R&D Investment, Exporting, and Productivity Dynamics*

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Abstract

A positive correlation between productivity and export market participation has been well documented in producer micro data. Recent empirical studies and theoretical analyses have emphasized that this may reflect the producer's other investment activities, particularly investments in R&D or new technology, that both raise productivity and increase the payoff to exporting. In this paper we develop a dynamic structural model of a producer's decision to invest in R&D and participate in the export market. The investment decisions depend on the expected future profitability and the fixed and sunk costs incurred with each activity. We estimate the model using plant-level data from the Taiwanese electronics industry and find a complex set of interactions between R&D, exporting, and productivity. The self-selection of high productivity plants is the dominant channel driving participation in the export market and R&D investment. Both R&D and exporting have a positive direct effect on the plant's future productivity which reinforces the selection effect. When modeled as discrete decisions, the productivity effect of R&D is larger, but, because of its higher cost, is undertaken by fewer plants than exporting. The impact of each activity on the net returns to the other are quantitatively unimportant. In model simulations, the endogenous choice of R&D and exporting generates average productivity that is 22.0 percent higher after 10 years than an environment where productivity evolution is not affected by plant investments.

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1 Introduction

A large empirical literature exists documenting the relationship in firm and plant-level data between exporting and productivity.[1] A universal finding is that, on average, exporting producers are more productive than nonexporters reflecting, at least partly, the self-selection of more productive firms into the export market. Many studies have measured the intertemporal correlations between exporting and productivity in an attempt to determine if firms that participate in the export market have higher productivity growth rates. The empirical evidence on this point is less uniform, with some studies finding higher productivity trajectories for firms after they begin exporting and others finding no effect.

One element that is missing from this literature is the possibility that firms undertake other investments that lead to both higher productivity and a higher propensity to export. Recently, several authors have begun to measure the potential role of the firms' own investments in R&D or technology adoption as another component of the productivity-export link. Bernard and Jensen (1997), Hallward-Driemeier, Iarossi, and Sokoloff (2002), Baldwin and Gu (2004), Aw, Roberts, and Winston (2007), Bustos (2007), Lileeva and Trefler (2007), Iacovone and Javorcik (2007), Aw, Roberts, and Xu (2008) and Damijan, Kostevc, and Polanec (2008) have found evidence from micro data sets that exporting is also correlated with firm investment in R&D or adoption of new technology that can also affect productivity. Complementing this evidence, Criscuolo, Haskel, and Slaughter (2005) analyze survey data collected for E.U. countries and find that firms that operate globally devote more resources to assimilating knowledge from abroad and generate more innovations and productivity improvement. An implication of this is that studies that use micro data to identify export-productivity links from the timing of these activities may be reflecting spurious effects of the firm's other investments to improve productivity.

Two recent theoretical papers have formalized the potential linkages between the firm's productivity and its choices to export and/or invest in R&D or new technology using dynamic industry models. Atkeson and Burstein (2007) and Constantini and Melitz (2008) model the interdependence between these two choices and firm productivity. Both papers share

[1] See Greenaway and Kneller (2007) for a recent survey of the micro econometric evidence on this topic.

several common features. First, productivity is the underlying state variable that distinguishes heterogeneous producers. Second, productivity evolution is endogenous, affected by the firm's innovation decisions, and contains a stochastic component. Third, while they differ in the specific structure of costs and information, they each identify pathways through which the dynamic export and investment decisions may be linked. In this paper we develop and estimate a dynamic, structural model of exporting and R&D investment and quantify three pathways linking exporting, R&D investment, and productivity. First, the return to each investment increases with the producer's underlying productivity which leads high-productivity producers to self-select into both investment activities. Second, each investment directly affects future productivity which acts to reinforce the selection effect. Third, as emphasized in the recent theoretical models, each activity alters the future return from undertaking the other activity, thus current R&D directly impacts the probability of exporting and current exporting alters the return to R&D.

We use the empirical model to study the sources of productivity change among Taiwanese manufacturing plants in the electronics products industry for the period 2000-2004. This industry is an excellent place to measure these relationships. It is characterized by high rates of productivity growth, significant export market participation (an export rate of approximately .39 in our plant data), and significant R&D investment by the plants (a .17 rate of participation in our sample). Our empirical model exploits data on the plant's domestic sales and costs to estimate how the plant's R&D investment and export status affect the distribution of its future productivity. We then estimate the decision rules for the plant's optimal choice of R&D and exporting, modeling each as a discrete choice. These decisions depend on the expected future profits and the current fixed or sunk costs the plant incurs with these choices. The empirical estimates provide the basis for quantifying the role of productivity heterogeneity, sunk investment costs, and interactions in the returns to each investment on R&D and export choice.

Our empirical results reveal a rich set of productivity determinants. Productivity evolution is endogenous, being impacted positively by both R&D investment and exporting and, when modeled as discrete activities, the impact of R&D is larger. There are significant entry costs for both activities, which introduces a second source of intertemporal linkages in the decisions, and the costs of undertaking R&D activities are larger than the costs of exporting. The self-selection of high productivity plants is the dominant channel driving export market participation and R&D investment and this is reinforced by the effect of each investment on future productivity. The indirect effect of each activity on the net returns to the other is small and has little impact on the probability the firm exports or conducts R&D. Overall, in model simulations, the endogenous choice of R&D and exporting generates average productivity that is 22 percent higher after 10 years than it would be in an environment where productivity evolution is not affected by plant investments.

The next section of this paper develops the theoretical model of the firm's dynamic decision to invest in R&D and exporting. The third section develops a two-stage estimation method for the model. The first stage estimates the underlying process for producer productivity and the second stage uses this to estimate the dynamic decision rules for R&D and export market participation. The fourth section provides a brief discussion of the data source. The fifth section summarizes the parameter estimates and uses them to quantify the costs and returns to R&D investment and export market participation and the sources of productivity evolution.

2 A Structural Model of Exporting and R&D

The theoretical model developed in this section is similar in several ways to the models of exporting developed by Roberts and Tybout (1997), Clerides, Lach, and Tybout (1998), Melitz (2003), and Das, Roberts, and Tybout (2007) and the models of exporting and investment by Atkeson and Burstein (2007) and Constantini and Melitz (2008). We abstract from the decision to enter or exit production and instead focus on the investment decisions and process of productivity evolution. Firms are recognized to be heterogeneous in their productivity and the export demand curve they face. Together these determine each firm's incentive to invest in R&D and to export. In turn, these investments have feedback effects that can alter the path of future productivity for the firm. We divide the firm's decision making into a static component, where the firm's productivity determines it's short-run profits from exporting, and a dynamic component where they make optimal R&D and export-market participation decisions.

2.1 Static Decisions

We begin with a model of the firm's revenue in the domestic and export market. Firm i's short-run marginal cost function is written as:

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

where k_{it} is firm capital stock, w_t is a vector of variable input prices common to all firms, and ω_{it} is firm productivity.[2] Several features of the specification are important. The firm is assumed to produce a single output which can be sold in both domestic and export markets and marginal cost is identical across the two markets for a firm. There are two sources of short-run cost heterogeneity, capital stocks that are observable in the data and firm productivity that is observable to the firm but not observable in our data. Marginal cost does not vary with the firm's output level which implies that 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 independently of the output level in the other market.[3]

Both the domestic and export market are assumed to be monopolistically competitive and segmented from each other. This rules out strategic interaction among firms in the each market but does allow firms to charge markups that differ across markets. The demand curves faced by firm i in the domestic and export markets are assumed to have the Dixit-Stiglitz form. In the domestic market it is:

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

where Q_t^D and P_t^D are the industry aggregate output and price index, I_t^D is total market size, and η_D is the constant elasticity of demand. The firm's demand depends on the industry aggregates, represented by Φ_t^D, its price p_{it}^D, and the constant demand elasticity.

A similar structure is assumed in the export market except that each firm's demand also depends on a firm-specific demand shifter z_{it}. The demand curve firm i faces in the export

[2] Other firm-level cost shifters can be included in the empirical specification. In this version we will focus on the heterogeneity that arises from differences in size, as measured by capital stocks, and productivity.

[3] The domestic market will play an important role in modeling the dynamic decision to invest in R&D developed later.

market is:

$$q_{it}^X = \frac{I_t^X}{P_t^X}(\frac{p_{it}^X}{P_t^X})^{\eta_X} \exp(z_{it}) = \Phi_t^X (p_{it}^X)^{\eta_X} \exp(z_{it}) \tag{3}$$

where Φ_t^X represents the aggregate export market size and price, p_{it}^X is the firm's export price, η_X is a common demand elasticity and z_{it} is a firm-specific demand shock. By including this last term we incorporate an exogenous source of firm-level variation which will allow a firm's relative demands in the domestic and export market to vary across firms and over time. The firm is assumed to observe z_{it} when making its export decision, but it is not observable in our data.

Given its demand and marginal cost curves, firm i chooses the price in each market to maximize the sum of domestic and export profits. The first-order condition for the domestic market price p_{it}^D implies that the log of domestic market revenue r_{it}^D is:

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

Specifically, the firm's revenue depends on the aggregate market conditions and the firm-specific productivity and capital stock. Similarly, *if the firm chooses to export*, export market revenue is:

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

depending on the aggregate export market conditions, firm productivity, capital stock, and the export market demand shock. In the context of this model, these two equations show that the firm's domestic revenue will provide information on its marginal cost, in particular the productivity level ω_{it}. The export market revenue will also provide information on the export demand shocks, but only for firms that are observed to export. In the empirical model developed below we will estimate the revenue functions and can interpret the two sources of unobserved heterogeneity ω_{it} and z_{it} more generally. The first term ω_{it} will capture any source of firm-level heterogeneity that affects the firm's revenue in both markets. While we will refer to this as productivity, it could include characteristics of the product, such as its quality, that would affect the demand for the firm's product, as well as its cost, in both markets. The z_{it} term will capture all sources of revenue heterogeneity, arising from either the cost or demand side, that are unique to the export market. We will refer to z_{it} as the firm's export market shock.

Given these functional form assumptions for demand and marginal cost, there is a simple link between firm revenue and profit in each market. The firm's profit in the domestic market is:

$$\pi_{it}^{D} = -(\frac{1}{\eta_D})r_{it}^{D}(\Phi_t^D, k_{it}, \omega_{it}) \tag{6}$$

where revenue is given above. Similarly, if the firm chooses to export, the profits they will earn are linked to export market revenue as:

$$\pi_{it}^{X} = -(\frac{1}{\eta_X})r_{it}^{X}(\Phi_t^X, k_{it}, \omega_{it}, z_{it}) \tag{7}$$

These equations allow us to measure firm profits from observable data on revenue in each market. These short-run profits will be important determinants of the firm's decision to export and to invest in R&D in the dynamic model developed in the next two sections.

