The Dynamic Impact of R&D Investment on Productivity and Export Demand in Swedish Manufacturing

Florin G. Maican
KU Leuven
Matilda Orth
Research Institute of Industrial Economics (IFN), Stockholm
Mark J. Roberts
The Pennsylvania State University and NBER
Van Anh Vuong
University of Cologne

April 3, 2017

Preliminary. Do not quote

Abstract

This article develops and estimates a dynamic structural model of firm R&D investment in the Swedish manufacturing industries. The model allows R&D to affect firm profitability through two different channels. R&D investments can either improve the firm's productivity or can enhance the demand for the firm's final product in foreign markets or both. R&D investment and its impact on firm's profitability is highly heterogeneous across firms and industries. The long-run marginal return to one additional krona R&D investment of the median firm varies between 1.003 and 1.023 in the high-tech and varies between 1.001 and 1.003 in the low-tech sector. Simulation results show that a reduction in R&D variable cost strongly increases R&D investment on the intensive and only slightly on the extensive margin, whereas reducing R&D startup cost has a stronger impact on R&D investment on the extensive margin.

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 firm's dynamic investment decision in R&D. In particular, we allow for R&D to affect firm profitability through two channels. In the first channel, R&D investment can impact the firm's productivity and lower its production marginal cost. More favorable productivity level 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. Firm optimal R&D investment depends on the long-run return it receives from the investment net the investment cost.

Using micro data for Swedish manufacturing firms from 2003-2010 we estimate the long-run return to R&D investment as a combination of the impact of R&D investment on firm's productivity and export market demand. Firm specific productivity and export demand shock levels along with R&D cost function affect the firms' investment choices on the extensive and intensive margin.

The empirical model incorporates several components of the recent literature. First, we build on the stochastic productivity framework developed by Olley and Pakes (1995) and extended 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 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, the median observation has an elasticity of productivity with respect to R&D expenditures of slightly under 1 percent. The impact of R&D on the foreign demand in the high-tech industries is slightly smaller at the median but is more heterogeneous across firms. The elasticity of productivity with respect to R&D is smaller and less dispersed in low-tech than in high-tech industries. For the low-tech industries, the median observation has an impact of R&D expenditures on productivity that is almost double that on foreign demand.

Second, our dynamic structural model of firm's R&D decision extends the work by Peters, Roberts, Vuong, and Fryges (2017). They 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, one of the mechanisms we estimate in this paper. We extend this framework to also incorporate the effect of R&D investment on export demand. 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, we estimate different impacts of R&D on the evolution of productivity and export demand, the firm R&D cost function, and quantify the expected return to R&D activity at the extensive and intensive margin.

The empirical results show that the long-run expected benefit of investment is highly heterogeneous. The marginal benefit of an additional krona spent on R&D is higher in the high-tech industries than in low-tech ones. There is also more heterogeneity across firms in the marginal benefits in the high-tech industries than in low-tech. The median return in the high-tech industries varies from 1.003 to 1.023. The corresponding return in the low-tech industries ranges from 1.001 to 1.003.

The estimated model of R&D investment is used to assess the impact of R&D subsidies on the firm's investment decisions and the return to its investments. We find that a 25 percent subsidy on R&D spending results in a 30 percent increase in the firm's R&D investment level and generates more than 7.4 percent increase in firm's total benefit from investment. A 20 percent startup cost reduction encourages firms to start R&D. The probability of investing increases by 4 percent for non-investing firms. Furthermore, these firms earn a 26 percentage increase in their firm value through the subsidy induced investment.

In the next section we develop the theoretical model of firm's R&D investment and export participation. Section 3 develops the econometric model and outlines the estimation procedure. In section 4 we summarize the data sources for Swedish manufacturing firms. Section 5 discusses the empirical results and reports on the counterfactual exercises.

