# Environmental Investment and Export Dynamics

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**Abstract**

This paper presents and estimates a dynamic model of investment in environmental abatement technology (EAT) and exports with heterogeneous firms. The model highlights the interaction between firms' environmental investment and export decisions and the impact of trade or environmental policy on firms' optimal choices. The model is structurally estimated using Indonesian manufacturing data that captures firm-level variation in investment in environmental abatement and export behavior. The results suggest that across a number of industries, environmental investment has little impact on productivity dynamics, but does encourage growth in export demand. Counterfactual policy experiments suggest that while trade liberalization moderately encourages increased exports and investment in EAT, increasing environmental restrictions on exports from Indonesia generally can have very different effects depending on the extent to which additional regulatory costs are borne by producers. If producers bear the cost of increased regulation, both the adoption of EAT and exporting fall. To the extent that environmental regulations serve as trade barriers they can discourage firms from entering export markets and reduce the incentive to invest in EAT. However, if more stringent regulation does not increase the cost of EAT adoption, abatement increases (often substantially), while the increased regulation has a smaller effect on exports in the long-run. The paper demonstrates that evaluating the interaction of export and environmental investment decisions at the firm-level can have substantial influence on the aggregate outcomes of changes in trade or environmental policy.

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# 1 Introduction

This paper develops a dynamic model of investment in environmental abatement technology (EAT) and exports with heterogeneous firms. We generally refer to investment in EAT as all actions taken to minimize environmental impacts both in the domestic and export markets. For example, these expenditures include actions taken to reduce waste, certify products which meet foreign environmental standards, improve environmental sustainability practices, and upgrade product characteristics that may affect the environment both during and after its final use. The model emphasizes how firms' current investment in environmental abatement technology or export decisions influence the evolution of the distribution of abatement and exports over time. The model is estimated using Indonesian manufacturing data and counterfactual policy experiments are used to assess the policy implications of trade and environmental regulation.

There is a long tradition linking international trade with environmental outcomes, particularly in developing countries. For example, Copeland and Taylor (1994, 1995) argue that international trade may be particularly likely to increase pollution in countries that have a comparative advantage in pollution-intensive industries. Numerous papers[1] cast doubt on the hypothesis that freer international markets will create pollution havens like Antweiler, Copeland and Taylor (2001) who argue that free trade generally tends to decrease pollution across countries. In particular, they find that when trade increases income by 1 percent, pollution concentrations tend to fall by 1 percent, largely driven by improvements in production techniques. In contrast, Ederington, Levinson and Minier (2005) argue that when we examine trade between developed and developing countries, there are often significant effects in mobile industries with large abatement costs. We contribute to this literature by examining environmental abatement and exporting activities across heterogeneous firms and characterizing their behavior across industries.

Recent research on export dynamics has emphasized the complementarity between investment and exporting activities. Ekholm and Midelfart (2005), Yeaple (2005) and Bustos (2007) highlight this link across firm-level decisions, while Atkeson and Burstein (2009), Ederington and McCalman (2008), Constantini and Melitz (2008), Lileeva and Trefler (2010) and Aw, Roberts and Xu (2010) further examine the impact it has on the evolution of firm-level outcomes over time. We follow this literature by examining the relationship between exporting and the investment in technology that reduces negative outcomes on the natural environment. While the preceding literature has stressed the link between investment and exporting through the impact of investment on the evolution of firm-level productivity, our paper, in contrast, emphasizes the impact of environmental investment on the evolution of *export demand* at the firm-level. In this sense, our paper is also related the literature on firm-level decisions and export demand as in

[1] See Tobey (1990), Grossman and Krueger (1995), Jaffe et al. (1995) and Ederington, Levinson and Minier (2004) for examples.

Arkolakis (2008), Nguyen (2008), Eaton et al (2009) and Foster et al (2010).

Similarly, numerous papers have studied whether environmental investment improves firm-level performance, with mixed results. While Xepapadeas and de Zeeuw (1999) and Dorfman, Muir, and Miller (1992) find some evidence of firm-level productivity gains in response to abatement, Gray (1987) and Gray and Shadbegian (2006) find no significant improvement in firm-level performance. Gollop and Roberts (1983) report large productivity decreases while Berman and Bui (2001) find significant productivity improvements in response to more stringent environmental policy regulations, but their studies are limited to fossil-fueled electric power generators and oil refineries, respectively. Moreover, Porter (1991), and Porter and van der Linde (1995) argue that any measured productivity gain from environmental investment may actually reflect an increase in the demand for goods from "environmentally clean" sources.

In this study we are able to distinguish between effects on domestic performance and demand for exports abroad by separately examining movements in domestic and export revenues. In particular, using variation in domestic sales in response to firm-level changes in export and abatement behavior over time we will be able to identify the effect of abatement on domestic sales in a developing country. Pargal and Wheeler (1996) report that larger, more efficient firms tend to produce less local pollution on average in Indonesia. Our paper, in contrast, emphasizes the internal incentive firms may have to reduce local pollution: an increase in profits. Moreover, conditional on the domestic market response to abatement behavior we are able to separately distinguish whether there are further gains in export markets. In fact, our results will suggest that these two activities are linked closely within firms.

None of the above papers that examine the impact of environmental investment on firm performance capture the impact of trade decisions on firm behavior. Kaiser and Schulze (2003) and Girma, Hanley and Tintelnot (2008) explicitly examine the interaction of firm-level abatement investment in conjunction with the decision to export abroad. While they confirm that exporting firms from Indonesia and the UK are more likely to invest in EAT, they do not study the impact of environmental expenditures or exporting on the evolution of productivity, export demand and export/abatement decisions over time.

In this paper, we build a dynamic structural model of exporting and investment in EATs. The model in this paper builds on the framework outlined in Aw, Roberts, and Xu (2010) by allowing abatement and export decisions to influence the evolution of future productivity. We extend their model by further allowing the evolution of export demand to be a function of investment in EATs. We link exporting and investment in EATs through 4 mechanisms. First, the return to either activity is increasing in the firm's underlying productivity, so that high-productivity firms self-select into both activities. Second, each activity potentially influences future productivity reinforcing the first effect. Third, we allow future export demand to depend directly on current investment in EATs, encouraging future entry into export markets. Last, entry into either activity influences the return from undertaking the other activity. The decision to export directly influences the probability of investing in EATs and vice-versa.

The data employed in this paper are uniquely suited to its purpose with detailed information on firm-level abatement expenditures, export decisions, and domestic and export revenues for all firm's with more than 20 employees in the Indonesian manufacturing sector. These data are matched with environmental regulations on imports in destination countries to provide a rich description of the Indonesian environmental and trade environment. In particular, by exploiting the differential variation in domestic and export revenues across similar firms over time we are able to separately identify the impact of environmental expenditures on firm performance and export demand across firms and industries.

Estimating the model is separated into two steps. First, the parameters governing the evolution of productivity and export demand are estimated using control function techniques as in Olley and Pakes (1996) and Doraszelski and Jaumandreu (2007). In contrast to previous findings, the results from this stage indicate that abatement has little effect on firm productivity or on the evolution of domestic sales in the industries we study. The remaining dynamic parameters are estimated by Bayesian Markov Chain Monte Carlo (MCMC) methods. These results suggest that deciding to abate does have a significantly positive effect on the evolution of export demand, though the size of the effect varies considerably across industries. This appears to be particularly true in export intensive industries where the product exported is subject to environmental regulations in the destination countries. Counterfactual experiments suggest that while trade liberalization moderately encourages increased exports and investment in EAT, increasing environmental restrictions on exports from Indonesia can have differing effects on abatement and exports depending on how they are implemented. To the extent that environmental regulations raise costs of adopting EATs to producers, the regulations serve as additional trade barriers[2] which discourage firms from entering export markets and reduce the incentive to invest in abatement. However, if the cost of EAT adoption does not rise with increased regulation, abatement rates rise dramatically across industries, while exporting behavior falls by a smaller amount in the long-run.

The next section presents basic patterns of exporting and investment in EAT behavior. The third and fourth sections present the model and describe the estimation methodology, while the fifth section describes the data and the sixth section presents the results. The last section concludes.

## 2 Empirical and Policy-Oriented Motivation

This section describes export and investment in EAT behavior in the Indonesian manufacturing sector between 1994 and 1996 and the policy environment under which manufacturing industries

[2]See Ederington and Minier (2003) for evidence that countries may explicitly choose environmental policy as domestic trade protection.

Table 1: Exporting vs. Pollution Abatement

Panel A

| | % EAT | Avg. EAE | Obs. |
|---|---|---|---|
| Exporter | 20.23 | 198.48 | 8280 |
| Non-Exporter | 13.06 | 45.69 | 45837 |

Panel B

| | % Exporter | Avg. Exp. Rev. | Obs. |
|---|---|---|---|
| EAT | 21.86 | 68,766.27 | 7662 |
| Non-EAT | 14.22 | 40,134.99 | 46455 |

in Indonesia operate. While it is well known that exporting is relatively uncommon, only 15 percent of all manufacturing firms engage in such activity, there are few estimates of abatement rates among manufacturing firms in developing nations.[3] Panel A of Table 1[4] presents two telling statistics: the average number of firms who invest in environmental abatement technology and the average environmental abatement expenditures across exporting and non-exporting firms.[5] We observe that exporters are much more likely to also invest in EAT (column 1) and incur greater EAT expenditures (among those who invest) on average (column 2).[6] Overall, 16 percent of firms choose to abate in some fashion, similar to the exporting rate. Panel B examines the probability of exporting and the average size of export revenues among firms which invest in EAT and those which do not. Similarly, we find that firms who choose to invest in EAT are more likely to export and, among those who export, they tend to have higher export sales.

Table 1 suggests that there may be reason to believe that these activities are inherently related. However, if both export and investment in EAT activities are costly we might expect that only the most productive firms are able to engage in either activity. Any correlation across activities may be completely spurious and offer no real indication of an important interaction at the firm-level. Moreover, if there is a causal relationship between EAT investment and exporting, the simple correlations offer little indication on the mechanism through which exporting affects the decision to invest in EAT or vice-versa. For example, if exporting encourages firms to improve firm-level productivity,[7] then this causes exporting firms to become profitable and encourages the adoption of costly pollution abating technology. Similarly, investment in EAT may introduce new highly productive technology to the firm, improve productivity and profitability to the point where firms are willing to enter export markets. These effects are analogous to those emphasized in the R&D and exporting framework proposed by Aw, Roberts and Xu (2010). We argue that investment in EAT may have further effects on export dynamics through export demand which in turn can separately affect entry to export markets and the adoption of EAT. Our model and empirical estimation will explicitly attempt to disentangle and identify these various effects below.

The Indonesian manufacturing sector is a particularly interesting environment to study in

[3]Kaiser and Schulze (2003) and Girma, Hanley and Tintelnot (2008) are other examples.

[4]In Table (1)-(3) EAE refers to environmental abatement expenditure. Abatement expenditures and export revenues are measured in 1983 Indonesian rupiahs.

[5]We exclude foreign-owned firms throughout this paper.

[6]This is true even after normalizing by the number of workers in each firm.

[7]See Lileeva and Trefler (2010) for an example where exporting raises firm-level productivity.

this context. Indonesian manufacturers faced few domestic environmental regulations during our period of study. There were notable environmental programs in place by 1986 which encompassed a number of recommodations for air and water quality and harzardous waste control (Afsah, Blackman and Ratunanda, 2000). In the wood industry, the Indonesian government extended an environmental act in 1990 to include an export ban on log and lumber particularly on the island of Borneo due to widespread anxiety over increased deforestation. However, Afsah and Vincent (1997) argue that compliance was extremely low since enforcement was non-existant. Nonetheless, Pargal and Wheeler (1996) find that in general, larger productive manufacturing firms located in wealthier parts of Indonesia emit less local water pollution on average. We believe that our study complements theirs in that we are able to observe both abatement behavior directly and provide an additional incentive for large, productive firms to engage in environmental upgrading: access to export markets.[8]

Over the same period, numerous Indonesian manufacturing firms faced considerable environmental restrictions on exports. Among the most notable are the restrictions on wood and textile exports during this period from Indonesia. For example, the U.S. toxic substances control act, last amended in 1992, addresses the production, importation, use, and disposal of specific chemicals requiring that importers of any article that contains a chemical substance or mixture provide a certification statement. Failure to comply with any rule in effect under the law results in the article being refused entry into the customs territory of the United States.[9] Dyestuffs in textiles potentially contain chemical substances identified as being harmful. For example, the dye on textiles themselves has been linked to certain skin diseases in human and the disposal of the chemical residues affects people, firms, and the natural environment via both air and water pollution.

Similarly, the Fifth European Commission Environmental Action Programme of 1993, required that wood could only be imported from tropical areas that were managed and practiced sustainable wood harvesting practices. Indonesia and Malaysia, who both had lax environmental regulations, were two of the largest exporters of wood to Europe during this period.[10] The wood industry is also of particular interest since Pargal and Wheeler (1996) report that the wood industry does not create nearly as much local pollution as the other industries they studied, suggesting that firms in this industry should have some other incentive to invest in abatement.

In addition, voluntary eco-certification schemes such as Oeko-Tex (1992), the European eco-label (1992), Certisource, and the U.S. sustainable forest initiative have become a standard way of identifying environmentally friendly businesses and products. While these standards are

[8]We cannot, unfortunately, link our data with the local water pollution data in their study. At the same time, it is unlikely that water pollution would be the primary cause of local environmental concern in a number of the industries we examine.

[9]Section 13: Import Certification, http://www.epa.gove/oppt/import-export/pubs/sec13.html.