2.2 Transition of the State Variables

In order to model the firm's dynamic optimization problem for exporting and R&D we begin with a description of the evolution of the process for firm productivity ω_{it} and the other state variables $\ln\Phi_t^D$, $\ln\Phi_t^X$, z_{it}, and k_{it}. We assume that productivity evolves over time as a Markov process that depends on the firm's investments in R&D, its participation in the export market, and a random shock:

$$\begin{aligned} \omega_{it} &= g(\omega_{it-1}, d_{it-1}, e_{it-1}) + \xi_{it} \qquad (8) \\ &= \alpha_0 + \alpha_1\omega_{it-1} + \alpha_2(\omega_{it-1})^2 + \alpha_3(\omega_{it-1})^3 + \alpha_4 d_{it-1} + \alpha_5 e_{it-1} + \alpha_6 d_{it-1}e_{it-1} + \xi_{it} \end{aligned}$$

d_{it-1} is the firm's R&D investment, e_{it-1} is the firm's export market participation in the previous period. The inclusion of d_{it-1} recognizes that the firm may affect the evolution of its productivity by investing in R&D. The inclusion of e_{it-1} allows for the possibility of learning-by-exporting, that participation in the export market is a source of knowledge or expertise that can improve future productivity. The stochastic nature of productivity improvement is captured by ξ_{it} which is treated as an *iid* shock with zero mean and variance σ_ξ^2.[4] This stochastic

[4]This is a generalization of the productivity process used by Olley and Pakes (1996) in their work on productivity evolution in the U.S. telecommunications industry. They modeled productivity as an exogenous Markov

component represents the role that randomness plays in the evolution of a firm's productivity. It is the innovation in the productivity process between $t-1$ and t that is not anticipated by the firm and by construction is not correlated with ω_{it-1}, d_{it-1}, and e_{it-1}. This specification also recognizes that the stochastic shocks to productivity in any year t will carry forward into productivity in future years. The second line of the equation gives the assumed functional form for this relationship: a cubic function of lagged productivity and a full set of interactions between lagged exporting and R&D. d and e can each be modeled as continuous variables, treating them as flows of R&D expenditure and export market sales, respectively. Alternatively, they can be modeled as discrete 0/1 variables that reflect whether or not the firm undertakes its own R&D in prior years or participates in the export market. In the empirical model developed below, we treat both variables as discrete. This is consistent with the evidence reported by Aw, Roberts, and Winston (2007) who estimate a reduced-form model consistent with the structural model we develop here. They find that productivity evolution for Taiwanese electronics producers is affected by the discrete export and R&D variables. They also find that firm productivity is a significant determinant of the discrete decision to undertake each of these activities, but find little evidence that productivity is correlated with the level of export market sales for firms that choose these investments.

The firm's export demand shock will be modeled as a first-order Markov process:

$$z_{it} = \rho_z z_{it-1} + \mu_{it}, \mu_{it} \sim N(0, \sigma_\mu^2). \tag{9}$$

If a source of firm-level heterogeneity like z was not included in this model, there would be a perfect cross-section correlation between domestic and export revenue. In our application it is important to allow persistence in the evolution of z because it is going to capture factors like the nature of the firm's product, the set of countries they export to, and any long-term contractual or reputation effects that lead to persistence in the demand for its exports over time.[5]

process $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$. Doraszelski and Jaumandreu (2007) have endogenized productivity by allowing it to depend on the firm's choice of R&D. They model productivity as $\omega_{it} = g(\omega_{it-1}, d_{it-1}) + \xi_{it}$ where d_{it-1} is the firm's past R&D expenditure. They also show how their specification generalizes the "knowledge capital" model of productivity developed by Griliches (1979, 1998).

[5]This formulation does not imply that the firm's R&D cannot affect its profitability in the export market. We just assume that whatever role R&D plays it works through ω and affects the firm's revenue and profits

The firm's capital stock will be treated as fixed over time k_i. We will recognize the differences in capital stocks across plants but not attempt to model the firm's investment in capital. Given the relatively short time series in our data, most of the variation in capital stocks is across firms and the intertemporal effects of changes in the capital stock on marginal cost are going to be difficult to quantify precisely in this data even without the complexity of productivity variation. In addition, the dynamic model developed in the next section focuses on the dynamic choices to undertake R&D investment and export and we do not attempt to model the firm's physical investment. Finally, the aggregate state variables $\ln\Phi_t^D$, $\ln\Phi_t^X$ are treated as exogenous first-order Markov processes that will be controlled for using time dummies in the empirical model.

2.3 Dynamic Decisions - R&D and Exporting

In this section we develop the firm's dynamic decision to export and invest in R&D. A firm entering the export market will incur a nonrecoverable sunk cost and this implies that the firm's past export status is a state variable in the firm's export decision. This is the basis for the dynamic models of export participation developed by Roberts and Tybout (1997) and Das, Roberts, and Tybout (2007). We will also incorporate a sunk startup cost for the firm when it begins investing in R&D and this will make the firm's past R&D status a state variable in the investment choices. This is similar to Xu (2008) who estimates a dynamic model of firm R&D choice where R&D expenditures affect the future productivity of the firm. Finally, in our model there is one additional intertemporal linkage in the firm's investment decisions: the firm's export and R&D choices can affect it's future productivity as shown in equation 8.

While the static profits, equations 6 and 7, earned by the firm are one important component of its decisions, these will also depend on the combination of markets it participates in and the fixed and sunk costs it must incur. It is necessary to make explicit assumptions about the timing of the firm's decision to export and undertake R&D. We assume that the firm first

in both the domestic and export market. In our data, the R&D variable measures the firm's investments to develop and introduce new products and to improve its production processes. This variable is best incorporated in our model by allowing it to affect both markets. If separate data were available on R&D expenditures to develop new products and expenditures to improve production processes then some other specifications could be developed. For example, it would be possible to allow the process R&D variable to affect both markets through ω while the new product expenditures acted to shift export demand through z.

observes values of the fixed and sunk costs of exporting, γ_{it}^F and γ_{it}^S, and makes its discrete decision to export in year t. Following this, it observes a fixed and sunk cost of investment, γ_{it}^I and γ_{it}^D, and makes the discrete decision to undertake R&D.[6] All four costs are assumed to be *iid* draws from a known joint distribution G^γ.

The state vector for firm i in year t is $s_{it} = (\omega_{it}, z_{it}, k_i, \Phi_t, e_{it-1,} d_{it-1})$ and the firm's value function in year t, before it observes its fixed and sunk costs, can be written as:

$$V_{it}(s_{it}) = \int (\pi_{it}^D + \max_{e_{it}} \{(\pi_{it}^X - e_{it-1}\gamma_{it}^F - (1 - e_{it-1})\gamma_{it}^S) + V_{it}^E(s_{it}), V_{it}^D(s_{it})\}) dG^\gamma \tag{10}$$

where e_{it-1} is a discrete 0/1 variable identifying the firm's export status in $t-1$. If the firm exported in $t-1$ it pays the fixed cost γ_{it}^F when exporting in period t, otherwise it pays the sunk entry cost γ_{it}^S to participate. V^E is the value of an exporting firm after it makes its optimal R&D decision and, similarly, V_{it}^D is the value of a non-exporting firm after it makes its optimal R&D decision. This equation shows that the firm chooses to export in year t when the current plus expected gain in future export profit exceeds the relevant fixed or sunk cost. In this equation the value of investing in R&D is subsumed in V_{it}^D and V_{it}^E. Specifically,

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

The first term shows that if the firm chooses to undertake R&D ($d_{it} = 1$) then it pays a current cost that depends on its prior R&D choice. If it invested in R&D in $t-1$ then it pays the fixed investment cost γ_{it}^I otherwise it pays the sunk startup cost γ_{it}^D. It has an expected future return which depends on how R&D affects future productivity. If they do not choose to invest ($d_{it} = 0$) they have a different future productivity path. The larger the impact of R&D on future productivity, the larger the difference between the expected returns of doing R&D versus not doing R&D and thus the more likely the firm is to invest in R&D. Similarly, the value of R&D to a non-exporting firm is:

[6] An alternative assumption is that the firm simultaneously chooses d and e. This will lead to a multinomial model of the four possible combinations of exporting and R&D investment. In the empirical application, it is more difficult to calculate the probability of each outcome in this environment.

$$V_{it}^D(s_{it}) = \int \max_{d_{it}\in(0,1)} \{\delta E_t V_{it+1}(s_{it}|e_{it}=0, d_{it}=1) - d_{it-1}\gamma_{it}^I - (1-d_{it-1})\gamma_{it}^D, \\ \delta E_t V_{it+1}(s_{it}|e_{it}=0, d_{it}=0)\} dG^\gamma \tag{12}$$

where the firm faces the same tradeoff, but now the future productivity paths will be those for a non-exporter. Finally, to be specific, the expected future value conditional on different choices for e_{it} and d_{it} is:

$$E_t V_{it+1}(s_{it}|e_{it}, d_{it}) = \int_{\Phi'} \int_{z'} \int_{\omega'} V_{it+1}(s') dF(\omega'|\omega_{it}, e_{it}, d_{it}) dF(z'|z) dG(\Phi'|\Phi) \tag{13}$$

In this equation the evolution of productivity $dF(\omega'|\omega_{it}, e_{it}, d_{it})$ is conditional on both e_{it} and d_{it} because of the assumption in equation 8.

In this framework, the net benefits of both exporting and R&D investment are increasing in current productivity. This leads to the usual *selection effect* where high productivity firms are more likely to export and invest in R&D. By making future productivity endogenous this model recognizes that current choices lead to improvements in future productivity and thus more firms will self-select into, or remain in, exporting and R&D investment in the future.

When we have two choice variables for the firm, there are new forces in addition to the selection effect which make the decisions interdependent. First, whether or not the firm chooses to export in year t affects the return to investing in R&D. For any state vector, we can define the marginal benefit of doing R&D from equations 11 and 12 as the difference in the expected future returns between choosing and not choosing R&D:

$$MBR_{it}(s_{it}|e_{it}) = E_t V_{it+1}(s_{it}|e_{it}, d_{it}=1) - E_t V_{it+1}(s_{it}|e_{it}, d_{it}=0). \tag{14}$$

This will depend on the impact of R&D on future productivity but also on the firm's export choice e_{it} because of the effect of the sunk cost of exporting and the direct effect of exporting on future productivity through equation 8. In the special case where the sunk cost of exporting $\gamma_{it}^S = 0$ and exporting does not affect the evolution of productivity ($\alpha_5 = \alpha_6 = 0$ in equation 8), exporting becomes a static decision and MBR_{it} will not be a function of e_{it} implying that an exporter and a non-exporter will have the same valuation of R&D investment.[7]

In general, MBR_{it} will differ for exporters and nonexporters and the sign and magnitude of the difference will depend on the combined effect of the sunk cost of exporting and the sign of the interaction effect between R&D and exporting on productivity, which is given by the coefficient α_6 in equation 8. Define the difference in the future benefit of R&D between exporters and nonexporters as $\Delta MBR_{it}(s_{it}) = MBR_{it}(s_{it}|e_{it} = 1) - MBR_{it}(s_{it}|e_{it} = 0)$. If $\alpha_6 > 0$ then R&D will be more valuable to exporters and this will increase ΔMBR. If $\alpha_6 < 0$ the impact of R&D on future productivity will be larger for nonexporters and this will decrease ΔMBR. If the sunk cost is low, a negative α_6 can result in $\Delta MBR < 0$ in which case nonexporters will be more likely to undertake R&D projects. One way to interpret this is to recognize that d and e are both tools that the firm can employ to acquire knowledge and expertise in order to improve its future productivity. If the two activities are essentially substitutes in the type of knowledge or expertise they bring to the firm, there will be diminishing returns to additional activities. In this case, $\alpha_6 < 0$ and the marginal benefit of adding R&D investment will be smaller for a firm that is already exporting. Other things fixed, exporting firms are less likely to begin R&D investment. Conversely, if the knowledge and expertise acquired through the two activities are complementary, so that, for example a firm that conducts its own R&D program is better able to assimilate knowledge gained from its export contacts, then there are increasing returns to activities,.$\alpha_6 > 0$, and productivity will rise more when the firm adds the second activity.[8] This implies that exporting firms are more likely to begin R&D investment than nonexporters.

