partial answer in the evidence that some channels are more active than others, and therefore could be magnified by policy interventions.

Based on the methodology of Foster et al. (2008), we decompose aggregate *intensity* into within-unit effects, intensive margin reallocation effects (across continuing units) and extensive margin reallocation effects (from entry and exit). The methodology was originally applied at the aggregate level, but extending it to the firm-level is trivial.

To begin, consider a decomposition similar to Foster et al. (2008) at the aggregate level:

$$\begin{aligned}\Delta z_{it} = &\underbrace{\sum_{f\in C}\theta_{f,t-1}\Delta z_{f,t}}_{Technology} + \underbrace{\sum_{f\in C}(z_{f,t-1}-z_{f,t-1})\Delta\theta_{f,t} + \sum_{f\in C}\Delta z_{f,t}\Delta\theta_{f,t}}_{Intensive\ Margin\ Reallocation}\\ &+ \underbrace{\sum_{f\in N}\theta_{f,t}(z_{f,t}-z_{i,t-1}) - \sum_{f\in X}\theta_{f,t-1}(z_{f,t-1}-z_{i,t-1})}_{Extensive\ Margin\ Reallocation},\end{aligned} \tag{27}$$

where z_{it} indicates emission intensity at the industry level in year t, $z_{f,t}$ is firm f's emission intensity in period t, $\theta_{f,t}$ is the output share for firm f in industry i's total production. The sets C, N, and X, respectively, represent the sets of continuing, entering, and exiting firms within industry i. (27) is an accounting identity, and so holds with equality. The first component of the decomposition represents the within-firm over time effect of different technologies. The next two terms represent the across-firm reallocation effect (holding technology fixed) and the interaction effect of technology and reallocation. These two terms both apply only to continuing firms, and hence together account for the "intensive margin". The last two terms represent the change to industry level emission intensity from entry and exit of new firms, i.e. "extensive margin."

We compute each element of (27) separately year by year and report five year averages in Table 6. Column 1 reports the total growth in emission intensity at the economy level. Column 2 reports the across-industry component of this economy-wide growth. Column 3 reports total within-industry growth in emission intensity, the left hand side of (27). Next, columns 4-8 report the five components of (27) in order. Column 4 represents the change in emission intensity from within-firm changes. Columns 5 and 6 represent together the intensive margin, and column 7 and 8 represent the extensive margin.

The entries in Table 6 are computed as average annual growth rates, and so are not exactly comparable to the "long difference" changes in Figure 6, but Table 6 reveals the same basic pattern. Within-firm changes over time contribute little to aggregate emissions growth (+0.48% annually), but across-firm reallocations contributes significantly to the clean up (-1.21% annually). This reduction is driven mostly by intensive margin reallocation across continuing firms (-0.92% annually), while net entry contributed only mildly to aggregate reductions (-0.31%).

Table 6: Decomposition of Emission Intensity Growth At Economy Level

	Total Growth	Across Ind.	Within Industry					
	(1)	(2)	(3) Total	(4) Within	(5) Between	(6) Cross	(7) Entry	(8) Exit
1991-1995	-4.47	-0.84	-3.63	-1.46	0.48	-2.04	0.34	-0.95
1996-2000	-1.17	-2.68	1.51	0.59	3.67	-1.84	-0.02	-0.88
2001-2005	-3.29	-4.06	0.77	-1.12	2.04	-1.20	1.66	-0.61
2006-2010	-3.03	-1.45	-1.58	3.90	-0.38	-4.40	-0.29	-0.41
All Years	-2.99	-2.26	-0.73	0.48	1.45	-2.37	0.42	-0.71

Notes: This table reports total year over year average growth rates (for 5-year intervals) in CO_2 emission intensity (tonnes of CO_2 emitted for tonnes of physical unit produced) for the entire Indian manufacturing sector (Column 1) and component channels (Columns 2-8). Column 2 reports the across industry contributions to total emission intensity growth. Column 3 reports the within industry component. The within industry component is then broken down into within firms (column 4), between firms (column 5), cross-product (column 6), firm entry (column 7) and firm exit (column 8). Growth rates are expressed in percentage terms.

Interestingly, entry sometimes increases and sometimes decreases emission intensity, while exit always contributes significantly to emission intensity reductions. The latter is consistent with competition forcing out old, inefficient firms. The former indicates that entering firms are not necessarily at the technological frontier of the industry, even though they are newer. This pattern is consistent with the dynamics highlighted by Melitz (2003), where selection effects are more pronounced for exiting firms than entering firms in the face of increased competition.

Finally, we decompose the within-firm component further to understand the drivers of within-firm changes in Table 7. Column 1 reproduces the total within-firm effect from Table 6.[23] In columns 2-6, we then present empirical analogues of the five components of (27), taking the firm-product as the unit of observation. Thus, column 2 represents technology adoption effects within firm-product over time. Columns 3 and 4 represent together intensive margin reallocations across existing products. Columns 5 and 6 represent product adding and dropping (respectively) for continuing firms. Finally, columns 7-9 report the number of continuing, entering, and exiting products, respectively.

Figure 6 revealed that within-firm-product technological change lowers emission intensity, while product mix changes increase emission intensity, and that these forces were nearly offsetting. In Table 7, we find that the negative product-mix effect results mostly from the intensive margin (+1.05% annually) compared to small contributions from net entry (+0.15%).[24] This is

[23]Note that due to different weighting, the numbers change slightly.

[24]This is not contradictory with the results from Table 5 where both entering and exiting products are dirtier than core products, since the decomposition (27) uses previous year firm level rather than simultaneous year core level.

Table 7: Decomposition of Emission Intensity Changes within Firms

	Growth	Components of Decomposition					# Products		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δz/z	Within	Between	Cross	Entry	Exit	Continuing	Entry	Exit
1990-1995	-1,79	-1,92	-0,42	-0,02	0,09	0,48	858	42	31
1996-2000	0,65	-1,16	1,49	-0,17	-0,11	0,60	1380	38	49
2001-2005	-1,07	-0,55	-0,03	-0,09	0,04	-0,45	1143	33	39
2006-2010	4,21	0,58	3,76	-0,01	-0,15	0,03	855	19	29
All years	0,39	-0,82	1,12	-0,07	-0,03	0,18	1050	33	37

Notes: This table decomposes year-over-year average growth rates (for 5-year intervals) in firm emission intensity into the five components of (27) and then averages over firms. Columns 1-6 express growth rates in percentage terms. Columns 2-6 sum to column 1. Columns 7-9 report the average number of continuing, entering, and exiting products per year. Calculations rely only on the product-specific energy dataset. Output units are restricted to be the same within firm both within years and over time. Sample includes only firms that produce more than one product over the period.

perhaps not surprising, given the low levels of product churn (columns 8-9), and consistent with previous work that found low rates of product entry and exit (Goldberg et al., 2010b).

We explore across-product reallocation further in Table 8, wherein we decompose changes in output shares across varieties of different ranks-m within the firm. We divide products into continuing products (intensive margin), and entering and exiting products (extensive margin). Among the former, we then break out products by product rank m. In Table 8 we see that firms reallocate output toward their existing non-core varieties, as products of rank higher than 2 gain relatively more output shares than core products. This reallocation makes sense in light of the positive impact of product-mix on emission intensity – firms reallocate production towards higher emission intensive products, which increase firm-average and aggregate intensity. We also see that on net, entry and exit play little role within firms.

The relative contributions of the technology and product mix channels we find are important in thinking about how firms adjust to changes in market conditions. During the period 1990-2010, firm emission intensity declines in some years and increases in other years (column 1). This measure is more precise than the results obtained from Figure 6 which reflects a cumulative effect on firm-level emission intensity. On average, firm emission intensity increases during the period 1990-2010, and this is due to product mix reallocations that outweigh technology improvements. This suggests that firms faced lower competition (for instance, as trade barriers were dismantled)

As continuing products reduce their emission intensity from year $t-1$ to t (column 2), both results are consistent. Foster et al. (2008) also consider a related decomposition where the comparison is made with an average of the variables across $t-1$ and t. However, this methodology is more difficult to interpret in the context of reallocation dynamics.

Table 8: Average change in output share of each variety within multi-product firms

	Intensive Margin					Extensive Margin	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total	Prod 1	Prod 2	Prod 3	Prod 4+	Entry	Exit
1991-1995	-0.005	0.002	-0.011	-0.023	0.000	0.036	-0.031
1996-2000	0.005	-0.003	0.012	0.012	0.000	0.028	-0.033
2001-2005	0.001	0.002	0.000	0.000	0.001	0.031	-0.032
2006-2010	0.004	0.004	0.006	0.025	0.002	0.017	-0.021
All Years	0.001	0.001	0.002	0.003	0.001	0.028	-0.029

Notes: This table reports the average change in output share of each variety within multi-product firms during 5-year intervals. We restrict the sample to output denominated in tonnes. "Prod 1" reflects the product with the highest output share within the firm-year, "Prod 2" the product with the second highest share, etc. "Entry" and "exit" correspond to entering and exiting products, while "Intensive margin" reflects the average change in output share of continuing products.

in most years. Had the market conditions been different, product mix reallocations would have had different implications on the environmental performance of firms. Policies that strengthen competition, encourage firms to invest more in new technologies for their existing products, and alleviate the credit constraints they might face, could help mitigate this negative environmental impact.

6 Conclusion

The paper explores the contributions of sector and firm reallocations, technology adoption, and product mix changes to the Indian manufacturing emission intensity decline over the period 1990-2010. We construct a heterogeneous multi-product firm model that shows that tougher competition leads to an improvement in the aggregate emission intensity at the sector level, even though firms can become cleaner or dirtier through product mix and technology adoption. Using a novel dataset of emissions and output at the firm-product level, we find that emission intensity in India dropped significantly between 1990-2010 through reallocations across firms, while product-mix and technology played important – though counteracting – roles at the firm level.