[10]http://ec.europa.eu/environment/actionpr.htm.

voluntary, Chen, Otsuki and Wilson (2008) find meeting foreign standards does have a significant impact on export performance among manufacturing firms in developing countries. Obtaining voluntary certification in these industries is one mechanism by which firms can signal that their product meets foreign standards.

Last, during this period Indonesia was preparing to enter the world trade organization. As such, trade barriers fell broadly across most manufacturing industries, which in turn encouraged firms to enter export markets. Even though we can only observe the investment in EAT over a short-time period, the policy environment during this period provides us with an ideal setting to study the interaction of trade and pollution abatement at the firm-level. Unfortunately, in some industries, such as the paper industry, there are too few firms in Indonesia during this period to study the interaction with exporting in detail. However, in industries such as textile production, wood furniture and the saw mill industry we have sufficient data to examine these interactions at the firm-level.

# 3 A Model of Pollution Abatement and Exporting

This model is similar to those developed in the firm-level exporting literature: Roberts and Tybout (1997), Clerides, Lach and Tybout (1998), Melitz (2003), Das, Roberts and Tybout (2007), Aw, Roberts and Xu (2010) and models of exporting and investment as in Atkeson and Burstein (2007), Constantini and Melitz (2008), Lileeva and Trefler (2010). While we will also allow investment in EAT to influence the evolution of productivity, we do not need (or necessarily expect) that this is the primary mechanism through which the adoption of EAT influences export decisions. Rather we prefer to emphasize the positive impact that EAT adoption may have on export demand.

In principle, our model also allows us to separately identify *productivity* effects from *demand* effects in export markets, allowing us to test one version of the "Porter Hypothesis": that adoption of EAT may increase firm-specific demand (Porter and van der Linde, 1995). To be specific, we can separately identify the impact of EAT adoption on the variation in domestic revenues from that of export revenues.[11] To the extent that EAT adoption may encourage growth in domestic demand (rather than improving firm productivity), our estimates in export markets identify the differential growth rate in demand across domestic and export markets. Similarly, this paper provides new developing country estimates for the effect of firm-level environmental expenditures on productivity evolution (Gray, 1987) and the effect of environmental abatement on learning-by-doing (Bramoullé and Olson, 2005).

[11] Specifically, in this paper we do not consider versions of the Porter hypothesis that extend to the possibility of raising rivals costs or cases where there are spillovers in abatement research and development as described in Innes (2010).

### 3.1 Static Decisions

We first consider the total costs for each firm. Firm $i$'s short-run marginal cost function is modeled as:

$$\ln c_{it} = \ln c(k_{it}, \omega_{it}) = \beta_0 + \beta_k \ln k_{it} + \beta_w w_t - \omega_{it} \tag{1}$$

where $k_{it}$ is the firm's stock of productive capital, $w_t$ is the set of relevant variable input prices and $\omega_{it}$ is firm-level productivity.[12] Data limitations require a number of assumptions. First, we assume that each firm is a separate organizational entity and that each firm produces a single output which can be sold at home or abroad.[13] Second, there are two sources of short-run cost heterogeneity: differences in firm-level capital stocks and productivity. Investing in EAT can only affect short-run costs through its impact on productivity. Last, we assume that marginal costs do not vary with firm-level output. As such, demand shocks in one market do not affect the static output decision in the other market (and allows us to model revenue and profits in each market separately).[14]

Both domestic and export markets are assumed to be monopolistically competitive in Dixit and Stiglitz (1977) sense. However, we allow that each firm may face a different demand curve and charge different markups in each market. Firm $i$ faces the domestic demand curve $q_{it}^D$:

$$q_{it}^D = Q_t^D (p_{it}^D / P_t^D)^{\eta_D} = \frac{I_t^D}{P_t^D} \left( \frac{p_{it}^D}{P_t^D} \right)^{\eta_D} = \Phi_t^D (p_{it}^D)^{\eta_D} \tag{2}$$

where $Q_t^D$ and $P_t^D$ are the industry aggregate output and price index, $I_t^D$ is total market size and $\eta_D$ is the elasticity of demand, which is constant. The individual firm's demand depends on industry aggregates $\Phi_t^D$, the elasticity of demand and its own price $p_{it}$.

A similar structure is assumed in the export market with the exception that demand now depends on a firm-specific demand shifter $z_{it} = z(d_{it})$ which, in turn, depends on the firm's decision to invest in environmental abatement.[15] The firm's demand in the export market is

$$q_{it}^X = Q_t^X (p_{it}^X / P_t^X)^{\eta_X} e^{z^D(d_{it})} = \frac{I_t^X}{P_t^X} \left( \frac{p_{it}^X}{P_t^X} \right)^{\eta_X} e^{z(d_{it})} = \Phi_t^X (p_{it}^X)^{\eta_X} e^{z(d_{it})} \tag{3}$$

[12] As noted in Gray (1987) not all inputs may be devoted to production in the context of environmental abatement.

[13] The first part of this assumption is not too restrictive. Blalock, Gertler and Levine (2008) report that 95% of the firms in the Indonesian manufacturing census are separate organizational entities.

[14] Previous results on the Indonesian manufacturing sector do not report large departures from constant returns to scale in production (See Amiti and Konings (2008) for an example relevant to manufacturing firms in Indonesia). However, if there were increasing returns to scale in production this would suggest an even larger impact of EAT adoption on export sales.

[15] While we assume that environmental abatement expenditures do not affect domestic demand, we do allow them to affect firm-level productivity. If environmental expenditure does result in strong improvements in domestic demand we would not be able to separately identify it from improvements in firm-level productivity. However, in this case, we can still interpret the component of the export demand shifter that depends on environmental abatement as relative difference between domestic and export markets.

where $\Phi_t^X$ captures the industry aggregates abroad, $p_{it}^X$ is the firm's export price and $\eta_{it}^X$ is the constant elasticity of demand faced by all producers on export sales. We will be more specific regarding the functional form of $z_{it}$ in the following section.

Firm $i$ decides whether or not to export, whether or not to invest in EAT and sets the price for its output in each market to maximize the discounted sum of domestic and export profits. The firm's optimal domestic market price $p_{it}^D$ implies that the log of domestic market revenue $r_{it}^D$ can be written as:

$$\ln r_{it}^D = (\eta_D + 1)\ln\left(\frac{\eta_D}{\eta_D + 1}\right) + \ln \Phi_t^D + (\eta_D + 1)(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t - \omega_{it}) \qquad (4)$$

so that the firm's domestic revenue is a function of aggregate market conditions, the firm's capital stock and the firm-specific productivity. Similarly, exporting firms also earn the following revenue from export sales if they chose to export

$$\ln r_{it}^X = (\eta_X + 1)\ln\left(\frac{\eta_X}{\eta_X + 1}\right) + \ln \Phi_t^X + (\eta_X + 1)(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t - \omega_{it}) + z_{it} \qquad (5)$$

which is the export counterpart to the domestic revenue function (4). Export revenue will depend on EAT decisions through both firm-specific productivity and the export demand shock whereas EAT investments can only influence domestic revenues through the evolution of productivity.

Both firm-specific productivity and the export demand shock capture various sources of heterogeneity, and as such, it is important to interpret their effect cautiously. For instance, the term $\omega_{it}$ captures any source of firm-level heterogeneity that affects the firm's revenue in both markets; this may be product quality, for example, but we will refer to it as productivity. So, if adopting EAT affects domestic demand then it will show up as a productivity effect in domestic revenues. Similarly, $z_{it}$ captures all sources of export revenue heterogeneity, arising from differences in either cost or demand, that are unique to the export market. Thus, if the firms abatement decision improves product appeal or the efficiency with which the firm produces the "version" of the product for export, we cannot separately identify these effects.

The structure of the model allows us to calculate operating profits in each market

$$\begin{aligned} \pi_{it}^D &= -\left(\frac{1}{\eta_D}\right) r_{it}^D(\Phi_t^D, k_{it}, \omega_{it}) \\ \pi_{it}^X &= -\left(\frac{1}{\eta_X}\right) r_{it}^X(\Phi_t^X, k_{it}, \omega_{it}) \end{aligned} \qquad (6)$$

and, as such, the short-run profits are observable with data on revenue in each market. These will be important for determining the export and EAT investment decisions over time developed in the dynamic model below.

### 3.2 Transition of the State Variables

We begin with a description of the evolution of productivity, export demand shocks and the state variables $\Phi_t^D$, $\Phi_t^X$, and $k_{it}$. We assume that productivity evolves over time as a Markov process that depends on the firm's investments in EAT, its participation in the export market, and a random shock:

$$\begin{aligned} \omega_{it} &= g(\omega_{it-1}, d_{it-1}, e_{it-1}) + \xi_{it} \\ &= \alpha_0 + \alpha_1 \omega_{it-1} + \alpha_2 d_{it-1} + \alpha_3 e_{it-1} + \alpha_4 d_{it-1} e_{it-1} + \xi_{it} \end{aligned} \quad (7)$$

where $d_{it-1}$ is the firm's investment in EAT, and $e_{it-1}$ is the firm's participation in export market in the previous period.[16] The inclusion of $e_{it-1}$ allows for the possibility of learning-by-exporting and, in this case, we expect that $\alpha_3 > 0$. The term $d_{it-1}$ captures the impact of adopting EAT on the evolution of productivity. If environmental technology is more costly to operate (e.g. maintenance costs, emission control costs, fewer resources allocated to production) we would expect that EAT investment would reduce firm productivity and $\alpha_2 < 0$. However, if environmental technology is more advanced such that firms which invest in EAT also experience productivity improvements, we would expect $\alpha_2 > 0$.[17] We further argue that there may be important interactions between exporting and investment in EAT. For instance, if foreign contacts allow firms to make better use of new technology we would expect that $\alpha_4 > 0$. The stochastic element of productivity evolution is captured by $\xi_{it}$. We assume that any effect EAT investment has on productivity occurs in the year subsequent to when the expense was incurred due to the time necessary to install new technology, for certification to be verified and processed and for upgraded product characteristics to be noticed in the market. We assume that $\xi_{it}$ is an *iid* draw from a distribution with zero mean and variance $\sigma_\xi^2$. Note that the stochastic element of productivity is carried forward into future periods.

We also assume that the export demand shock evolves according to the following first-order Markov-process:

$$\begin{aligned} z_{it} &= h(z_{it-1}, d_{it-1}, e_{it-1}) + \mu_{it} \\ &= \gamma_0 + \gamma_1 z_{it-1} + \gamma_2 d_{it-1} + \mu_{it} \end{aligned} \quad (8)$$

where $\mu_{it} \sim N(0, \sigma_\mu^2)$. The persistence in $z$ captures factors such as the nature of the firm's product, destination markets, or long-term contractual or reputation effects that lead to persistence in the demand for its exports over time. The coefficient $\gamma_2$ captures any effect that adopting

[16] We experimented with versions of (7) that included higher powers of $\omega$. The coefficients on those variables were always very close to zero and statistically insignificant.

[17] Another possible explanation for a positive coefficient on $\alpha_2$ is an example of the "Porter effect" at home. If investment in environmental abatement creates an increase in demand within Indonesia the firm may also experience an increase in the measured productivity.

EAT technology has on export sales over and above any effect it had on firm-level productivity. If there is an export specific boost in export sales from investing in EAT we expect that $\gamma_2 > 0$.[18]

As in Aw, Roberts and Xu (2010) we will assume that capital is fixed over time for each firm $i$. Due to the short time series in our data, there is little variation over time in firm-level capital stock (particularly relative to the cross-sectional variation). We will, however, allow for cross-sectional variation in capital stock across firms. Last, we treat the aggregate state variables $\ln \Phi_t^D$ and $\ln \Phi_t^X$ as exogenous first-order Markov processes.

### 3.3 Abatement and Export Decisions Over Time

We next turn to examining the firm's dynamic decisions to invest in EAT and export. Following Aw, Roberts and Xu (2010) we assume that the firm first observes the fixed and sunk costs of exporting, $\gamma_{it}^F$ and $\gamma_{it}^S$, and decides whether or not to export in the current year. After making its export decision, the firm observes the fixed and sunk costs of abatement, $\gamma_{it}^A$ and $\gamma_{it}^D$, and makes the discrete decision to invest in EAT in the current year. All four costs are assumed to be *iid* draws from the joint distribution $G^\gamma$.[19]

We denote the value of firm $i$ in year $t$ before it observes fixed or sunk costs by $V_{it}$:

$$V_{it}(s_{it}) = \int (\pi_{it}^D + \max_{e_{it}} \{(\pi_{it}^X - e_{it-1}\gamma_{it}^F - (1 - e_{it-1})\gamma_{it}^S) + V_{it}^E(s_{it}), V_{it}^D(s_{it})\}) dG^\gamma \tag{9}$$

where $s = (\omega_{it}, z_{it}, k_i, \Phi_t, e_{it-1}, d_{it-1})$ is a vector of state variables, $e_{it-1}$ is a variable indicating whether a firm exports or not in year $t-1$, $V^E$ is the value of an exporting firm after it makes its optimal abatement decision and $V_{it}^D$ is the value of a non-exporting firm after it makes its optimal abatement decision.

