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R&D Dynamics and Its Impact on Productivity and Export Demand in Swedish Manufacturing

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Preliminary and Incomplete

1 Introduction

In today's global economy, the need for firms to innovate in order to remain competitive in export markets has become increasingly important for many countries and industries. Investments in R&D that can generate new product or process innovations are one important way through which firms improve their competitive position in world markets. R&D investment is particularly important in developed countries that are trying to maintain a technological advantage for their products over lower-cost manufacturers from Asia. Sweden is an excellent example of a country that both invests heavily in R&D, it is one of the top EU countries in R&D expenditures, and is heavily dependent on export markets for sales of its technologically-advanced products.

Firm R&D investment can have different impacts on firm's profitability depending on the characteristics of the firm. One dimension that has been emphasized in the literature is that firms operating in international markets may have more opportunities to exploit innovations developed from their R&D efforts. Grossman and Helpman (1993) develop models that incorporate a larger return to R&D investment by exporting firms as a result of the larger set of opportunities they face in international markets.

In this article we develop a structural empirical model that allows us to estimate the impact of R&D on firm profitability through two channels. In the first channel, R&D investment by the firm can impact the firm's production efficiency and lower its marginal cost. This productivity channel raises the firm's sales and profits in both the domestic and export market. The second channel is specific to exporting firms where R&D acts to increase the demand for the firm's products in foreign markets. Both of these channels can be in operation and, if important, will both contribute to the return the firm earns on its R&D investment. If both channels are important, this leads to differences in the return to R&D, and thus to differences in the incentives to invest in R&D, between non-exporting and exporting firms.

Using micro data for Swedish manufacturing firms from 2000-2010 we estimate the impact of R&D investment on the unobserved component of the firm's productivity and export market demand. The empirical model builds on the exogenous stochastic productivity framework developed by Olley and Pakes (1995) and extended to endogenous productivity evolution by

Aw, Roberts, and Xu (2011) and Doraszelski and Jaumandreu (2013). In our model, the firm's R&D investment can alter the path of future productivity and future export demand in different ways. Following the stochastic production literature, we use proxy variables to uncover the underlying firm variables and estimate their pattern of persistence. We extend this literature to include two unobserved variables and show how both can be uncovered using two proxy variables. One of the variables contains information on the firm's unobserved productivity while the second contains information on the firm's unobserved export demand shock.

Our empirical results show that firm R&D investment has a statistically significant, positive effect on both the future productivity and the future export demand of the firm. The impact of R&D investments depends on firm productivity and the demand shock levels. For high-tech industries, we find that the impact of R&D investments on the demand shocks is twice as large as its impact on productivity. On the other hand, the impact of R&D investments on productivity in the low-tech industries is higher than on demand shocks.

The results from the estimation of the developed dynamic structural model of the firm's demand for R&D are used to understand the observed heterogeneity in R&D levels within an industry and to measure the expected long-run benefits of R&D investments. Peters, Roberts, Vuong, and Fryges (forthcoming) develop a dynamic model of R&D demand that provides a measure of the long-run expected benefit of R&D for an investing firm. This benefit is the difference in the expected future value of the firm between a firm that invests in R&D and one that does not. The magnitude of the expected future benefit depends upon how R&D impacts the future path of firm productivity and export demand, exactly the mechanisms we estimate in this paper. The main advantage of our dynamic model over the existing empirical work that measures the linkages between R&D and firm productivity, is that it more fully specifies the model of firm R&D investment.¹ The novel aspect of our application is that, since we find that R&D has a different impact on the evolution of productivity and export demand, the expected return to R&D, and thus the incentive to invest, are likely to differ between Swedish firms that choose to export and those that do not.

¹Most of the empirical literature follows the knowledge production function framework developed by Griliches (1979). Crepon, Duguet, and Mairesse (1998) extend this to an empirical framework that could utilize firm-level information on R&D investment, innovations, and productivity or profits. A recent survey of the empirical studies using the knowledge production model is provided in Hall, Mairesse, and Mohnen (2010).

In the remaining sections we summarize the data sources for Swedish manufacturing firms, develop the econometric model characterizing the evolution of productivity and export demand, and provide parameter estimates for the effect of R&D on these processes for firms in high-tech and low-tech industries in Swedish manufacturing.

2 A Model of the Firm's Investment in R&D

In this section we develop a model of the firm's choice of R&D investment. The first part of the model characterizes a set of period-by-period decisions by the firm including the number of export destinations and its optimal domestic and export price. This allows us to derive the firm's revenue function in the domestic and export market and its profit function. The key state variables in the short run are a measure of the firm's revenue productivity in the domestic and export market. The second part of the model develops the firm's decision rule for R&D investment where the key mechanism is that, through its choice of R&D, the firm can affect the evolution of its domestic and foreign productivity and thus future profits.

2.1 Domestic Revenue, Export Revenue, and Short-Run Profits

The framework begins with a definition of firm productivity. The short-run marginal cost function for firm j is

$$\ln c_{jt} = \beta_0 + \beta_k \ln k_{jt} + \beta_w \ln w_t - \omega_{jt},$$

where k_{jt} is firm capital stock and w_t are the prices of variable inputs which are assumed to be equal across all firms. The firm's production efficiency is denoted by ω_{jt} and is assumed to be known by the firm but not observed by the researcher.

The demand curve for the firm j in the domestic market is given by

$$q_{jt}^d = \Phi_t^d (p_{jt}^d)^{\eta_d}, \tag{1}$$

where Φ_t^d is the industry aggregates, p_{jt}^d is the price for firm j 's product on the domestic market; η_d denotes the constant elasticity of demand.

Each firm also faces a demand for its output in world markets. We treat the firm as facing an identical CES demand curve in each foreign market. If the firm sells in z_{jt} different foreign

markets, then the total demand for the firms output in foreign markets is:

$$q_{jt}^f = \Phi_t^f (p_{jt}^f)^{\eta_f} \exp(\mu_{jt}) (z_{jt})^{\beta_z} \quad (2)$$

where Φ_t^f is the aggregate component of demand in the export market; p_{jt}^f denotes the price in each destination market; η_f is the constant elasticity of demand; and μ_{jt} is a firm-specific export demand shifter. The term μ_{jt} captures differences in the demand for the firm's output in each foreign market and this is observed by the firm but not by the researcher. This assumes that the total foreign demand curve faced by the firm is the per destination demand multiplied by $(z_{jt})^{\beta_z}$. If $\beta_z = 1$ then total foreign demand faced by the firm is just the per-destination demand multiplied by the number of destinations. If $\beta_z > 1$ then total demand will increase more than proportionately as the number of markets expands. This abstracts from virtually all differences in demand across destination but allows us to represent the firm's total export demand as a function of a firm-specific demand component μ_{jt} and the number of destinations the firm exports to z_{jt} , which are the key variables we will use in the dynamic R&D model.

We represent the cost of serving z foreign markets to the firm as $c_{jt}^z z_{jt}^2$. This allows the marginal cost of adding a new destination to be increasing in the number of already served destinations. Given knowledge of μ_{jt} , ω_{jt} , c_{jt}^z , and c_{jt} , firm j chooses its domestic output price, foreign price, and number of destinations, assuming it exports, to maximize short-run profits. We can then express the firm's revenue in the domestic market as:

$$\ln r_{jt}^d = \beta_0^d + \tilde{\Phi}_t^d + (\eta_d + 1)(\beta_k \ln k_{jt} - \omega_{jt}) + \varepsilon_{jt}^d \quad (3)$$

where $\beta_0^d = (\eta_d + 1) \left[\ln \left(\frac{\eta_d}{1 + \eta_d} \right) + \beta_0 \right]$ captures all constant terms and $\tilde{\Phi}_t^d = \ln \Phi_t^d + (1 + \eta_d) \beta_w \ln w_t$ incorporates all time-varying demand and cost factors that are common across firms. The error term ε_{jt}^d captures transitory shocks to domestic revenue that are unknown to the firm when it chooses prices and destination markets. The term ω is the firm's domestic revenue productivity and, using data on the domestic sales of the firm, will be an important factor to estimate in the empirical model.