Our analysis is the first to reveal a systematic pattern in the efficiency of production across product lines within the firm. In particular, we find that emission intensity is increasing in distance from core competency. This indicates that Indian firms tend to specialize in products that are relatively cleaner to produce. Policies or market developments that lead Indian firms to focus on core competency should thus lower firm-average emission intensity. However, the sign of the correlation between efficiency and distance from the core is theoretically ambiguous, and thus could be different in a different setting. Thus, researchers should take care in interpreting firm-level impacts as representing "technological" change, since product-mix could influence firm averages in either direction.

Altogether, the results indicate that market forces significantly impact the emission intensity of production, even absent environmental regulation. In the context of climate leakage – in which some countries maintain weak environmental regulation, and hence attract dirty production – the results imply that emission intensity may change in the unregulated country regardless, due simply to market forces. Additionally, as the process of globalization and market reforms continues in the developing world, the dynamics we uncover are likely to continue to alter emission intensity, even if global climate negotiations are ineffective.

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Appendix

A Theoretical Framework

In this appendix, we present the proofs of the lemmas and propositions of the theoretical model. These results are presented for a closed economy where increased competition arises from an increase in the size of the market. Subsection A.7 extends the model to open economies and presents results on the impacts of trade liberalization.

A.1 Proofs of Lemma 1 and 2

Given the unit-cost function (5) for variety m, we have

$$\frac{d\Phi(\varphi,m)}{dm}=\frac{1}{\varphi}\left[\tau^{\frac{\epsilon}{\epsilon-1}}e^{\frac{\nu m\epsilon}{\epsilon-1}}+e^{\frac{\sigma m\epsilon}{\epsilon-1}}\right]^{\frac{-1}{\epsilon}}\left[\nu\tau^{\frac{\epsilon}{\epsilon-1}}e^{\frac{\nu m\epsilon}{\epsilon-1}}+\sigma e^{\frac{\sigma m\epsilon}{\epsilon-1}}\right]$$

which is positive if $\nu>0,\sigma>0$.

Given the emission intensity $E(\varphi,m)$ equation (6), we have

$$\frac{dE(\varphi,m)}{dm}=\frac{1}{\varphi}\left[e^{-\nu m\epsilon}+\left(\tau e^{m(\epsilon\nu-\sigma)}\right)^{\frac{\epsilon}{1-\epsilon}}\right]^{\frac{-1-\epsilon}{\epsilon}}\left[\nu e^{-\nu m\epsilon}-\frac{\epsilon\nu-\sigma}{1-\epsilon}\left(\tau e^{m(\epsilon\nu-\sigma)}\right)^{\frac{\epsilon}{1-\epsilon}}\right],$$

which is positive (negative) if and only if

$$\epsilon-(1-\epsilon)\left(\tau e^{m(\nu-\sigma)}\right)^{\frac{\epsilon}{\epsilon-1}}<(>)\frac{\sigma}{\nu}.$$

The sign is unambiguously positive if $\epsilon\leq 0$, or if $\sigma>\nu$.

A.2 Proof of Existence and Uniqueness of the Equilibrium

We need to prove the existence and unicity of the solution of Equation (16). Let define

$$\chi\equiv\frac{2\Phi_D^{k+2}}{(k+2)(k+1)}+\frac{k(1-\frac{1}{\rho^2})(\Phi_{\bar{A}}^{k+2}-\Phi_{\underline{A}}^{k+2})}{k+2}+\frac{2k\Phi_D(1-\frac{1}{\rho})(\Phi_{\underline{A}}^{k+1}-\Phi_{\bar{A}}^{k+1})}{k+1}-\frac{4\gamma f(\Phi_{\underline{A}}^{k}-\Phi_{\bar{A}}^{k})}{L},$$

which must equal $4\gamma f_E/(\Omega L)$, a constant. We obtain, after rearranging terms,

$$\begin{aligned}\frac{\partial \chi}{\partial \Phi_D} =& \frac{2}{k+1}\left[\Phi_D^{k+1} + k(1-\frac{1}{\rho})(\Phi_{\underline{A}}^{k+1} - \Phi_{\bar{A}}^{k+1})\right] \\ &+ k(1-\frac{1}{\rho})\Phi_{\bar{A}}^{k-1}\frac{\partial \Phi_{\bar{A}}}{\partial \Phi_D}\left[(1+\frac{1}{\rho})\Phi_{\bar{A}}^2 - 2\Phi_D\Phi_{\bar{A}} + \frac{4\gamma f}{L(1-1/\rho)}\right] \\ &- k(1-\frac{1}{\rho})\Phi_{\underline{A}}^{k-1}\frac{\partial \Phi_{\underline{A}}}{\partial \Phi_D}\left[(1+\frac{1}{\rho})\Phi_{\underline{A}}^2 - 2\Phi_D\Phi_{\underline{A}} + \frac{4\gamma f}{L(1-1/\rho)}\right].\end{aligned}$$

The bracketed terms in the second and third lines of this expression are equivalent to (12), which equals zero for both $\Phi_{\bar{A}}$ and $\Phi_{\underline{A}}$ by definition of the technology cutoffs. As a result, this expression simplifies into the first line, which is strictly positive given $\Phi_{\bar{A}} < \Phi_{\underline{A}}$. Thus, χ is an increasing function of Φ_D, which tends toward zero when Φ_D tends toward zero. Therefore, there exists a unique solution for Φ_D, obtained when χ crosses the constant $4\gamma f_E/(\Omega L) > 0$.

A.3 Intermediate Results

Given a mass of entrants N_E, the distribution of costs across all varieties is determined by the optimal firm product range choice $M(\varphi)$ as well as the distribution of productivity $G(\varphi)$. Let $M_\Phi(\Phi)$ denote the measure function for varieties produced at total marginal cost Φ or lower, given N_E entrants. Further define $H(\Phi) \equiv M_\Phi(\Phi)/N_E$ as the normalized measure of varieties per unit mass of entrants. Thus

$$H(\Phi) = \sum_{m=0}^{\infty}\left[1 - G\left(\left[\tau^{\frac{\epsilon}{\epsilon-1}}e^{\frac{\nu m\epsilon}{\epsilon-1}} + e^{\frac{\sigma m\epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}}/\Phi\right)\right],$$

which is exogenously given by the distribution function $G(.)$. Given a unit mass of entrants, there will be a mass $1 - G\left(\left[1+\tau^{\frac{\epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}}/\Phi\right)$ of varieties with cost Φ or less; a mass $1 - G\left(\left[e^{\frac{\sigma\epsilon}{\epsilon-1}} + \tau^{\frac{\epsilon}{\epsilon-1}}e^{\frac{\nu\epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}}/\Phi\right)$ of first varieties away from core competency (with cost Φ or less), and so forth. The measure $H(\Phi)$ sums over all these varieties.

Using (9) gives a relationship between average cost and price since $\bar{\Phi} = 2\bar{p} - \Phi_D$. We thus have $M = \frac{2\gamma(\alpha-\Phi_D)}{\eta(\Phi_D-\bar{\Phi})}$, where the average total cost of all varieties

$$\bar{\Phi} = \frac{1}{M}\int_0^{\Phi_D}\Phi dM_\Phi(\Phi) = \frac{1}{N_E H(\Phi_D)}\int_0^{\Phi_D}\Phi N_E dH(\Phi) = \frac{1}{H(\Phi_D)}\int_0^{\Phi_D}\Phi dH(\Phi)$$

depends only on Φ_D. Similarly, this cutoff also uniquely pins down the average price across all varieties:

$$\bar{p} = \frac{1}{M}\int_0^{\Phi_D} p(\Phi)dM_\Phi(\Phi) = \frac{1}{H(\Phi_D)}\int_0^{\Phi_D} p(\Phi)dH(\Phi).$$

Finally, the mass of entrants is given by $N_E = M/H(\Phi_D)$, which can in turn be used to obtain the mass of producing firms $N = N_E[1 - G(\varphi_D)]$. When productivities are distributed Pareto, then all produced varieties will share the same Pareto distribution:

$$H(\Phi) = \sum_{m=0}^{\infty}\left[1 - G\left(\left[\tau^{\frac{\epsilon}{\epsilon-1}} e^{\frac{\nu m\epsilon}{\epsilon-1}} + e^{\frac{\sigma m\epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}}/\Phi\right)\right] = \Phi^k\Omega$$

which implies $dH(\Phi)/d\Phi = \Omega k\Phi^{k-1}$. This yields $\bar{\Phi} = \frac{1}{\Phi_D^k\Omega}\int_0^{\Phi_D}\Phi\Omega k\Phi^{k-1}d\Phi = \frac{k\Phi_D}{k+1}$. Similarly, the average markup is such that

$$\bar{\lambda} = \frac{1}{2\Phi_D^k\Omega}\int_0^{\Phi_D}[\Phi_D - \Phi]\Omega k\Phi^{k-1}d\Phi = \frac{\Phi_D}{2(k+1)}.$$

Plugging the expression of $\bar{\Phi}$ into the definitions of M and $\bar{p}$ also yields

$$M = \frac{2\gamma(k+1)(\alpha - \Phi_D)}{\eta\Phi_D}, \;\; \bar{p} = \frac{(2k+1)\Phi_D}{2(k+1)}.$$

A market with tougher competition (lower Φ_D) also features more product variety M and a lower average price $\bar{p}$ because of the combined effect of product selection towards the lowest cost varieties and of lower markups.

In equilibrium, the average number of products produced across all surviving firms is thus constant since $M/N = \frac{H(\Phi_D)N_E}{[1-G(\varphi_D)]N_E} = \Omega\left[1 + \tau^{\frac{\epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}}$. Increases in the toughness of competition do not affect the average number of varieties because the mass of surviving firms N rises by the same proportion as the mass of produced varieties M.