The expected payoff to exporting will, in general, depend on the firm's past choice of R&D. From equation 10 exporting provides current export profits π_{it}^X and a future benefit that depends on the difference between being in the export market V_{it}^E and remaining only in the domestic market V_{it}^D. For any state vector we can define the marginal benefit of exporting as:

$$MBE_{it}(s_{it}) = \pi_{it}^X(s_{it}) + V_{it}^E(s_{it}) - V_{it}^D(s_{it}) \tag{15}$$

[7]This does not imply that the ability to export has no effect on the firm's choice of R&D. Atkeson and Burstein's (2007) model treats exporting as a static decision but the expectation of lower future fixed costs in the export market increases the firm's incentive to invest in current R&D. They study the implications of this market size effect on the evolution of industry structure and productivity.

[8]This is the basis for the model of Cohen and Levinthal (1989). In their model R&D acts to increase the firm's own innovation rate but also to increase its ability to learn or assimilate new information from others.

If there is a sunk cost to initiating an R&D program, this difference will depend on the firm's previous R&D choice $d_{it-1.}$ In the special case where there is no sunk cost of R&D then V_{it}^E and V_{it}^D, and thus MBE_{it}, do not depend on $d_{it-1.}$ Once again the coefficient α_6 will affect whether MBE is larger for firms that previously invested in R&D ($d_{it-1} = 1$) or did not ($d_{it-1} = 0$). For the same reasons discussed above, when $\alpha_6 > 0$ exporting is more valuable to plants that already do R&D while if $\alpha_6 < 0$ then exporting is more valuable to plants that do not conduct their own R&D. The incremental impact of R&D on the return to exporting can be measured by $\Delta MBE_{it} = MBE_{it}(s_{it}|d_{it-1} = 1) - MBE_{it}(s_{it}|d_{it-1} = 0)$.

To summarize the model, firm's differ in their past export market experience, capital stocks, productivity, and export demand and these determine their short-run profits in the domestic and export market. The firm can affect its future productivity and thus profits by investing in R&D or participating in the export market. These processes, combined with fixed and sunk costs of exporting and R&D investments, determine the firm's optimal decisions on export market participation and whether or not to undertake R&D. In the next section we detail how we estimate the structural parameters of the profit functions, productivity process, and costs of exporting and conducting R&D.

3 Empirical Model and Estimation

The model of the last section can be estimated using firm or plant-level panel data on export market participation, export market revenue, domestic market revenue, capital stocks, and the discrete R&D decision. In this section we develop an empirical model which can be estimated in two stages. In the first stage, parameters of the domestic revenue function and the productivity evolution process will be jointly estimated and used to construct the measure of firm productivity. In the second stage, a dynamic discrete choice model of the export and R&D decision will be developed and used to estimate the fixed and sunk cost of exporting and R&D and the export revenue parameters. The second-stage estimator is based on the model of exporting developed by Das, Roberts, and Tybout (2007) augmented with the R&D decision and endogenous productivity evolution. The full set of model parameters includes the market demand elasticities η_X and η_D, the aggregate demand shifters, Φ_t^X and Φ_t^D, the marginal cost parameters β_0, β_k, and β_w, the function describing productivity evolution $g(\omega_{it-1}, d_{it-1}, e_{it-1})$, the variance of the productivity shocks σ_ξ^2, the distribution of the fixed and sunk costs of exporting and R&D investment G^γ and the Markov process parameters for the export market shocks, ρ_z and σ_μ^2.

3.1 Demand and Cost Parameters

We begin by estimating the domestic demand, marginal cost, and productivity evolution parameters. The domestic revenue function in equation 4 is appended with an iid error term u_{it} to give:

$$\ln r_{it}^D = (\eta_D + 1)\ln(\frac{\eta_D}{\eta_D + 1}) + \ln \Phi_t^D + (\eta_D + 1)(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t - \omega_{it}) + u_{it} \quad (16)$$

where the composite error term, $(\eta_D + 1)(-\omega_{it}) + u_{it}$ contains firm productivity. We utilize the insights of Olley and Pakes (1996) to rewrite the unobserved productivity in terms of some observable variables that are correlated with it. In our case, the firm's choice of the variable input levels for materials, m_{it}, and electricity, n_{it}, will depend on the level of productivity and the export market shock (which are both observable to the firm). Ackerberg, Benkard, Berry, and Pakes (2007, section 2.4.3) show that if the input demand functions m_{it} and n_{it} are a bijection in (ω_{it}, z_{it}), conditional on k_{it}, then they can be inverted to express $\omega_{it}(k_{it}, m_{it}, n_{it})$. This allows us to use the materials and electricity expenditures by the firm to control for the productivity in equation 16. By combining the demand elasticity terms into an intercept γ_0, and the time-varying aggregate demand shock and market-level factor prices into a set of time dummies D_t, equation 16 can be written as:

$$\begin{aligned} \ln r_{it}^D &= \gamma_0 + \sum_{t=1}^{T} \gamma_t D_t + (\eta_D + 1)(\beta_k \ln k_{it} - \omega_{it}) + u_{it} \\ &= \gamma_0 + \sum_{t=1}^{T} \gamma_t D_t + h(k_{it}, m_{it}, n_{it}) + v_{it} \end{aligned} \quad (17)$$

where the function $h(\cdot)$ captures the combined effect of capital and productivity on domestic revenue. We specify $h(\cdot)$ as a cubic function of its arguments and estimate equation 17 with ordinary least squares. The fitted value of the $h(\cdot)$ function, which we denote $\hat{\phi}_{it}$, is an estimate of $(\eta_D+1)(\beta_k \ln k_{it}-\omega_{it})$.[9] Next, as in Olley and Pakes (1996) and Doraszelski and Jaumandreu (2007), we construct a productivity series for each firm. This is done by estimating the parameters of the productivity process, equation 8. Substituting $\omega_{it} = -(\frac{1}{\eta_D+1})\hat{\phi}_{it} + \beta_k \ln k_{it}$ into equation 8 for productivity evolution gives an estimating equation:

$$\begin{aligned} \hat{\phi}_{it} \quad = \quad & \beta_k^* \ln k_{it} - \alpha_0^* + \alpha_1(\hat{\phi}_{it-1} - \beta_k^* \ln k_{it-1}) - \alpha_2^*(\hat{\phi}_{it-1} - \beta_k^* \ln k_{it-1})^2 + \\ & \alpha_3^*(\hat{\phi}_{it-1} - \beta_k^* \ln k_{it-1})^3 - \alpha_4^* d_{it-1} - \alpha_5^* e_{it-1} - \alpha_6^* d_{it-1} e_{it-1} - \xi_{it}^* \end{aligned} \tag{18}$$

where the star represents that the α and β_k coefficients are multiplied by $(\eta_D + 1)$.[10] This equation can be estimated with nonlinear least squares and the underlying α and β_k parameters can be retrieved given an estimate of η_D. Finally, given estimates $\hat{\beta}_k$ and $\hat{\eta}_D$, we construct an estimate of productivity for each observation as:

$$\hat{\omega}_{it} = -(1/(\hat{\eta}_D + 1))\hat{\phi}_{it} + \hat{\beta}_k \ln k_{it}. \tag{19}$$

The final estimating equation in the static demand and cost model exploits the data on total variable cost (tvc). Since each firm's marginal cost is constant with respect to output and equal for both domestic and export output, tvc is the sum of the product of output and marginal cost in each market. Using the first-order condition for profit maximization, marginal cost is equal to marginal revenue in each market and thus tvc is an elasticity-weighted combination of total revenue in each market:

$$tvc_{it} = q_{it}^D c_{it} + q_{it}^X c_{it} = r_{it}^D(1 + \frac{1}{\eta_D}) + r_{it}^X(1 + \frac{1}{\eta_X}) + \varepsilon_{it} \tag{20}$$

where the error term ε is included to reflect measurement error in total cost. This equation provides estimates of the two demand elasticity parameters.

Three key aspects of this static empirical model are worth noting. First, we utilize data on the firm's domestic revenue to estimate firm productivity, an important source of firm heterogeneity that is relevant in both the domestic and export market. In effect, we use domestic

[9]In this stage of the estimation we recognzie that the firm's capital stock changes over time and incorporate that into the variation in $\hat{\phi}_{it}$. In the estimation of the dynamic export and R&D decisions in section 4.2 we simplify the process and keep the firm's capital stock fixed at its mean value over time.

[10]The only exceptions are that $\alpha_2^* = \alpha_2(1 + \eta_D)^{-1}$ and $\alpha_3^* = \alpha_3(1 + \eta_D)^{-2}$

revenue data to estimate and control for one source of the underlying profit heterogeneity in the export market. Second, like Das, Roberts, and Tybout (2007) we utilize data on the firm's total variable cost to estimate demand elasticities and markups in both markets. Third, the method we use to estimate the parameters of the productivity process, equation 8, can be extended to include other endogenous variables that impact productivity. Estimation of the process for productivity evolution is important for estimating the firm's dynamic investment equations because the parameters from equation 8 are used directly to construct the value functions that underlie the firm's R&D and export choice, equations 11, 12, and 13.

3.2 Dynamic Parameters

The remaining parameters of the model, the fixed and sunk costs of exporting and investment and the process for the export revenue shocks, can be estimated using the discrete decisions for export market participation, R&D, and export revenue for the firm's that choose to export. Intuitively, entry and exit from the export market provide information on the distribution of the sunk entry costs γ_{it}^S and fixed cost γ_{it}^F, respectively. The level of export revenue provides information on the distribution of the demand shocks z_{it} conditional on exporting, which can be used to infer the unconditional distribution for the export shocks. The distribution of the fixed and sunk cost of R&D investment, γ_{it}^I and γ_{it}^D, are estimated from the discrete R&D choice.