We can also express the firm's export market revenue for firms that choose to export as:

$$\ln r_{jt}^f = \beta_0^f + \tilde{\Phi}_t^f + (\eta_f + 1)(\beta_k \ln k_{jt} - \omega_{jt}) + \beta_z \ln(z_{jt}) + \mu_{jt} + \varepsilon_{jt}^f \quad (4)$$

where $\beta_0^f = (\eta_f + 1) \left[\ln \left(\frac{\eta_f}{1 + \eta_f} \right) + \beta_0 \right]$ and $\tilde{\Phi}_t^f = \ln \Phi_t^f + (1 + \eta_f) \beta_w \ln w_t$. The error term ε_{jt}^f captures transitory shocks to export revenue that are unknown to the firm when it makes its pricing and destination decisions. In this equation, the number of destination markets z_{jt} and the foreign demand shock μ_{jt} enters as well as the productivity shock ω_{jt} . An important part of the empirical model will be to use data from firm export sales to estimate μ_{jt} .

Based on the above assumptions, we can express the firm j 's short-run profits in the domestic and export markets as fractions of their sales in each market. Specifically, the gross profits in each market are:

$$\begin{aligned} \pi_{jt}^d &= -\frac{1}{\eta_d} r_{jt}^d(\tilde{\Phi}_t^d, k_{jt}, \omega_{jt}) \\ \pi_{jt}^f &= -\frac{1}{\eta_f} r_{jt}^f(\tilde{\Phi}_t^f, k_{jt}, \omega_{jt}, \mu_{jt}), \end{aligned} \quad (5)$$

where domestic and export profits are a fraction of the respective revenue. In the case of exporting firms the net profits will take into account the cost of supplying z markets. Net profits in the export market are $\pi_{jt}^f - c_{jt}^z z_{jt}^2$. Domestic and export profits as a function of ω and μ will be important factors in explaining a firm's export participation and R&D expenditures.

We can derive the condition for the firm to export. Given that $z_{jt}^*(\tilde{\Phi}_t^f, k_{jt}, \omega_{jt}, \mu_{jt})$ is the profit-maximizing number of export destinations if the firm chooses to export, they will export as long as the net profit from exporting to z^* destinations is greater than zero. We treat the per-market export cost as stochastic, hence the probability the firm exports as a function of the state variables is:

$$P_{jt}^f = \Pr(z_{jt}^* > 0) = \Pr(\pi_{jt}^f > c_{jt}^z z_{jt}^2) \quad (6)$$

The expected short-run profits of the firm, before the realization of the export cost, are the sum of the domestic market profits and the expected export profits:

$$\pi(\omega_{jt}, \mu_{jt}) = \pi^d(\tilde{\Phi}_t^d, k_{jt}, \omega_{jt}) + P_{jt}^f [\pi^f(\tilde{\Phi}_t^f, k_{jt}, \omega_{jt}, \mu_{jt}) - E(c_{jt}^z z_{jt}^2 | \pi_{jt}^f > c_{jt}^z z_{jt}^2)]. \quad (7)$$

The last term is the expected firm export cost to z markets conditional on choosing to export. The short-run expected profits of the firm are determined by their capital stock, market level factors in both the domestic and export market, the cost of adding an additional export destination, and the firm-specific productivities ω_{jt} and μ_{jt} . To simplify the discussion of the dynamic model in the next section, we have written profits as just a function of ω_{jt} and μ_{jt} .

since these are the state variables that will be affected by the firm's R&D decision. In the empirical model we will control for the firm's capital stock and market-level factors.

2.2 The Role of R&D

The two key factors that capture heterogeneity in the firm's production costs and export demand are ω_{jt} and μ_{jt} . We treat these two firm shocks as factors that evolve stochastically over time but that the firm can affect through its investment in research and development. We model the evolution of the firm's revenue productivity as:

$$\omega_{jt} = g_{\omega}(\omega_{jt-1}, rd_{jt-1}) + \xi_{jt}, \quad (8)$$

where ξ_{jt} are *iid* productivity shocks between $t - 1$ and t with $\mathbb{E}[\xi_{jt}] = 0$ and $Var[\xi_{jt}] = \sigma_{\xi}^2$. rd_{jt-1} is the log of the firm's prior period investment in R&D. This specification captures the fact that revenue productivity is persistent over time, that R&D investment shift the path of future productivity, and there is a stochastic component to the evolution of productivity. The productivity shocks ξ_{jt} are assumed to be unanticipated by the firm when they make input-output or R&D investment decisions, so that ξ_{jt} is not correlated with ω_{jt-1} or rd_{jt-1} . This stochastic productivity framework captures the effect of R&D investment and unanticipated productivity shocks in the firm's productivity level, which then carries over into the firm's productivity in future periods. In this way we capture the cumulative effect of R&D investment on the evolution of firm productivity.

Similarly, we recognize that the firm's export demand shock may also be affected by the firm's investment in R&D. For example, R&D that is designed to develop new products can result in an increased demand for the firm's exports over time. The demand shocks in the export market are modeled as:

$$\mu_{jt} = g_{\mu}(\mu_{jt-1}, rd_{jt-1}) + v_{jt} \quad (9)$$

where the shocks v_{jt} are i.i.d. with $E[v_{jt}] = 0$ and $Var[v_{jt}] = \sigma_v^2$. As with the process for revenue productivity, equation (8), there is both persistence in the demand shock, captured by the presence of lagged μ , but the firm is able to shift the demand process through investments in R&D.

The presence of both an unobserved productivity and export demand shock that are affected by the firm's investment in R&D generalize the stochastic productivity models that have been used in the literature. Olley and Pakes (1996) developed the general model of stochastic productivity but their firms operate in a single market and productivity evolves exogenously so that $\omega_{jt} = g_{\omega}(\omega_{jt-1}) + \xi_{jt}$. This assumption has been the basis for a large empirical literature estimating firm productivity. Doraszelski and Jaumandreu (2013) extend the Olley and Pakes framework to allow productivity to evolve endogenously with investments in R&D. They also have a single market and model productivity evolution as in equation (8) where rd is the firm's expenditure on R&D. Peters, Roberts, Vuong, and Fryges (forthcoming) model revenue productivity as evolving endogenously with realizations of product and process innovations by the firm: $\omega_{jt} = g_{\omega}(\omega_{jt-1}, d_{jt}, x_{jt}) + \xi_{jt}$ where d and x are discrete indicators of whether the firm reported a product or process innovation, respectively. In their framework, firm R&D investment affects the probability the firm realizes each kind of innovation. Aw, Roberts, and Xu (2011) extend the stochastic productivity framework to an interrelated export and domestic market. They model productivity evolution as affected by the firm's discrete investment in R&D and discrete participation in the export market: $\omega_{jt} = g_{\omega}(\omega_{jt-1}, rd_{jt-1}, e_{jt-1}) + \xi_{jt}$ where e_{jt-1} is a measure of the firm's prior export market experience, which captures the possibility of learning-by-exporting. They model the evolution of the export demand shock as an exogenous Markov process: $\mu_{jt} = g_{\mu}(\mu_{jt-1}) + v_{jt}$.

The framework developed here, in which there are two underlying sources of persistent heterogeneity and each can be affected by the firm's investment in R&D, has not been previously estimated in the literature. It is a useful approach to modeling the role of R&D in affecting both the production costs of Swedish manufacturers, which affects their size in both the domestic and export market, as well as their demand in foreign markets. If R&D works primarily by increasing the attractiveness of Swedish firms' products in foreign markets, R&D investment can induce new firms to enter the export market but can also lead to differences in the profitability path between exporting firms and those that focus solely on the domestic market.