The value of adopting EAT is embedded in $V_{it}^D$ and $V_{it}^E$:

$$\begin{aligned} V_{it}^E(s_{it}) \quad = \quad & \int \max_{d_{it} \in (0,1)} \{\delta E_t V_{it+1}(s_{it} | e_{it} = 1, d_{it} = 1) - d_{it-1}\gamma_{it}^A - (1 - d_{it-1})\gamma_{it}^D, \\ & \delta E_t V_{it+1}(s_{it} | e_{it} = 1, d_{it} = 0) dG^\gamma \end{aligned} \tag{10}$$

$$\begin{aligned} V_{it}^D(s_{it}) \quad = \quad & \int \max_{d_{it} \in (0,1)} \{\delta E_t V_{it+1}(s_{it} | e_{it} = 0, d_{it} = 1) - d_{it-1}\gamma_{it}^A - (1 - d_{it-1})\gamma_{it}^D, \\ & \delta E_t V_{it+1}(s_{it} | e_{it} = 0, d_{it} = 0) dG^\gamma \end{aligned} \tag{11}$$

The net benefit (or loss) to investing in EAT and exporting, conditional on previous decisions,

[18] We also experimented with versions of (8) that included higher powers of $z_{t-1}$. The coefficients on those variables again were always very close to zero and statistically insignificant.

[19] An alternative assumption is that the export and environmental abatement decisions are made simultaneously. While this leads to a similar model, in the empirical estimation, it is substantially more difficult to calculate the probability of each decision.

are embedded in the value functions. The tradeoffs facing the firms are most clearly captured in the expected future value of any possible choice:

$$E_t V_{it+1}(s_{it}|e_{it}, d_{it}) = \int_{\Phi'} \int_{z'} \int_{\omega'} V_{it+1}(s') dF(\omega'|\omega_{it}, e_{it}, d_{it}) dF(z'|z) dG(\Phi'|\Phi) \tag{12}$$

In numerous papers it is assumed that the return to exporting and abatement are both increasing in productivity. Here, we make no such assumption; EAT adoption may reduce productivity and increase the cost of production. We do expect, however, that return to exporting and investment are both increasing with respect to export demand. In industries where this second effect is dominant we expect a typical selection effect: only highly productive firms that expect large export sales will choose to export and invest in EAT.

The model explicitly recognizes that current choices affect the evolution of export demand (and productivity), and potentially influence future export and EAT decisions. However, it is important to emphasize that the structure of the model further implies that the return to either decision may depend very much on the other. For example, the return to EAT adoption depends on export decisions both through the evolution of productivity and the sunk cost associated with export behavior. Similarly, the return to exporting intuitively depends on the past EAT investment decisions which influence the path of export demand and the productivity directly through equations (7) and (8), but also influences the export decision through the sunk cost of investment in EAT. In essence, the marginal benefit of abating from equations (10) and (11) may be defined as the difference in expected future returns between investing or not investing in EAT for any given vector of state variables, $s$:

$$MBA_{it}(s_{it}|e_{it}) = E_t V_{it+1}(s_{it+1}|e_{it}, d_{it} = 1) - E_t V_{it+1}(s_{it+1}|e_{it}, d_{it} = 0) \tag{13}$$

As alluded to earlier, the marginal benefit of investing in environmental abatement technology will not only depend on the effect that EAT investment has on future productivity but also on the decision to export. [20] Thus, overall, the marginal benefit of EAT investment will vary for exporters and non-exporters where the difference in the future benefit of investing in EAT between both groups can be defined as:

$$\Delta MBA_{it}(s_{it}) = MBA_{it}(s_{it}|e_{it} = 1) - MBA_{it}(s_{it}|e_{it} = 0). \tag{14}$$

This difference will be positive if investing in EAT is more worthwhile to exporters relative to non-exporters in which case we might expect that $\alpha_4$ in equation (7) and/or $\gamma_2$ in equation (8) are positive, suggesting complementarity between the decision to export and invest in EAT.

[20] If the exporting decision does not influence productivity growth and there are no sunk costs of exporting making exporting a static decision, exporters and non-exporters will not differ in how they value investing in EAT. However, exporting may still affect the decision to invest in EAT if firms expect that the fixed costs of exporting will be lower in the future (Atkeson and Burstein, 2009).

Likewise, for any given state vector, the marginal benefit of exporting can be defined as:

$$MBE_{it}(s_{it}|d_{it-1}) = \pi^X_{it}(s_{it}) + V^E_{it}(s_{it}|d_{it-1}) - V^D_{it}(s_{it}|d_{it-1}) \quad (15)$$

This reflects current export profits plus the expected gain in future export profit from being an exporter as opposed to serving only the domestic market. Analogous to the marginal benefit of abatement discussion, in general the marginal benefit of exporting will depend on past EAT investment choice when there is a sunk cost to abating where $\Delta MBE_{it}(s_{it}) = MBE_{it}(s_{it}|d_{it} = 1) - MBE_{it}(s_{it}|d_{it} = 0)$ indicates the marginal effect of investing in EAT on the return to exporting. In the next section we examine how we might empirically estimate the interdependence of these decisions.

# 4 Estimation

Here we develop the empirical counterpart to the model presented in the previous section and describe the estimation procedure. We estimate the model in two steps; in the first step we employ control function techniques similar to Olley and Pakes (1996), Levinsohn and Petrin (2003) and Doraszelski and Jaumandrau (2007) to recover the parameters of the revenue function, the evolution of productivity and export demand. In the second stage, we describe a Bayesian MCMC method to estimate the dynamic parameters and capture the impact of EAT adoption on export decisions over time.[21]

## 4.1 Mark-ups and Productivity

Below we describe a two step process to recovering the parameters of the revenue functions, mark-ups, capital and the evolution of productivity. In the first step, we recover an estimate of the mark-ups at home and abroad. As in Aw, Roberts and Xu (2010) we assume that each firm's marginal cost, $c_{it}$ is constant with respect to total output and equal across domestic and export output. Setting marginal revenue equal to marginal cost in each market we can write total variable cost, $tvc_{it}$, as a combination of domestic and export revenue weighted by their

[21] Our methodology follows Das, Roberts and Tybout (2007) and Aw, Roberts and Xu (2010) closely. The literature on estimating firm-level unobserved productivity using classical estimation methods is well-established and has been shown to produce consistent estimates of total factor productivity (See Olley and Pakes (1996); Levinsohn and Petrin (2003); and Blundell and Bond (2000)). However, given our short panel data (3 years) and the generalized type II tobit likelihood function in our model, classical estimation techniques such as Maximum Likelihood Estimation often do not perform well, hence the use of Bayesian MCMC to estimate the dynamic parameters.

respective elasticities:

$$
\begin{aligned}
tvc_{it} &= q_{it}^{D} c_{it} + q_{it}^{X} c_{it} \\
&= r_{it}^{D}\left(1+\frac{1}{\eta_D}\right) + r_{it}^{X}\left(1+\frac{1}{\eta_X}\right) + \varepsilon_{it} \qquad (16)
\end{aligned}
$$

where the error term $\varepsilon_{it}$ captures measurement error in total variable cost. Estimating equation (16) by OLS we retrieve the estimates of $\eta_D$, and $\eta_X$ and turn next to estimating the parameters of the productivity process.

Recall, that the domestic revenue function is

$$
\ln r_{it}^{D} = (\eta_D+1)\ln\left(\frac{\eta_D}{\eta_D+1}\right) + \ln \Phi_t^{D} + (\eta_D+1)(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t - \omega_{it}) + u_{it} \qquad (17)
$$

where we have added an *iid* error term to equation (4). The composite error includes both unobserved *iid* component and firm-specific, time varying productivity: $-(\eta_D+1)\omega_{it} + u_{it}$. As in Olley and Pakes (1996) we pursue a strategy where we will rewrite unobserved productivity as an approximation of a non-parametric function of observables that are correlated with it. Under certain regularity conditions, observed material and electricity demand, $m_{it}$ and $n_{it}$, are invertible so that we can write productivity as an unknown function of the input choices[22]

$$
\omega_{it} = \omega(k_{it}, m_{it}, n_{it}, d_{it-1}).
$$

Letting a constant capture the intercept term we can rewrite the domestic revenue function in (17) as

$$
\begin{aligned}
\ln r_{it}^{D} &= \gamma_0 + \sum_{t=1}^{T} \gamma_t D_t + (\eta_D+1)(\beta_k \ln k_{it} - \omega_{it}) + u_{it} \\
&= \gamma_0 + \sum_{t=1}^{T} \gamma_t D_t + f(k_{it}, m_{it}, n_{it}, d_{it-1}) + v_{it} \qquad (18)
\end{aligned}
$$

where $D_t$ is a set of year dummies and $f(\cdot)$ is a cubic function of its arguments. The essence of the above method is that the approximated function $f(\cdot)$ captures the combined effects of exporting, abatement, capital and productivity on domestic revenue. We denote the fitted value of the $f(\cdot)$ function as $\hat{\phi}_{it}$. According to our model the estimate of $\hat{\phi}_{it}$ captures $(\eta_D+1)(\beta_k \ln k_{it} - \omega_{it})$ which is a function of capital and productivity. We first estimate (18) by OLS and recover an estimate of the composite term, $\hat{\phi}_{it}$. Following Olley and Pakes (1996), Doraszelski and Jaumandreu (2007) and Aw, Roberts and Xu (2010) we construct a productivity series for each

[22] Ackerberg, Benkard, Berry and Pakes (2007) demonstrate that if input demand is a bijection in $(\omega_{it}, z_{it})$, conditional of capital stock $k_{it}$ and EAT investment $d_{it-1}$, then we can invert the input demand function to express productivity as a function of the observed inputs.

firm. Inserting $\phi_{it}$ into (7) we write the estimating equation

$$\hat{\varphi}_{it} = \beta_k^* \ln k_{it} - \alpha_0^* + \alpha_1(\hat{\varphi}_{it-1} - \beta_k^* \ln k_{it-1}) - \alpha_2^* d_{it-1} - \alpha_3^* e_{it-1} - \alpha_4^* d_{it-1} e_{it-1} + \xi_{it}^* \quad (19)$$

where the asterisk indicates that the coefficients are scaled by $(\eta_D + 1)$. This equation can be estimated by non-linear least squares and the parameters retrieved for a given value of $\eta_D$. This completes the second step.[23]

## 4.2 Dynamic Parameters

The remaining parameters of the model can be estimated using discrete decisions for exporting and investment in EAT. Given the first-stage parameter estimates we can construct a firm-level productivity series, $\omega_i \equiv (\omega_{i0}, ..., \omega_{iT})$ and in combination with the observed firm-level series of exporting $e_i \equiv (e_{i0}, ..., e_{iT})$, export revenues $r_i^X \equiv (r_{i0}^X, ..., r_{iT}^X)$, and firm-level investment in EAT $d_i \equiv (d_{i0}, ..., d_{iT})$ we can write the $i^t h$ firm's contribution to the likelihood function as

$$P(e_i, d_i, r_i^X | \omega_i, k_i, \Phi) = P(e_i, d_i | \omega_i, k_i, \Phi, z_i^+) h(z_i^+) \quad (20)$$

where $z_i^+$ is the time series of export market shocks for firm $i$ in years in which it exports. Equation (20) expresses the joint probability of discrete export and EAT decisions, conditional on export market shocks and the marginal distribution of $z$. Given the estimated parameters of the export shock process we can simulate exports shocks, construct the density $h(z_i^+)$ as in Das, Roberts and Tybout (2007), and evaluate the likelihood function.[24]

The model allows us to express the probabilities of exporting or investing in EAT as functions of the value functions and sunk and fixed cost parameters. Specifically, assuming that the sunk and fixed costs are *iid* draws from a known distribution, the joint probabilities of exporting and investing in EAT can be written as product of the choice probabilities for $d_{it}$ and $e_{it}$ in each year, conditional on $s_{it}$. The probability of exporting can be written as:

$$P(e_{it} = 1 | s_{it}) = P(e_{it-1}\gamma_{it}^F + (1 - e_{it-1})\gamma_{it}^S \leq \pi_{it}^X + V_{it}^E - V_{it}^D) \quad (21)$$

Intuitively, the sunk and fixed costs are identified from differential entry and exit behavior across similar firms with different export histories.

[23] Standard errors are computed by repeatedly bootstrapping the first stage of estimation for equations (16),(18), and (19).

[24] Das, Roberts and Tybout (2007) demonstrate how to extend the Tobit model to a case where the (export) shocks are serially correlated.

Similarly, the probability of investing in EAT can be calculated as:

$$\begin{aligned} P(d_{it}=1|s_{it}) &= P(d_{it-1}\gamma^A_{it} + (1-d_{it-1})\gamma^S_{it} \leq \\ &\delta E_t V_{it+1}(s_{it}|e_{it}, d_{it}=1) - \delta E_t V_{it+1}(s_{it}|e_{it}, d_{it}=0)) \end{aligned} \tag{22}$$

Here the probability of investing in EAT depends on the *current* export decision due to the timing assumption in the model that requires that export decisions are made ahead of EAT investment decisions.[25]

The probabilities depend on sunk and fixed cost parameters, export and abatement histories, and the expected value functions, $E_t V_{it+1}$, $V^D_{it}$ and $V^E_{it}$. For a given set of parameters we employ a Bayesian Monte Carlo Markov Chain (MCMC) estimator to characterize the posterior distribution of the sunk and fixed cost parameters. We assume that all fixed and sunk costs are drawn from separate, independent exponential distributions. The sunk and fixed costs we estimate should then be interpreted as the the means of those distributions.