The dynamic estimation is based on the likelihood function for the observed patterns of firm i exporting $e_i \equiv (e_{i0}, ...e_{iT})$, export revenue $r_i^X \equiv (r_{i0}^X, ...r_{iT}^X)$, and the discrete patterns of firm R&D investment $d_i \equiv (d_{i0}, ...d_{iT})$. Once we recover the first-stage parameter estimates and construct the firm-level productivity series $\omega_i \equiv (\omega_{i0}, ...\omega_{iT})$, we can write the ith firm's contribution to the likelihood function as:

$$P(e_i, d_i, r_i^X | \omega_i, k_i, \Phi) = P(e_i, d_i | \omega_i, k_i, \Phi, z_i^+) h(z_i^+) \tag{21}$$

This equation expresses the joint probability of the data as the product of the joint probability of the discrete e and d decisions, conditional on the export market shocks z, and the marginal distribution of z.[11] The variable z_i^+ denotes the time series of export market shocks in the years

[11] In this equation we treat the intercepts of the domestic and export revenue equations as a constant, Φ. We have estimated the model with time-varying intercepts but they were not statistically different from each other in our short panel and we have simplified the estimation by treating them as constant.

$(0, 1, ...T)$ when firm i exports. Das, Roberts and Tybout (2007) show how to construct the density $h(z_i^+)$ given our assumptions on the process for the export market shocks in equation 9. Given knowledge of $h(z_i^+)$ the export market shocks can be simulated and used in the evaluation of the likelihood function.[12]

A key part of the likelihood function is the joint probability of (e_i, d_i). By assuming that the sunk and fixed costs for each firm and year are *iid* draws from a known distribution, the joint probability of (e_i, d_i) can be written as the product of the choice probabilities for e_{it} and d_{it} in each year. These choice probabilities in year t are conditioned on the state variables in that year: $\omega_{it}, z_{it}, k_i, \Phi_t, e_{it-1,}$and d_{it-1}. The lagged export and R&D choice are part of the state vector because they determine whether the firm pays the sunk cost to enter or the fixed cost to remain in year t. The model developed above allows us to express the conditional choice probabilities in terms of these costs and the value functions that summarize the payoffs to each activity. Specifically, equation 10 shows the firm's decision to export involves a comparison of the expected profit from exporting relative to remaining in the domestic market with the fixed cost, for previous period exporters, and the sunk cost for nonexporters. From this equation, the probability of exporting can be written as:

$$P(e_{it} = 1|s_{it}) = P(e_{it-1}\gamma_{it}^F + (1 - e_{it-1})\gamma_{it}^S \leqslant \pi_{it}^X + V_{it}^E - V_{it}^D) \tag{22}$$

Similarly, equations 11 and 12 show that the firm compares the increase in expected future value if it chooses to do R&D with the current period cost of R&D. The firm's conditional probability of investing in R&D is equal to:

$$P(d_{it} = 1|s_{it}) = P(d_{it-1}\gamma_{it}^I + (1 - d_{it-1})\gamma_{it}^D \leqslant \delta E_t V_{it+1}(s_{it}|e_{it}, d_{it} = 1) - \delta E_t V_{it+1}(s_{it}|e_{it}, d_{it} = 0)) \tag{23}$$

Notice that there is one slight difference in state vector for the R&D decision. The current period exports, rather than the lagged exports, are the relevant state variable because of the

[12] Given the assumptions in equation 9, the distribution $h(z_i^+)$ is normal with a zero mean and a covariance matrix that depends on ρ_z and σ_μ^2. If the export market shocks were not serially correlated, equation 21 would take the form of a tobit model. Das, Roberts, and Tybout (2007, section 3) show how to extend the model to the case where z is serially correlated and we use their methodology to allow the export market shocks to be serially correlated.

timing assumption made in the theoretical model. There it was assumed that the firm makes its export and R&D decisions sequentially, so that current period export status is known prior to choosing R&D.[13] .

The probabilities of investing in R&D and exporting in equations 22 and 23 depend on the value functions $E_t V_{it+1}, V_{it}^E$, and V_{it}^D. For a given set of parameters, these can be constructed by iterating on the equation system defined by 10, 11, 12, and 13. The details of the value-function solution algorithm is contained in the appendix to this paper. We will evaluate the likelihood function for each set of parameters and rather than attempt to maximize the likelihood function we will utilize a Bayesian Monte Carlo Markov Chain (MCMC) estimator. This changes the objective of estimation to characterizing the posterior distribution of the dynamic parameters. The details of the implementation are contained in the appendix. The final detail needed for estimation is a distributional assumption on the fixed and sunk costs. We assume that each of the four costs are drawn from separate independent exponential distributions. The fixed and sunk cost parameters that we estimate are the means of these distributions. With this method it is also simple to allow the cost distributions to vary with some observable characteristic of the firm. For example, we allow the fixed and sunk cost distributions to be different for large and small firms (based on their observed capital stock) and estimate separate exponential distributions for each group.

4 Data

4.1 Taiwanese Electronics Industry

The model developed in the last section will be used to analyze the sources of productivity change of manufacturing plants in the Taiwanese electronics industry. The micro data used in estimation was collected by the Ministry of Economic Affairs (MOEA) in Taiwan for the years 2000, and 2002-2004.[14] There are four broad product classes included in the electronics

[13] The choice probabilities in equations 22 and 23 are accurate for time periods $1, 2...T$ in the data. In the first year of the data, period 0, we do not observe the prior period choices for d and e and this leads to an initial conditions problem in estimating the probabilities of exporting or investing in R&D. We deal with this using Heckman's (1981) suggestion and model the decision to export and conduct R&D in year 0 with separate probit equations. The explanatory variables in year 0 are the state variables $\omega_{i0}, k_i,$and z_{i0}.

[14] The survey was not conducted in 2001. In that year a manufacturing sector census was conducted by the Directorate General of Budget, Accounting, and Statistics. This cannot be merged at the plant level with the

industry: consumer electronics, telecommunications equipment, computers and storage equipment, and electronics parts and components. The electronics industry has been one of the most dynamic industries in the Taiwanese manufacturing sector. Sun (2005) reports that over the two decades 1981-1999, the electronics industry averaged tfp growth of 2.0 percent per year, while the total manufacturing sector averaged 0.2 percent. It is also a major export industry. For example, in 2000, the electronics subsector accounted for approximately 40 percent of total manufacturing sector exports. Several authors have discussed the nature of information diffusion from developed country buyers to export producers in this country and industry.[15] In addition, electronics has also been viewed as Taiwan's most promising and prominent high-tech industry. As reported by National Science Council of Taiwan, R&D expenditure in the electronics industry accounted for more than 72 percent of the manufacturing total in 2000. Overall, it is an excellent industry in which to examine the linkages between exporting, R&D investment, and productivity.

The data set that we use is a balanced panel of 1237 plants that were in operation in all four sample years and that reported the necessary data on domestic and export sales, capital stocks, and R&D expenditure. While the survey is conducted at the plant level, the distinction between plant and firm is not important in this sample. Of the sample plants, 1126, 91 percent of the total, are owned by firms that had only a single plant in the electronics industry. The remaining 111 plants are owned by firms that had at least one other plant in the industry in at least one year. Only one plant was owned by a firm that had more than two plants under ownership. This closely mirrors the ownership pattern in the industry as a whole. In that case, over the period 2000-2004, 92.8 percent of the manufacturing plants were owned by single-plant firms. In the discussion of the empirical results that follows we will use the word plant to refer to the observations in our sample.

Table 1 provides summary measures of the size of the plants, measured as sales revenue. The top panel of the table provides the median plant size across the 1237 plants in our sample

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MOEA survey data for the other years. We use the dynamic model developed in the last section to characterize the plant's productivity, R&D and export choice for the years 2002-2004 and utilize the information from 2000 to control for the initial conditions problem in the estimation.

[15] The initial arguments for learning-by-exporting, made by Pack (1992), Levy (1994), Hobday (1995), and Westpahl (2002), were based on case-study evidence for East Asian countries including Taiwan.

in each year, while the bottom panel summarizes the average plant size. The first column summarizes the approximately 60 percent of the plants that do not export in a given year. The median plant's domestic sales varies from 17.0 to 22.2 million new Taiwan dollars.[16] Among the exporting plants, the median plant's domestic market sales is approximately twice as large, 36.4 to 52.8 million NT dollars. The export sales of the median plant are approximately 32 million NT dollars. It is not the case, however, that there is a perfect correlation between domestic market size and export market size across plants. The simple correlation between domestic and export market revenue is .48 across all plant-year observations and .49 for observations with positive export sales. This suggests that it will be necessary to allow at least two factors to explain the plant-level heterogeneity in revenues in the two markets. The empirical model developed above does this with productivity ω_{it} and the export market shock z_{it}.

The distribution of plant revenue is highly skewed, particularly for plants that participate in the export market. The average domestic plant sales are larger than the medians by a factor of approximately ten for the exporting plants and the average export sales are larger by a factor of approximately 17. The skewness in the revenue distributions can also be seen from the fact that the 100 largest plants in our sample in each year account for approximately 75 percent of the total domestic sales and 91 percent of the export sales in the sample. The skewness in revenues will lead to large differences in profits across plants and a heavy tail in the profit distribution. To fit the participation patterns of all the plants it is necessary to allow the possibility that a plant has large fixed and/or sunk costs. We allow for this in our empirical model by, first, assuming exponential distributions for the fixed and sunk costs and, second, allowing large and small plants to draw their costs from exponential distributions with different means. Together these assumptions allow for substantial heterogeneity in the costs across plants.

The other important variable in the data set is the discrete indicator of R&D investment. In the survey, R&D expenditure is reported as the sum of the salaries of R&D personnel (researchers and scientists), material purchases for R&D, and R&D capital (equipment and

[16] In the period 2002-2004, the exchange rate between Taiwan and U.S. dollars was approximately 34 NT$/US$. The median plant size is approximately .5 million U.S. dollars

buildings) expenses. We convert this into a discrete 0/1 variable if the expenditure is positive.[17] Overall, 18.2 percent of the plant-year observations have positive R&D expenditures and, for this group, the median expenditure is 11.2 million NT dollars and the mean expenditure is 60.9 million NT dollars. When expressed as a share of total plant sales, the median plant value is .031 and the mean is .064. The R&D expenditure corresponds to the realization of the fixed cost of R&D in our model and, as with the export costs, we allow for substantial cost heterogeneity by both assuming exponential distributions for the fixed costs and allowing them to differ for large and small plants.