A.4 Proof of Proposition 1

Let denote $A(m) \equiv \left[\tau^{\frac{\epsilon}{\epsilon-1}} e^{\frac{\nu m \epsilon}{\epsilon-1}} + e^{\frac{\sigma m \epsilon}{\epsilon-1}}\right]^{\frac{\epsilon-1}{\epsilon}}$ so that $\Phi(\varphi, m) = A(m)/\varphi$. The economic productivity measure for a firm with productivity φ producing $M(\varphi)$ varieties is

$$\psi_C(\varphi) = \frac{Q(\varphi)}{C(\varphi)} = \frac{\sum_{m=0}^{M(\varphi)-1} q(\Phi(\varphi, m))}{\sum_{m=0}^{M(\varphi)-1} \Phi(\varphi, m) q(\Phi(\varphi, m))}.$$

For a fixed product scope M with $1 < M \leq M(\varphi)$, this can be written as

$$\psi_C(\varphi) = \frac{M\Phi_D - \sum_{m=0}^{M-1} \Phi(\varphi, m)}{\Phi_D \sum_{m=0}^{M-1} \Phi(\varphi, m) - \sum_{m=0}^{M-1} \Phi(\varphi, m)^2},$$

subject to $\varphi \in [A(M)/\Phi_D, A(M-1)/\Phi_D]$. We have

$$\frac{d\psi_C(\varphi)}{d\Phi_D} = \frac{-M \sum_{m=0}^{M-1} \Phi(\varphi, m)^2 + \left(\sum_{m=0}^{M-1} \Phi(\varphi, m)\right)^2}{\left[\Phi_D \sum_{m=0}^{M-1} \Phi(\varphi, m) - \sum_{m=0}^{M-1} \Phi(\varphi, m)^2\right]^2}.$$

Using Jensen's inequality for a real convex function, here the quadratic function, we have

$$\frac{\left(\sum_{m=0}^{M-1} \Phi(\varphi, m)\right)^2}{\sum_{m=0}^{M-1} \Phi(\varphi, m)^2} \leq M,$$

and thus we get $d\psi_C(\varphi)/d\Phi_D < 0$. This proves that, holding $M \geq 1$ constant, the average cost efficiency of the firm improves when import competition increases (lower Φ_D).

Even when product scope M drops due to the decrease in Φ_D, the average cost efficiency must still increase due to the continuity of $\psi_C(\varphi)$ with respect to Φ_D (both $Q(\varphi)$ and $C(\varphi)$ are continuous in Φ_D as the firm produces zero units of a variety right before it is dropped when competition gets tougher). Following the argument of Mayer et al. (2014), consider a large downward change in the cost cutoff Φ_D. The result for given M tells us that the cost efficiency for a firm with productivity φ improves on all ranges of Φ_D's where the firm changes the number of varieties produced. Because $\psi_C(\varphi)$ is continuous at those Φ_D's, and increasing everywhere else, it must be increasing everywhere.

Similarly, the emission intensity for a firm φ producing $M(\varphi)$ varieties is

$$\psi_Z(\varphi) = \frac{Z(\varphi)}{Q(\varphi)} = \frac{\sum_{m=0}^{M(\varphi)-1} E(\varphi, m) q(\Phi(\varphi, m))}{\sum_{m=0}^{M(\varphi)-1} q(\Phi(\varphi, m))}.$$

For a fixed product scope M with $1 < M \leq M(\varphi)$, this can be written as

$$\psi_Z(\varphi) = \frac{\Phi_D \sum_{m=0}^{M-1} E(\varphi, m) - \sum_{m=0}^{M-1} E(\varphi, m)\Phi(\varphi, m)}{M\Phi_D - \sum_{m=0}^{M-1} \Phi(\varphi, m)},$$

subject to $\varphi \in [A(M)/\Phi_D, A(M-1)/\Phi_D]$. We have

$$\frac{d\psi_Z(\varphi)}{d\Phi_D} = \frac{M \sum_{m=0}^{M-1} E(\varphi, m)\Phi(\varphi, m) - \sum_{m=0}^{M-1} E(\varphi, m) \sum_{m=0}^{M-1} \Phi(\varphi, m)}{\left[M\Phi_D - \sum_{m=0}^{M-1} \Phi(\varphi, m)\right]^2}.$$

For all $M \in N^*$, denote the numerator of this expression as D_M, where $(\Phi(\varphi, m))_{m\in N}$ and $(E(\varphi, m))_{m\in N}$ are real positive sequences. First, consider some examples such as $M = 2$. Simplifying notations using E_m and Φ_m, we have

$$D_2 = 2(E_0\Phi_0 + E_1\Phi_1) - (E_0 + E_1)(\Phi_0 + \Phi_1) = (E_1 - E_0)(\Phi_1 - \Phi_0).$$

Now for $M = 3$, $D_3 = (E_1 - E_0)(\Phi_1 - \Phi_0) + (E_2 - E_0)(\Phi_2 - \Phi_0) + (E_2 - E_1)(\Phi_2 - \Phi_1)$. Using a recursive argument, we thus deduce that

$$D_M = \sum_{0\leq i<j\leq M-1} (E_j - E_i)(\Phi_j - \Phi_i)$$

By assumption $(\Phi_m)_{m\in N}$ is strictly increasing, thus for all $0 \leq i < j \leq M-1$ we have $\Phi_j > \Phi_i$. Thus D_M is positive, hence $\psi_Z(\varphi)$ increases in Φ_D, if and only if $(E_m)_{m\in N}$ is also strictly increasing whereas it is negative if and only if $(E_m)_{m\in N}$ is strictly decreasing.

As before, even when product scope M drops due to the decrease in Φ_D, the average emission intensity must still have the same variation as $E(\varphi, m)$ due to the continuity of $\psi_Z(\varphi)$ with respect to Φ_D (both $Z(\varphi)$ and $Q(\varphi)$ are continuous in Φ_D as the firm produces zero units of a variety right before it is dropped when competition gets tougher).

A.5 Proof of Proposition 2

Let denote $B(m) \equiv \left[e^{-\nu m\epsilon} + \left(\tau e^{m(\epsilon\nu-\sigma)}\right)^{\frac{\epsilon}{1-\epsilon}}\right]^{-1/\epsilon}$ so that $z(\varphi,m) = E(\varphi,m)q(\varphi,m) = \frac{B(m)}{\varphi}\frac{L}{2\gamma}\left[\Phi_D - \Phi(\varphi,m)\right]$, where, as previously, $\Phi(\varphi,m) = A(m)/\varphi$. We have

$$\int_{\varphi_D}^{\infty} Q(\varphi)dG(\varphi) \equiv \int_{\varphi_D}^{\infty}\left[\sum_{m=0}^{M(\varphi)-1} q(\Phi(\varphi,m))dm\right]dG(\varphi)$$
$$= \sum_{m=0}^{\infty}\int_{\frac{A(m)}{\Phi_D}}^{\infty}\frac{L}{2\gamma}\left[\Phi_D - \frac{A(m)}{\varphi}\right]k\varphi^{-k-1}d\varphi = \frac{L\Phi_D^{k+1}\Omega}{2\gamma(k+1)},$$

and

$$\int_{\varphi_D}^{\infty} C(\varphi)dG(\varphi) \equiv \int_{\varphi_D}^{\infty}\left[\sum_{m=0}^{M(\varphi)-1} \Phi(\varphi,m)q(\Phi(\varphi,m))dm\right]dG(\varphi)$$
$$= \sum_{m=0}^{\infty}\int_{\frac{A(m)}{\Phi_D}}^{\infty}\frac{L}{2\gamma}\frac{A(m)}{\varphi}\left[\Phi_D - \frac{A(m)}{\varphi}\right]k\varphi^{-k-1}d\varphi = \frac{Lk\Phi_D^{k+2}\Omega}{2\gamma(k+1)(k+2)}.$$

This leads to

$$\bar{\psi}_C \equiv \frac{\int_{\varphi_D}^{\infty} Q(\varphi)dG(\varphi)}{\int_{\varphi_D}^{\infty} C(\varphi)dG(\varphi)} = \frac{k+2}{k}\frac{1}{\Phi_D},$$

which gives $d\bar{\psi}_C/d\Phi_D = -(k+2)/(k\Phi_D^2) < 0$. Thus tougher competition (a decrease in Φ_D) increases aggregate productivity. Denoting $\bar{Q} \equiv \int_{\varphi_D}^{\infty} Q(\varphi)dG(\varphi)$ yields a positive scale effect from a bigger market: $d\bar{Q}/dL = \frac{\Phi_D^{k+1}\Omega}{2\gamma(k+1)}\left[1 - \frac{k+1}{k+2}\right] > 0$.

Aggregate emissions can be calculated as

$$\int_{\varphi_D}^{\infty} Z(\varphi)dG(\varphi) = \sum_{m=0}^{\infty}\int_{\frac{A(m)}{\Phi_D}}^{\infty}\frac{L}{2\gamma}\frac{B(m)}{\varphi}\left[\Phi_D - \frac{A(m)}{\varphi}\right]k\varphi^{-k-1}d\varphi$$
$$= \frac{Lk\Phi_D^{k+2}}{2\gamma(k+1)(k+2)}\sum_{m=0}^{\infty} B(m)A(m)^{-k-1}$$

where, after some computations,

$$\Gamma \equiv \sum_{m=0}^{\infty} B(m)A(m)^{-k-1} = \tau^{\frac{1}{\epsilon-1}}\sum_{m=0}^{\infty}\left[e^{\frac{m\epsilon[(\nu-\sigma)\epsilon+\sigma k(1-\epsilon)]}{(\epsilon-1)[k(1-\epsilon)-\epsilon]}} + \tau^{\frac{\epsilon}{\epsilon-1}}e^{\frac{\nu m\epsilon k}{\epsilon-k(1-\epsilon)}}\right]^{\frac{k(1-\epsilon)-\epsilon}{\epsilon}}.$$