## 5 Data

We estimated the model using firm-level data from Indonesia between 1994-1996. Collected annually by the Central Bureau of Statistics, *Budan Pusat Statistik* (BPS), the survey covers the population of manufacturing firms in Indonesia with at least 20 employees. The data capture the formal manufacturing sector and record detailed firm-level information on domestic and export revenues, capital, intermediate inputs, energy and expenditures on pollution abatement. Data on revenues, investment and inputs are combined with detailed wholesale price indices to deflate for price changes across years.[26]

Since the Indonesian manufacturing sector covers a wide scope of industries, and each industry faces very different environmental regulations, we will focus on a few (4-digit ISIC code) industries which face explicit environmental restrictions in major export markets. Specifically, we will examine the interaction of exporting and EAT adoption in the saw mill (3311), wood furniture (3321), and spinning and weaving (3211) industries. The saw mill, wood furniture and spinning and weaving industries follow 583, 460 and 737 continuing firms over 3 years. Blalock, Gerter and Levine (2008) report that approximately 95% of Indonesian manufacturing plants are separate entities, leaving little distinction between a plant and a firm in the sample. Table 2 describes size differences across firms measured by average sales across industries and over time.

[25] In the first year of the data we do not observe $d_{it-1}$ and $e_{it-1}$. We deal with this initial conditions problem by using Heckman's (1981) suggestion and model the decision to export and invest in EAT in the first year with separate probit equations.

[26] Price deflators are constructed as closely as possible to Blalock and Gertler (2004) and include separate deflators (1) output and domestic intermediates, (2) capital, (3) energy, (4) imported intermediates and (5) export sales.

Table 2: Average Sales

| Saw Mills | Non-Exporters | Exporters | |
|---|---|---|---|
| | Average Domestic Sales | Average Domestic Sales | Average Export Sales |
| 1994 | 19267 | 23913 | 140742 |
| 1995 | 18159 | 28657 | 115485 |
| 1996 | 12207 | 27884 | 142923 |

| Wood Furniture | Non-Exporters | Exporters | |
|---|---|---|---|
| | Average Domestic Sales | Average Domestic Sales | Average Export Sales |
| 1994 | 3702 | 6352 | 13147 |
| 1995 | 3616 | 7304 | 11717 |
| 1996 | 3933 | 6616 | 14588 |

| Spinning and Weaving | Non-Exporters | Exporters | |
|---|---|---|---|
| | Average Domestic Sales | Average Domestic Sales | Average Export Sales |
| 1994 | 66751 | 157226 | 93382 |
| 1995 | 62577 | 168671 | 98254 |
| 1996 | 47867 | 154399 | 108404 |

Notes: Sales measured in thousands of 1983 Indonesian Rupiahs.

In all industries, exporters report larger average sales than non-exporters which is indicative of the superior productivity enjoyed by firms who self-select into export markets.

It is worth noting, however, that the distribution of productivity is highly skewed in each industry; the average level of domestic sales among domestic non-exporters is approximately 7.6 and 4.7 times the size of the median level of domestic sales in the saw mill and wood furniture industries, while it is roughly 13 times the median level of domestic sales in the spinning and weaving industry. The distributions of domestic and export sales among exporters are similarly skewed.

The survey reports the total expenditure on EAT at the firm-level but does not provide any description on the exact nature of the expenditures. However, by studying narrowly defined industries where the production process is well-known we can describe and compare the opportunities for environmental investment across industries. In this manner we can characterize the extent to which the actions taken by the firm are likely to affect consumers in both local or foreign markets.

In the sawmill industry, operations range from the handling and transportation of logs to drying the timber, sorting and classification with the primary production process involving the transformation (sawing) of logs into dimension lumber, boards, and beams. Deforestation, waste minimization, and energy efficiency are the main environmental issues that affect the sawmill industry. Indonesian firms minimize waste and increase energy efficiency by processing sawdust and other mill waste into particle board or use the waste to heat wood-drying kilns, fire boilers that provide mills with electricity, press the sawdust into wood pellets for pellet stoves, or chip the larger waste pieces into wood chips for the paper mills industry. [27] Managing deforestation, however, is more challenging and necessitates collective action by both the government and firms. As described in Section 2, Indonesian saw mill producers did face stringent deforestation

[27] A detailed description of the sawmills industry can be found at http://www.referenceforbusiness.com/industries/Lumber-Wood/Sawmills-Planing-Mills-General.html

restrictions in important destination markets. Still, Indonesian sawmill producers could certify their products as a way to signal that the timber comes from sustainably managed forests.

Despite numerous similarities, the production process of the wood furniture industry diverges from that of other wood products in important ways. First, the integrated design of wood furniture for esthetic and functional attributes is a major part of the value added in the wood furniture industry and emits essentially no pollution as it is a service.[28] Second, aside from design, typical operations in the wood furniture manufacturing industry include finishing, gluing, cleaning, and wash-off.[29] Although these processes may generate environmental concerns due to air toxins contained in certain solvents and glue adhesives, a number of affordable, less toxic substitutes are available. For example, manufacturers can switch to water-based coatings and adhesives instead of using more harmful solvent-based materials or use heat instead of solvent to reduce coating viscosity. Finally, Indonesian firms could use other wood products such as boards and beams that have already been coated and are environmentally friendly in the production of wood furniture, lessening the amount of resources that they allocate to environmental abatement.

Spinning and weaving manufactures are typically produced using either a mule or a ring spinning machine to create yarn and wind it onto a bobbin, checking or rewinding the bobbin, plying, and gassing where yarn is swiftly passed through a series of Bunsen gas flames in a gassing frame.[30] The production process for weaving involves a power loom used to shred, pick, and beat-up the warp threads. Inefficient energy and water usage in addition to the dyes used in textiles and wastewater are the main sources of local environmental problems in the spinning and weaving industry. Roughly 34 per cent of energy is consumed in spinning, 23 per cent in weaving, 38 per cent in chemical wet processing and five per cent in miscellaneous processes.[31] Local Indonesian firms could maintain water-supply equipment or recycle and reuse water to conserve water. Also, substituting usage towards new spinning equipment such as open-end spinning, which consumes less energy, or performing quality control for incoming fiber could eliminate contaminants in the effluent of the finishing mill or in the finished consumer product.[32] Spinning and weaving industries can also impact the environment in destination countries. In particular, the type of dye, bleach and finishing agent used on the textile itself can have harmful effects on the natural environment where the textile is sold or used. To the extent that the textiles spun and woven in Indonesia contain harmful substances that are then exported, the

[28] http:www.census.gov/econ/census02/naics/sector31/337.htm.

[29] Wash-off refers to the process of removing a cured coating of a product that does not meet specification:http://www.pinellascounty.org/environment/pageshtml/pollutionPrevent/p2r2PDFs/mangmentPDFIndustry/Wood_furnMan.pdf.

[30] Curtis, H P (1921), "Glossary of Textile Terms", Arthur Roberts Black Book. (Manchester: Marsden & Company, Ltd. 1921), http://www.oneguyfrombarlick.co.uk/forum_topic.asp?whichpage=1&TOPIC_ID=6424& FORUM_ID=99&CAT_ID=3&Forum_Title=Rare+Text+(Book+Transcriptions)&Topic_Title=A+Glossary+of+Textile+Terms, retrieved 2009-01-11

[31] http://www.t2trade.co.uk/downloads/ComparingConventionalCottontoOrganic-TheFacts.pdf

[32] Pollution Prevention in the Textile Industry developed by U.S. EPA/SEMARNAP Pollution Prevention Work Group, December 1996: http://www.p2pays.org/ref/20/19041.pdf

destination markets can, and often do, regulate entry into their markets. For example, the U.S. Toxic Substances Control Act would prohibit the importation of substances which did not meet this environmental criterion. As noted in Section 2, Indonesian textile manufacturers did have the option to voluntarily certify their products as environmentally safe through certifications such as Oeko-Tex.

We convert the environmental expenditure variable into a binary variable if a firm reports positive EAT associated expenditures and 0 otherwise.[33] Overall, 15 percent of producers in each industry reported positive EAT expenditures during this period. The average EAT expenditure in the saw mill, wood furniture and spinning and weaving industries were respectively, 18.8, 1.1 and 56.0 thousand 1983 Indonesian rupiahs, and these represent approximately 1 percent of the median firm's total revenue in each industry. Even though we assume EAT investment can be represented by a binary variable it is important to note that we do allow for cost heterogeneity in EAT investment costs by drawing fixed and sunk costs from exponential distributions.

Finally, Table 3 reports the transitions in and out of exporting and EAT investment across all four possible previous combinations these variables could have taken in the preceding year. In general, we see that there is a fair amount of persistence in all four states activity in both industries. A small fraction of firms invest in EAT across industries: approximately 20 percent in the saw mill industry, 11 percent in the wood furniture industry and 23 percent in the spinning and weaving industry. Very few firms both export and invest in EAT. Only 9 percent of firms invest in EAT and export in the wood industry, while only 4 percent of firms are simultaneously engaged in both activities in the wood furniture and spinning and weaving industries.

There are a number of notable differences across industries. While 32 and 25 percent of firms export in the saw mill and wood furniture industries, only 12 percent of firms choose to enter export markets in the spinning and weaving industry. Export status is also more persistent in the saw mill and wood furniture industries where exporters receive almost 73 and 67 percent of revenues from export sales on average, respectively. In contrast, it is less persistent in the spinning and weaving industry where exporters receive 40 percent of total revenues from export sales on average.

Table 3 suggests the potential interdependence of the export and EAT investment decisions. Firms engaged in either activity are much more likely to begin the other than firms that are not engaged in either activity. Moreover, the persistence in each state is suggestive of potential sunk costs associated with each behavior. We next examine the implications of these patterns in the estimated model below.

[33] Given the short time dimension of the panel data, and the small number of firms which choose to abate estimating a model with a continuous abatement choice variable is practically very difficult in this context given the small number of observations we have to identify the firm's abatement policy rule.

Table 3: Annual Transition Rates for Continuing Plants

Saw Mills

| | Status in $t+1$ | | | |
|---|---|---|---|---|
| Status in $t$ | Neither | only Exp. | only EAT. | Both |
| All Firms | 0.566 | 0.231 | 0.105 | 0.098 |
| Neither | 0.857 | 0.069 | 0.063 | 0.012 |
| only Exp. | 0.112 | 0.729 | 0.000 | 0.155 |
| only EAT | 0.344 | 0.156 | 0.547 | 0.094 |
| Both | 0.059 | 0.314 | 0.098 | 0.529 |

Wood Furniture

| | Status in $t+1$ | | | |
|---|---|---|---|---|
| Status in $t$ | Neither | only Exp. | only EAT | Both |
| All Firms | 0.682 | 0.209 | 0.065 | 0.045 |
| Neither | 0.901 | 0.054 | 0.041 | 0.005 |
| only Exp. | 0.167 | 0.790 | 0.016 | 0.027 |
| only EAT | 0.375 | 0.063 | 0.469 | 0.094 |
| Both | 0.000 | 0.200 | 0.029 | 0.771 |

Spinning and Weaving

| | Status in $t+1$ | | | |
|---|---|---|---|---|
| Status in $t$ | Neither | only Exp. | only EAT. | Both |
| All Firms | 0.674 | 0.088 | 0.184 | 0.054 |
| Neither | 0.848 | 0.063 | 0.076 | 0.013 |
| only Exp. | 0.385 | 0.495 | 0.022 | 0.099 |
| only EAT | 0.202 | 0.044 | 0.667 | 0.088 |
| Both | 0.044 | 0.109 | 0.130 | 0.717 |

Table 4: First Stage Parameter Estimates

| | Saw Mills | | Wood Furniture | | Spin. & Weaving | |
|---|---|---|---|---|---|---|
| $1+1/\eta_D$ | 0.817 | (0.025) | 0.864 | (0.170) | 0.597 | (0.069) |
| $1+1/\eta_X$ | 0.598 | (0.032) | 0.600 | (0.043) | 0.890 | (0.166) |
| $\beta_k$ | -0.028 | (0.011) | -0.005 | (0.013) | -0.040 | (0.020) |
| $\alpha_0$ | 0.245 | (0.067) | 0.053 | (0.099) | 0.147 | (0.086) |
| $\alpha_1$ | 0.863 | (0.028) | 0.901 | (0.033) | 0.980 | (0.010) |
| $\alpha_2$ | -0.029 | (0.018) | 0.011 | (0.031) | -0.040 | (0.040) |
| $\alpha_3$ | 0.040 | (0.018) | 0.024 | (0.048) | 0.028 | (0.061) |
| $\alpha_4$ | 0.036 | (0.025) | -0.023 | (0.047) | 0.049 | (0.082) |

Notes: Bootstrap standard errors are in parentheses.

# 6 Empirical Results

## 6.1 Elasticity of Demand, Cost and Productivity Evolution

The first-stage parameter estimates are reported in Table 4. The estimated elasticity parameters vary substantially across industries and markets. The point estimate of the domestic market elasticity varies between -2.5 and -7.4 across industries. The estimates imply domestic mark-ups ranging from a high of 68 percent in the spinning and weaving industry to 16 and 32 percent in the wood furniture and saw mill industries. Foreign market demand is estimated to be more elastic in the spinning and weaving industry with estimated export elasticity parameters of -9.1. In contrast, the estimated elasticity parameters in the wood furniture and saw mill industries are both near -2.5 which is less elastic than that charged on the domestic market in either case. Export mark-ups range from 12 percent in the spinning and weaving industry to 67 percent in the saw mill industry.

The coefficient on the log of capital stock is negative in all three industries and implies that firms with larger capital stocks generally have lower marginal costs. The parameter $\alpha_1$ captures the effect of lagged productivity on current productivity and implies a strong linear relationship between the two variables.[34] The coefficients $\alpha_2$ and $\alpha_3$ measure the impact of past EAT investment and export experience on future productivity. In all industries $\alpha_2$ is estimated to be insignificantly different from zero, implying that firms which in invest in EAT witness almost identical productivity evolution to those that do not. In contrast, there appear to be small, but positive and significant learning-by-exporting effects in the saw mill industry. The estimated parameter implies that manufacturing firms in the saw mill industry can expect productivity to improve by an extra 4.0 percent, in years subsequent to exporting. The estimated effect is similar in the spinning and weaving industry although its standard error implies that it is not significantly different from zero. The parameter $\alpha_4$ captures the interaction between export experience and investment in EAT and is also insignificantly different from zero in all industries.