2.3 Dynamic R&D Investments

In this section we model the firm's dynamic decision to invest in R&D. The cost of investing in R&D is modeled as the sum of a variable cost, which depends on the level of R&D chosen, and a fixed cost which will differ between firms that have prior R&D experience and firms that are just beginning to invest. Let $I(rd_{jt-1})$ be the discrete indicator equal to one if the firm invested in R&D in year $t - 1$, then the cost of R&D can be expressed as:

$$C(rd_{jt}, I(rd_{jt-1})) = VC(rd_{jt}) + FC(I(rd_{jt-1})). \quad (10)$$

The fixed cost will be treated as containing a stochastic component, which the firm observes prior to making its R&D decision, but which is not observed by the researcher. This makes the firm's past R&D participation a state variable in the dynamic model.

Given this setup, the firm's value function can be expressed as:

$$V(\omega_{jt}, \mu_{jt}, I(rd_{jt-1})) = \pi(\omega_{jt}, \mu_{jt}) + \max\{\beta V^0(\omega_{jt+1}, \mu_{jt+1}), \quad (11)$$

$$\max_{rd > 0} [\beta V^1(\omega_{jt+1}, \mu_{jt+1}) - C(rd_{jt}, I(rd_{jt-1}))]\} \quad (12)$$

where $V^0(\omega_{jt}, \mu_{jt})$ and $V^1(\omega_{jt}, \mu_{jt})$ are the expected future value of the firm if they choose to not invest in R&D or invest in R&D, respectively. They are defined as

$$V^0(\omega_{jt+1}, \mu_{jt+1}) = \int_{\xi} \int_v V(g^{\omega}(\omega, \xi), g^{\mu}(\mu, v) | rd_{jt} = 0) d\xi dv \quad (13)$$

and

$$V^1(\omega_{jt+1}, \mu_{jt+1}) = \int_{\xi} \int_v V(g^{\omega}(\omega, rd, \xi), g^{\mu}(\mu, rd, v)) d\xi dv \quad (14)$$

The firm that does not invest in R&D has its subsequent period value of ω and μ determined solely by the persistence in the Markov process and the random shocks ξ and v . The firm that invests in R&D at the optimal, positive level, has its future value also affected by the shift in the ω and μ process that result from R&D investment.

3 Estimation

3.1 Estimating the Evolution of Productivity and Demand

The goal of the empirical model is to estimate the parameters of the revenue functions, equations (3) and (4), the parameters of the productivity and demand processes, equations (8) and (9), and construct estimates of firm revenue productivity ω_{jt} and export demand μ_{jt} . To do this we rely on insights from the stochastic productivity literature as originally developed by Olley and Pakes (1996) and summarized in Akerberg, Benkard, Berry, and Pakes (2007) but extended to the case of two unobserved firm-level shocks.

In the case of the domestic revenue function, the firm's choice of variable inputs including materials will be determined by the state variables in the firm's environment. These are the firm's capital stock, revenue productivity, and export market demand shock. Focusing on the firm's choice of materials we can write the factor demand function as

$$m_{jt} = m(k_{jt}, \omega_{jt}, \mu_{jt}). \quad (15)$$

In particular, it will vary across firms with differences in the underlying productivity and export demand shocks.

In addition to the short-run decision on material usage, the model developed in the last section also provides a first-order condition for the optimal number of destination markets the firms will export to. This leads to a second policy function giving the number of destination markets, z_{jt} , as a function of the same state variables:

$$z_{jt} = z(k_{jt}, \omega_{jt}, \mu_{jt}). \quad (16)$$

The variable z_{jt} provides information about the destination networks of the exporters. It does not only measure pure demand shocks, it also provides information about exporter efficiency in expanding its network of countries. The dynamic problem gives a policy function for the number of destinations z as a function of the state variables. At the beginning of the period, each exporting firm observes their realizations of productivity ω_{jt} and export shock μ_{jt} and makes a decision related to their export destinations, $z_{jt} = z_t(k_{jt}, \omega_{jt}, \mu_{jt})$. Therefore, the innovation in the demand shocks v_{jt} are correlated with z_{jt} . Under certain regularity conditions

(monotonicity and supermodularity) (Pakes, 1994) the two policy functions can be inverted to express the unobserved productivity and demand factors as functions of the observable capital stock, material usage, and number of export destinations:²

$$\begin{aligned}\omega_{jt} &= m^{-1}(k_{jt}, m_{jt}, z_{jt}) \\ \mu_{jt} &= z^{-1}(k_{jt}, m_{jt}, z_{jt})\end{aligned}\tag{17}$$

Substituting the expressions in equation (17) into the domestic and export revenue functions allows us to express sales in each market as a function of observable variables. Replacing ω in the domestic revenue function with a general function of k, m , and z and adding a transitory error u_{jt}^d gives:

$$\begin{aligned}\ln r_{jt}^d &= (\eta_d + 1) \left(\beta_0 + \ln \frac{\eta_d}{1 + \eta_d} \right) + \ln \tilde{\Phi}_t^d \\ &\quad + (\eta_d + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt}, m_{jt}, z_{jt})) + u_{jt}^d \\ &= \gamma_0 + \sum \gamma_t + h(k_{jt}, m_{jt}, z_{jt}) + u_{jt}^d\end{aligned}\tag{18}$$

where the function $h(k_{jt}, m_{jt}, z_{jt}) = (\eta_d + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt}, m_{jt}, z_{jt}))$.

Using equation (17) to substitute for both ω and μ in the export revenue function, we can express this in terms of the observable variables:

$$\begin{aligned}\ln r_{jt}^f &= (\eta_f + 1) \left(\beta_0 + \ln \frac{\eta_f}{1 + \eta_f} \right) + \ln \tilde{\Phi}_t^f \\ &\quad + (\eta_f + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt}, m_{jt}, z_{jt})) + \beta_z \ln z_{jt} + \mu_{jt}(k_{jt}, m_{jt}, z_{jt}) + u_{jt}^f \\ &= \rho_0 + \sum \rho_t + b(k_{jt}, m_{jt}, z_{jt}) + u_{jt}^f\end{aligned}\tag{19}$$

where the function $b(k_{jt}, m_{jt}, z_{jt}) = (\eta_f + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt}, m_{jt}, z_{jt})) + \beta_z \ln z_{jt} + \mu_{jt}(k_{jt}, m_{jt}, z_{jt})$ which includes the effects of capital, productivity, and the export demand shifters on export revenue. By treating $h(k_{jt}, m_{jt}, z_{jt})$ and $b(k_{jt}, m_{jt}, z_{jt})$ as polynomial functions of their arguments, we can estimate equations (18) and (19) using ordinary least squares.

Using estimates of \hat{h} and \hat{b} we can express the unobserved productivity and demand shock as functions of these fitted values and the unknown parameters η_d, η_f, β_k and β_z

²See also Maican (2014) for a detailed discussion of the properties of policy functions in complex dynamic programming problems with endogenous states.

$$\begin{aligned}
\omega_{jt} &= -\frac{1}{(\eta_d + 1)}\hat{h} + \beta_k \ln k_{jt} \\
\mu_{jt} &= \hat{b} - (\eta_f + 1)(\beta_k \ln k_{jt} - \omega_{jt}) - \beta_z \ln z_{jt} \\
&= \hat{b} - \frac{(\eta_f + 1)}{(\eta_d + 1)}\hat{h} - \beta_z \ln z_{jt}
\end{aligned} \tag{20}$$

The demand elasticities η_d and η_f are estimated from the static demand and cost model using the data on total variable cost (tvc). Because 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 fact that marginal cost is equal to marginal revenue in each market, the first-order condition for profit maximization implies that, tvc is an elasticity-weighted combination of total revenue in each market:

$$tvc_{jt} = q_{jt}^d c_{jt} + q_{jt}^f c_{jt} = r_{jt}^d \left(1 + \frac{1}{\eta_d}\right) + r_{jt}^f \left(1 + \frac{1}{\eta_f}\right) + u_{jt}, \tag{21}$$

where the error term u_{jt} is the measurement error in total cost. Substituting the estimates for demand elasticities into equations (20) leaves only the parameters β_k and β_z as unknowns in those equations.