4.2 Empirical Transition Patterns for R&D and Exporting

The empirical model developed in the last section explains a producer's investment decisions. In this section we summarize the patterns of R&D and exporting behavior in the sample, with a focus on the transition patterns that are important to estimating the fixed and sunk costs of R&D and exporting. Table 2 reports the proportion of plants that undertake each combination of the activities and the transition rates between pairs of activities over time. The first row reports the cross-sectional distribution of exporting and R&D averaged over all years. It shows that in each year, the proportion of plants undertaking neither of these activities is .563. The proportion that conduct R&D but do not export is .036, export only is .255, and do both activities is .146. Overall, 731 of the sample plants (60 percent) engage in at least one of the investments in at least one year. One straightforward explanation for the difference in export and R&D participation is that differences in productivity and the export demand shocks affect the return of each activity and the plant's with favorable values of these underlying profit

[17] Another possible source of knowledge acquisition is the purchase of technology from abroad. The survey form asks each plant if it made any purchases of technology. This is a much less common occurence than investing in R&D. In our data, 18.2 percent of the plant-year observations report positive R&D expenditures but only 4.9 percent report purchasing technology from abroad. Importantly for estimation of our model, only 31 observations (0.62 percent of the sample) report purchasing technology but not conducting their own R&D. It is not going to be possible to estimate separate effects of R&D and technology purchases on productivity with this sample. Given our discrete model of R&D investment, there would be virtually no difference in the data if we defined the discrete variable as investing in R&D or purchasing technology. We have not used the technology purchase variable in our estimation. Branstetter and Chen (2006) use this survey data for an earlier, longer time period, 1986-1995, and a more broadly defined industry, electrical machinery and electronics products, and include both technology purchases and R&D expenditures, measured as continuous variables, in a production function model. They find that both variables are significant in the production function when estimated with random effects and the R&D elasticity is larger. Neither variable is significant in fixed effects estimates of the production function and they suspect that measurement error in the variables is the reason.

determinants self-select into each activity.

The transition patterns among R&D and exporting are important for the model estimation. The last four rows of the table report the transition rate from each activity in year t to each activity in $t+1$. Several patterns are clear. First, there is significant persistence in the status over time. Of the plants that did neither activity in year t, .871 of them are in the same category in year $t+1$. Similarly, the probability of remaining in the same category over adjacent years is .336, .708, and .767 for the other three categories. This can reflect a combination of high sunk costs of entering a new activity and a high degree of persistence in the underlying sources of profit heterogeneity, which, in our model, are capital stocks k, productivity ω and the export market shocks z.

Second, plants that undertake one of the activities in year t are more likely to start the other activity than a plant that does neither. If the plant does neither activity in year t, it has a probability of .115 that it will enter the export market. This is lower than the .291 probability that a plant conducting R&D only will then enter the export market. Similarly, a plant that does neither activity has a .019 probability that it will start investing in R&D, but an exporting plant has a .080 probability of adding R&D investment as a second activity. Third, plants that conduct both activities in year t are less likely to abandon one of the activities than plants than only conduct one of them. Plants that both export and conduct R&D have a .171 probability of abandoning R&D and a .086 probability of leaving the export market. Plants that only do R&D have a .430 probability of stopping while plants that only export have a .223 probability of stopping.

The transition patterns reported in Table 1 illustrate the need to model the R&D and exporting decision jointly. In our model, there are three mechanisms linking these activities. One is that plants that do one of the activities may have more favorable values of k, ω, or z that lead them to self-select into the other. A second pathway is that an investment in either activity can affect the future path of productivity as shown in equation 8 and thus the return to both R&D and exporting. A third pathway is possible for exporting. Even if exporting does not directly enter the productivity evolution process, the return to R&D can be higher or lower for exporting versus nonexporting plants, which makes the probability that the plant will conduct R&D dependent on the plant's export status.

5 Empirical Results

5.1 Demand, Cost, and Productivity Evolution

The parameter estimates from the first-stage estimation of equations 18 and 20 are reported in Table 3. The coefficients on the ω, d, and e variables are the α coefficients in equation 8. We report estimates in column 1 using the discrete measure of R&D, which we also use in the dynamic model.

Focusing on the first column, the demand elasticity parameters are virtually identical in the domestic and export market. The implied value of η_D is -6.38 and the value of η_X is -6.10. These elasticity estimates imply markups of price over marginal cost of 18.6 percent for domestic market sales and 19.6 percent for foreign sales. The coefficient on lnk_{it-1} is an estimate of the elasticity of capital in the marginal cost function β_k. It equals -0.063 (s.e.=.0052), implying, as expected, total variable costs are lower for plants with higher capital stock. More interesting are the coefficients for productivity evolution. The coefficients α_1, α_2, and α_3 measure the effect of the three powers of ω_{it-1} on ω_{it}. They imply a clear significant non-linear relationship between current and lagged productivity. The coefficient α_4 measures the effect of the lagged discrete R&D investment on current productivity and it is positive and significant. Plants that are engaged in R&D investment have 4.79 percent higher productivity. The direct effect of past exporting on current productivity is given by α_5 and is also positive and significant. This is a measure of the productivity impact of learning-by-exporting and implies the past exporters have productivity that is 1.96 percent higher. The magnitude of the export coefficient is less than half of the magnitude of the R&D coefficient implying a larger direct productivity impact from R&D than exporting. The last coefficient α_6 measures an interaction effect from the combination of past exporting and R&D on productivity evolution. Plants that do both R&D and exporting have productivity that is 5.56 percent higher than plants that do neither activity.[18] Plants that do both activities have the highest intercept in the productivity process,

[18] Aw, Roberts, and Winston (2007) also studied this industry using data from a 10-year time period, 1986-1996, analyzed at 5-year intervals, and found a similar pattern (Table 6, p. 100). Compared with firms that did neither activity, firms that only exported had productivity that was 4.2 percent higher, firms that only did R&D

but the negative sign on the interaction term implies that the *marginal* contribution to future productivity of adding the second activity is less than the *marginal* contribution of adding that same activity when the plant makes no investment.[19]

The coefficients α_4, α_5, and α_6 imply that the mean long-run productivity level for a plant will depend on the combinations of e and d. Relative to a plant that never exports or invests in R&D ($e = 0$, $d = 0$), a plant that does both in each year ($e = d = 1$) will have mean productivity that is 123 percent higher. A plant that only conducts R&D ($d = 1, e = 0$) in every year will be twice as productive. The smallest improvement is for the firms that only export ($e = 1, d = 0$). They will be 34 percent more productive than the base group. While this provides a summary of the technology linkages between exporting, R&D, and productivity, it does not recognize the impact of this process on the plant's choice to enter exporting or conduct R&D. This behavioral response is the focus of the second stage estimation. Given the estimates in Table 3 we construct an estimate of plant productivity from equation 19. The mean of the productivity estimates is .446 and the (.05, .95) percentiles of the distribution are (.092, .831). This variation in productivity will be one important dimension of heterogeneity in the returns to R&D and exporting and be important in explaining which plants self-select into these activities.[20]

We can assess how well the productivity measure correlates with the plant's R&D and export choice. In the top panel of Table 4 we report estimates of a bivariate probit regression of exporting and R&D on the firm's productivity, log capital stock, lagged export dummy,

had productivity that was 4.7 percent higher, and firms that did both had 7.8 percent higher productivity.

[19] Column 2 of Table 2 repeats the estimation using the log of R&D expenditure rather than the discrete variable. This change has no effect on any of the model coefficients except the two coefficients on R&D, α_4 and α_6. The statistical signifiance of α_4 and the insignificance of α_6 is not affected. Among the plants that conducted R&D the mean value of the log of R&D expenditure is 9.14. At this mean expenditure, plants that conducted R&D have productivity that is 6.1 percent higher (.0610=.00667*9.14) than plants that make no investment and this is similar to the magnitude of the R&D effect reported in column 1. In either specification the conclusion about the important role of R&D is the same. We will utilize the discrete specification in the dynamic model.

[20] These estimates are based on a balanced panel of plants. They are robust if we extend the sample to include all plants that enter or exit during the period. Following the framework in Olley and Pakes (1996) we estimate a probit model for plant exit and include a predicted probability of exit in equation 18. In the probit regression, capital, and the productivity proxies (material and energy use), explain very little of the exit variation. Adding this correction term to equation 18 has virtually no effect on the estimated coefficients reported in Table 3. Finally, there is virtually no difference in the export and R&D propensities between exiting and surviving plants in the sample. Overall, selection into the domestic market is not an important feature of our data set.

lagged R&D dummy, and a set of time dummies. This regression is similar to the reduced form policy functions that come from our dynamic model. The only difference is the fact that the export demand shocks z are not included explictly but rather captured in the error terms. The bivariate probit model allows the error terms of the two probits to be correlated, as they would be if z was a common omitted factor. In both probit models, all the variables, particularly the productivity variable, are highly significant. The correlation in the errors is also positive and statistically significant implying that the decisions are driven by some other common factors, such as the export demand shocks z. In the second and third panel of Table 4 we report regressions of export revenue, equation 5, for plants that are in the export market. The explanatory variables are productivity, the capital stock, and time dummies. (The lagged export and R&D dummies do not affect the volume decision once the firm is in the export market). The middle panel reports OLS estimates of the revenue function and the bottom panel treats the export demand shocks as time-invariant plant effects. In both cases the productivity variable is positive and highly significant.[21] It is important to recognize that this productivity measure has been estimated from the domestic market revenue data. From the fixed effect regression the variation in the plant-specific export demand shocks account for 72 percent of the error variance, suggesting that, even after controlling for productivity, export demand heterogeneity will be an important source of size and profit differences in the export market. Overall, it is clear from these reduced form regressions that the productivity variable we have constructed is measuring an important plant characteristic that is correlated with the discrete export and R&D decisions and the plant's export revenue once they choose to participate in the market.[22] In the next section we report the estimates of the dynamic investment equations.

[21]The coefficients on productivity will be subject to a selection bias if the export demand shocks z are correlated with firm productivity x. Our estimation of the full structural model recognizes the endogeneity of the decision to export and the fact that the observed realizations of z are drawn from a truncated distribution.

[22]Similar results are reported in Aw, Roberts, and Winston (2007). They estimate a bivariate probit investment model and find that productivity is significant in both investments. They also find that the lagged exporting status is also an important determinants of the current investments, which is consistent with the presence of sunk costs of exporting.

5.2 Dynamic Estimates

The remaining cost and export demand parameters are estimated in the second stage of our empirical model using the likelihood function that is the product over the plant-specific joint probability of the data given in equation 21. Each of the four values γ^I,γ^D, γ^F and γ^S is the parameter of an exponential distribution for, respectively, the R&D fixed cost, R&D sunk cost, fixed cost of exporting, and the sunk cost of exporting. The coefficients reported in Table 5 are the means and standard deviations of the posterior distribution of the parameters. The first set of estimates, labeled Model 1, assumes that all plants face the same distributions for the four costs. While, we will delay precise statements about the magnitudes of realized sunk and fixed costs until later, two broad patterns are immediately clear from the parameter estimates. First, for each activity, the estimated fixed cost parameter is less than the sunk cost parameter, indicating that the startup costs of each activity are more substantial than the per-period costs of maintaining the activity. Second, the fixed and sunk costs parameters for R&D are larger than for exporting, indicating that it will be more costly to begin or maintain an R&D investment program than an export program.