## 6.2 Dynamic Estimates

The remaining parameters are estimated using the likelihood function. Table 5 reports the means and standard deviations of the posterior distributions for all parameters in all three industries. The first set of estimates apply to the dynamic process on export demand and indicate that EAT investment has a strong influence on future export demand growth in the Indonesian saw mill, wood furniture, and spinning and weaving industries. However, the size of the estimate varies substantially across industries. In the saw mills industry, the parameter $\gamma_2$ implies that firms which invest in EAT investment are more likely to expect export demand to grow 28.3 percent faster than similar firms who do not while in the wood furniture industry firms which invest in EAT investment highly expect that export demand will grow 0.6 percent faster. This difference is somewhat puzzling since the firms in both industries produce different types of wood products. Some intuition for this result may be found by examining the production process of the wood industry relative to the saw mill industry. Most importantly, the first operation in the saw mill industry, the handling and transportation of logs, had gained more international scrutiny due to complaints about deforestation during the period we study. Thus, processes such as finishing and gluing in the wood furniture industry may be a cause environmental concern, our estimates would suggest that *foreign* consumers find these to be secondary to the effect of abatement in the sawmill industry where deforestation caused by logging appears to play a larger role in both domestic and international environmental debates.

The impact of abatement on exporting in the spinning and weaving industry is the largest across industries; firms which invest in abatement are more likely to observe an export demand growth of over 57 percent than those that do not invest in abatement. This result is important since the textiles produced may potentially have an environmental impact in the *destination* country, whereas the environmental restrictions on the exports from the saw mills industry and

[34] We experimented with various non-linear relationships, but the additional parameters were always estimated to be very small and insignificantly different from zero.

Table 5: Dynamic Parameter Estimates

| | Saw Mills | | Wood Furniture | | Spin. & Weaving | |
|---|---|---|---|---|---|---|
| $\gamma_0$(Export Shock Intercept) | -0.103 | (0.023) | 0.429 | (0.019) | -0.015 | (0.005) |
| $\gamma_1$(Export Shock AR process) | 0.894 | (0.013) | 0.947 | (0.004) | 0.907 | (0.010) |
| $\gamma_2$(EAT effect on Export Shock) | 0.283 | (0.029) | 0.006 | (0.003) | 0.577 | (0.024) |
| $\gamma^A$(EAT FC) | 27.107 | (0.569) | 2.309 | (0.406) | 0.051 | (0.046) |
| $\gamma^D$(EAT SC) | 93.895 | (1.946) | 53.066 | (4.605) | 182.931 | (1.524) |
| $\gamma^F$(Export FC) | 21.408 | (1.198) | 1.622 | (0.315) | 178.547 | (0.288) |
| $\gamma^S$(Export SC) | 155.564 | (1.760) | 54.297 | (2.569) | 404.783 | (2.410) |
| $\Phi_X$ (Export Rev Intercept) | 10.128 | (0.113) | 8.740 | (0.297) | -67.326 | (0.076) |
| $\sigma_\mu$(Export Shock Std Dev) | 0.767 | (0.042) | 0.604 | (0.006) | 0.253 | (0.013) |

Notes: Standard deviations are in parentheses.

wood products industry apply more directly to deforestation or to the production process in Indonesia (the *source* country).[35] This may reflect the superior ability of destination countries to place environmental restrictions on imported products rather than production processes in exporting countries. For instance, the World Trade Organization requires that imported goods are treated at least as favorably as *like* domestic products where the notion of likeness is easier to establish for the final good, making the environmental impact of similar products more visible.

This evidence is in stark contrast to the finding in the previous section which indicated that EAT investment had little if any effect on productivity and, thus, domestic revenues. Finally, the parameter $\gamma_1$ is the autocorrelation parameter in the export demand process and indicates that export demand tends to be a highly persistent process across industries and that decisions to abate may have a long-lived impact on export sales.

The reported values of the fixed and sunk cost parameters, $\gamma^A$, $\gamma^D$, $\gamma^F$ and $\gamma^S$, capture the mean of the exponential distributions for EAT fixed costs, EAT sunk costs, export fixed costs and export sunk costs, respectively.[36] In each case, the sunk costs parameters are estimated to be much larger than the fixed cost parameters, though the difference is greatest for exporting. This implies that for each activity the sunk cost distribution will have more mass concentrated in the high cost values. Thus, for the same marginal benefit, a firm will be more likely to continue exporting or investing EAT than to begin exporting or investing in EAT. The sunk cost parameters are larger for exporting which implies that there is a greater start-up maintenance costs associated with this activity. If all else were equal, we would expect firms that have previously invested in entering export markets to be particularly persistent in this activity. However, the fixed cost for EAT investment is higher than the fixed cost for exporting in the saw mill and wood furniture industries, which implies that the year-to-year payments for continuing to abate are more likely to be greater than those for exporting in those industries.

[35] Following our intuition of industry characterization, we are currently studying the effects of abatement on export performance among Indonesian plastic producers. Our preliminary results find an effect of abatement on the evolution of export demand similar in magnitude to that in the spinning and weaving industry.

[36] They are measured in millions of 1983 Indonesian rupiahs. Note that the Penn World Tables report that in 1983 1 US dollar was worth approximately 909 Indonesian Rupiahs.

The largest sunk cost estimates for abating are observed in the spinning and weaving industry while the saw mill industry exhibits larger per-period abatement fixed costs than either the wood furniture or spinning and weaving industries. The production process in the spinning and weaving industry suggests that majority of EAT expenditures may be used to purchase new environmentally friendly spinning machines that perhaps occur only upon entry into the activity rather than on a per-period basis. The saw mill industry on the other hand, has to continuously address the problem of deforestation either by replanting trees or paying to prevent illegal logging each period. Thus, EAT costs tend to be more fixed in nature compared to abatement costs in the wood furniture and spinning and weaving industries. This ranking of fixed costs across industries is different for exporting, however, as Table 5 shows that the fixed costs of exporting are likely to be largest in the spinning and weaving industry as opposed to the saw mill industry, suggesting for example higher per-period distribution margins or product modification costs than in the wood furniture or saw mill industry. The sunk costs of entering the export market are biggest in the spinning and weaving industry as well possibly reflecting larger one-time product verifications costs required to show that dyes used in the textiles do not contain hazardous chemicals that could be potentially harmful to living organisms in the export market.

## 6.3 Model Performance

We simulate the model in order to assess its predictive ability relative to the observed empirical patterns. Specifically, we compute patterns of EAT and export choice, transition patterns between choices and productivity trajectories to compare the simulated patterns with those observed in the data.

Table 6: Predicted EAT and Export Rates and Productivity in 1996

| | EAT Rate | | | Export Rate | | |
|---|---|---|---|---|---|---|
| | Saw Mills | Wood Furn | Spin & Weave | Saw Mill | Wood Furn | Spin & Weave |
| Actual Data | 0.203 | 0.111 | 0.250 | 0.329 | 0.263 | 0.114 |
| Predicted | 0.211 | 0.135 | 0.121 | 0.336 | 0.259 | 0.034 |

Table 7: Predicted EAT and Export Rates and Productivity in 1996

| | Productivity | | |
|---|---|---|---|
| | Saw Mills | Wood Furn | Spin & Weave |
| Actual Data | 3.175 | 0.876 | 6.954 |
| Predicted | 2.976 | 0.851 | 6.946 |

To accomplish this task we take the initial year status $(\omega_{i0}, z_{i0}, d_{i0}, e_{i0}, k_i)$ of all firms in our data as given and simulate the next 3 sample year's export demand shocks $z_{it}$, EAT costs $\gamma^A$,

$\gamma^I$ and export costs $\gamma^F$, $\gamma^S$. Solving the firm's dynamic problem we compute the optimal export and EAT decisions year-by-year. For each firm, we repeat the simulation exercise 100 times and report the average of these simulations.

Table 6 reports the mean EAT investment rate and export market participation rate in the data and in the model for each industry, while Table 7 captures the average productivity in each industry. The model matches the empirical predictions very closely in both the saw mill industry and the wood furniture industry, but underpredicts the export and EAT rate in the spinning and weaving industry. Table 8 reports the actual and predicted transition rates for the saw mill industry.[37] The model is successful in matching the broad patterns in the empirical transition matrix, though it does somewhat underpredict the persistence in export status and EAT status, while slightly overpredicting the persistence of engaging in both activities simultaneously.

Table 8: Predicted Transition Rates: Saw Mills

Saw Mills

| Status in $t$ | | Status in $t+1$ | | | |
|---|---|---|---|---|---|
| | | Neither | only Exp. | only EAT. | Both |
| Neither | Actual | 0.857 | 0.069 | 0.063 | 0.012 |
| | Predicted | 0.828 | 0.070 | 0.084 | 0.018 |
| only Exp. | Actual | 0.112 | 0.729 | 0.000 | 0.155 |
| | Predicted | 0.253 | 0.531 | 0.029 | 0.186 |
| only EAT | Actual | 0.344 | 0.156 | 0.547 | 0.094 |
| | Predicted | 0.560 | 0.050 | 0.326 | 0.064 |
| Both | Actual | 0.059 | 0.314 | 0.098 | 0.529 |
| | Predicted | 0.086 | 0.264 | 0.051 | 0.599 |

## 6.4 Determinants of EAT Investment and Exporting

In this section we isolate the roles export and EAT investment history play across the distribution of firms on the subsequent export or EAT decisions. Table 9 reports the marginal benefit to exporting for a firm with different EAT status (columns) across productivity levels (rows). The second and third columns present the value of exporting $V_t^E(\omega_t, d_{t-1})$, while the fourth and fifth document the value of only producing for the domestic market $V_t^D(\omega_t, d_{t-1})$. In each case, we find that firm value is increasing in productivity and past EAT status. However, it is notable that the marginal benefit to exporting differs little across EAT status.

Similarly, we decompose expected firm value across export status and productivity in Table 10 in order to capture the marginal benefit of investing in EAT implied by the estimates. Again, the value of the firm is increasing in productivity and export status. However, in contrast, to the results in Table 9, the marginal benefit to EAT is not always increasing or even positive.

[37] Similar tables for the wood furniture industry and spinning and weaving industry are presented in an extended appendix that is available on request or at the following webpage: http://www.people.vanderbilt.edu/∼omolola.y.soumonni/index.html.

Table 9: Marginal Benefit of Exporting (Millions of Rupiahs)

Saw Mills

| | $V_t^E$ | | $V_t^D$ | | $MBE = \pi_t^X + V_t^E - V_t^D$ | |
|---|---|---|---|---|---|---|
| $\omega_t$ | $d_{t-1} = 1$ | $d_{t-1} = 0$ | $d_{t-1} = 1$ | $d_{t-1} = 0$ | $d_{t-1} = 1$ | $d_{t-1} = 0$ |
| 2.78 | 911.1 | 908.5 | 890.3 | 889.1 | 28.7 | 27.3 |
| 3.16 | 951.5 | 947.9 | 921.8 | 920.6 | 43.7 | 41.4 |
| 3.55 | 1040.8 | 1034.8 | 991.2 | 989.6 | 74.5 | 70.0 |
| 3.93 | 1235.2 | 1224.9 | 1143.9 | 1141.7 | 135.2 | 127.2 |
| 4.31 | 1651.8 | 1636.7 | 1482.4 | 1481.4 | 247.1 | 233.0 |
| 4.70 | 2602.3 | 2578.0 | 2253.6 | 2253.6 | 486.1 | 461.8 |
| 5.08 | 4742.3 | 4705.9 | 4020.0 | 4020.0 | 965.2 | 928.8 |
| 5.46 | 9236.7 | 9194.4 | 7831.3 | 7831.3 | 1834.7 | 1792.5 |
| 5.84 | 17196.0 | 17157.0 | 14940.0 | 14918.0 | 3014.9 | 2997.2 |
| 6.23 | 28037.0 | 27997.0 | 25272.0 | 25246.0 | 4106.1 | 4093.1 |

Among exporting firms, Table 10 implies that marginal benefit to EAT investment is positive and increasing in productivity for exporting firms, while the marginal benefit to EAT investment is small and sometimes negative among non-exporting firms. The primary source of this difference is the fact that non-exporting firms do not reap any immediate benefit from investing in EAT, but are required to incur start-up costs associated with this activity. Moreover, our first-stage point estimates implied that EAT investment had small, but negative effects on productivity growth. While EAT investment has the potential to improve the firm's future export demand, this benefit is mitigated by start-up sunk costs associated with EAT investment and slower productivity growth. In sum, Table 10 indicates that among firms who are likely to export in the future, it is often optimal to wait until entering the export market before investing in EAT.