Using only the firms that export to recover the export shocks μ , induces a selection effect that affects the identification of β_k . To control for selection, we estimate the probability of exporting, i.e., $P_{jt}^f = \lambda(m_{jt-1}, k_{jt-1}, z_{jt-1})$, where the nonparametric function $\lambda(\cdot)$ is approximated by a polynomial series of order 2 in its arguments. The estimation of this equation gives the predicted probabilities to export, \hat{P}_{jt-1}^f . Notice that this estimate of the probability of exporting does not take full advantage of the structure of the export decision outlined in section XX, but rather is a reduced-form approximation that controls for the endogenous choice of exporting when estimating the process for the export shocks μ .

The Markov process for the export shocks, equation (9) will now include the probability of exporting as an additional control:

$$\mu_{jt} = g_\mu(\mu_{jt-1}, rd_{jt-1}, \hat{P}_{jt-1}^f) + v_{jt} \tag{22}$$

The nonparametric functions $g_\omega(\cdot)$ and $g_\mu(\cdot)$ can be approximated using a 3rd order polynomial

series:

$$\omega_{jt} = \alpha_0 + \alpha_1\omega_{jt-1} + \alpha_2\omega_{jt-1}^2 + \alpha_3\omega_{jt-1}^3 + \alpha_4rd_{jt-1} + \alpha_5(\omega_{jt-1} * rd_{jt-1}) + \xi_{jt} \quad (23)$$

$$\mu_{jt} = \delta_0 + \delta_1\mu_{jt-1} + \delta_2\mu_{jt-1}^2 + \delta_3\mu_{jt-1}^3 + \delta_4rd_{jt-1} + \delta_5(\mu_{jt-1} * rd_{jt-1}) + \delta_6\hat{P}_{jt-1} + \delta_7\hat{P}_{jt-1}^2 + \delta_8\hat{P}_{jt-1}^3 + v_{jt} \quad (24)$$

Substituting equations (20) into (23) and (24) allows them to be written in terms of observables $\hat{b}_{jt}, \hat{h}_{jt}, \hat{\eta}_f, \hat{\eta}_d, k_{jt}, k_{jt-1}, \hat{P}_{jt-1}^f$, and rd_{jt-1} . The structural parameters β_k, β_z are estimated using moment conditions that rely on the orthogonality of the errors in the process for productivity and demand evolution ξ_{jt} and v_{jt} and the observable variables $k_{jt-1}, k_{jt}, z_{jt-1}$. Specifically, the moment conditions $E[\xi_{jt}|k_{jt-1}] = 0$, $E[v_{jt}|k_{jt-1}] = 0$, $E[\xi_{jt}|k_{jt}] = 0$, $E[v_{jt}|k_{jt}] = 0$ identify β_k . In this way, we use the information from both the domestic and foreign markets to estimate β_k . The moment $E[v_{jt}|z_{jt-1}] = 0$ identifies β_z .³ The α and δ coefficients in the evolution processes are identified from moment conditions that specify that the errors in equations (23) and (24) are uncorrelated with all the right-hand side variables.⁴ Once the structural parameters have been estimated, the state variable ω_{jt} can be constructed for all observations and μ_{jt} can be constructed for all exporting observations from equation (20). To construct μ_{jt} for nonexporting observations, we use the material demand, equation (15). Solving for μ_{jt} expresses it as a function of m_{jt}, k_{jt} , and ω_{jt} . This is estimated with a polynomial approximation using the firms that export. We then impute μ for each nonexporter given their observed values of m_{jt}, k_{jt} , and ω_{jt} .

3.2 Specifying the R&D and Export Cost Function

In the dynamic part of the model we estimate the cost function for R&D, equation (10). We specify this using a parametric form for the variable cost function and a stochastic specification

³The moment $E[\xi_{jt}|z_{jt-1}] = 0$ can also be used but is unlikely to be informative because z does not enter the domestic revenue equation. The empirical results were not affected by including it.

⁴There are two important points about the estimation. First, it is important to note that we cannot use nonlinear least squares, like Aw et al. (2011) and Peters et al. (forthcoming), because we have to use the information from both the domestic and export market and the observed export variables z_{jt} is endogenous (i.e. $cov(v_{jt}, z_{jt}) \neq 0$). Second, estimating (β, α, δ) together (13 parameters) or sequentially (2 parameters, i.e., for a given β_k get (α, δ) by OLS until GMM's objective function reaches the global minimum) using GMM produce similar results because we use the same information (moments) in the estimation (Pagan, 1986). The sequential procedure is much faster since we optimize the nonlinear objective function over only two parameters. This is preferable given optimization errors when there is a large state space.

for the fixed cost.

$$VC(rd_{jt}) = rd_{jt} + \theta rd_{jt}^2 \quad (25)$$

This specification recognizes that the actual expenditure on R&D is the major part of the variable cost but the quadratic term is included to recognize that the variable costs also include adjustment costs and unobserved inputs such as the capital used in the R&D process. The stochastic fixed cost is specified as a draw from an exponential distribution where the mean of the distribution depends on the firm's prior period R&D choice:

$$FC(I(rd_{jt-1})) \sim \exp(\gamma^m I(rd_{jt-1}) + \gamma^s (1 - I(rd_{jt-1}))) \quad (26)$$

The parameter γ^m is interpreted as the mean fixed cost for firms that are maintaining an ongoing R&D investment and γ^s is the mean fixed cost for firms that are just starting to invest in R&D.

We also estimate the cost to the firm of exporting to an additional destination. This cost is assumed to be firm-time specific and is modeled as a draw from an exponential distribution with mean parameter γ^f : $c_{jt}^z \sim \exp(\gamma^f)$. Given the specification of the export decision in section XX, we can then express the probability of exporting, equation (6) as:

$$P_{jt}^f = 1 - \exp(-(\pi_{jt}^f / z_{jt}^2) / \gamma^f) \quad (27)$$

and the mean export cost, conditional on exporting, as

$$E(c_{jt}^z z_{jt}^2 | \pi_{jt}^f > c_{jt}^z z_{jt}^2) = \gamma - \pi_{jt}^f / z_{jt}^2 [(1 - P_{jt}^f) / P_{jt}^f] \quad (28)$$

These two equations can be substituted into the firm's short-run profit function, equation (7) to complete the specification of the model parameters.

Overall, the parameters for the R&D costs distribution θ, γ^m , and γ^s , and the export cost distribution γ^f are estimated in the dynamic part of the model.