In the right side of the table, labeled Model 2, we divide the plants into two groups based on the size of the capital stock and allow the cost distributions to differ for the small (size 1) and large (size 2) plants. The two patterns observed in Model 1 are still present and, in addition, there are differences in the cost distributions faced by large and small plants. The parameter values differ the most for the two fixed cost categories. The smaller parameter value for the size 1 plants implies that the scale of operations, either exporting or investing in R&D, will tend to be smaller for the plants with smaller capital stocks. The final group of parameters describe the stochastic process driving the export market shocks z. This is characterized by a first-order autoregressive process with serial correlation parameter equal to 0.763 and a standard deviation for the transitory shocks equal to exp(-0.289)=0.75. This positive serial correlation parameter implies persistence in theplant's export status and export revenue if they choose to be in the market. The parameters estimates for the z process are very similar for Models 1 and 2.

5.3 In-Sample Model Performance

To assess the overall fit of the model, we use the estimated parameters from Model 2 to simulate patterns of R&D and exporting choice, transition patterns between the choices, and productivity trajectories for the plants in the sample and compare the simulated patterns with the actual data. Since each plant's productivity ω_{it} evolves endogenously according to equation 8, we need to simulate each plant's trajectory of productivity jointly with its dynamic decisions.[23] In Table 6 we report the actual and predicted percentage of R&D performers, export market participation rate, and industry mean productivity. Overall, the simulations do a good job of replicating these average data pattern for all three variables.

Second, we summarize the transition patterns of each plant's export and R&D status in table 7. The simulated panel performs reasonably well on the transition patterns for all four groups of plants. In particular for the two groups that account of 81.8 percent of the sample observations, those who engage in neither activities and those who only export, the predicted transition patterns match the data very closely. The most difficult transition patterns to fit closely are the ones related to starting or stopping R&D. Among the group of plants that only conduct R&D in year t, the model tends to overpredict the proportion of plants that will stop R&D and underestimate the proportion that will continue in year $t+1$. This group of plants accounts for only 3.6 percent of the total observations, however. The model simulations also capture the inter-dependence of the two activities. Plants that undertake one of the activities in year t are more likely to start the other than a plant that does neither. If a plant does neither activity in year t, it has a probability of .110 of entering the export market, lower than the .193 probability that a plant conducting R&D only will also enter the export market. Similarly, a plant that does neither activity has a .019 probability of starting R&D only, but an exporting plant has a .077 probability of adding R&D investment. These four transition rates are all similar to what is observed in the data.

[23] To do this we take the initial year status $(\omega_{i0}, z_{i0}, e_{i0}, k_i)$ of all plants in our data as given and simulate their next three sample year's export demand shocks z_{it}, R&D costs γ_{it}^{I}, γ_{it}^{D}, and export costs γ_{it}^{F}, γ_{it}^{S}. We then use equations 10, 11, 12, and 13 to solve each plant's optimal R&D and export decisions year-by-year. Note that these simulations do not use any data information on a plant's characteristics after their first year. We calculate each plant's domestic and export revenues using equations 4 and 5. For each plant, we repeat the simulation 100 times and report averages over the simulations.

5.4 The Determinants of R&D and Exporting: Productivity, Costs, and History

In our model the determinants of a plant's export and R&D choice are its current productivity, prior export and R&D status, export market shock, capital stock, and cost draws. In this section we will isolate the role of current productivity, the plant's export and R&D history, and the cost shocks on current R&D and export choice. Isolating the role of current productivity allows us to understand the importance of market selection effects while isolating the role of the plant's history allows us to understand the importance of sunk costs in the decision process. We do this by calculating the marginal benefit to each activity. Table 8 reports the marginal benefits of exporting for a plant with different combinations of productivity (rows) and previous R&D (columns). The second and third columns report values of $V_t^E(\omega_t, d_{t-1})$,the future payoff to being an exporter, while columns four and five report $V_t^D(\omega_t, d_{t-1})$, the future payoff to remaining in the domestic market.[24] All the values are increasing in the productivity level, reflecting the increase in profits in both markets with higher productivity. For each value of $(\omega_t, d_{t-1}), V_t^E(\omega_t, d_{t-1}) > V_t^D(\omega_t, d_{t-1})$ reflecting both the fact that current exporters do not have to pay the sunk cost of entering the export market in the next period and the impact of learning-by-exporting on future productivity.

The sixth column reports the marginal benefit of exporting for a plant that conducted R&D in $t-1$,defined in equation 15 as $MBE(\omega_t, d_{t-1} = 1)$. It is positive, reflecting the fact that a plant that does both activities has a higher future productivity trajectory, and is increasing in current productivity implying that a high productivity producer is more likely to self select into the export market. The benefit of exporting for a plant that did not invest in R&D, $MBE(\omega_t, d_{t-1} = 0)$, is reported in the last column and it also is positive and increasing in the level of current productivity. Interestingly, comparing the last two columns we see that $\Delta MBE(\omega_t) = MBE(\omega_t, d_{t-1} = 1) - MBE(\omega_t, d_{t-1} = 0) < 0$. The marginal benefit of exporting is greater for a plant that did not do their own R&D. This is the result of the negative coefficient on the parameter α_6 in the productivity evolution equation. The value of R&D is greatest for a plant that does not export because the marginal effect on future productivity will

[24] These are averages across values of the capital stock and export demand shock and use the dynamic parameter estimates from Model 2 in Table 5

be larger for this group. The magnitudes of $\Delta MBE(\omega_t)$ are very small, implying that the prior R&D experience has very little impact on the return to exporting. In particular, it is very small when compared with the difference in benefits across plants with low versus high levels of current productivity. Heterogeneity in current productivity will be a major factor distinguishing which plants participate in the export market and its effect will swamp differences due to past R&D experience.

The marginal benefits of exporting can be translated into probabilities of exporting by comparing them with the relevant cost faced by the plant: the sunk cost if the plant was not an exporter in the prior year ($e_{t-1} = 0$) and the fixed cost if it was ($e_{t-1} = 1$). As seen from the coefficients γ^F and γ^S in Table 5, the sunk cost distribution will have much more of the mass concentrated in high cost values, so, for the same marginal benefit, a plant will be more likely to remain in the export market than to enter the export market. The probabilities of exporting are reported in Table 9 for different combinations of productivity (the rows) and d_{t-1} for both nonexporters and exporters (columns 2-5). First, the export probabilities are always increasing in current productivity. The difference between a low and high productivity plant is substantial and this shows the importance of selection based on current productivity. Second, the probabilities are largest for past exporters ($e_{t-1} = 1$). For example, a plant with productivity level 0.49 and prior R&D investment, will have a .710 probability of remaining in the export market but only a .309 probability of entering. This is the effect of the sunk cost of entry and it can also be substantial for the intermediate range of plant productivity. Finally, the incremental effect of prior R&D on the probability of exporting is very small. The last two columns of the table report the effect of $\Delta MBE(\omega_t)$ on the probability of exporting. The slight differences in the marginal benefit of exporting observed in Table 8 translate into very small differences in the probability of exporting. The fact that $\Delta MBE(\omega_t) < 0$ implies that plants with prior R&D experience are less likely to export, holding their prior export status fixed.

A comparison of Tables 8 and 9 provides insight on the realized fixed and sunk costs of exporting. The value of MBE in Table 8 is the cost threshold for a plant to be an exporter. Plants with the relevant fixed or sunk cost less than this threshold will choose to export. The exporting probabilities in columns 2-5 of Table 9 show the proportion of plants that will have costs less than the threshold. For example, the MBE of a plant with $(\omega_t = 0.49, d_{t-1} = 1)$ is 31.3 million NT dollars and 71.0 percent of the prior period exporting plants will have a fixed cost less than this value and 30.9 percent of the prior period nonexporters will have a sunk cost less than this value and thus choose to export in the current year. For each combination of the state variables $(\omega_t, d_{t-1}, e_{t-1})$ we can calculate the mean fixed/sunk cost of the plants that choose to export as the truncated mean of an exponential distribution with location parameter given in Table 5 and truncation point given by MBE. These means are reported in the 2nd and 3rd columns of Table 10 for different values of ω.[25] For example, for the productivity level $\omega_t = 0.49$, the plants that choose to continue in the export market will have a mean fixed cost of 6.21 million NT dollars while the plants that choose to enter the export market will have a mean sunk cost of 12.32 million NT dollars. The sunk cost of entry is always larger than the fixed cost of maintaining an export market presence. The mean fixed and sunk cost of the exporters rises with the plant's productivity level since the return to exporting, MBE, rises with productivity. Thus plants facing higher cost levels will find it profitable to export when they have high productivity but not if they have low productivity. Alternatively, high productivity plants will find it profitable to make larger fixed or sunk cost outlays in order to export than their low productivity competitors.

Tables 11 and 12 conduct a similar analysis of the marginal benefit and probability of conducting R&D. Columns 2-5 of Table 11 report the values of $E_t V_{t+1}(\omega_t | e_{it}, d_{it})$ defined in equation 13. First, the future plant value is increasing in the level of productivity and the magnitudes vary substantially between low and high productivity plants. Second, for any value of ω, EV_{t+1} is greatest for plants that do both activities, followed by R&D plants, exporting plants, and plants that do neither activity. This reflects the difference in the parameters of the productivity process reported in Table 3 as well as the impact of sunk costs. The last two columns report the marginal benefit of R&D, MBR defined in equation 14, and recognize that this depends on the export decision. This increases with the level of productivity implying

[25] We report the values for plants that conducted R&D in the prior year, $d_{t-1} = 1$. The cost values for plants that did not conduct R&D are approximately .1 to .4 million NT dollars higher, reflecting the slightly higher value of MBE in Table 8 for these plants.

that high productivity plants will be more likely to self select into R&D investment. The interaction effect can be seen from the last two columns of the table: MBR is larger for the plants that do not export implying that $\Delta MBR < 0$. This occurs because of the negative value of α_6 which implies that the marginal impact of R&D on future productivity is greater for non-exporting plants. However the choice of exporting has relatively little impact on the magnitude of ΔMBR.

Table 12 reports the probability of undertaking R&D for different combinations of ω_t, e_t, and d_{t-1}. The probabilities increase with productivity for all combinations of e_t and d_{t-1}. Comparing columns 2 and 3 we observe that, for any level of productivity, the probability of R&D is always higher when $d_{t-1} = 1$. This reflect the fact that the sunk cost of starting the operation is more substantial than the fixed cost of maintaining it. The same pattern holds in columns 4 and 5. The incremental effect of exporting on the probability of conducting R&D is reported in the last two columns. The negative sign implies that exporting lowers the probability of conducting R&D. The magnitude of this interaction effect is small particularly compared with the differences in operabilities arising from heterogeneity in productivity and history of R&D investment.