Table 10: Marginal Benefit of EAT Investment (Millions of Rupiahs)

Saw Mills

| | $EV_{t+1}(d_t = 1, e_t)$ | | $EV_{t+1}(d_t = 0, e_t)$ | | $MBEAT$ | |
|---|---|---|---|---|---|---|
| $\omega_t$ | $e_t = 1$ | $e_t = 0$ | $e_t = 1$ | $e_t = 0$ | $e_t = 1$ | $e_t = 0$ |
| 2.78 | 969.1 | 944.2 | 955.2 | 935.8 | 14.0 | 8.4 |
| 3.16 | 1013.2 | 977.0 | 996.3 | 969.3 | 16.9 | 7.7 |
| 3.55 | 1109.5 | 1049.9 | 1086.1 | 1043.5 | 23.4 | 6.4 |
| 3.93 | 1315.9 | 1210.7 | 1281.5 | 1209.0 | 34.3 | 1.8 |
| 4.31 | 1759.6 | 1563.5 | 1709.3 | 1579.4 | 50.3 | -15.9 |
| 4.70 | 2762.8 | 2372.2 | 2686.9 | 2442.2 | 76.0 | -70.0 |
| 5.08 | 5017.7 | 4231.6 | 4894.4 | 4428.8 | 123.3 | -197.2 |
| 5.46 | 9742.8 | 8243.5 | 9508.8 | 8664.8 | 234.0 | -421.3 |
| 5.84 | 18118.0 | 15737.0 | 17618.0 | 16334.0 | 499.4 | -596.9 |
| 6.23 | 29529.0 | 26614.0 | 28611.0 | 27070.0 | 918.9 | -456.4 |

Table 11 reports the average abatement and exporting fixed/sunk costs for each combination of past export and environmental abatement status across different values of $\omega$. Note that these values correspond to actual costs *incurred* by firms with different export and abatement histories. Given a productivity level of say 4.31, the fixed cost of exporting and abating for firms that have previous exporting and abatement experience is 21.2 and 15.5 million Indonesian Rupiahs respectively. Similarly, for the same productivity level and no past experience in either activity, the sunk cost of exporting and abating is 77.7 and 69.0 million, respectively. As in Table 5, the sunk cost of entry is always larger than the fixed cost of both exporting and environmental abatement. Also, the mean fixed and sunk cost of both activities increases with the productivity level of the firm but more so for exporting than abating. This may be as a result of the higher marginal benefit accrued from exporting relative to abatement given firm-level productivity. Thus, firms facing higher cost levels will find it profitable to export and/or to abate when their productivity is high but not if they have low productivity. On the other hand, more productive firms may find it worthwhile to incur larger fixed or sunk cost expenses in order to abate or to export than less productive firms.

Table 11: Fixed and Sunk Export and Abatement Costs (Incurred)

Saw Mills

| | Export Fixed and Sunk Costs | | | | Abatement Fixed and Sunk Costs | | | |
|---|---|---|---|---|---|---|---|---|
| | $d_{t-1}=1$ | $d_{t-1}=0$ | $d_{t-1}=1$ | $d_{t-1}=0$ | $d_{t-1}=1$ | $d_{t-1}=0$ | $d_{t-1}=1$ | $d_{t-1}=0$ |
| $\omega_t$ | $e_{t-1}=1$ | $e_{t-1}=1$ | $e_{t-1}=0$ | $e_{t-1}=0$ | $e_{t-1}=1$ | $e_{t-1}=1$ | $e_{t-1}=0$ | $e_{t-1}=0$ |
| 2.78 | 8.4 | 13.3 | 8.1 | 12.7 | 8.6 | 15.9 | 6.6 | 13.5 |
| 3.16 | 10.9 | 19.6 | 10.5 | 18.6 | 9.8 | 17.4 | 7.5 | 16.9 |
| 3.55 | 15.0 | 31.3 | 14.5 | 29.6 | 11.7 | 20.2 | 12.2 | 33.5 |
| 3.93 | 19.3 | 51.5 | 19.0 | 49.0 | 15.0 | 27.9 | 17.6 | 51.6 |
| 4.31 | 21.2 | 81.1 | 21.2 | 77.7 | 15.5 | 21.2 | 21.2 | 69.0 |
| 4.70 | 21.4 | 121.2 | 21.4 | 117.7 | 19.3 | 30.3 | 27.1 | 93.9 |
| 5.08 | 21.4 | 149.1 | 21.4 | 147.7 | 22.9 | 43.8 | 27.1 | 93.9 |
| 5.46 | 21.4 | 155.0 | 21.4 | 154.8 | 27.0 | 83.1 | 27.1 | 93.9 |
| 5.84 | 21.4 | 155.5 | 21.4 | 155.5 | 27.1 | 91.1 | 26.6 | 83.9 |
| 6.23 | 21.4 | 155.6 | 21.4 | 155.6 | 27.1 | 91.5 | 27.1 | 92.3 |

# 7 Policy Experiments

In this section we consider three distinct policy experiments. The policy experiments are done in the same manner as the model simulation except that in each case we have changed one parameter of the model in order to determine how the firm-level decisions would change over time. In the first experiment, we consider the effect of trade liberalization, while in the second we examine the effects of increased screening and tighter environmental restrictions imposed by countries which import Indonesian products. In the last experiment, we study the effect of greater maintenance costs associated with EAT investment. In each experiment, we simulate the industry for a 10 year period following the change in policy.[38] Last, we assume throughout that Indonesia is a small country relative to the rest of the world and that any general equilibrium effects from changes in trade policy towards Indonesia generate small feedback effects. We

[38]It is important to recall that we are only looking at the reaction from domestic producers and our results do not capture the effect of policy change on multinational location decisions.

Table 12: Predicted Probability of Exporting in $t+1$ by Productivity

Baseline Estimates

| | $d_t = 1$ | $d_t = 0$ | $d_t = 1$ | $d_t = 0$ |
|---|---|---|---|---|
| $\omega_t$ | $e_t = 1$ | $e_t = 1$ | $e_t = 0$ | $e_t = 0$ |
| 2.78 | 0.673 | 0.642 | 0.212 | 0.192 |
| 3.16 | 0.720 | 0.692 | 0.244 | 0.225 |
| 3.55 | 0.785 | 0.761 | 0.302 | 0.282 |
| 3.93 | 0.860 | 0.842 | 0.394 | 0.375 |
| 4.31 | 0.925 | 0.913 | 0.518 | 0.501 |
| 4.70 | 0.968 | 0.962 | 0.661 | 0.647 |
| 5.08 | 0.989 | 0.987 | 0.796 | 0.787 |
| 5.46 | 0.997 | 0.997 | 0.898 | 0.893 |
| 5.84 | 1.000 | 0.999 | 0.958 | 0.955 |
| 6.23 | 1.000 | 1.000 | 0.985 | 0.984 |

After Trade Liberalization

| | $d_t = 1$ | $d_t = 0$ | $d_t = 1$ | $d_t = 0$ |
|---|---|---|---|---|
| $\omega_t$ | $e_t = 1$ | $e_t = 1$ | $e_t = 0$ | $e_t = 0$ |
| 2.78 | 0.701 | 0.666 | 0.241 | 0.216 |
| 3.16 | 0.745 | 0.713 | 0.273 | 0.248 |
| 3.55 | 0.804 | 0.778 | 0.329 | 0.304 |
| 3.93 | 0.872 | 0.852 | 0.419 | 0.394 |
| 4.31 | 0.931 | 0.918 | 0.538 | 0.516 |
| 4.70 | 0.970 | 0.963 | 0.675 | 0.657 |
| 5.08 | 0.990 | 0.988 | 0.804 | 0.793 |
| 5.46 | 0.998 | 0.997 | 0.902 | 0.895 |
| 5.84 | 1.000 | 0.999 | 0.959 | 0.956 |
| 6.23 | 1.000 | 1.000 | 0.986 | 0.985 |

present detailed results for the saw mills industry in the main text along with summary results for all industries.[39]

## 7.1 Trade Liberalization

The first experiment we examine is a 10 percent increase in the size of the foreign market which may be interpreted as a reduction in variable trade costs.[40] The change in trade policy has positive, but relatively small initial effects on the probability of exporting. As documented in Table 12, the largest increases are found among firms with little experience exporting and mid-range productivity. The reason for this is two-fold. First, the export market is already very large in this industry. Among exporters, 80 percent of total revenues are from export sales in the data. As such, firms already have an extremely strong incentive to try and enter export markets. Second, export entry costs are very large which encourages the persistence in export status among those who have previously exported, with or without the change in policy.

Figure 1 captures the change in the percentage of exporters or abaters over time following the policy change. Note that the change is measured relative to baseline simulation using the estimated parameters. The left panel of Figure 1 suggests that these small changes do have an effect over time. While the increase in the export participation rate is less than 10 percent over the first three years after the change in policy, by the tenth year aggregate export participation has increased by over 20 percent.

In the wood furniture and spinning and weaving industries we observe that liberalization similarly induces a large increase in exporting shortly after liberalization. The response is particularly large in the spinning and weaving industry where the export participation rate doubles, though it is important to that the large percentage increase in export participation

[39]We document further results for the wood furniture and spinning and weaving industries in an extended appendix available upon request or at the following webpage: http://www.people.vanderbilt.edu/∼omolola.y.soumonni/index.html.

[40]We assume that embedded in the effective size of the foreign market is an iceberg transport cost as in the Melitz (2003) setting. As such, reducing variable trade costs is equivalent to increasing the size of the foreign market, $\Phi_X$.

Table 13: Predicted Probability of Investing in EAT in $t+1$ by Productivity

Baseline Estimates

| $\omega_t$ | $d_t=1$ $e_t=1$ | $d_t=0$ $e_t=1$ | $d_t=1$ $e_t=0$ | $d_t=0$ $e_t=0$ |
|---|---|---|---|---|
| 2.78 | 0.395 | 0.144 | 0.297 | 0.103 |
| 3.16 | 0.428 | 0.162 | 0.311 | 0.111 |
| 3.55 | 0.483 | 0.193 | 0.338 | 0.129 |
| 3.93 | 0.562 | 0.242 | 0.388 | 0.163 |
| 4.31 | 0.656 | 0.311 | 0.468 | 0.222 |
| 4.70 | 0.750 | 0.399 | 0.578 | 0.313 |
| 5.08 | 0.820 | 0.494 | 0.696 | 0.426 |
| 5.46 | 0.842 | 0.571 | 0.776 | 0.529 |
| 5.84 | 0.816 | 0.615 | 0.795 | 0.594 |
| 6.23 | 0.766 | 0.626 | 0.767 | 0.619 |

After Trade Liberalization

| $\omega_t$ | $d_t=1$ $e_t=1$ | $d_t=0$ $e_t=1$ | $d_t=1$ $e_t=0$ | $d_t=0$ $e_t=0$ |
|---|---|---|---|---|
| 2.78 | 0.495 | 0.197 | 0.409 | 0.154 |
| 3.16 | 0.524 | 0.215 | 0.420 | 0.163 |
| 3.55 | 0.572 | 0.247 | 0.441 | 0.181 |
| 3.93 | 0.640 | 0.298 | 0.479 | 0.215 |
| 4.31 | 0.721 | 0.367 | 0.544 | 0.274 |
| 4.70 | 0.801 | 0.455 | 0.636 | 0.365 |
| 5.08 | 0.859 | 0.547 | 0.738 | 0.476 |
| 5.46 | 0.873 | 0.618 | 0.809 | 0.574 |
| 5.84 | 0.841 | 0.651 | 0.821 | 0.631 |
| 6.23 | 0.784 | 0.651 | 0.786 | 0.645 |

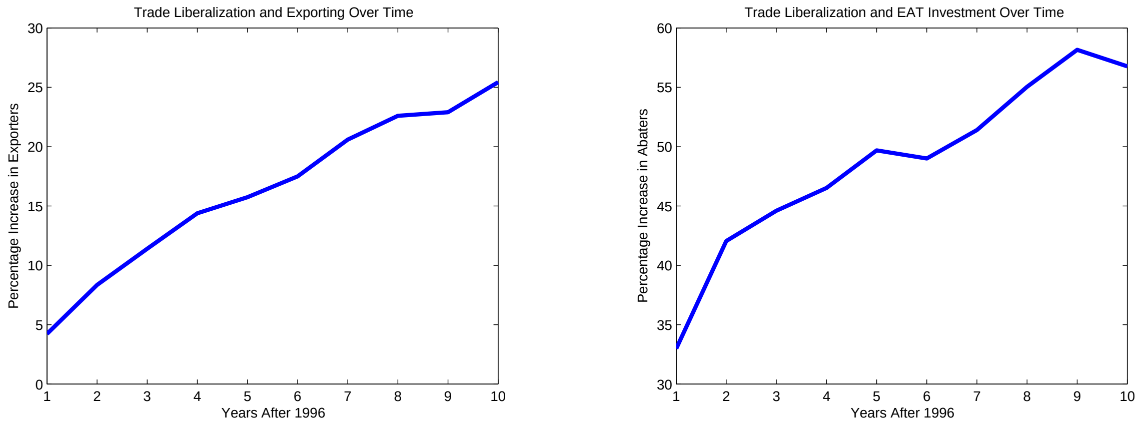
partially reflects a small initial participation rate. Overall, the absolute export participation rate only has increased from 4.2 to 9.4 percent in this industry.

Over time we observe that the percentage increase of firms exporting falls in the wood furniture and spinning and weaving industries. This does not reflect fewer firms exporting over time; the export participation rate increases monotonically in both the baseline case and after trade liberalization. Rather, our model predicts that export demand is growing for all firms in both the wood furniture and spinning and weaving industries before we changed the size of the export market. This implies that more and more firms were already optimally choosing to export over time. The change in policy encouraged many of those firms to enter export markets earlier than they would have otherwise. However, as time passes and the export market grows at the rate estimated in the dynamic estimation, there are fewer potential new exporters in each year. The intuition is that many of the firms that would have been most likely to enter export markets in any given year are already exporting under the policy change. In this sense, the baseline model partially *catches up* to the model with trade liberalization.[41] We emphasize that given these differences over time, it is crucial that policymakers are able to distinguish between immediate and longer-run effects established here.