3.3 Computing the Value Function and R&D Policy Function

To estimate the dynamic parameters for R&D and export costs, we must calculate the value function for each firm at a given value for the dynamic parameters. We use Chebyshev basis

functions to approximate the value functions $V^0(g^\omega(\omega, \xi), g^\mu(\mu, v))$ and $V^1(g^\omega(\omega, rd, \xi), g^\mu(\mu, rd, v))$. Specifically, we approximate the two value functions as:

$$\begin{aligned} V^1(g^\omega(\omega, rd, \xi), g^\mu(\mu, rd, v)) &\approx \Phi(g^\omega(\omega, rd, \xi), g^\mu(\mu, rd, v))\mathbf{c}_1 \\ V^0(g^\omega(\omega, \xi), g^\mu(\mu, v), k) &\approx \Phi(g^\omega(\omega, \xi), g^\mu(\mu, v), k)\mathbf{c}_0 \end{aligned}$$

where \mathbf{c}_0 and \mathbf{c}_1 are vectors of approximation parameters that differ for firms that do and do not choose to do R&D. The functions $\Phi(g^\omega, g^\mu)$ are the Chebyshev basis functions and are the same in both cases. The left hand side of the value function equation (11) can be approximated as either V^0 or V^1 depending on the firms past R&D:

$$V(\omega_{jt}, \mu_{jt}, I(rd_{jt-1})) = (1 - I(rd_{jt-1}))\Phi(\omega_{jt}, \mu_{jt})\mathbf{c}_0 + I(rd_{jt-1})\Phi(\omega_{jt}, \mu_{jt})\mathbf{c}_1 \quad (29)$$

This equation denotes that the value function for the state $(\omega_{jt}, \mu_{jt}, k_{jt})$ is either $\Phi(\omega_{jt}, \mu_{jt})\mathbf{c}_0$ or $\Phi(\omega_{jt}, \mu_{jt})\mathbf{c}_1$ depending on the state variable $I(rd_{jt-1})$. The value function approximation parameters \mathbf{c}_0 and \mathbf{c}_1 are found by solving equation (11) for optimal R&D choices in all states. (Need to say something about the size of the set of nodes/basis functions. Need to say that we do this separately for each industry and each capital stock which is defined on a grid).

3.4 Estimating the Dynamic Parameters

We use indirect inference criterion function to estimate the model with static export decision using the following R&D variable cost function (Li (2010), Gourieroux, Monfort, and Renault (1993), and Gourieroux and Monfort (1996)). The estimator matches regression coefficients of the policy functions from the data, denoted $\bar{\boldsymbol{\delta}}$, with the regression coefficients of the policy functions obtained from the dynamic model $\tilde{\boldsymbol{\delta}}(\boldsymbol{\theta})$, which are conditional of the R&D and export costs parameters $\boldsymbol{\theta}$.

To identify the dynamic parameters we use data on the discrete R&D decision over all firms, the observed level of R&D for firms with positive R&D expenditure, and the discrete export decision over all firms. In each case we summarize the data and model predictions with linear functions of parameters.

To estimate the maintenance and startup costs γ^m and γ^s we estimate the discrete R&D decision:

To estimate the variable cost of R&D θ we summarize the data and model predictions on the R&D expenditure as $rd_{jt} = \delta_0^{rd} + \delta_1^{rd}\omega_{jt} + \delta_2^{rd}\mu_{jt} + \delta_3^{rd}k_{jt} + \delta_4^{rd}\omega_{jt} \times \mu_{jt} + \delta_5^{rd}\omega_{jt} \times k_{jt} + \delta_6^{rd}\mu_{jt} \times k_{jt} + u_{jt}^{rd}$.

To estimate the export cost parameter γ we estimate a linear export policy function, as, $Prob(I_{jt}^f = 1) = \delta_0^f + \delta_1^f\omega_{jt} + \delta_2^f\mu_{jt} + \delta_3^fk_{jt} + \delta_4^f\omega_{jt} \times \mu_{jt} + \delta_5^f\omega_{jt} \times k_{jt} + \delta_6^f\mu_{jt} \times k_{jt} + u_{jt}^f$.

Estimating these policy functions on the observed and model-generated data we obtain the parameters $\bar{\delta} = (\delta^{rd}, \delta^f, \delta^m, \delta^s)$ and $\tilde{\delta}(\theta) = (\delta^{rd}(\theta), \delta^f(\theta), \delta^s(\theta), \delta^m(\theta))$. The criterion function minimizes the distance between the regression coefficients $\bar{\delta}$ and $\tilde{\delta}(\theta)$

$$J(\theta) = [\bar{\delta} - \tilde{\delta}(\theta)]' \mathbf{A} [\bar{\delta} - \tilde{\delta}(\theta)], \quad (30)$$

where \mathbf{A} is a weighting matrix. In the estimation, we use $\mathbf{A} = Var[\bar{\delta}]^{-1}$.⁵

4 Data for Swedish Manufacturing Firms

The estimation of our dynamic model of R&D investment requires firm-level panel data that includes input and output variables that can be used to measure productivity, R&D expenditures, the volume of the firm's exports, and domestic sales. We combine three different data sets including (1) firm production information, (2) R&D and innovation, and (3) detailed product level information on imports and exports. The main data set, Financial Statistics (FS), is a census of all Swedish manufacturing firms belonging to the Swedish Standard Industrial Classification (SNI) codes 15 to 37.⁶ The unit of observation is a firm. FS is register data collected for tax reporting. Over 99 percent of the firms are single-plant establishments. It contains annual information on capital, investment, materials, value-added, labor, wages, and revenues that are sufficient to measure firm productivity.

The second part of the data set contains R&D and innovation information from two different surveys conducted by Statistics Sweden: the R&D survey (SCB-RD) and the Community Innovation Survey (CIS). The SCB-RD survey includes the following information: own R&D

⁵However, the identity matrix can be also used.

⁶These numbers refer to SNI codes for 2002. The SNI standard builds on the Statistical Classification of Economic Activities in the European Community (NACE). The SNI standard is maintained by Statistics Sweden (<http://www.scb.se>).

expenditure in the year under study, expected own R&D expenditure in the next year, outsourced R&D in the year under study, expected outsourced R&D the next year, and number of full-time adjusted employees doing R&D every year. The survey is sent out to a representative sample of 600-1000 manufacturing firms per year. Importantly, it includes all firms with more than 200 employees and/or firms that are research institutes. The SCB-RD is carried out in the odd years (1999, 2001, 2003, 2005, 2007, 2009), but covers R&D information also for even years (2000, 2002, 2004, 2006, 2008, 2010).

The CIS survey comprises information about own R&D expenditure, outsourced R&D expenditure, and product and process innovations. The CIS survey covers about 2000 manufacturing firms per year and includes the total population of firms with more than 250 employees and/or firms that are research institutes. The CIS is carried out every second year in even years (2004, 2006, 2008, 2010), and the design follows the common standard across countries in the EU.⁷ In both the SCB-RD and CIS surveys, all firms above 250 employees and research institutes are investigated and the minimum number of full-time adjusted employees per firm is 3-5. Large firms account for a high share of total R&D, sales, and export volume but for a small share of the total number of firms. The CIS and SCB-RD surveys capture the majority of total R&D, exports, and sales, which is important for our purposes of obtaining accurate measures of R&D. Regarding smaller firms, the SCB-RD and CIS samples do not match perfectly. Importantly, we access the id-numbers for each firm in both R&D surveys and are thus able to link them exactly with their production data in the FS.

The final data source consists of detailed firm-level information on imports and exports. In particular, it contains annual domestic and foreign sales for each firm to each of almost 250 export destinations. The median number of export destinations across the firms is 21, the 90th percentile is 65 and the maximum is 188. The firms in the trade data can be linked to their production data in the FS.

Our sample contains firms that were included in the CIS or SCB-RD surveys because for these firms R&D data are available for the years 2003-2010. We aggregate the firms into two

⁷Swedish firms are obliged to answer. For 2010, the survey was sent out to a total of 5400 firms and 4600 answered, i.e., a response rate of 85%. This response rate is substantially higher than in many other European countries.

industry groups based on the use of R&D in the industry in the OECD countries. Industries assigned to the high-tech group all have R&D-sales ratios that exceed 0.05 while those in the low-tech group all have R&D-sales ratios less than 0.02. The high-tech industry group includes firms in eleven, two-digit manufacturing industries: chemicals (SNI 23,24), basic and fabricated metals (SNI 27,28), non-electrical machinery (SNI 29), electrical machinery (SNI 30-32), Instruments (SNI 33) and motor vehicles (SNI 34-35). The low-tech industry group includes firms in twelve manufacturing industries: food and beverages (SNI 15,16), textiles (SNI 17-19), wood and paper (SNI 20-22), plastics (SNI 25), ceramics (SNI 26) and miscellaneous (SNI 36-37).