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

In this section we develop a dynamic model of the firm's R&D investment. In each period t, upon observing its capital stock (k), production efficiency (ω) and export shock (μ), the firm maximizes its period profits by deciding its optimal prices, production quantity, and whether or not it sells to foreign markets. Additionally, the firm can make R&D investments to improve

[1] Most 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).

the future values of its state variables (ω, μ) and thus its future profits. First, we characterize a set of period-by-period decisions, which allow 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. Second, the model develops the firm's decision rule for R&D investment to affect the evolution of its domestic and foreign revenues and thus future profits.

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

Firm j produces at constant short-run marginal cost

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

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

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

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

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

Each firm also faces a CES demand for its output in the export market

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

where Φ_t^f is the aggregate component of demand in the export market; p_{jt}^f denotes the price firm j charges in the foreign markets; 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 total demand for the firm j's output in the export market such as consumers' taste for firm j's product or its export scope. Because the export market can contain a different number of export destinations, μ_{jt} measures differences in demand levels across these destinations. This abstracts from virtually all differences in demand across destinations but allows us to represent the firm's total export demand as a function of a firm-specific demand component μ_{jt} which is a key variable we will use in the dynamic R&D model. Similar to ω, μ is not observed by the researcher.

Firms in foreign markets receive an export cost c_{jt}^{z} that is stochastically drawn from a known distribution. This contains, for instance, transaction costs related to the export activities, and sunk costs and adjustment costs when firms alters their set of export destinations. Given knowledge of μ_{jt}, ω_{jt}, and c_{jt}^{z}, firm j chooses whether or not to export, its domestic, and if applicable, foreign output prices, to maximize its total period profit. The firm's revenue in the domestic market at optimal prices is:

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

where $\beta_0^d = (\eta_d + 1)\left[\ln \frac{\eta_d}{1+\eta_d} + \beta_0\right]$ 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 maximizes profits. The term ω captures differences in the firms' domestic revenue that are not already controlled for by observed capital stock. These differences in revenue can arise from the firm's cost efficiency, but it can also come from the domestic demand side such as product quality. We refer to ω as firm's productivity level.

Similarly, if the firm chooses to export, its export revenue at optimal p^f can be written as

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

where $\beta_0^f = (\eta_f + 1)\left[\ln \frac{\eta_f}{1+\eta_f} + \beta_0\right]$ and $\tilde{\Phi}_t^f = \ln \Phi_t^f + (1+\eta_f)\beta_w \ln w_t$. The firm's export revenue depends among other factors, on its capital stock k, also on its productivity level ω and export demand shock μ. Firm's export demand shock captures firm's revenue heterogeneity that arises specifically from the export activities. The error term in the export revenue is denoted by ε_{jt}^{f}.

Based on the assumptions made about cost and demand structure, the firm j's short-run profits in the domestic and export markets are fractions of their sales in the respective market. Specifically, the gross profits in domestic (π^d) and export (π^f) markets are:

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

Because exporting firms also have to incur export cost, a firm will choose to export if the net profit from exporting is greater than zero. Before the export cost is realized the probability of exporting for firm j is given by

$$P_{jt}^f = \Pr(e_{jt} = 1) = \Pr(\pi_{jt}^f > c_{jt}^z), \tag{6}$$

where e_{jt} takes value 1 if firm j engages in export activities and zero otherwise. The expected short-run total profit of the firm is

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

where $E(c_{jt}^z|\pi_{jt}^f > c_{jt}^z)]$ is the expected firm export cost conditional on the firm exporting. 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 productivity ω_{jt} and μ_{jt}.

2.2 The Role of R&D

The two key factors that capture firm heterogeneity are ω_{jt} and μ_{jt}. We let these two factors evolve persistently and stochastically over time but also allow for them to be affected by the firm's investment effort in R&D. Assuming the two processes are independent from each other, we specify the firm's revenue productivity process as

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

where ω_{jt-1} is the firm's previous productivity level, allowing for productivity to persist over time. The firm's last period's investment in R&D is denoted by rd_{jt-1}, allowing for R&D investment to affect the path of future productivity. Through the persistence in the productivity process, the impact of R&D investment will be carried over time and allow for the gain from R&D to be long-lived. The stochastic component of the process is ξ_{jt}, which is assumed to be *iid* across firm and time with $\mathbb{E}[\xi_{jt}] = 0$ and $Var[\xi_{jt}] = \sigma_\xi^2$. This allows for firms with the same R&D investment and current productivity levels to differ in their future productivity through luck or other sources of randomness. The productivity shocks ξ_{jt} are realized in t, they are 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}.