In order for Γ to converge, we need the bracketed term to the power $[k(1-\epsilon)-\epsilon]/\epsilon$ to approach 0 as $m \to +\infty$. This expression is equivalent to

$$\left[e^{\frac{m\epsilon[(\nu-\sigma)\epsilon+\sigma k(1-\epsilon)]}{(\epsilon-1)[k(1-\epsilon)-\epsilon]}} + \tau^{\frac{\epsilon}{\epsilon-1}} e^{\frac{\nu m \epsilon k}{\epsilon - k(1-\epsilon)}}\right]^{\frac{k(1-\epsilon)-\epsilon}{\epsilon}} = e^{\frac{m[(\nu-\sigma)\epsilon+\sigma k(1-\epsilon)]}{(\epsilon-1)}} \left[1+\tau^{\frac{\epsilon}{\epsilon-1}} e^{\frac{m\epsilon(\nu-\sigma)}{\epsilon-1}}\right]^{\frac{k(1-\epsilon)-\epsilon}{\epsilon}}$$

where sufficient conditions for the first exponential term to converge toward zero when $m \to +\infty$ are $\nu > \sigma$ and $0 < \epsilon < 1$, and the same conditions ensure that the exponential term inside the brackets also tends to zero. Thus, so long as we restrict our attention to cases where the relationship between $E(\varphi, m)$ and new varieties is ambiguous, which imposes that $\nu > \sigma$ and $\epsilon > 0$ given Lemma 2, Γ converges and $\bar{\psi}_Z = \frac{k\Gamma\Phi_D}{(k+2)\Omega}$, which yields $d\bar{\psi}_Z/d\Phi_D = \frac{k\Gamma}{(k+2)\Omega} > 0$. So an increase in competition (a fall in Φ_D) lowers aggregate emission intensity. Denoting $\bar{Z} \equiv \int_{\varphi_D}^{\infty} Z(\varphi)dG(\varphi) = kf_E\Gamma/\Omega$ yields $d\bar{Z}/dL = 0$.

A.6 Proof of Proposition 3

We investigate the impact of a variation in market size L in the full model with both technology and product mix channels. We first want to know how Φ_D varies with L. Given the implicit function theorem, we know that $\partial\Phi_D/\partial L = -(\partial\chi/\partial L)(\partial\chi/\partial\Phi_D)^{-1}$. From above, we know that $\partial\chi/\partial\Phi_D > 0$. We further obtain, after rearranging terms,

$$\begin{aligned}\frac{\partial\chi}{\partial L} =& \frac{4\gamma f(\Phi_{\underline{A}}^k - \Phi_{\bar{A}}^k)}{L^2} \\ &+ k(1-\frac{1}{\rho})\Phi_{\bar{A}}^{k-1}\frac{\partial\Phi_{\bar{A}}}{\partial L}\left[(1+\frac{1}{\rho})\Phi_{\bar{A}}^2 - 2\Phi_D\Phi_{\bar{A}} + \frac{4\gamma f}{L(1-1/\rho)}\right] \\ &- k(1-\frac{1}{\rho})\Phi_{\underline{A}}^{k-1}\frac{\partial\Phi_{\underline{A}}}{\partial L}\left[(1+\frac{1}{\rho})\Phi_{\underline{A}}^2 - 2\Phi_D\Phi_{\underline{A}} + \frac{4\gamma f}{L(1-1/\rho)}\right].\end{aligned}$$

The bracketed terms in the second and third lines of this expression are equivalent to (12), and thus equal to zero for both $\Phi_{\bar{A}}$ and $\Phi_{\underline{A}}$. As a result, this expression simplifies into the first line, which is strictly positive given $\Phi_{\bar{A}} < \Phi_{\underline{A}}$. We conclude that $\partial\Phi_D/\partial L < 0$.

We then investigate the impacts of a variation in L on the technology cutoffs. Using (13) yields

$$\frac{d\Phi_{\bar{A}}}{dL} = \frac{\rho}{1+\rho}\left[\frac{\partial\Phi_D}{\partial L} - \frac{\Phi_D\frac{\partial\Phi_D}{\partial L} + \frac{2(1+\rho)\gamma f}{L^2(\rho-1)}}{\sqrt{\Phi_D^2 - \frac{4(1+\rho)\gamma f}{L(\rho-1)}}}\right]$$

and

$$\frac{d\Phi_{\underline{A}}}{dL} = \frac{\rho}{1+\rho}\left[\frac{\partial \Phi_D}{\partial L} + \frac{\Phi_D \frac{\partial \Phi_D}{\partial L} + \frac{2(1+\rho)\gamma f}{L^2(\rho-1)}}{\sqrt{\Phi_D^2 - \frac{4(1+\rho)\gamma f}{L(\rho-1)}}}\right].$$

In both cases, the sign of the derivative is ambiguous given $\partial\Phi_D/\partial L < 0$ and $\Phi_D > \sqrt{\Phi_D^2 - \frac{4(1+\rho)\gamma f}{L(\rho-1)}}$. We can rewrite the first derivative as

$$\frac{d\Phi_{\bar{A}}}{dL} = \frac{2\gamma f}{(1+\frac{1}{\rho})L^2\sqrt{\Phi_D^2 - \frac{4(1+\rho)\gamma f}{L(\rho-1)}}}\left[\frac{(k+1)(\Phi_{\underline{A}}^k - \Phi_{\bar{A}}^k)[\Phi_D - \sqrt{\Phi_D^2 - \frac{4(1+\rho)\gamma f}{L(\rho-1)}}]}{\Phi_D^{k+1} + k(1-\frac{1}{\rho})(\Phi_{\underline{A}}^{k+1} - \Phi_{\bar{A}}^{k+1})} - \frac{1+\rho}{\rho-1}\right].$$

For large market size L, the bracketed term $\Phi_D - \sqrt{\Phi_D^2 - \frac{4(1+\rho)\gamma f}{L(\rho-1)}}$ tends toward zero. Hence, this could imply that the sign of the derivative is negative.

Numerical simulations are helpful in determining the impacts of an increase in market size when the sign of the derivatives is ambiguous. They illustrate these impacts for some parameter values, but cannot be generalized. We consider the following parameter values: $k = 2$, $f = 35$, $\gamma = 4$ or 2, $\rho = 5$ or 1.2, and $\Omega = 2.5$ or 1.5. Table A.1 illustrate all potential outcomes using simulations.

Table A.1: Simulation Results when Market Size Increases

Parameter values				Variation in L	Results		
γ	ρ	Ω	f_E		Φ_D	$\Phi_{\bar{A}}$	$\Phi_{\underline{A}}$
4	5	2.5	800	from 100 to 110	-3.5	-6.7	-3.4^{ni}
2	1.2	1.5	1000	from 400 to 500	-5.9	-20.8	$+1.1^{i}$
2	1.2	1.5	1000	from 500 to 600	-4.8	-15.9	-0.8^{i}

Notes: The results are described in terms of percent changes relative to the initial value when the market size L varies. The index ni indicates that $\Phi_{\underline{A}}$ is "non interior", while the index i indicates that it is "interior".

We observe that $\Phi_{\bar{A}}$ tends to decrease when the market size increases, which implies that more lowest cost varieties adopt technology h. When $\Phi_{\underline{A}}$ is non interior, all high cost varieties located above $\Phi_{\bar{A}}$ adopt technology h, hence the variation in this first technology cutoff is sufficient to determine that technology adoption increases. When both cutoffs are interior, technology adoption increases unambiguously when $\Phi_{\underline{A}}$ increases, whereas the results are ambiguous when $\Phi_{\underline{A}}$ decreases.

A.7 Open economy with Product Mix Channel

We extend the model to open economies that differ in their population, trade costs, and environmental regulations. We consider only two regions, India and the rest of the world. In this two-region setting, we denote Indian variables with the index j and foreign variables with f. This extension abstracts from the ability firms have to upgrade their technology, while focusing on the product mix channel. The reason is that the equilibrium can thus be summarized by only one productivity cutoff for domestic production, and another one for exporting.

A.7.1 Equilibrium

The demand side and the production side of the model are the same as in the closed economy. Firms in either country can produce in one market and sell in the other by incurring an iceberg trade cost $\theta_{lf} > 1$ ($\theta_{ll} = 1$). Thus, the delivered cost of a variety with manufacturing cost $\Phi(\varphi, m)$ to country l is $\theta_{jl}\Phi(\varphi, m)$.

Because markets are segmented, firms separately optimize for each market. A firm may decide to export some of its varieties at a delivered price $p_{jf}(\varphi, m)$, so that it can earn export profits $\pi_{jf}(\varphi, m) = [p_{jf}(\varphi, m) - \theta_{jf}\Phi(\varphi, m)]q_{jf}(\varphi, m)$. Firms must earn positive profits on a variety if they sell it in a given market. This yields a domestic cutoff Φ_{jj} and an export cost cutoff Φ_{jf}, at which a firm would make zero profit from exporting to country f. We obtain $\Phi_{jf} = p_f^{max}/\theta_{jf} = \Phi_{ff}/\theta_{jf}$. Trade barriers make it harder for exporters to break even relative to domestic producers. The cutoffs Φ_{jj} and Φ_{jf} summarize all the effects of market conditions in both countries relevant for country j's firm performance measures. We also obtain the firm productivity cutoff for exporters: $\varphi_{jf} = [1 + \tau_j^{\frac{\epsilon}{\epsilon-1}}]^{\frac{\epsilon-1}{\epsilon}}/\Phi_{jf}$.

When firms optimize for each market, the price and the markup are given by $p_{jl}(\varphi, m) = \frac{1}{2}[\Phi_{jl} + \theta_{jl}\Phi(\varphi, m)]$ and $\lambda_{jl}(\varphi, m) = \frac{1}{2}[\Phi_{jl} - \theta_{jl}\Phi(\varphi, m)]$. The maximized profit levels in the domestic and foreign markets are given by $\pi_{jj}(\varphi, m) = \frac{L_j}{4\gamma}[\Phi_{jj} - \Phi(\varphi, m)]^2$ and $\pi_{jl}(\varphi, m) = \frac{L_l}{4\gamma}[\Phi_{ll} - \theta_{jl}\Phi(\varphi, m)]^2$, respectively.