Table 1 summarizes R&D intensity, measured as R&D expenditure relative to total sales, and export intensity, export sales as a share of total firm sales, aggregated over the sample firms in each of our industry groups. There is a marked difference in R&D investment in the two sectors. In the high-tech industries R&D expenditures equals 6.5 percent of sales, on average across the years, while in the low-tech industries it equals 0.9 percent of sales. The sectors are much more similar in terms of their export market exposure. In the high-tech industries, exports account for 53.0 percent of total industry sales and in the low-tech industries they account for 47.6 percent of sales. In both sectors, the export market plays an important role.

Table 2 summarizes the variation in R&D investment across firms with variation in their export intensity. The top half of the table summarizes the relationship for firms in the high-tech sector and the bottom half of the table summarizes it for the low-tech sector. Firm observations are divided into four export categories. The first group are the non-exporting observations. In the remaining three, exporting firms are assigned into three groups based on their export intensity: below the 25th percentile of the intensity distribution, between the 25th and 50th, and above the 50th percentile. For observations in each of these four groups, the columns of the table summarize the distribution of R&D intensity. The first column is the fraction of firms that invest in R&D, the remaining three columns give the 10th, 50th, and 90th percentile of the R&D intensity distribution.

Focusing on the high-tech industries, the first column shows that the fraction of firms investing in R&D rises with the export intensity of the firm. Among the non-exporters, the

probability of investing in R&D is 0.175 and this rises monotonically to 0.776 for firms that are in the upper half of the export intensity distribution. Among the firms that invest in R&D, the intensity of investment varies substantially across observations. Among the non exporters, 10 percent of the observations have R&D investment that is less than two-tenths of one percent of sales (0.0017). The median firm has an investment equal to 1.54 percent of sales and the firm at the 90th percentile has R&D expenditure equal to 13.80 percent of annual sales. The investment can be undertaken by the firm to impact future profits from its domestic market sales but also in order to increase expected future profits from export sales and possibly induce entry into exporting. Among the firms that export, the R&D intensity varies substantially, from .0021 at the 10th percentile to .1442 at the 90th percentile. The R&D intensity at the 10th and 50th percentiles rises monotonically as the export intensity increases, but this is not true at the 90th percentile. At this upper level the R&D intensity is always substantial, varying from 0.1107 to 0.1442, but it does not increase monotonically with export intensity.

For the low-tech industries, there are two primary differences in these patterns. The relationship between exporting and R&D investment is weaker and, consistent with the evidence seen in Table 1, there is less overall investment in R&D. The first column shows that the probability of investing in R&D rises from 0.162 among the nonexporters to 0.464 for firms with an export intensity above the median. Only about 46 percent of the high-intensity exporters invest in R&D compared with 77 percent in the high tech industries. The R&D intensity levels are much smaller than in the high-tech industries. At the median, the R&D intensity varies from 0.0066 to .0099 across the export groups. At the 90th percentile the R&D intensity varies from .0414 to .0686 across export categories but does not increase monotonically with the export intensity at either the 50th or 90th percentiles.

The simple summary, however, also indicates that a substantial group of firms invest in R&D but do not export and still others export at a high rate but do not invest in R&D. In our model we allow two sources of firm-level heterogeneity to impact these decisions.

5 Empirical Results

5.1 Productivity and Export Demand Shocks

In this section we report estimates of the distribution of productivity and the export demand shock, constructed from equation (20), across firms and time. Table 3 reports estimates of the structural parameters $\eta_d, \eta_f, \beta_k, \beta_z$ and the revenue function intercepts for each of the twelve manufacturing industries. For the high-tech industries, the demand elasticity estimates vary from -2.015 to -4.395 in the domestic market and -2.052 to -4.427 in the export market. Within each industry, the domestic and foreign demand elasticities are very similar. In the low-tech industries, elasticities vary from -2.283 to -3.656. In the food, plastics, and miscellaneous industry, demand elasticities are slightly larger in magnitude in the domestic industry. The coefficient β_k is negative in both sectors, implying that increases in the capital stock lower the short-run marginal cost of production. β_z is positive and greater than 1.0, implying that average foreign sales per destination are larger for firms that sell in many markets. Using the structural parameter estimates and the estimates of \hat{h} and \hat{b} from the domestic and export revenue function, productivity and the export market shock can be constructed from equation (20).

Table 4 reports estimates of the parameters in the evolution process for productivity and the export demand shock, equations (8) and (9), that are specified in detail in equations (23) and (24). Columns (2) and (3) report the estimates for the productivity process for each technology group. The parameters on the lagged ω terms in Table 4 can be combined into an estimate of the persistence of productivity $\frac{\partial \omega_{it}}{\partial \omega_{it-1}}$ for each observations. The estimates indicate that productivity is highly persistent over time. The median value of $\frac{\partial \omega_{it}}{\partial \omega_{it-1}}$ is 0.937 in the high-tech industries and 0.921 in low tech. The distribution of these estimates is tightly concentrated in both sectors, the difference in the 90th and 10th percentiles relative to the median is 0.0075 in the high-tech sector and 0.0496 in the low-tech.

The last two columns of Table 4 report the parameter estimates for the foreign demand shock. The parameters on lagged μ can be used to construct an estimate of the persistence of the foreign demand shock $\frac{\partial \mu_{it}}{\partial \mu_{it-1}}$ for each observation. The median value is 0.918 in the high-tech industries and 0.963 in low tech. Across observations there is more dispersion in the

persistence of μ than in the persistence of ω . The difference in the 90th and 10th percentiles relative to the median is 0.2390 in the high-tech industry and 0.1139 in low tech. While the median firm has both productivity and foreign demand shocks that are highly persistence the greater heterogeneity in the persistence of the foreign demand shocks is consistent with greater volatility in export market sales relative to domestic sales.

In each case, the high level of persistence in ω and μ implies that any increase due to the firm's investment in R&D will have a long-lived impact. Even if the initial impact of R&D on ω or μ is small, the fact that its contribution is long-lived, will raise the long-run expected payoff to R&D and the firm's incentive to invest in R&D. The persistence in gain from R&D can have a substantial effect on the firm's investment decision.

The remaining parameters in Table 4 show the impact of R&D on ω and μ . In the high-tech industries, the coefficient of the interaction term $\omega_{jt-1} * \ln(rd_{jt-1})$ is statistically significant, while the straight log R&D expenditure is significant in the low-tech industries. For the foreign demand shock, the coefficient of the interaction term $\mu_{jt-1} * \ln(rd_{jt-1})$ is statistically significant in both industry groups. The interaction terms allow firms with different productivity and export demand to be affected differently by R&D investment. Overall, the evolution of productivity and export demand is positively impacted by the firm's investment in R&D, and in three of the four cases, this R&D impact is increasing in the level of ω and μ . Firms with high productivity or export demand will find that R&D investment has a larger impact on their future performance than firms with low values of ω or μ . Differences in the expected returns to R&D depending on firm's levels of productivity and export demand will be important for capturing heterogeneity in firm's dynamic decisions to invest different levels in R&D in the second part of the model.

Given the parameter estimates for productivity and demand evolution we construct the elasticity of ω and μ with respect to R&D at each data point and report the 10th, 50th, and 90th percentiles of these distribution across firm and time observations in Table 5. In the high-tech industries, the median observation has an elasticity of productivity with respect to R&D expenditures of 0.0025. A one-percent increase in R&D expenditure increases productivity by 0.25 percent. The 10th and 90th percentile of the distribution are 0.0006 and 0.0059,

respectively. The impact of R&D on the foreign demand is slightly smaller. The elasticity of foreign demand with respect to R&D equals -0.0030, 0.0017, and 0.0041 at the 10th, 50th, and 90th percentile, respectively.