The value of MBR in Table 11 provides the marginal benefit of conducting R&D which is also the threshold cost value for a plant to undertake R&D. Plants with sunk or fixed costs less than this threshold will choose to invest in R&D. As with exporting, we construct the mean value of the fixed and sunk cost of R&D for the set of plants that choose to invest. These means are reported in the last two columns of Table 10.[26] For example, for plants with productivity level $\omega_t = 0.49$ and $e_t = 1$, the value of conducting R&D is 34.3 million NT dollars, 32.9 percent of the plants that previously conducted R&D will have fixed costs less than this value, and the average realized R&D expenditure among this group is 12.8 million NT dollars. In addition, 7.5 percent of the plants that did not previously invest in R&D will choose to enter and the average sunk startup cost among this group is 15.64 million NT dollars. As we observed with exporting, the mean sunk startup costs for R&D are greater than the mean fixed

[26] We report the mean cost values for the plants that choose to export. The mean realized costs for plants that do not export will be slightly higher because of the higher value of *MBR* for these plants seen in Table 11. The differences in magnitude, however, are small and the patterns are identical to the ones we discuss in the text.

cost of continuing an R&D program. Comparing the two activities, the mean costs of R&D are greater than the mean costs of exporting at each productivity level, which contributes to the fact that R&D investment rates are lower than export rates. For plants with productivity above 0.32, this is reinforced by the fact that the marginal return to R&D is less than the marginal return to exporting, $MBR < MBE$, so that high productivity plants are more likely to export than invest in R&D. This is particularly true for high productivity plants that are entering the activity.

Overall, the results in Tables 8-12 show that there are three important determinants of the plant's decision regarding exporting and R&D investment. First, current productivity has a large positive impact on the return to both activities, particularly exporting. Self-selection based on the plant's productivity is a major reason a plant chooses to export or invest in R&D. It is further reinforced by the dynamic impact this choice has on the plant's future productivity. Second, the costs of exporting are less than the comparable costs of conducting R&D and this contributes to the fact that plants are more likely to export than invest in R&D. Third, a history of prior investment in the activity, so that fixed costs rather than sunk costs are the relevant cost comparison, leads to substantially higher participation rates. In contrast, one factor that does not have much impact is the interdependence of the two decisions. R&D investment has relatively little impact on the return to exporting and there is very little difference in the return to R&D between exporting and nonexporting plants.

5.5 Endogenous Productivity Evolution

One of the contributions of the model developed in this paper is that it treats productivity as endogenous, allowing its evolution to be affected by the plant's choice of both R&D and exporting. In this section we contrast the endogenous productivity path implied by the parameter estimates for equation 8 with two restrictive cases. The first removes the direct learning-by-exporting channel and only allows R&D to affect future productivity by restricting $\alpha_5 = \alpha_6 = 0$ in equation 8. This is the case modeled by Doraszelski and Jaumandreu (2007). The second special case occurs when productivity is unaffected by the firm's choices and only determined by past productivity and random shocks. This is the case of exogenous productivity evolution treated by Olley and Pakes (1996) and is modeled by restricting $\alpha_4 = \alpha_5 = \alpha_6 = 0$. In each case we use the model to calculate the optimal R&D and export decisions for a plant in each year given its state variables and cost shocks using the methodology summarized in section 5.3 above. We then examine differences in the use of R&D, exporting, and the mean productivity path across the three different environments.

The top panel of Table 13 compares the fully endogenous productivity process with the fully exogenous case. Over a 10 year horizon, when the plant is able to improve its future productivity by investing in R&D and exporting, the mean productivity rises by 22.0 percent relative to the purely exogenous environment. Over a 15 year horizon, the difference increases to 24.9 percent.[27] The source of the productivity increase is both the direct effect of R&D and exporting on productivity through equation 8 but also the increased use of these investments as a result. The second line of Table 13 shows that there is an enormous increase in the probability of exporting when productivity is endogenous. After 15 years, the probability a plant exports is 276.3 percent higher than when productivity is purely exogenous (i.e. an export probability of .342 versus .091). The higher probability of exporting reflects two forces: the direct effect of learning-by-exporting which raises the return to exporting and the fact that higher levels of future productivity induce more self-selection into the export market. While not reported in Table 13, the probability of R&D is much higher in the endogenous productivity environment. In the exogenous environment, a plant will never invest in R&D because there is no productivity effect and thus no return to the investment ($MBR = 0$). In the endogenous productivity environment, the probability of investing in R&D varies from .17 to .15 over time.

The bottom panel of Table 13 contrasts the exogenous productivity environment with an environment where R&D, but not exporting, affects future productivity. Here the productivity gain is more modest, 11.5 percent higher average productivity after 15 years. It is also the case that there is a much more modest increase in the probability of exporting, 47.8 percent after 15 years (i.e. an export probability of .134 versus .091). In this case the increase in the probability of exporting is driven by the fact that higher productivity results in more self-selection into the

[27]Notice that this gain is substantially less than the 123 percent long run productivity difference between a plant that always exports and invests in R&D and a plant that never does either. This latter difference is based solely on the technology while the differences reported here incorporate the fact that it is not optimal for the plant to always export or invest in R&D.

export market. Comparing the two cases reveals that a substantial part of the overall gain in the endogenous productivity case results from the impact of learning-by-exporting. Even though the direct effect of exporting on productivity is less than the direct effect of R&D, the fact that it is less expensive leads to a higher proportion of plants choosing this activity and the cumulative effect of this increased propensity to export on productivity is substantial.

6 Conclusions

This paper estimates a dynamic structural model that captures both the behavioral and technological linkages between R&D, exporting, and productivity. It characterizes a producer's joint dynamic decision process for exporting and R&D investment as depending on their productivity, export demand, plant size, prior export and R&D experience, and fixed and sunk costs of both activities. It also describes how a plant's R&D and exporting endogenously affect their future productivity trajectories. We estimate the model using plant-level data for the Taiwan electronics industry from the period 2000-2004.

There are six broad conclusions we draw about the sources of productivity evolution among Taiwan's electronics producers. First, plant productivity evolves endogenously in response to the plant's choice to export or invest in R&D. Relative to a plant that does neither activity, export market participation raises future productivity by 1.96 percent, R&D investment raises it by 4.79 percent and undertaking both activities raises it by 5.56 percent. Second, the marginal benefits of both exporting and R&D increase with the plant's productivity and high productivity plants have particularly large benefits from exporting. This leads to the self selection of high productivity plants into both activities. When combined with the fact that exporting and R&D investment then lead to endogenous productivity improvements, this further reinforces the importance of self selection based on current productivity as the major factor driving the decision to export and invest in R&D. Third, the sunk cost of beginning either activity is greater than the fixed cost of maintaining the activity. For a given productivity level, an existing exporter is much more likely to continue exporting than a nonexporter is to enter the market and the differences in the probability of exporting are often quite substantial between the two groups. The same is true of R&D investment. Fourth, the sunk and fixed costs of investing in R&D are greater than the sunk and fixed costs of exporting which results in a larger proportion of plants choosing to export than to conduct R&D. This occurs even though R&D has a larger direct effect on future productivity. Fifth, the results indicate that the interdependence of the two activities is not a very important factor in the plant's decisions. Investment in R&D has relatively little impact on the return to exporting and there is very little difference in the return to R&D between exporters and nonexporters. As a result, the fact that a plant exports, for example, has virtually no effect on its probability of investing in R&D. Finally, in model simulations, the endogenous choice of R&D and exporting generates average plant productivity that is 22.0 percent higher after 10 years than an environment where productivity evolution is not affected by plant investments.

Overall, the empirical findings emphasize the important role of underlying heterogeneity in productivity as the driving force determining which Taiwanese electronics plants choose to export and/or invest in R&D. This is further reinforced by the fact that these activities result in future productivity improvements. The framework used here can be extended in several ways. If more detailed data were available on the uses of R&D, particularly the distinction between R&D used to improve the efficiency of the production process versus develop new products or improve product quality, it would be possible to distinguish the return to each type of investment. In particular, whether one of the investment tools had a more substantial impact on the return in the export market. In addition, while we have focused attention on heterogeneity in productivity in this paper, we also find, like Das, Roberts, and Tybout (2007) find using Colombian manufacturing data, that plant-specific export market shocks also play an important role in the export decision. If more detailed data were available on the characteristics of the products it could be possible to augment this framework with a richer demand structure that would allow us to treat export market heterogeneity as resulting from the plant's R&D or product quality choices, rather than as an exogenous process.

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Table 1			
Domestic and Export Sales (millions of NT$)			
	Nonexporters	Exporters	
	Median Domestic Sales	Median Domestic Sales	Median Export Sales
2000	22.2	52.8	33.6
2002	17.0	36.4	32.5
2003	17.3	42.7	30.9
2004	17.8	38.6	30.7
	Average Domestic Sales	Average Domestic Sales	Average Export Sales
2000	69.5	390.0	586.0
2002	55.8	363.1	490.5
2003	57.2	385.9	576.3
2004	83.3	354.3	522.8

Table 2				
Annual Transition Rates for Continuing Plants				
	Status Year t+1			
Status year t	Neither	only R&D	only Export	Both
All Firms	.563	.036	.255	.146
Neither	.871	.014	.110	.005
only R&D	.372	.336	.058	.233
only Export	.213	.010	.708	.070
Both	.024	.062	.147	.767

Table 3
Demand, Cost and Productivity Evolution
Parameter Estimates (standard errors)

Parameter	Discrete R&D	Continuous R&D
$1+1/\eta_D$	.8432 (.0195)*	.8432 (.0195)*
$1+1/\eta_X$	.8361 (.0164)*	.8361 (.0164)*
β_k	-.0633 (.0052)*	-.0636 (.0051)*
α_0	.0879 (.0198)*	.0866 (.0194)*
α_1	.5925 (.0519)*	.5982 (.0511)*
α_2	.3791 (.0915)*	.3777 (.0912)*
α_3	-.1439 (.0585)*	-.1592 (.0588)*
α_4	.0479 (.0099)*	.0067 (.0012)*
α_5	.0196 (.0046)*	.0197 (.0045)*
α_6	-.0118 (.0115)	-.0022 (.0014)
$SE(\xi_{it})$	.1100	.1098
sample size	3703	3703

Table 4
Reduced Form Participation and Export Revenue Equations

Dependent Variable	Coeff on ω_{it}	Coeff on k_{it}	Coeff on e_{it-1}	Coeff on d_{it-1}	Other
Bivariate Probit					
Exporting e_{it}	1.63 (t=10.3)	.064 (t=3.38)	1.80 (t=32.1)	.186(t=2.26)	
R&D d_{it}	1.65 (t=7.12)	.205 (t=7.52)	.344 (t=4.38)	1.86(t=23.3)	$\rho = .168$
Export Revenue					
lnr_{it}^X	6.45 (t=36.1)	.409 (t=20.3)			
Export revenue with fixed effect (z)					
lnr_{it}^X	5.55 (t=18.0)	.430 (t=4.16)			$Var(z) = .72$

Table 5
Dynamic Parameter Estimates
Means and Standard Deviations of the Posterior Distribution