We assume that the entry cost f_E and the productivity distribution $G(\varphi)$ are common across countries. A prospective entrant's expected profits are then given by

$$\int_{\varphi_{jj}}^{\infty} \left[\sum_{\{m|\Phi(\varphi,m)\leq\Phi_{hh}\}} \pi_{jj}(\varphi, m) \right] dG(\varphi) + \int_{\varphi_{jf}}^{\infty} \left[\sum_{\{m|\Phi(\varphi,m)\leq\Phi_{jf}\}} \pi_{jf}(\varphi, m) \right] dG(\varphi) - f_E,$$

which combines the expected profits obtained in the domestic and the export markets. The equilibrium free entry condition sets these expected profits to zero, which must pin down the endogenous cost cutoff Φ_{ll} in both regions. The free entry condition simplifies to

$$\Omega_j L_j \Phi_{jj}^{k+2} + \Omega_f L_f (\theta_{jf})^2 \Phi_{jf}^{k+2} = 2\gamma(k+1)(k+2) f_E,$$

given the Pareto distribution assumption for productivity draws. Using $\Phi_{jf} = \Phi_{ff}/\theta_{jf}$ and the symmetry across countries that gives a system of equations, we obtain the endogenous domestic cutoff for each country as

$$\Phi_{jj} = \left(\frac{2\gamma(k+1)(k+2) f_E (1-\xi_f)}{\Omega_j L_j (1 - \xi_f \rho_j)} \right)^{\frac{1}{k+2}},$$

where $\xi_f = \theta_{jf}^{-k} < 1$ is a measure of 'freeness' of trade from country j to country f.

A.7.2 Computing Number of Varieties and Entrants in Open Economy

The price distributions in country j of domestic firms producing in j, $p_{jj}(\varphi, m)$, and exporters producing in f, $p_{fj}(\varphi, m)$, are identical. Thus, as in the closed economy, the threshold price condition in country j (3), along with the resulting Pareto distribution of all prices for varieties sold in j, yield a zero-cutoff profit condition linking the domestic cost cutoff to the mass of varieties consumed in country j: $M_h = 2\gamma(k+1)(\alpha - \Phi_{jj})/(\eta\Phi_{jj})$.

Given a positive mass of entrants $N_{E,h}$ in country j, there will be $N_{E,h}[1 - G(\varphi_{jj})]$ firms producing in country j, and $N_{E,h}[1 - G(\varphi_{jf})]$ firms exporting $\xi_f \Phi_{jj}^k \Omega_j N_{E,j}$ varieties to country f. Summing over all varieties from countries j and f sold in country j, we get

$$M_j = N_{E,h} \Phi_{jj}^k \Omega_j + \xi_j N_{E,f} \Phi_{ff}^k \Omega_f.$$

Combining the two expressions for M_j, and similarly for M_f, gives the number of entrants in each country (by symmetry):

$$N_{E,j} = \frac{2\gamma(k+1)}{\eta(1 - \xi_j \xi_f)\Omega_j} \left[\frac{\alpha - \Phi_{jj}}{\Phi_{jj}^{k+1}} - \xi_j \frac{\alpha - \Phi_{ff}}{\Phi_{ff}^{k+1}} \right].$$

Assuming a non-specialized equilibrium where both countries produce the differentiated good ($N_{E,l} > 0,\ l = j, f$) implies that only a subset of relatively more productive firms choose to export in either country, since $N_{E,j} > 0$ is equivalent to

$$\frac{\alpha - \Phi_{jj}}{\Phi_{jj}^{k+1}} > \xi_j \frac{\alpha - \Phi_{ff}}{\Phi_{ff}^{k+1}} \Leftrightarrow \frac{\alpha/\theta_j - \Phi_{fj}}{\alpha - \Phi_{ff}} \left(\frac{\Phi_{ff}}{\Phi_{fj}}\right)^{k+1} > 1,$$

which is incompatible with $\Phi_{fj} \geq \Phi_{ff}$. Therefore, $\Phi_{fj} < \Phi_{ff}$.

A.7.3 Impacts of Bilateral Liberalization

Consider the case of bilateral liberalization where we assume that trade costs are symmetric, $\theta_{fj} = \theta_{jf} = \theta$. Thus we analyze the effect of a decrease in θ, or equivalently, of an increase in $\xi_h = \xi_f = \xi$. In this case, the equilibrium cost cutoff (16) can be written as

$$\Phi_{ll} = \left(\frac{2\gamma(k+1)(k+2)f_E}{\Omega_l L_l (1+\xi)}\right)^{\frac{1}{k+2}} \text{ for } l = j, f.$$

Bilateral liberalization thus increases competition in both markets by lowering Φ_{jj} and Φ_{ff} proportionally:

$$\frac{d\Phi_{ll}}{d\theta} = \Phi_{ll} \frac{k}{k+2} \theta^{-k-1} (1+\xi)^{-1} > 0 \text{ for } l = j, f.$$

However, the change in the export cutoff goes in the opposite direction since

$$\frac{d\Phi_{jf}}{d\theta} = \frac{\Phi_{ff}}{\theta^2} \left(\frac{k}{k+2} \xi (1+\xi)^{-1} - 1\right) < 0,$$

because $k\xi < (1+\xi)(k+2)$. Thus, there are two countervailing effects: a domestic competitive effect and an export scale effect. The first effect raises firm competition in the domestic market. The second effect is a countervailing force arising from the increased export market access. As it becomes less costly to ship goods to the trading partner, more firms start to export and more varieties are shipped.

The economic benefits of trade are relatively well known in this open economy setting with selection and pro-competitive effects of trade (Melitz & Ottaviano, 2008; Mayer et al., 2014). Therefore we focus on the novel environmental impacts of trade. Bilateral liberalization impacts the domestic and export cost cutoffs in opposite directions. While competition becomes tougher domestically, an export scale effect softens competition for exporting. This results in ambiguous impacts on the emission intensity at the sector level given Proposition 2. To fully assess the impacts of bilateral liberalization on the environment, we evaluate the aggregate level of emissions in country j, Z_h, as the sum of emissions from domestically consumed goods and exported goods:

$$Z_j = \int_{\varphi_{jj}}^{\infty} Z_{jj}(\varphi) dG(\varphi) + \int_{\varphi_{jf}}^{\infty} Z_{jf}(\varphi) dG(\varphi) = \frac{k\Gamma_h}{2\gamma(k+1)(k+2)} \left(L_h \Phi_{jj}^{k+2} + L_f \Phi_{jf}^{k+2} \right).$$

The domestic level of emissions from production in country j also depends on the regulation of its trading partner through the export cost cutoff, as well as on trade costs. By symmetry, the worldwide level of emissions, $Z^{wt} \equiv Z_j + Z_f$, is thus given by

$$Z^{wt} = \frac{k}{2\gamma(k+1)(k+2)} \left[L_j \Phi_{jj}^{k+2} \left(\Gamma_j + \frac{\Gamma_f}{\theta^{k+2}} \right) + L_f \Phi_{ff}^{k+2} \left(\Gamma_f + \frac{\Gamma_j}{\theta^{k+2}} \right) \right].$$

To assess the full effect of trade on the environment, we compare the worldwide level of emissions in autarky and in free trade. Full trade liberalization implies that $\theta = 1$. Comparing Z^{wt} with its equivalent in autarky ($Z^{wa} = k f_E \left[\Gamma_j/\Omega_j + \Gamma_f/\Omega_f \right]$) yields

$$Z^{wt} - Z^{wa} = \frac{k f_E}{2\Omega_j \Omega_f} (\Omega_j - \Omega_f)(\Gamma_j - \Gamma_f),$$

which is positive whatever the environmental regulation difference across countries as long as $d\Gamma_l/d\tau_l < 0$ for $l = j, f$, given $d\Omega_l/d\tau_l < 0$. We obtain

Proposition 4. *Assuming $\tau_l \geq 1$ for $l = j, f$, bilateral trade liberalization implies that*

- *i/ national emissions decrease when trade costs are high (incl. at autarky level), and increase, at least in the low regulation country, when trade costs are low;*
- *ii/ the worldwide level of emissions is larger under free trade than under autarky.*

Proof: The sign of $Z^{wt} - Z^{wa}$ depends on $d\Gamma_l/d\tau_l$, which, given the definition of Γ, is such

$$\frac{d\Gamma_l}{d\tau_l} = \frac{\Gamma_l}{(\epsilon - 1)\tau_l} + \frac{k(1-\epsilon) - \epsilon}{\epsilon - 1} \tau_l^{\frac{2}{\epsilon - 1}} \sum_{m=0}^{\infty} e^{\frac{m[2(\nu - \sigma)\epsilon + \sigma k(1-\epsilon)]}{(\epsilon - 1)}} \left[1 + \tau_l^{\frac{\epsilon}{\epsilon-1}} e^{\frac{m\epsilon(\nu - \sigma)}{\epsilon - 1}} \right]^{\frac{k(1-\epsilon) - 2\epsilon}{\epsilon}},$$

which is negative if and only if

$$[\epsilon - k(1-\epsilon)] \tau_l^{\frac{2}{\epsilon-1}} \sum_{m=0}^{\infty} e^{\frac{m[2(\nu-\sigma)\epsilon + \sigma k(1-\epsilon)]}{(\epsilon-1)}} \left[1 + \tau_l^{\frac{\epsilon}{\epsilon-1}} e^{\frac{m\epsilon(\nu-\sigma)}{\epsilon-1}} \right]^{\frac{k(1-\epsilon)-2\epsilon}{\epsilon}} < \frac{\Gamma_l}{\tau_l}. \tag{A.1}$$

This inequality holds for $k \geq \epsilon/(1-\epsilon)$, and a sufficient condition for this to hold is $\epsilon \leq 1/2$. For high values of ϵ, the condition may not hold, and thus $k(1-\epsilon) - \epsilon < 0$. In this case, we use the parameter restrictions of Lemma 2, i.e., $0 < \epsilon \leq 1$ and $\nu > \sigma > 0$, to obtain

$$\tau_l^{1/(\epsilon-1)} \sum_{m=0}^{\infty} e^{\frac{m[2(\nu-\sigma)\epsilon+\sigma k(1-\epsilon)]}{(\epsilon-1)}} \left[1 + \tau_l^{\frac{\epsilon}{\epsilon-1}} e^{\frac{m\epsilon(\nu-\sigma)}{\epsilon-1}}\right]^{\frac{k(1-\epsilon)-2\epsilon}{\epsilon}} < \Gamma_l,$$

since each element of the sum is smaller than its counterpart in Γ_l. Thus, condition (A.1) holds if $[\epsilon - k(1-\epsilon)]^{\frac{1-\epsilon}{\epsilon}} < \tau_l$, which holds for $\tau_l \geq 1$. Assuming that the relative price of emission compared to labor is higher than 1 implies that $d\Gamma_l/d\tau_l < 0$.