Similarly, we model the firm's export demand shock to depend on its previous level, its R&D effort and a stochastic component

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

where the shocks ν_{jt} are *iid.* with $E[\nu_{jt}] = 0$ and $Var[\nu_{jt}] = \sigma^2_{\nu}$. As specified in the productivity process, equation (8), there are both persistence and randomness in the demand shock, captured by the presence of lagged μ and ν. Firm's investment in R&D can create new products, improve product quality or adjust product characteristics to foreign market tastes and can result in an increased demand for the firm's exports over time.

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 (2017) 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: $\mu_{jt} = g_{\mu}(\mu_{jt-1}) + v_{jt}$.

Our framework allows for two underlying sources of persistent heterogeneity and each of them can be affected by the firm's investment choices. The role of R&D investment in improving firm's profitability can be distinguished to be coming from the firm's production efficiency which affects firm's performance in both domestic and foreign markets or from export demand. If R&D works primarily through improving 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 variable cost, which is deterministic in the level of R&D chosen, and a stochastic fixed cost, which the firm observes prior to making its R&D decision. The distribution F of the fixed cost differ between firms that have prior R&D experience and firms that just begin 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:

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

Given this setup, the firm's value function before the R&D fixed cost is realized is given by:

$$\begin{aligned} V(k_{jt}, \omega_{jt}, \mu_{jt}, I(rd_{jt-1})) \quad = \quad & \pi(k_{jt}, \omega_{jt}, \mu_{jt}) + \int \max\{V^0(k_{jt+1}, \omega_{jt+1}, \mu_{jt+1}), \\ & \max_{rd>0} \left[V^1(k_{jt+1}, \omega_{jt+1}, \mu_{jt+1}) - C(rd_{jt}, I(rd_{jt-1}))\right]\} dF \end{aligned} \tag{11}$$

where $V^0(k_{jt}, \omega_{jt}, \mu_{jt})$ and $V^1(k_{jt}, \omega_{jt}, \mu_{jt})$ are the discounted 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

$$V^0(k_{jt+1}, \omega_{jt+1}, \mu_{jt+1}) = \beta \int_\xi \int_v V(k, g^\omega(\omega, \xi), g^\mu(\mu, v) | rd_{jt} = 0) d\xi dv \tag{12}$$

and

$$V^1(k_{jt+1}, \omega_{jt+1}, \mu_{jt+1}) = \beta \int_\xi \int_v V(k, g^\omega(\omega, rd, \xi), g^\mu(\mu, rd, v)) d\xi dv \tag{13}$$

where β is the discount rate. 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 additionally 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 the insights from the stochastic productivity literature as originally developed by Olley and Pakes (1996), and extended to the case of two unobserved firm-level shocks in Ackerberg, Benkard, Berry, and Pakes (2007).

Though not explicitly modelled in our framework, we assume a firm makes capital investment decision in each period based on its current level of capital stock, the level of productivity and export demand shocks

$$i_{jt} = i(k_{jt}, \omega_{jt}, \mu_{jt}). \tag{14}$$

In particular, capital investment levels vary across firms with differences in the underlying productivity and export demand shocks.