Model 1			Model 2		
Parameter	Mean	St. Dev.	Parameter	Mean	St. Dev.
γ^I (R&D FC)	67.606	3.930	γ_1^I (size 1)	46.265	7.038
			γ_2^I (size 2)	66.596	3.423
γ^D (R&D SC)	354.277	31.377	γ_1^D (size 1)	381.908	66.521
			γ_2^D (size 2)	388.715	41.959
γ^F (Export FC)	11.074	0.389	γ_1^F (size 1)	5.733	0.295
			γ_2^F (size 2)	15.962	0.704
γ^S (Export SC)	50.753	3.483	γ_1^S (size 1)	51.852	6.046
			γ_2^S (size 2)	67.401	6.676
Φ_X (Export Rev Intercept)	3.813	0.063	Φ_X	3.873	0.063
ρ_Z (Export Rev AR process)	0.773	0.014	ρ_Z	0.763	0.015
$\log \sigma_\mu$ (Export Rev Std Dev)	-0.287	0.018	$\log \sigma_\mu$	-0.289	0.021

Table 6
R&D Investment Rates, Export Rates, and Productivity

	Year 2002	Year 2003	Year 2004
Export Market Participation Rate			
Actual Data	.395	.392	.390
Predicted	.370	.371	.371
R&D Investment Rate			
Actual Data	.177	.170	.169
Predicted	.172	.168	.167
Average Productivity			
Actual Data	.436	.444	.436
Predicted	.449	.441	.432

Table 7
Predicted Transition Rates for Continuing Plants - Model 2

Status year t		Status Year t+1			
		Neither	only R&D	only Export	Both
Neither	Predicted	.866	.019	.110	.008
	Actual	.871	.014	.110	.005
only R&D	Predicted	.476	.214	.116	.193
	Actual	.372	.336	.058	.233
only Export	Predicted	.292	.010	.622	.077
	Actual	.213	.010	.708	.070
Both	Predicted	.049	.028	.138	.784
	Actual	.024	.062	.147	.767

Table 8
Marginal Benefit of Exporting (millions of NT dollars)

	V_t^E		V_t^D		$MBE = \pi_t^X + V_t^E - V_t^D$	
ω_t	$d_{t-1} = 1$	$d_{t-1} = 0$	$d_{t-1} = 1$	$d_{t-1} = 0$	$d_{t-1} = 1$	$d_{t-1} = 0$
-0.19	132.5	132.4	130.9	130.7	2.08	2.11
-0.02	138.9	138.5	136.3	135.9	3.69	3.76
0.15	151.8	150.9	147.3	146.3	7.06	7.21
0.32	179.4	176.3	170.9	167.4	14.7	15.2
0.49	245.3	235.6	228.9	217.7	31.3	32.9
0.67	392.6	365.3	362.9	331.9	65.3	69.1
0.84	714.0	655.9	667.0	599.1	132.3	142.1
1.01	1206.3	1117.4	1143.7	1041.5	266.8	280.1
1.18	1911.3	1790.0	1834.0	1695.3	565.7	583.2
1.35	2689.1	2568.8	2610.8	2471.7	1246.9	1265.7

Table 9

Export Policy Functions: $Pr(e_t = 1 | e_{t-1}, d_{t-1})$

ω_t	$e_{t-1} = 1$	$e_{t-1} = 0$	$e_{t-1} = 1$	$e_{t-1} = 0$	Effect of d_{t-1} when	
	$d_{t-1} = 1$	$d_{t-1} = 1$	$d_{t-1} = 0$	$d_{t-1} = 0$	$e_{t-1} = 1$	$e_{t-1} = 0$
-0.19	0.156	0.032	0.157	0.032	-0.001	-0.000
-0.02	0.246	0.055	0.248	0.056	-0.003	-0.001
0.15	0.365	0.098	0.369	0.099	-0.004	-0.002
0.32	0.518	0.178	0.523	0.181	-0.005	-0.003
0.49	0.710	0.309	0.718	0.317	-0.007	-0.008
0.67	0.895	0.485	0.907	0.503	-0.012	-0.018
0.84	0.969	0.653	0.980	0.693	-0.011	-0.039
1.01	0.988	0.749	0.994	0.785	-0.006	-0.036
1.18	0.997	0.835	0.999	0.873	-0.002	-0.038
1.35	0.997	0.874	0.999	0.901	-0.002	-0.028

Table 10

Costs of Exporting and R&D (millions of NT dollars)

	Mean Export Costs among Exporters[a]		Mean R&D Costs among Investors[b]	
ω_t	Fixed Cost	Sunk Cost	Fixed Cost	Sunk Cost
-0.19	0.97	1.036	1.32	1.34
-0.02	1.61	1.80	2.06	2.12
0.15	2.64	3.33	3.41	3.59
0.32	4.18	6.50	6.55	7.28
0.49	6.21	12.32	12.83	15.64
0.67	8.50	21.06	24.01	33.74
0.84	9.86	30.72	36.28	60.78
1.01	10.35	37.17	43.49	86.61
1.18	10.67	43.54	49.35	113.93
1.35	10.70	47.02	48.26	114.87

a. For plants with $d_{t-1} = 1$

b. For plants with $e_t = 1$

	Table 11					
	Marginal Benefit of R&D Investment (millions of NT dollars)					
	$EV_{t+1}(d_t = 1, e_t)$		$EV_{t+1}(d_t = 0, e_t)$		MBR	
ω_t	$e_t = 1$	$e_t = 0$	$e_t = 1$	$e_t = 0$	$e_t = 1$	$e_t = 0$
-0.19	142.2	140.7	139.3	137.6	2.8	3.2
-0.02	150.2	147.9	145.8	142.9	4.5	5.0
0.15	166.2	162.1	158.6	153.7	7.6	8.4
0.32	200.3	192.1	184.6	175.1	15.7	17.0
0.49	278.6	262.5	244.3	224.6	34.3	37.9
0.67	447.3	417.5	371.2	333.0	76.1	84.5
0.84	797.2	749.5	654.2	583.3	143.0	166.3
1.01	1320.2	1255.6	1105.7	1004.1	214.5	251.5
1.18	2065.7	1985.2	1773.5	1637.5	292.2	347.7
1.35	2883.8	2802.5	2575.2	2425.5	308.6	377.0

	Table 12					
	R&D Policy Functions: $Pr(d_t = 1 \mid e_t, d_{t-1})$					
ω_t	$e_t = 1$	$e_t = 1$	$e_t = 0$	$e_t = 0$	Effect of e_t when	
	$d_{t-1} = 1$	$d_{t-1} = 0$	$d_{t-1} = 1$	$d_{t-1} = 0$	$d_{t-1} = 1$	$d_{t-1} = 0$
-0.19	0.041	0.007	0.046	0.008	-0.005	-0.001
-0.02	0.063	0.011	0.070	0.012	-0.007	-0.001
0.15	0.101	0.018	0.109	0.020	-0.008	-0.002
0.32	0.182	0.036	0.192	0.039	-0.011	-0.003
0.49	0.329	0.075	0.347	0.082	-0.018	-0.007
0.67	0.566	0.155	0.590	0.169	-0.024	-0.013
0.84	0.777	0.265	0.812	0.296	-0.035	-0.031
1.01	0.872	0.360	0.899	0.399	-0.027	-0.039
1.18	0.940	0.455	0.959	0.504	-0.019	-0.049
1.35	0.928	0.451	0.951	0.505	-0.023	-0.054

Table 13
Productivity Evolution under Alternative Processes

Year	1	5	10	15
Fully Endogenous Productivity				
Relative Mean Productivity	3.6	14.5	22.0	24.9
Relative Prob of Exporting	69.2	172.8	238.9	276.3
R&D Endogenously Affects Productivity				
Relative Mean Productivity	1.9	8.4	11.2	11.5
Relative Prob of Exporting	4.8	27.0	43.7	47.8

All entries are percentage increases relative to the exogenous productivity process

7 Appendix

7.1 Computation of the Firm's Dynamic Problem

To evaluate each plant's conditional choice probabilities for exporting and R&D $P(e_{it}|z_{it}, k_i, \omega_{it}, \Phi, e_{it-1}, d_{it-1})$ and $P(d_{it}|z_{it}, k_i, \omega_{it}, \Phi, e_{it}, d_{it-1})$, we solve each plant's dynamic optimization problem. For a state vector $z, \omega, e_{-1}, d_{-1}, k, \Phi$ we utilize equations 10, 11, 12, and 13 to calculate the value functions using the following algorithm:

1. Begin with an initial guess of the value function $V^0(z, \omega, e_{-1}, d_{-1}, k, \Phi)$.

2. Calculate $EV^0 = \int_{z'} \int_{\omega'} V^0(z', \omega', e, k, \Phi) dF(\omega'|\omega, e, d) dF(z'|z)$, where $F(\omega'|\omega, e, d)$ is calculated using equation 8 and $F(z'|z)$ follows 9. Notice that EV^0 depends on e and d for two reasons: (1) both e and d affect future productivity, (2) entry into either activity involves a sunk cost.

3. Calculate V_t^{E0} and V_t^{D0} using equations 11 and 12. We can express them in analytical form depending on EV^0:

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

and

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

4. Finally, we can get the value function $V^1(z,\omega,e_{-1},d_{-1},k,\Phi)$ using equation 10 by:

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

5. Iterate across steps 2-4 until $|V^{j+1} - V^j| < \epsilon$.

Since the state space for our problem is very large, we adopt Rust's (1997) method to discretize the state space. We choose $N = 100$ low-discrepancy points for (ω, z). Denote the random grid points as $(\omega_1, z_1), ...(\omega_n, z_n), ...(\omega_N, z_N)$. The grid values for k are fixed with 8 categories. The firm's dynamic problem and value function $\hat{V}$ can be solved exactly on each grid point by the value function iteration method described in the previous section. For the data points that are not on the grid points, we can calculate EV using the discrete Markov operator given by:

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

where $p^N(z_n, \omega_n|z, \omega, e, d) = \frac{p(z_n|z)p(\omega_n|\omega,e,d)}{\sum_{n=1}^{N} p(z_n|z)p(\omega_n|\omega,e,d)}$. Then the calculations of V^E and V^D follow from steps 2-4 of the previous section.

7.2 Details of Bayesian MCMC Estimation

Define the set of dynamic parameters as: $\Theta = (\gamma^I, \gamma^D, \gamma^F, \gamma^S, \Phi^X, \rho_z, \sigma_\mu, \theta_0^e, \theta_0^d)$, where θ_0^e and θ_0^d are, respectively, the parameters for probit equations for the initial conditions of exporting and R&D. Using the model, the likelihood function defining the data set (D) as a function of the parameters $L(D|\Theta)$, and a set of prior distributions of Θ, the posterior distribution $P(\Theta|D)$ is well defined. We use MCMC techniques to calculate the moments of the posterior distribution. The details of our sampling algorithm follows the discussion and references in Das, Roberts, and Tybout (2007) closely. We adopt very diffuse priors for the parameters. The means of all fixed and sunk cost distributions are assumed to have priors that are N(0,1000). The prior for the export revenue intercept is N(0, 1000), for the autoregressive coefficient in the export demand shocks is U[-1,1], and log σ_μ is N(0,10) The means and standard deviations of the posterior distribution are reported in Table 5.