Using the expression for Z_j, the impact of bilateral liberalization on national emissions is

$$\frac{dZ_j}{d\theta} = \frac{k\Gamma_j}{2\gamma(k+1)} \left(L_j \frac{d\Phi_{jj}}{d\theta} \Phi_{jj}^{k+1} + L_f \frac{d\Phi_{jf}}{d\theta} \Phi_{jf}^{k+1} \right),$$

which is positive if and only if

$$\frac{\Omega_f}{\Omega_j} > \frac{2 + 2\xi + k}{\theta^2 k}. \tag{A.2}$$

When θ tends toward infinity (hence ξ tends toward 0), then the inequality holds. When θ tends toward 1 (hence ξ too), the right hand side (RHS) is larger than 1. Additionally the RHS is monotonically decreasing in θ. Hence, if $\Omega_f/\Omega_j > (4+k)/k$, the inequality (A.2) holds whatever the trade cost, and domestic emissions decrease in country j. If $\Omega_f/\Omega_j < (4+k)/k$, emissions decrease for high trade costs, and increase when trade costs are low.

Symmetrically, the impact of bilateral liberalization on country f's emissions is also positive if and only if

$$\frac{\Omega_f}{\Omega_j} < \frac{\theta^2 k}{2 + 2\xi + k}. \tag{A.3}$$

The RHS here is monotonically increasing in θ, starting at $k/(4+k)$ for $\theta = 1$ and tending toward infinity when θ tends toward infinity. Hence, if $\Omega_f/\Omega_j < k/(4+k)$, the inequality (A.3) holds whatever the trade cost, and domestic emissions decrease in country f. If $\Omega_f/\Omega_j > k/(4+k)$, emissions decrease for high trade costs, and increase when trade costs are low.

To summarize, consider the case where $\tau_j < \tau_f$, which implies that $\Omega_f/\Omega_j < 1 < (4+k)/k$. We obtain two cases for the impacts of bilateral liberalization:

i/ if $\Omega_f/\Omega_j < 4/(4+k)$, Z_f decreases with trade liberalization, whereas Z_j decreases for high values of θ and increases for low values of θ;

ii/ if $\Omega_f/\Omega_j > 4/(4+k)$, both Z_j and Z_f decrease with trade liberalization for high values of θ, and increase for low values of θ. ■

Proposition 4 reveals the impacts of bilateral liberalization on the environment. Recall that we have two countervailing effects playing a role here: tougher competition in the domestic markets, and increased export opportunities. The domestic competitive effect dominates when countries face high trade costs. National emissions thus decrease through the reallocation of factors toward more productive firms. When trade costs are lower, the export scale effect pushes emissions upward, especially in the country with lax regulations. This can be interpreted as a "pollution haven" story since the low regulation country free rides on the global pollution problem, and its firms benefits more from trade liberalization as they gain market shares over their foreign competitors. Overall, the export scale effect dominates the domestic competitive effect when countries fully liberalize their markets. Indeed, bilateral trade liberalization increases the worldwide level of emissions compared to autarky.

B Data Construction

In this appendix, we describe the construction of our panel production dataset. Key steps include converting energy intensities of production into CO_2 intensities, standardizing output units, identifying and removing outlying observations, and finally merging product-specific output data to product-specific input data. We first discuss the output data and the energy input data separately, and then our procedure for merging the two.

B.1 Output Data

Outputs are reported in Prowess by firm-product-year, where individual entries are distinguished by product string names. Within a firm-year set, any given product string name appears only once. These string names are provided by the firms themselves and appear to be constant over time.[25] Each observation is also assigned to a unique product classification code designed by CMIE; however, this code varies over time within product string name. Additionally, firms often report separate products in the same year that CMIE assigns to the same product code. Hence, we take firm name/product name combinations as unique identifiers of "firm-product" instead of the CMIE code. With this definition of a firm-product, there are 269,922 firm-product-year observations in the raw data, which include information on physical quantity of output, unit of physical output (e.g., tonnes, numbers, etc.), and sales value (among other variables).

The only issue we face in the output data is that output units are not always constant across firm-products over time. This is problematic for assessing changes in emission intensity. We standardize units as much as possible within physical dimension (e.g., converting all observations denominated in mass units to "tonnes"), but this process does not catch all cases of unit switching. When our standardization process fails, we drop the entire firm-product line (6,603 observations, or about 2.5% of the data). This leaves 260,498 firm-product-year output observations to merge to energy inputs.

B.2 Energy Input Data

Energy data in Prowess is reported in physical units of energy source per 1 unit of output by output product and energy source. For example, a firm would report separately the number of Kwhs of electricity and litres of diesel used to produce 1 tonne of tea in a given year. In the raw data, we have 125,120 such firm-product-source-year observations. We multiply energy use

[25]For example, upon inspection of the data, there does not appear to be any spelling inconsistencies across firm-products over time.

by source specific CO_2 emission factors, sum over energy types within a firm-product-year, and drop outlier observations before merging to the output data. We discuss various issues with these procedures here.

First, as in the output data, there is an issue related to standardization of output units. Here, we need output goods denominated in the same units across firm-product-source-year observations so that we can sum emissions over energy types and within firm-products over time. We first attempt to standardize units within dimensions as before, but finally must drop firm-product-years for which we cannot standardize units across energy types (1,562 firm-year observations, or about 2% of the data). We then drop firm-products that do not have constant output units over the period (about 1% of the data).

Next, we merge to each energy source type (e.g., coal, diesel fuel, etc.) a source-specific CO_2 emissions factor. These factors are based on estimates of carbon content of different fuel sources from the US Environmental Protection Agency and are reported in Table B.2. We are able to assign an emission factor to 83% of energy source energy unit pairs (e.g., Kwh of electricity). Of the 17% of such pairs that we cannot assign an emission factor, in many cases it appears that units have been entered incorrectly. For example, we cannot assign an emissions factor to observations denominated in "liters" of "electricity" because it does not make sense to consume electricity in liters. The correct denomination in this example probably should have been "Kwh" of electricity, but since electricity is also denominated sometimes in "Mwh" or even "Gwh", it is hard to know for sure what the real denomination should be.

Other cases involve instances when the units of denomination for the energy source do not match to a known unit for the CO_2 factor. For example, some observations are denominated in "cubic meters" of "firewood," while our emissions factor is denominated in "tonnes" of "firewood". Since the density of firewood could vary quite a lot, it is difficult to assign a meaningful emissions factor in this cases. Thus, we drop all observations for which we cannot assign a reasonable CO_2 emissions factor (2,089 firm-product-source-year observations, or less than 2% of the data).

After merging source-specific emission intensity factors, we multiply energy intensity of production by CO_2 emissions factors and sum over the firm-product-year. This results in a dataset of 81,433 firm-product-year emission intensities denominated in kg CO_2 per unit of production (where "unit" may take several different values, but is unique for a given firm-product-year).

Next, we standardize product string names across years. This process is not necessary in the output data because product names seem to be constant over time. But here, it happens that between two years, a product string name within the same firm can change so slightly that it seems reasonable to assume that the two string names refer to the same products. For example, in one year, a product is reported as "T-shirts", while in the next year the same firm reports a product "t-shirts." The string names are not exactly the same, so if we take strings as the unique identifier of firm-products, we will count these two observations as different products, though clearly they represent the same output. To address this data entry problem, we examine the data observation by observation and standardize names by hand. This procedure affects about 5% of the data.

Next, we address an issue relating to intermediate outputs. In the input dataset, firms often report electricity as an output good, though this output does not appear in the output dataset. Additionally, none of the firms in the dataset are identified as electricity providers. Thus, we consider these cases to be instances of intermediate input production and drop them from the dataset. These observations would be dropped from the analysis dataset anyway, since there is no match in the output dataset, but we mention it here. This procedure drops 21,803 observations, or 27% of the data.

Finally, we treat outlier observations in the input dataset. To this point, we have culled the data to 56,955 firm-product-year observations. Product names and output units are constant across years, but the dataset clearly contains some extreme outlier observations. We treat these outliers in two ways. First, we identify firm-product emission intensities which look like entry errors and assign those values instead the average emission intensity of the firm-product over the period. This procedure affects about 1% of the data. Next, we drop the entire firm-product profile if the emission intensity of the dirtiest year of the firm-product is at least 10 times greater than the cleanest year of the firm-product. This procedure drops 8785 observations, or about 15% of the data. Finally, we look within 6-digit product codes (across firms) and drop observations which look implausibly far from the rest of the producers in the product code (about 1% of the data). In the end, we are left with 47,530 firm-product-year observations with which to try to merge to the output data.

B.3 Merging Outputs to Inputs

Our final step in constructing our analysis dataset is to merge the product-specific emissions estimates to the product-specific output data. Since we have string names of both firms and products, a candidate procedure would be to merge on exact string matches, but in many cases matches are not exact. Luckily, in most cases, it is fairly straightforward to merge the two datasets by hand (see appendix B for details). An additional challenge is to harmonize output units across the two datasets. We discuss these procedures here.