When the firm decides about its export activities that maximize total period profit, it implicitly chooses the number of destination markets it exports to. The number of destination markets z_{jt} depends on the state variables

$$z_{jt} = z(k_{jt,}\omega_{jt}, \mu_{jt}). \tag{15}$$

The variable z_{jt} provides information about the destination networks of the exporters. It does not only measure pure demand shocks in foreign markets, it also provides information about exporter efficiency in expanding its network of countries. 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, $z_{jt} = z_t(k_{jt}, \omega_{jt}, \mu_{jt})$.[2] 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:[3]

$$\begin{aligned} \omega_{jt} &= i^{-1}(k_{jt,} i_{jt}, z_{jt}) \\ \mu_{jt} &= z^{-1}(k_{jt,} i_{jt}, z_{jt}) \end{aligned} \tag{16}$$

Substituting the expressions in equation (16) 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, i, and z and adding a transitory error u^d_{jt} gives:

$$\begin{aligned} \ln R^d_{jt} &= (\eta_d + 1)\left(\beta_0 + \ln \frac{\eta_d}{1+\eta_d}\right) + \ln \tilde{\Phi}^d_t \\ &\quad +(\eta_d + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt,} i_{jt}, z_{jt})) + u^d_{jt} \\ &= \gamma_0 + \sum \gamma_t + h(k_{jt,} i_{jt}, z_{jt}) + u^d_{jt} \end{aligned} \tag{17}$$

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

Replacing (ω, μ) in the export revenue function by equation (16), we can express firm export revenue as:

$$\begin{aligned} \ln R^f_{jt} &= (\eta_f + 1)\left(\beta_0 + \ln \frac{\eta_f}{1+\eta_f}\right) + \ln \tilde{\Phi}^f_t \\ &\quad +(\eta_f + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt,} i_{jt}, z_{jt})) + \mu_{jt}(k_{jt,} i_{jt}, z_{jt}) \ + u^f_{jt} \\ &= \rho_0 + \sum \rho_t + b(k_{jt,} i_{jt}, z_{jt}) + u^f_{jt} \end{aligned} \tag{18}$$

[2] Recent empirical studies have shown that several dimensions of firm heterogeneity are important in explaining patterns of dynamic export entry, the number of markets a firm serves, the specific destinations a firm enters, and the distribution of exporting firm sales. Eaton, Kortum, and Kramarz (2011), Das, Roberts and Tybout (2007), and Arkolakis (2010) find that differences in efficiency and entry costs are two important dimensions of firm heterogeneity that are related to export patterns. Johnson (2012) and Khandelwal (2010) incorporate demand side heterogeneity reflecting differences in product quality that lead to differences in market shares across firms in foreign markets. Roberts, Xu, Fan and Zhang (2012) recognize the importance of productivity, demand, and entry cost differences in explaining pricing, output, and entry decisions across destination markets for exporting Chinese firms.

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

where the function $b(k_{jt,}i_{jt}, z_{jt}) = (\eta_f + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt,}i_{jt}, z_{jt})) + \mu_{jt}(k_{jt,}i_{jt}, z_{jt})$ includes the combined effects of capital, productivity, and the export demand shifters on export revenue. We approximate $h(k_{jt,}i_{jt}, z_{jt})$ and $b(k_{jt,}i_{jt}, z_{jt})$ by polynomial functions in their arguments and estimate equations (17) and (18) 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, andβ_k

$$\begin{aligned} \omega_{jt} &= -\frac{1}{(\eta_d + 1)}\hat{h} + \beta_k \ln k_{jt} \\ \mu_{jt} &= \hat{b} - (\eta_f + 1)(\beta_k \ln k_{jt} - \omega_{jt}) \\ &= \hat{b} - \frac{(\eta_f + 1)}{(\eta_d + 1)}\hat{h} \end{aligned} \tag{19}$$

We estimate the demand elasticities η_d and η_f relying on the static demand and short-run marginal cost assumptions. Specifically, we regress firm's total variable cost (tvc) on domestic and export revenues scaled by demand elasticities. Because each firm's marginal cost is constant with respect to its output tvc is the product of the firm's total output and marginal cost. At profit maximizing prices and quantity, marginal cost is equal to marginal revenue in each market, such that

$$tvc_{jt} = q^d_{jt}c_{jt} + q^f_{jt}c_{jt} = R^d_{jt}(1 + \frac{1}{\eta_d}) + R^f_{jt}(1 + \frac{1}{\eta_f}) + u_{jt}, \tag{20}$$

where the error term u_{jt} is the measurement error in total cost.