Similar results are found for environmental investment. Since the incentive to export has increased, the incentive to invest in EAT does as well. As documented in Table 13 the largest increases are again found among firms without EAT experience and of mid-range productivity. The right panel of Figure 1 shows that over time the aggregate effect is larger, we see a 30 percent jump in EAT investment after the change in trade policy and an overall increase by 56.8 percent after 10 years. Table 14 highlights the percentage increase in exporting and abatement over time across industries. The proportion of firms that choose to export and abate in the saw mill industry continues to increase over time, while in the other industries there is a similar "catch up

[41] Note that these types of effects will be found consistently across policy experiments. While we could remove these effects from the policy experiments by setting many of the dynamic coefficients to 0 (e.g. export market growth, mean productivity growth, etc) this would reduce the relevance of experiments to the Indonesian manufacturing environment.

Figure 1: The Effect of Trade Liberalization on Export and EAT Investment Probabilities




effect" in abatement rates due to the complementarity between exporting and abatement across industries. After ten years, however, our model implies a substantial increase in abatement activity; abatement rates are predicted to rise by 22 to 57 percent across industries.

Table 14: Percentage Increase In Exporting and Abatement Over Time

| | Exporting | | | Abatement | | |
|---|---|---|---|---|---|---|
| Year | 2 | 5 | 10 | 2 | 5 | 10 |
| Saw Mills | 11.4 | 15.8 | 25.1 | 42.2 | 50.0 | 56.8 |
| Wood Furniture | 17.8 | 28.4 | 22.2 | 48.2 | 69.2 | 47.5 |
| Spinning and Weaving | 123.8 | 91.1 | 57.7 | 26.1 | 30.5 | 22.0 |

## 7.2 Increased Environmental Restrictions

The second policy experiment examines the effect of increasing environmental restrictions in destination markets. Specifically, we constrain export markets in such a fashion that firms which have not previously invested in EAT are completely cut off from export markets. It is important to note that we explicitly assume that the cost of EAT adoption to Indonesian producers does not change. The change in policy has a remarkably large impact on the probability of EAT investment across heterogeneous firms. Table 16 documents that the absolute increases in the probability of EAT adoption are large across the entire distribution of productivity and all export and EAT investment histories. This is entirely due to the fact that firms that do not adopt EAT technology are completely cut off from large, foreign markets which are very lucrative once firms have entered them. It is important to note that this is the only reason to adopt EAT technology here. Our static estimates imply little or no effect of EAT investment on productivity growth so there is much less benefit to firms who are unlikely to export. However, because the export market is large for these producers where even low productivity firms are more likely to consider

Table 15: Predicted Probability of Exporting in $t+1$ by Productivity

Baseline Estimates

| $\omega_t$ | $d_t=1$, $e_t=1$ | $d_t=0$, $e_t=1$ | $d_t=1$, $e_t=0$ | $d_t=0$, $e_t=0$ |
|---|---|---|---|---|
| 2.78 | 0.673 | 0.642 | 0.212 | 0.192 |
| 3.16 | 0.720 | 0.692 | 0.244 | 0.225 |
| 3.55 | 0.785 | 0.761 | 0.302 | 0.282 |
| 3.93 | 0.860 | 0.842 | 0.394 | 0.375 |
| 4.31 | 0.925 | 0.913 | 0.518 | 0.501 |
| 4.70 | 0.968 | 0.962 | 0.661 | 0.647 |
| 5.08 | 0.989 | 0.987 | 0.796 | 0.787 |
| 5.46 | 0.997 | 0.997 | 0.898 | 0.893 |
| 5.84 | 1.000 | 0.999 | 0.958 | 0.955 |
| 6.23 | 1.000 | 1.000 | 0.985 | 0.984 |

After Environmental Restrictions

| $\omega_t$ | $d_t=1$, $e_t=1$ | $d_t=0$, $e_t=1$ | $d_t=1$, $e_t=0$ | $d_t=0$, $e_t=0$ |
|---|---|---|---|---|
| 2.78 | 0.617 | 0 | 0.207 | 0 |
| 3.16 | 0.671 | 0 | 0.242 | 0 |
| 3.55 | 0.747 | 0 | 0.303 | 0 |
| 3.93 | 0.834 | 0 | 0.401 | 0 |
| 4.31 | 0.911 | 0 | 0.532 | 0 |
| 4.70 | 0.962 | 0 | 0.677 | 0 |
| 5.08 | 0.988 | 0 | 0.810 | 0 |
| 5.46 | 0.997 | 0 | 0.907 | 0 |
| 5.84 | 0.999 | 0 | 0.962 | 0 |
| 6.23 | 1.000 | 0 | 0.987 | 0 |

EAT adoption on the chance that they get a large enough export demand shock and it becomes profitable to enter export markets. Remarkably, Figure 2 displays that over the ten year period of simulation, the adoption of EAT technology almost doubles under the change in policy. This is a 10 year increase of about 90 percent over our baseline estimates.

Table 16: Predicted Probability of Investing in EAT in $t+1$ by Productivity

Baseline Estimates

| $\omega_t$ | $d_t=1$, $e_t=1$ | $d_t=0$, $e_t=1$ | $d_t=1$, $e_t=0$ | $d_t=0$, $e_t=0$ |
|---|---|---|---|---|
| 2.78 | 0.395 | 0.144 | 0.297 | 0.103 |
| 3.16 | 0.428 | 0.162 | 0.311 | 0.111 |
| 3.55 | 0.483 | 0.193 | 0.338 | 0.129 |
| 3.93 | 0.562 | 0.242 | 0.388 | 0.163 |
| 4.31 | 0.656 | 0.311 | 0.468 | 0.222 |
| 4.70 | 0.750 | 0.399 | 0.578 | 0.313 |
| 5.08 | 0.820 | 0.494 | 0.696 | 0.426 |
| 5.46 | 0.842 | 0.571 | 0.776 | 0.529 |
| 5.84 | 0.816 | 0.615 | 0.795 | 0.594 |
| 6.23 | 0.766 | 0.626 | 0.767 | 0.619 |

After Environmental Restrictions

| $\omega_t$ | $d_t=1$, $e_t=1$ | $d_t=0$, $e_t=1$ | $d_t=1$, $e_t=0$ | $d_t=0$, $e_t=0$ |
|---|---|---|---|---|
| 2.78 | 0.636 | 0.223 | 0.530 | 0.221 |
| 3.16 | 0.683 | 0.245 | 0.563 | 0.242 |
| 3.55 | 0.751 | 0.287 | 0.618 | 0.280 |
| 3.93 | 0.832 | 0.353 | 0.697 | 0.344 |
| 4.31 | 0.907 | 0.445 | 0.790 | 0.433 |
| 4.70 | 0.959 | 0.556 | 0.876 | 0.542 |
| 5.08 | 0.987 | 0.662 | 0.940 | 0.651 |
| 5.46 | 0.997 | 0.732 | 0.977 | 0.727 |
| 5.84 | 0.999 | 0.750 | 0.993 | 0.751 |
| 6.23 | 1.000 | 0.731 | 0.998 | 0.734 |

The additional environmental cost reduces the return from exporting as EAT costs are now effectively additional entry costs to export markets. Figure 2 shows that the simulated economy predicts an initial fall in exporting by over 70 percent in the saw mills industry as many exporters without EAT are forced out of the export market (since most exporters in the initial year do not abate). However, as firms invest in EAT technology over time the export rate under the new policy rises very rapidly as new environmentally sound exporters enter the export market. Our experiment suggests that in the saw mills industry the export participation rate has regained 73 percent of its initial fall 10 years after the change in policy. Table 17 finds the effect consistently over each industry. There are two reasons for this effect. First, by encouraging EAT adoption the policy effectively grows the average size of the export market faced by Indonesian producers. Secondly, the sunk abatement and export costs generate persistence in export status.

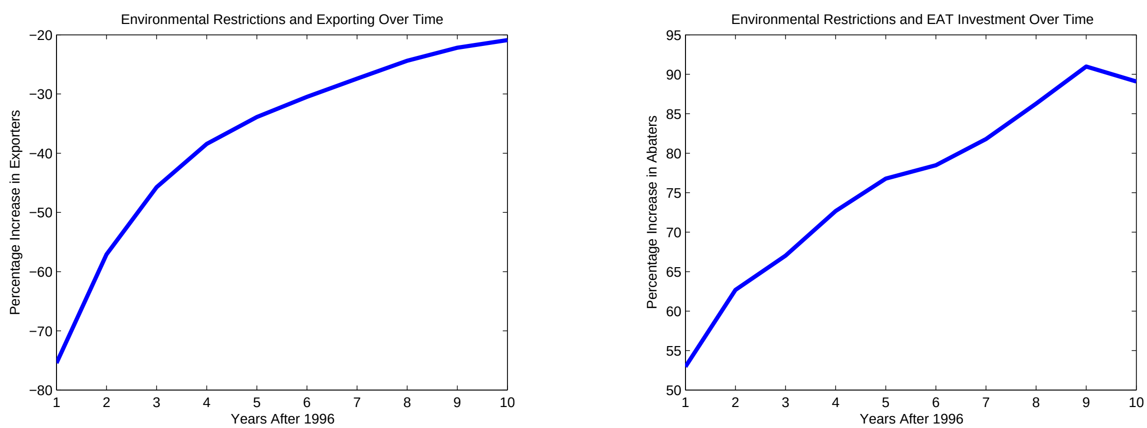
Despite the recovery of exporters, our experiments suggest that export participation is still about 21 percent below the baseline level in the saw mill industry, while it is 22 and 38 percent

Table 17: Percentage Increase In Exporting and Abatement Over Time

| | Exporting | | | Abatement | | |
|---|---|---|---|---|---|---|
| Year | 2 | 5 | 10 | 2 | 5 | 10 |
| Saw Mills | -57.2 | -33.8 | -20.9 | 62.8 | 78.4 | 89.3 |
| Wood Furniture | -79.3 | -56.3 | -21.6 | 141.6 | 184.4 | 111.0 |
| Spinning and Weaving | -57.1 | -37.5 | -23.1 | 10.2 | 9.8 | 4.6 |

below the baseline level in the wood furniture and spinning and weaving industries. While exporters are able to adjust to the policy relatively quickly, our evidence would suggest that the least productive exporters optimally choose to exit foreign export markets altogether. We interpret this results as suggesting that while policies which join export and abatement activity may reduce exporting by a large magnitude after the initial change in policy it is likely that the long-run effects on exports will be substantially smaller.

Figure 2: The Effect of Environmental Restrictions on Export and EAT Investment Probabilities




## 7.3 Increased Costs of EAT Investment

The last experiment we consider is one where we increase the cost of EAT adoption. We think of this experiment as increasing the administrative, verification or certification costs associated with environmental regulations which fall on the Indonesian producer. We will capture this change in policy by increasing the fixed cost associated with EAT investment by 50 percent.

Our simulated results indicate that even a small increase in the fixed cost associated with EAT investment has substantial implications for the rates of exporting and EAT adoption. In particular, the probability of EAT investment falls across heterogeneous firms in Table 19, though this effect is mitigated among high productivity firms who are less sensitive to the change in policy. Examining Figure 3 we observe that the decrease in EAT investment probabilities are relatively large over time as the rate of EAT investment is 36 percent lower after 10 years

Table 18: Predicted Probability of Exporting in $t+1$ by Productivity

Baseline Estimates

| $\omega_t$ | $d_t = 1$ $e_t = 1$ | $d_t = 0$ $e_t = 1$ | $d_t = 1$ $e_t = 0$ | $d_t = 0$ $e_t = 0$ |
|---|---|---|---|---|
| 2.78 | 0.673 | 0.642 | 0.212 | 0.192 |
| 3.16 | 0.720 | 0.692 | 0.244 | 0.225 |
| 3.55 | 0.785 | 0.761 | 0.302 | 0.282 |
| 3.93 | 0.860 | 0.842 | 0.394 | 0.375 |
| 4.31 | 0.925 | 0.913 | 0.518 | 0.501 |
| 4.70 | 0.968 | 0.962 | 0.661 | 0.647 |
| 5.08 | 0.989 | 0.987 | 0.796 | 0.787 |
| 5.46 | 0.997 | 0.997 | 0.898 | 0.893 |
| 5.84 | 1.000 | 0.999 | 0.958 | 0.955 |
| 6.23 | 1.000 | 1.000 | 0.985 | 0.984 |

After Increase in EAT fixed costs

| $\omega_t$ | $d_t = 1$ $e_t = 1$ | $d_t = 0$ $e_t = 1$ | $d_t = 1$ $e_t = 0$ | $d_t = 0$ $e_t = 0$ |
|---|---|---|---|---|
| 2.78 | 0.657 | 0.634 | 0.202 | 0.188 |
| 3.16 | 0.706 | 0.685 | 0.234 | 0.220 |
| 3.55 | 0.773 | 0.755 | 0.291 | 0.278 |
| 3.93 | 0.851 | 0.837 | 0.383 | 0.371 |
| 4.31 | 0.919 | 0.911 | 0.508 | 0.498 |
| 4.70 | 0.965 | 0.960 | 0.652 | 0.645 |
| 5.08 | 0.988 | 0.987 | 0.790 | 0.786 |
| 5.46 | 0.997 | 0.997 | 0.894 | 0.892 |
| 5.84 | 0.999 | 0.999 | 0.956 | 0.955 |
| 6.23 | 1.000 | 1.000 | 0.985 | 0.984 |

relative to our baseline estimates in the saw mills industry. This result is particularly important in light of the previous experiment. Taken together they imply that environmental policies set on exports can have widely different results on EAT investment depending on the size of the costs associated with stricter regulation which are born be producers.