In each of the output and input datasets, we take product string name as a unique identifier of firm-products. While the names of firm-products are standardized over time within these two datasets, they are not always standardized across the two reports. Sometimes we find that products are reported in the output dataset and not in the input dataset, or vice versa. We need data on both outputs and inputs to be able to use the observation in the analysis, hence we drop all observations that fail to merge on string name. If the match fails because the two reports actually pertain to different outputs, then we can safely drop the failed merges from the dataset. However, in many cases, it appears that the merge fails only because products are described differently in the two reports. In this case, it seems reasonable to match product string names by hand. For example, in the output dataset, the firm Aadi Industries Ltd. lists two products – "Shopping Bags/Carry Bags" and "Tarpaulin/Wagon Cover" – and two different products in the energy dataset – "Plastic Bags" and "Tarpaulin". No other products are listed for this firm in either dataset. Though the products do not match on exact string names, the two reports are clearly describing the same outputs. Here, we match the "Shopping Bags/Carry Bags" from the output dataset with the "Plastic Bags" reported in the energy dataset, and "Tarpaulin/Wagon Cover" from the output to "Tarpaulin" in the energy. Proceeding in this way, we increase the size of the merged dataset by 72% (relative to merging on exact string match).

We proceed as follows. First, we match all the firm-product-year observations that we can on firm name and product name (18,420 observations). We then set aside all these successful merges. Next, we compare the list of firm-products in the output data to the firm-products in the input data for the same firm-year and attempt to match by hand. We only consider one-to-one matches. I.e, we attempt to match each product in the output dataset to a unique product from the input dataset. Sometimes it is straightforward to match output goods between the two reports, as in the example described in the main text, but sometimes we still cannot match the two reports. Comparing reports by hand, we increase the size of the dataset by 15,932 observations, or 86% over matching on exact string name.

After harmonizing firm-product names across the two reports, there still remains an issue sometimes with output units being denominated differently between the two reports. When the discrepancy cannot be resolved, we drop the observations (about 1% of the data). We also drop a few outlier observations with implausibly large implied CO_2 emissions (1% of the data). This leaves 32,327 matched output and input observations in the analysis dataset.

B.4 Product-specific Energy Intensities

In this appendix, we test alternative hypotheses regarding how firms assign product-specific energy intensities.

As part of the 1988 Amendment to the Indian Companies Act, firms are required to report energy intensity by energy source and output. However, this reporting requirement presumably imposes some cost on firms, and there is no formal mechanism to ensure accuracy of reports. Thus, it is possible that the product-specific energy data suffers from mis-reporting errors. Without an independent audit of each firm, we cannot test globally for mis-reporting errors; but, we can generate hypotheses for likely forms of mis-reporting errors and test for them.

If we assume that accurate reporting is costly and that the cost of mis-reporting is low, then two likely strategies emerge. First, firms could report pure noise for the product-specific energy intensities. In this case, firm-product emission intensity would be uncorrelated with any variable. The evidence in Section 4 would already seem to disprove this hypothesis. However, we can test formally the hypothesis here.

Second, if firms choose to report some value for product-specific energy intensity that is not pure noise, but also choose not to pay the cost of learning the true value, then perhaps the firm employs some heuristic for estimating product-specific energy use. For example, perhaps the firm simply assigns the energy use based on revenue shares, or labor shares, or capital shares. While there are many possible heuristics that firms can employ, the only ones we can test are heuristics that utilize observable product-specific information. This unfortunately rules out all input-based heuristics, because energy is the only input for which we have product-specific information. We then consider output-based metrics: sales shares and output shares.

Formally, let Z_{eij} indicate the quantity of energy (in physical units - e.g., tons of coal, KwH of electricity, etc.) firm i uses from energy source e (e.g., coal, electricity, etc.) to manufacture Q_{ij} units of product j. The revenue earned from product j is $R_{ij} = Q_{ij} * P_{ij}$. Denote the revenue share and energy-type share associated with each product j:

$$r_{ij} = \frac{R_{ij}}{\sum_{j \in \Delta_i} R_{ij}} \quad , \quad z_{eij} = \frac{Z_{eij}}{\sum_{j \in \Delta_i} Z_{eij}} \tag{B.4}$$

for each energy source e, and where Δ_i is as before the set of products manufactured by a firm in a given year.

To test the hypotheses above, we estimate a linear regression model

$$z_{eijt} = \beta_e r_{ijt} + \gamma' W_{ijt} + \epsilon_{ijt}, \tag{B.5}$$

where t denotes years and W_{ijt} represents controls. The parameter of interest is β_e, the energy-source specific correlation between energy-use share and revenue share. If the first hypothesis above were true, we would have $\beta_e = 0$, i.e. product-specific energy share would be uncorrelated with product-specific revenue share. If the second hypothesis were true, we would have $\beta_e = 1$.

In Table B.3, we test both hypotheses at once. We group all energy sources into five categories– electricity, fuel, coal, gas, and biofuel – and report estimates separately by panel. Firm-products are only included in the regressions if we have firm-product energy intensity information for the given energy source and if at least one other product within the firm takes the source as an input (so both z_{eijt} and r_{ijt} lie strictly between 0 and 1). Note that firms need not use all possible energy sources to produce all output goods. In the case that a firm only generates a subset of all products reported using a given energy source, we re-compute r_{ijt} in columns 5-8 using total revenues of products that take the given energy source as an input as the denominator in (B.4). Standard errors are clustered at the firm-level throughout.

Columns 1 and 2 report OLS estimates both without controls (column 1) and with controls (column 2). In these first two columns, we find that energy-use share is positively correlated with revenue share, and these correlations are for the most part highly statistically significant. In all cases, z_{eijt} and r_{ijt} range between 0 and 1, so the point estimates imply that a 1 percentage point increase in revenue share translates into between 0.376 percentage points (biofuel) and 0.751 percentage points (coal) increases in energy-use share. In almost all cases, we can easily reject both $\beta_e = 0$ and $\beta_e = 1$, providing strong evidence against both hypotheses discussed above. We find similar results in columns 5-6 where we use adjusted revenue shares.

One reason that β_e lies consistently below 1 could be that revenue share is measured with errors. In this case, estimates in Table B.3 would suffer from attenuation bias. The possibility of measurement errors in revenues seems less of a problem than in many variables; but nevertheless, we address this possibility by instrumenting the current-year product-specific revenue share with lagged revenue share in columns 3-4, 7-8. In most cases, the point estimates increase, as one would expect to happen given attenuation bias, but in no case is the increase very large, and in all cases we can still easily reject $\beta_e = 1$.

Table B.2: CO_2 emission factors

Energy Source (1)	Kg CO_2 per Unit of Energy Source (2)	Unit of Energy Source (3)	Kg CO_2 per MMBTU of Energy Source (4)
Acetylene	.1053	scf	71.61
Agricultural Byproducts	974.9	short ton	118.17
Anthracite	2597.82	short ton	103.54
Biogas (Captured Methane)	.0438	scf	52.07
Coke	2530.59	short ton	102.04
Coke Oven Gas	.0281	scf	46.85
Distillate Fuel Oil No. 1	10.18	gallon	73.25
Distillate Fuel Oil No. 2	10.21	gallon	73.96
Electricity			278
Fuel Gas	.0819	scf	59
Kerosene	10.15	gallon	75.2
Kraft Black Liquor	1131.11	short ton	94.42
LPG	5.79	gallon	62.98
Lignite	1369.28	short ton	96.36
Lubricants	10.69	gallon	74.27
Motor Gasoline	8.78	gallon	70.22
Naptha (<401 deg F)	8.5	gallon	68.02
Natural Gas (US average)	.0545	scf	53.02
Petroleum Coke (Liquid)	14.64	gallon	102.41
Petroleum Coke (Solid)	3072.3	short ton	102.41
Propane (Liquid)	5.59	gallon	61.46
Residual Fuel Oil No. 6	11.27	gallon	75.1
Solid Byproducts	2725.32	short ton	105.51
Wastewater Treatment Biogas			52.07
Waxes	9.57	gallon	72.6
Wood and Wood Residuals	1442.64	short ton	93.8

Notes: The first column lists the energy source as named by the EPA. Prowess does not use exactly the same naming convention, so we mapped by hand these energy types to the energy types listed in Prowess. The second column reports kg CO_2 associated with a given unit of energy type in column 1, where the unit is reported in column 3. For most energy types, we use the CO_2 intensity listed in column 2. However, for some observations, we were unable to standardize units across the two datasets. In some cases, we were able to use an alternative CO_2 intensity reported per mmBTU. We list this alternative CO_2 intensity in column 4.

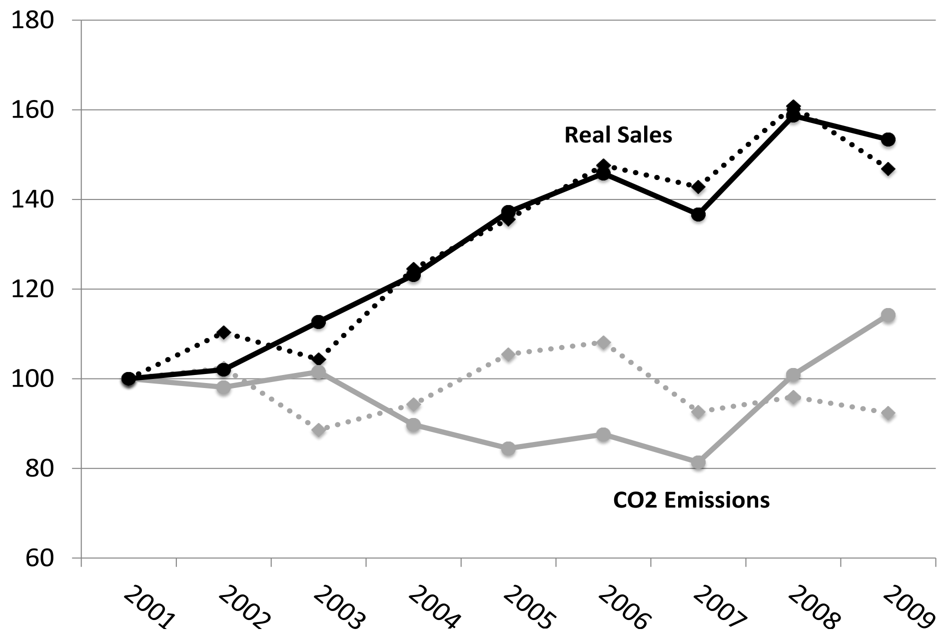
Table B.3: Energy Shares and Revenue Shares