In our model, R&D can impact the firm's sales through both its impact on productivity, which will affect sales in both the domestic and export market, and its impact on export demand. We can use the empirical results to measure the effect of a change in R&D on the revenues in each market. The elasticity of domestic market revenue with respect to an increase in R&D expenditure is affected by the impact on productivity and can be constructed as: $\frac{\partial \ln r_t^d}{\partial \ln(rd_{t-1})} = -(\eta^d + 1) \frac{\partial \omega}{\partial \ln(rd_{t-1})}$. The impact on foreign market sales depends on the R&D impact through both channels and can be constructed as: $\frac{\partial \ln r_t^f}{\partial \ln(rd_{t-1})} = -(\eta^f + 1) \frac{\partial \omega}{\partial \ln(rd_{t-1})} + \frac{\partial \mu}{\partial \ln(rd_{t-1})}$.

The last three rows of Table 5 summarize these revenue elasticities. In the high-tech industries, an expansion of R&D always acts to raise domestic, foreign, and total firm revenue. At the median, the revenue elasticity with respect to R&D is 0.0047 for domestic sales, 0.0068 for foreign sales, and 0.0120 for total firm sales. The latter figure implies that a one percent expansion in R&D increases total firm sales by 1.2 percent with slightly more than half of the increase resulting from the impact on export sales. This elasticity increases from 0.0061 at the 10th percentile to 0.0183 at the 90th implying substantial revenue effects from R&D investment for many firms. R&D investment thus increases foreign revenues about three times more at the 90th percentile than at the 10th. There are important differences between domestic and foreign markets. At the median, a one percent increase in R&D expenditure increases foreign sales about 0.21 percentage points more than domestic sales. The corresponding difference is 0.32 percentage points at the 10th percentile and 0.13 percentage points at the 90th percentile. The dispersion in revenue elasticities is larger in domestic than in exporting markets. The elasticity in the domestic market is ten times larger at the 90th percentile than at the 10th, as indicated by elasticities being equal to 0.01 and 0.0012. In foreign markets the elasticity at the 90th percentile is only double that at the 10th, i.e., 0.0044 as compared to 0.0087. This result in a difference in the 10th to 90th percentiles relative to the median that is three times larger in the domestic market than in the foreign. Different magnitudes of the elasticities with respect to R&D investment on domestic and export revenue indicate that, to provide a more

complete model of R&D investment in exporting industries, it is crucial to account for that R&D investment has a different impact on revenues in domestic and foreign markets, as we do in our model.

In the low-tech industries, the productivity, foreign demand, and revenue elasticities are similar to what is observed in the high-tech sector. At the median, the productivity and export demand elasticities with respect to R&D are 0.0027 and 0.0010, respectively. The median estimates of the revenue elasticities are 0.0059, 0.0066, and 0.0126, for domestic, foreign, and total revenue, respectively. There are two noticeable differences between the estimates for the two sectors. There is slightly more dispersion in the revenue elasticities in the low-tech sector. Although the medians are similar, the dispersion in elasticities of export market revenue is higher in low-tech than in high-tech industries. For exporting markets the difference in the 10th and 90th percentiles relative to the median is about double in low-tech than in high-tech. This finding is consistent with that we observe larger dispersion in R&D investment in low-tech industries, as indicated by a difference in the 10th and 90th percentiles relative to the median of 0.628 for low-tech and 0.609 for high-tech. Another difference is that the elasticities for domestic market revenue indicate that the return to R&D investment is higher in low-tech than in high-tech sectors. The elasticities for total sales are fairly similar for high-tech and low-tech sectors but the magnitudes varies between domestic and foreign markets. This finding is consistent with the weaker relationship between exporting and R&D investment for low-tech found in Table 2, and with the fact that the export intensity is the same in the two sectors but the R&D intensity is lower low-tech, as shown in Table 1.

5.2 The Firm's Investment in R&D

The results reported in the last two sections indicate that firm productivity ω and export demand μ will improve over time if the firm invests in R&D. This is the basis for estimating the marginal benefit of investing in R&D and the firm's dynamic demand for R&D. In our model, the firm's optimal choice of R&D and exporting are both functions of the state variables ω_{jt} , μ_{jt} , and the capital stock k_{jt} . Before estimating the firm's dynamic demand for R&D we can assess the usefulness of our estimates of ω_{jt} and μ_{jt} by examining how well they correlate

with the firm's R&D investment and export market participation.

Using the estimated ω_{jt} and μ_{jt} , we estimate the reduced-form R&D policy functions. Table 6 reports estimates of regressions of three choice variables, the discrete R&D decision, the log expenditure on R&D, and the discrete export decision, on a quadratic function of the state variables. The second, third, and fourth columns report results for the three choice variables for the high-tech industries and the last three columns report results for the low-tech industries. Columns labeled "discrete" report estimates using a discrete indicator of exporting or R&D and the columns labeled "log" report results using the log of the R&D expenditure.

Overall, the policy function estimates demonstrate that ω , μ , and the capital stock are all important determinants of the firm's export and R&D decisions. In each case, several coefficients of the variables are statistically significant in the regressions. Rather than summarize the patterns of each variable, we test the null hypotheses that the coefficients related to each of the three state variables are jointly equal to zero. The test statistics for these hypotheses are presented in the last three rows of the table. The null hypothesis that one of the state variables is unimportant is rejected in every case.⁸

6 Conclusion

This paper develops an empirical model to estimate the impacts of firm R&D investment on underlying firm productivity and export market demand. Both productivity and export demand are modeled as unobserved, time-varying, firm characteristics and we infer their magnitudes using information on the firm's domestic and export market revenues. The firm's investment in R&D can work through two channels. In the first, R&D can impact the firm's productivity which raises profits in both the domestic and export market. In the second, R&D can increase the demand, and thus profits, for the firm's products in foreign markets.

⁸We also estimated the policy functions using a third-order polynomial in the three state variables and found similar results. In particular, the hypothesis test that all the coefficients related to each state variable jointly equal zero is rejected in every case.

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Table 1: R&D and Export Participation				
Year	High-Tech Industries		Low-Tech Industries	
	R&D Intensity	Export Intensity	R&D Intensity	Export Intensity
2003	0.078	0.540	0.006	0.600
2004	0.073	0.531	0.010	0.430
2005	0.064	0.532	0.009	0.532
2006	0.058	0.516	0.009	0.435
2007	0.068	0.554	0.017	0.585
2008	0.054	0.521	0.006	0.384
2009	0.070	0.529	0.011	0.480
2010	0.056	0.517	0.007	0.365
Average	0.065	0.530	0.009	0.476

Table 2: R&D Investment by Export Category				
	Pr(R&D>0)	Percentiles for R&D Intensity		
		P(10)	P(50)	P(90)
High-Tech Industries				
No Exports	0.175	0.0017	0.0154	0.1380
Export Intensity $\leq P(25)$	0.393	0.0021	0.0167	0.1442
$P(25) < \text{Export Intensity} \leq P(50)$	0.582	0.0028	0.0190	0.1107
Export Intensity $> P(50)$	0.776	0.0040	0.0330	0.1429
Low-Tech Industries				
No Exports	0.162	0.0009	0.0086	0.0901
Export Intensity $\leq P(25)$	0.259	0.0010	0.0081	0.0686
$P(25) < \text{Export Intensity} \leq P(50)$	0.292	0.0010	0.0066	0.0414
Export Intensity $> P(50)$	0.464	0.0014	0.0099	0.0470
Note: For high-tech $P(25)=$, $P(50)=$. For low-tech, $P(25)=$, $P(50)=$				