Table 18 demonstrates that exporting also suffers after the change in policy, though the effect is significantly smaller than what we observe in Table 19. This is intuitive since the large majority of export costs are associated with export behavior not EAT adoption. Nonetheless, Figure 3 documents a fall in export participation by almost 10 percent over 10 years.

Table 19: Predicted Probability of Investing in EAT in $t+1$ by Productivity

Baseline Estimates

| $\omega_t$ | $d_t = 1$ $e_t = 1$ | $d_t = 0$ $e_t = 1$ | $d_t = 1$ $e_t = 0$ | $d_t = 0$ $e_t = 0$ |
|---|---|---|---|---|
| 2.78 | 0.395 | 0.144 | 0.297 | 0.103 |
| 3.16 | 0.428 | 0.162 | 0.311 | 0.111 |
| 3.55 | 0.483 | 0.193 | 0.338 | 0.129 |
| 3.93 | 0.562 | 0.242 | 0.388 | 0.163 |
| 4.31 | 0.656 | 0.311 | 0.468 | 0.222 |
| 4.70 | 0.750 | 0.399 | 0.578 | 0.313 |
| 5.08 | 0.820 | 0.494 | 0.696 | 0.426 |
| 5.46 | 0.842 | 0.571 | 0.776 | 0.529 |
| 5.84 | 0.816 | 0.615 | 0.795 | 0.594 |
| 6.23 | 0.766 | 0.626 | 0.767 | 0.619 |

After Increase in EAT fixed costs

| $\omega_t$ | $d_t = 1$ $e_t = 1$ | $d_t = 0$ $e_t = 1$ | $d_t = 1$ $e_t = 0$ | $d_t = 0$ $e_t = 0$ |
|---|---|---|---|---|
| 2.78 | 0.264 | 0.111 | 0.189 | 0.077 |
| 3.16 | 0.293 | 0.126 | 0.202 | 0.084 |
| 3.55 | 0.342 | 0.152 | 0.228 | 0.099 |
| 3.93 | 0.415 | 0.195 | 0.276 | 0.129 |
| 4.31 | 0.509 | 0.257 | 0.354 | 0.182 |
| 4.70 | 0.612 | 0.340 | 0.467 | 0.266 |
| 5.08 | 0.702 | 0.434 | 0.593 | 0.374 |
| 5.46 | 0.752 | 0.516 | 0.691 | 0.478 |
| 5.84 | 0.755 | 0.572 | 0.732 | 0.552 |
| 6.23 | 0.728 | 0.596 | 0.726 | 0.588 |

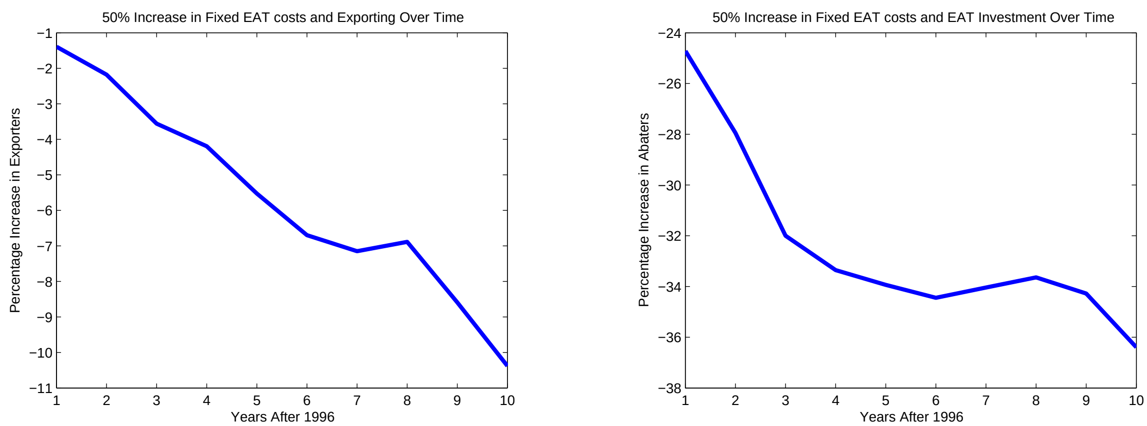
Much of the difference in the two policies can be traced to how the timing of investment is affected by the policy. Because of the increase in the cost of EAT investment, firms are less willing to adopt EAT investment *until* they have entered the export market. Thus, while the previous policy experiment was very effective in encouraging the adoption of EAT by using export markets as a potential reward for these investments, here the policy change encourages firms to wait until they have already begun exporting and are more likely to draw benefits from the improved export demand shocks associated with EAT investment. However, even across exporters, the return to EAT investment has fallen which in turn mitigates low productivity firms from investing in EAT or exporting. These results are consistent in the saw mill and wood

Table 20: Percentage Increase In Exporting and Abatement Over Time

| | Exporting | | | Abatement | | |
|---|---|---|---|---|---|---|
| Year | 2 | 5 | 10 | 2 | 5 | 10 |
| Saw Mills | -2.4 | -5.5 | -10.6 | -27.8 | -33.9 | -36.4 |
| Wood Furniture | -0.4 | -0.9 | -0.6 | -81.8 | -77.2 | -57.8 |
| Spinning and Weaving | 0 | -1.8 | 0 | 0 | 0 | 0 |

furniture industries as shown in Table 20. There seems to be little or no impact of increasing the fixed cost of abating on exporting or abatement in the spinning and weaving industry. This is not surprising considering our extremely small dynamic fixed EAT cost estimate and, as such, the very small change in the absolute cost charged to producers.[42]

Figure 3: The Effect of Increased EAT Fixed Costs on Export and EAT Investment Probabilities




# 8 Concluding Remarks

This paper presents and estimates a dynamic model of investment in environmental abating technology (EAT) and exports with heterogeneous firms. The model is estimated using a panel of Indonesian manufacturing firms. Counterfactual policy experiments are employed to assess the impact of changing environmental or trade policy on firm-level decision and aggregate outcomes.

Our model is able to broadly match the features of Indonesian manufacturing data. The model captures export decisions at the firm-level and documents the differential export behavior across firms which have invested in EAT and those that have not. The model emphasizes that accounting for the interaction between firm-level abatement and export decisions is essential to recovering accurate estimates of the impact of changes in trade or environmental policy on either outcome. The empirical estimates of the model's parameters suggest firm-level envi-

[42]Larger absolute increases in fixed abatement costs produces similar qualitative results to the other industries.

ronmental investment may increase export demand by as much as 58 percent across industries. The complementarity between exporting and abatement is estimated to be largest in industries where the manufactured products have important environmental consequences in destination markets.

The counterfactual experiments imply that environmental restrictions that act as trade barriers can have a variety of effects on environmental investment. The experiments suggest that the effect of more restrictive environmental policy hinges critically on the additional costs borne by the producers after the change in policy. Increased environmental restrictions that do not change the cost of adopting EAT will increase adoption rates dramatically. Relative to our baseline model, we find that by requiring all exporting firms adopt abatement technology, total abatement rates will increase by as much as 111 percent after 10 years. In contrast, policies which increase the fixed cost of abatement by 50 percent cause abatement rates to fall by as much as 58 percent after 10 years. Our experiments suggest that these policies will cause exports to fall.

Trade liberalization, in contrast, generally seems to have positive effects on environmental investment. Since export demand shocks are modeled as proportional to market size, increasing the size of the export market increases the return to EAT investment increases even more causing a significant increase in EAT investment. Across industries we find that abatement rates increase by 22 to 57 percent in response to the change in policy.

These results lend support for the "Porter hypothesis" in international markets and add a new dimension to the debate regarding trade liberalization and transboundary pollution. In particular, the results suggest that domestic exporters in a developing country will respond to reductions in trade barriers by adopting environmental abating technology in order to access foreign markets.

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# Appendix

# A Computation of the Firm's Dynamic Problem

We need to solve each firm's dynamic optimization problem in order to compute the conditional choice probabilities for exporting , $P(e_{it}|z_{it}, k_{it}, \omega_{it}, \Phi_X, e_{it-1}, d_{it-1})$, and investing in EAT, $P(d_{it}|z_{it}, k_{it}, \omega_{it}, \Phi_X, e_{it-1}, d_{it-1})$. For a state vector $s = (z, \omega, e_{-1}, d_{-1}, k, \phi_X)$ we use equations (9)-(12) and the following algorithm to calculate the value functions for each firms.

1. Guess the value of the initial value function $V^0(s)$.

2. Calculate the expected value

$$EV^0 = \int_{z'} \int_{\omega'} (z', \omega', e, k, \Phi_X) dF(\omega'|\omega, d, e) dF(z'|z, d)$$

   where we calculate $F(\omega'|\omega, d, e)$ and $F(z'|z, d)$ are calculated according to equations (7) and (8), respectively.

3. Using $EV^0$ we calculate $V_t^{E0}$ and $V_t^{D0}$ using equations (10) and (11):

$$\begin{aligned} V^{E0}(d_{-1}) \quad = \quad & P[\delta EV^0(e=1, d=1) - \delta EV^0(e=1, d=0) > d_{-1}\gamma^A + (1-d_{-1})\gamma^D] \cdot \\ & (EV^0(e=1, d=1) - d_{-1}E(\gamma^A|\cdot) - (1-d_{-1})E(\gamma^D|\cdot)) + \\ & P[\delta EV^0(e=1, d=1) - \delta EV^0(e=1, d=0) \leq d_{-1}\gamma^A + (1-d_{-1})\gamma^D] \cdot \\ & EV^0(e=1, d=0) \end{aligned}$$

   and

$$\begin{aligned} V^{D0}(d_{-1}) \quad = \quad & P[\delta EV^0(e=0, d=1) - \delta EV^0(e=0, d=0) > d_{-1}\gamma^A + (1-d_{-1})\gamma^D] \cdot \\ & (EV^0(e=0, d=1) - d_{-1}E(\gamma^A|\cdot) - (1-d_{-1})E(\gamma^D|\cdot)) + \\ & P[\delta EV^0(e=0, d=1) - \delta EV^0(e=0, d=0) \leq d_{-1}\gamma^A + (1-d_{-1})\gamma^D] \cdot \\ & EV^0(e=0, d=0) \end{aligned}$$

4. Using our calculations in step (3) we construct the value function $V^1(z, \omega, e_{-1}, d_{-1}, k, \Phi_X)$ using equation 10 as:

$$\begin{aligned} & V^1(z, \omega, e_{-1}, d_{-1}, k, \Phi_X) = \\ & \quad \pi^D(z, \omega, k) + P[\pi^X(z, \omega, k, \Phi_X) + V^{E0}(d_{-1}) - V^{D0}(d_{-1}) > e_{-1}\gamma^F + (1-e_{-1})\gamma_S] \cdot \\ & \quad (\pi^X(z, \omega, k, \Phi_X) + V^{E0}(d_{-1}) - V^{D0}(d_{-1}) - e_{-1}E(\gamma^F|\cdot) - (1-e_{-1})E(\gamma_S|\cdot)) \\ & \quad P[\pi^X(z, \omega, k, \Phi_X) + V^{E0}(d_{-1}) - V^{D0}(d_{-1}) \leq e_{-1}\gamma^F + (1-e_{-1})\gamma_S] \cdot V^{D0}(d_{-1}) \end{aligned}$$

5. We then repeat steps (2)-(4) until convergence, $V^{j+1} - V^j < \epsilon$.

We adopt Rust's (1997) method to discretize the state space since it is very large in this case. We fix the grid values for $k$ with 8 categories and select $N = 100$ low-discrepancy points for $\omega$ and $z$: $(\omega_1, z_1), \ldots, (\omega_n, z_n), \ldots, (\omega_N, z_N)$. On each grid point we solve the firm's dynamic problem as described above for the value function $\hat{V}$. We can then calculate $EV$ using the discrete Markov operator:

$$\begin{aligned} EV &= \int_{z'} \int_{\omega'} V^0(z', \omega', e, k, \Phi_X) dF(\omega'|\omega, d, e) dF(z'|z, d) \\ &= \frac{1}{N} \sum_{n=1}^{N} \hat{V}(z_n, \omega_n, e, d, k, \Phi_X) p^N(z_n, \omega_n | z, \omega, e, d) \end{aligned}$$

where $p^N(z_n, \omega_n | z, \omega, e, d) = \frac{p(z_n|z)p(\omega_n|\omega,e,d)}{\sum_{n=1}^{N} p(z_n|z)p(\omega_n|\omega,e,d)}$.

# B Details of Bayesian MCMC Estimation

The set of dynamic parameters we estimate in the second stage are $\Theta = (\gamma^A, \gamma^D, \gamma^F, \gamma^S, \gamma_0, \gamma_1, \gamma_2, \sigma_z, \Phi_X, \theta^d, \theta^e)$ where $\theta^d$ and $\theta^e$ are, respectively, the parameters for the probit equations for the initial conditions of EAT investment and exporting. Our sampling algorithm follows Das, Roberts and Tybout (2007) and Aw, Roberts and Xu (2009) closely and we adopt their priors where possible. In general, the priors we adopt are very diffuse; the means of all fixed and sunk cost distributions are assumed to have priors that follow a $N(0, 1000)$ distribution while the prior for the revenue intercept and the prior for the effect of EAT investment on export demand are also set to follow a $N(0, 1000)$ distribution. The autoregressive coefficient in export demand is set to follow a $U[-1, 1]$ distribution while the log $\sigma_z$ distribution is set to follow a $N(0, 10)$ distribution as in the above citations.