	True Revenue Shares				Re-Adjusted Revenue Shares			
	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) OLS	(6) OLS	(7) IV	(8) IV
Panel A: Electricity								
Revenue Share	0.674***	0.688***	0.682***	0.695***	0.698***	0.600***	0.705***	0.606***
	(0.031)	(0.040)	(0.033)	(0.013)	(0.028)	(0.037)	(0.030)	(0.011)
Num of Obs	11175	11175	11175	11175	11118	11118	11118	11118
R squared	0.338	0.320	0.337		0.446	0.321	0.446	
Controls		Y		Y		Y		Y
Panel B: Fuel								
Revenue Share	0.555***	0.611***	0.556***	0.617***	0.708***	0.513***	0.715***	0.512***
	(0.059)	(0.077)	(0.063)	(0.032)	(0.039)	(0.061)	(0.040)	(0.025)
Num of Obs	3194	3194	3194	3194	3011	3011	3011	3011
R squared	0.168	0.185	0.168		0.450	0.223	0.450	
Controls		Y		Y		Y		Y
Panel C: Coal								
Revenue Share	0.751***	0.877***	0.758***	0.887***	0.812***	0.744***	0.813***	0.746***
	(0.072)	(0.084)	(0.075)	(0.032)	(0.058)	(0.077)	(0.060)	(0.027)
Num of Obs	1916	1916	1916	1916	1835	1835	1835	1835
R squared	0.346	0.422	0.346		0.560	0.446	0.560	
Controls		Y		Y		Y		Y
Panel D: Gas								
Revenue Share	0.406***	0.529**	0.354**	0.473***	0.549***	0.061	0.534***	-0.011
	(0.125)	(0.211)	(0.134)	(0.110)	(0.116)	(0.221)	(0.124)	(0.082)
Num of Obs	410	410	410	410	370	370	370	370
R squared	0.070	0.109	0.069		0.291	0.003	0.290	
Controls		Y		Y		Y		Y
Panel E: Biofuel								
Revenue Share	0.376*	0.538**	0.342	0.535***	0.663***	0.526**	0.643***	0.517***
	(0.203)	(0.244)	(0.218)	(0.106)	(0.136)	(0.199)	(0.154)	(0.084)
Num of Obs	208	208	208	208	192	192	192	192
R squared	0.114	0.224	0.113		0.487	0.319	0.486	
Controls		Y		Y		Y		Y

Notes: Each panel reports estimates that result from taking the energy source share listed as the dependent vairbale and the product-specific revenue share as the independent variable. All shares are constructed to lie between 0 and 1 (exclusive). Columns 1-4 take total firm-product revenue as the denomintor of revenue share, while columns 5-8 condition on products for which the firm explicitly reports using the given energy source. Even-numbered columns include controls for firm-year fixed effects. Columns 3-4 and 7-8 instrument current-year revenue share with lagged revenue share. Standard errors are clustered throughout on the firm, and asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels

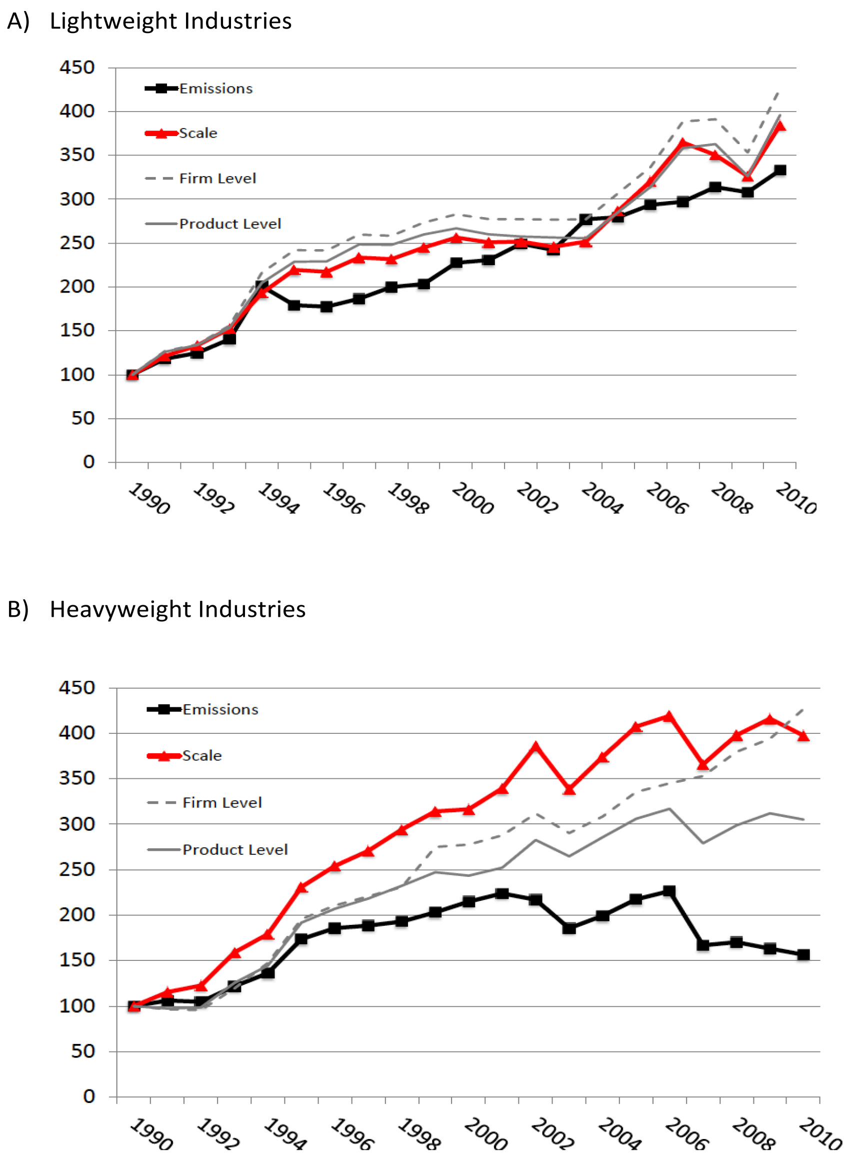
C Tables and Figures

Figure C.1: Real Sales Vs. CO_2 Emissions in ASI and Prowess



Notes: Figure plots total real output index ("Real Sales") vs total CO_2 emissions computed from the Annual Survey of Industries (solid lines) and Prowess (dashed lines). Real sales are total nominal sales deflated by India CPI from the World Development Indicators. All values indexed to the year 2001.

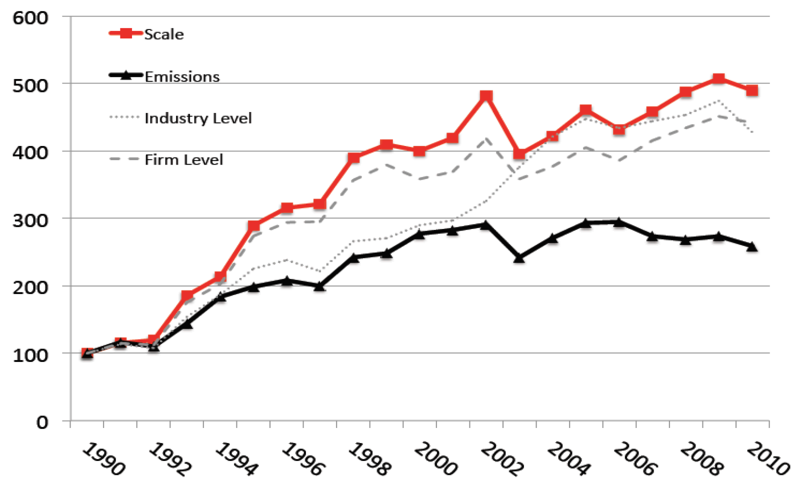
Figure C.2: Light versus Heavy Industries Decomposition



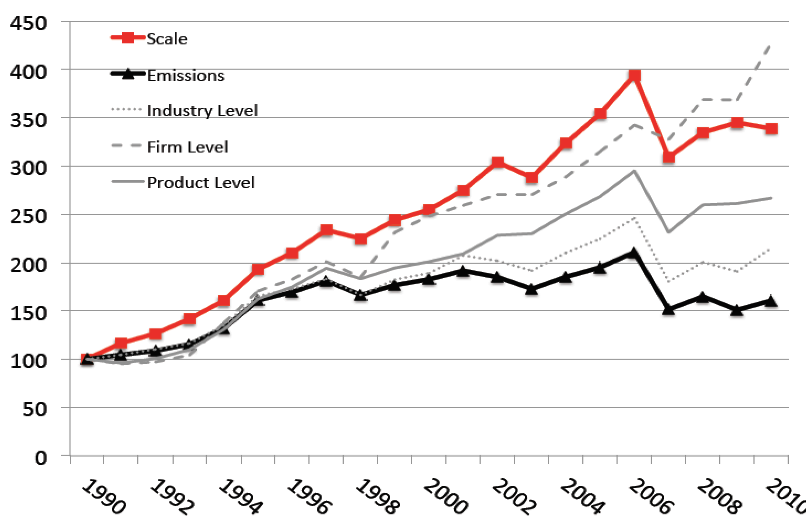
Notes: Figure plots total output index ("scale"), total CO_2 emissions ("Emissions") and counterfactual emissions at the industry, firm, and product levels. Only data denominated in tonnes are used. Industry definitions are the same as in Table 1. Heavy vs Light industry classification are explained in the main text.

Figure C.3: Single-product versus Multi-product Firms Decomposition

A) Single-product Firms



B) Multi-product Firms



Notes: Figure plots total output index ("scale"), total CO_2 emissions ("Emissions") and counterfactual emissions at the industry, firm, and product levels. Only data denominated in tonnes are used. Single and multi-product firms are defined as in the main text.