Parameter	High-Tech Industries		Parameter	Low-Tech Industries	
	Domestic Revenue	Export Revenue		Domestic Revenue	Export Revenue
β_k		-0.131	β_k		-0.087
β_z		1.365	β_z		1.294
η_d - chemicals	-2.523	-2.547	η_f - food	-3.656	-2.283
η_d - metals	-2.875	-2.966	η_f - textiles	-2.946	-2.995
η_d - non el machine	-2.853	-2.926	η_f - paper	-3.335	-3.338
η_d - el machine	-4.395	-4.427	η_f - plastics	-3.121	-2.603
η_d - instruments	-2.015	-2.052	η_f - ceramics	-2.780	-2.659
η_d - vehicles	-3.324	-3.429	η_f - miscell	-3.150	-2.785
γ_0 - chemicals	-0.031 (0.048)	-0.007 (0.073)	ρ_0 - food	-0.066 (0.034)*	-0.205 (0.153)
γ_0 - metals	-0.026 (0.037)	-0.049 (0.068)	ρ_0 - textiles	-0.220 (0.047)**	0.008 (0.097)
γ_0 - non el machine	0.033 (0.038)**	-0.189 (0.067)**	ρ_0 - paper	-0.060 (0.033)*	-0.319 (0.097)**
γ_0 - el machine	0.025 (0.041)	-0.113 (0.074)	ρ_0 - plastics	-0.091 (0.042)**	0.149 (0.093)
γ_0 - instruments	0.072 (0.051)	-0.043 (0.077)	ρ_0 - ceramics	-0.084 (0.050)	0.419 (0.138)**
γ_0 - intercept	1.932 (0.066)**	-2.998 (0.245)**	ρ_0 - intercept	1.880 (0.077)**	-2.995 (0.257)**

All models include a full set of year dummies.

Table 4: Structural Parameters - Evolution of Productivity and Export Demand

Parameter (variable)	Productivity ω			Export Demand μ		
	High-Tech	Low-Tech	Parameter (variable)	High-Tech	Low-Tech	
α_0 intercept	0.0707 (0.0084)**	0.0787 (0.0121)**	δ_0 intercept	-0.2475 (0.2175)	-0.0921 (0.2453)	
$\alpha_1(\omega_{t-1})$	0.8958 (0.0195)**	0.7641 (0.0598)**	$\delta_1(\mu_{t-1})$	0.9406 (0.0308)**	0.8528 (0.0721)**	
$\alpha_2(\omega_{t-1}^2)$	0.0184 (0.0153)	0.2914 (0.0849)**	$\delta_2(\mu_{t-1}^2)$	0.0426 (0.0209)**	0.0965 (0.0638)	
$\alpha_3(\omega_{t-1}^3)$	-0.0018 (0.0026)	-0.1433 (0.0356)**	$\delta_3(\mu_{t-1}^3)$	-0.0810 (0.0094)**	-0.0243 (0.0155)	
$\alpha_4(\ln(rd_{t-1}))$	0.0001 (0.0013)	0.0064 (0.0026)**	$\delta_4(\ln(rd_{t-1}))$	-0.0029 (0.0018)	-0.0042 (0.0027)	
$\alpha_5(\ln(rd_{t-1}) * \omega_{t-1})$	0.0031 (0.0015)**	-0.0057 (0.0032)	$\delta_5(\ln(rd_{t-1}) * \mu_{t-1})$	0.0068 (0.0026)**	0.0066 (0.0026)**	
			$\delta_6(Pr(export_{t-1}))$	2.2796 (1.1251)**	0.1281 (1.2801)	
			$\delta_7(Pr(export_{t-1})^2)$	-3.7398 (1.8314)**	0.6802 (2.0928)	
			$\delta_8(Pr(export_{t-1})^3)$	1.7367 (0.9358)*	-0.6237 (1.0707)	
adj R ²	0.918	0.856		0.859	0.909	
sample size	4554	2320		4123	1832	

Table 5: Elasticities With Respect to R&D						
	High-Tech Industries			Low-Tech Industries		
	10th	Median	90th	10th	Median	90th
Productivity: $\frac{\partial \omega_{it}}{\partial \ln(rd_{it-1})}$	0.0006	0.0025	0.0059	0.0007	0.0027	0.0052
Export Demand: $\frac{\partial \mu_{it}}{\partial \ln(rd_{it-1})}$	-0.0030	0.0017	0.0041	-0.0021	0.0009	0.0085
Domestic Revenue: $-(\eta^d + 1) \frac{\partial \omega_{it}}{\partial \ln(rd_{it-1})}$	0.0012	0.0047	0.0100	0.0015	0.0059	0.0118
Export Revenue: $-(\eta^f + 1) \frac{\partial \omega_{it}}{\partial \ln(rd_{it-1})} + \frac{\partial \mu_{it}}{\partial \ln(rd_{it-1})}$	0.0044	0.0068	0.0087	0.0031	0.0066	0.0115
Total Revenue: $-(\eta^d + \eta^f + 2) \frac{\partial \omega_{it}}{\partial \ln(rd_{it-1})} + \frac{\partial \mu_{it}}{\partial \ln(rd_{it-1})}$	0.0061	0.0120	0.0183	0.0055	0.0126	0.0200

Table 6: Policy Functions for R&D and Exporting

	High-Tech Industries			Low-Tech Industries		
	R&D Discrete	R&D Log	Export Discrete	R&D Discrete	R&D Log	Export Discrete
Intercept	-3.206** (0.284)	5.941** (0.306)	-1.722** (0.322)	-1.335** (0.264)	5.709** (0.359)	-0.042 (0.293)
ω_t	1.309** (0.339)	0.106 (0.302)	3.380** (0.525)	0.649 (0.758)	-1.058 (0.990)	5.555** (0.885)
ω_t^2	-0.226* (0.118)	0.223** (0.066)	-0.687** (0.225)	0.751 (0.656)	2.441** (0.721)	0.316 (0.867)
k_t	0.668** (0.097)	0.858** (0.092)	0.083 (0.174)	0.563** (0.125)	0.550** (0.155)	0.448** (.129)
k_t^2	-0.011 (0.014)	0.024** (0.012)	0.031 (0.030)	-0.028 (0.022)	0.030 (0.021)	-0.003 (0.030)
μ_t	3.402** (0.469)	-0.411 (0.397)	0.297 (0.737)	-0.172 (0.388)	-0.559 (0.637)	-1.167** (0.474)
μ_t^2	-0.786** (0.257)	0.280 (.177)	6.647** (0.795)	0.462** (0.090)	0.137 (0.085)	1.512** (0.227)
$\mu_t \times \omega_t$	-1.104** (0.303)	0.338 (0.202)	-3.131** (0.709)	-1.478** (0.458)	-0.426 (0.637)	-4.790** (0.915)
$k_t \times \omega_t$	0.000 (0.063)	-0.213** (0.045)	0.562** (0.142)	-0.111 (0.171)	-0.437* (0.220)	-0.623** (0.216)
$k_t \times \mu_t$	-0.395** (0.081)	-0.298** (0.064)	-0.312 (0.254)	0.031 (0.045)	0.095** (0.046)	0.665** (0.116)
Goodness of fit ^a	0.235	0.590	0.757	0.169	0.321	0.505
Sample Size	4554	2896	4554	2320	811	2320
Test Stat (P-value) ^b						
H ₀ : coeffs on $\omega = 0$	20.96 (0.00)	9.11 (0.00)	111.30 (0.00)	15.54 (0.00)	7.32 (0.00)	73.31 (0.00)
H ₀ : coeffs on $\mu = 0$	122.53 (0.00)	34.52 (0.00)	485.58 (0.00)	29.37 (0.00)	2.80 (0.02)	78.15 (0.00)
H ₀ : coeffs on $k = 0$	257.01 (0.00)	278.99 (0.00)	110.11 (0.00)	85.63 (0.00)	20.47 (0.00)	159.97 (0.00)

All models contain industry and time dummies.

^a Likelihood ratio $[1 - LL(\beta)/LL(0)]$ for logit models, R^2 for OLS models.

^b Likelihood ratio test for logit models, F-test for OLS models. All tests have 3 restrictions.