Relying solely on export revenues of exporting firms to uncover the export shocks μ, induces a selection effect that affects the identification of β_k. Similar to Olley and Pakes (1996), we control for the selection bias by including the export probability into the Markov process of the export shocks:

$$\mu_{jt} = g_\mu(\mu_{jt-1}, rd_{jt-1}, \hat{P}^f_{jt}) + v_{jt} \tag{21}$$

The probability of exporting is estimated as $P^f_{jt} = \lambda(i_{jt-1}, k_{jt-1}, z_{jt-1})$, where the nonparametric function $\lambda(\cdot)$ is approximated by a polynomial series of order 2 in its arguments. Notice that this estimate of the probability of exporting does not take full advantage of the structure of the export decision outlined in section 3.2, but rather is a reduced-form approximation that controls for the endogenous choice of exporting when estimating the process for the export shocks μ.

Furthermore, we specify the functions $g_\omega(\cdot)$ and $g_\mu(\cdot)$ as:

$$\begin{aligned} \omega_{jt} &= I(rd_{jt-1}=0)\left[\alpha_0^0+\alpha_1^0\omega_{jt-1}+\alpha_2^0\omega_{jt-1}^2+\alpha_3^0\omega_{jt-1}^3\right] \\ &+ I(rd_{jt-1}>0)\left[\alpha_0^1+\alpha_1^1\omega_{jt-1}+\alpha_2^1\omega_{jt-1}^2+\alpha_3^1\omega_{jt-1}^3\right. \\ &\left. +\alpha_4\ln rd_{jt-1}+\alpha_5(\ln rd_{jt-1})^2\right]+\xi_{jt} \end{aligned} \tag{22}$$

$$\begin{aligned} \mu_{jt} &= I(rd_{jt-1}=0)\left[\delta_0^0+\delta_1^0\mu_{jt-1}+\delta_2^0\mu_{jt-1}^2+\delta_3^0\mu_{jt-1}^3\right. \\ &\left.+\delta_6^0\hat{P}_{jt}^f+\delta_7^0(\hat{P}_{jt}^f)^2+\delta_8^0(\hat{P}_{jt}^f)^3\right] \\ &+I(rd_{jt-1}>0)\left[\delta_0^1+\delta_1^1\mu_{jt-1}+\delta_2^1\mu_{jt-1}^2+\delta_3^1\mu_{jt-1}^3+\delta_4\ln rd_{jt-1}+\delta_5(\ln rd_{jt-1})^2\right. \\ &\left.+\delta_6^1\hat{P}_{jt}^f+\delta_7^1(\hat{P}_{jt}^f)^2+\delta_8^1(\hat{P}_{jt}^f)^3\right]+v_{jt} \end{aligned} \tag{23}$$

Substituting equations (19) into (22) and (23) allows them to be written in terms of observed $\hat{b}_{jt},\hat{h}_{jt},\hat{\eta}_f,\hat{\eta}_d,k_{jt},k_{jt-1},\hat{P}_{jt}^f$,and rd_{jt-1}. The structural parameter β_k is 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 observed variables (k_{jt-1},k_{jt}). 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 α and δ coefficients in the evolution processes are identified from moment conditions that specify that the errors in equations (22) and (23) are uncorrelated with all the right-hand side variables.[4] We use the estimated values of $(\hat{b}_{jt},\hat{h}_{jt},\hat{\eta}_f,\hat{\eta}_d,\beta_k)$ to construct ω_{jt} and μ_{jt} according to equation (19). Because the measure $\hat{b}_{jt}$ is estimated from the export revenue equation, equation (19) only gives us μ_{jt} for exporting firms. To impute the export demand shock μ_{jt} for non-exporting observations, we invert the capital investment equation (14) and regress the obtained μ_{jt} for exporters on their $(k_{jt},i_{jt},\omega_{jt})$. Because the investment policy

[4] There 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 markets. Second, estimating $(\boldsymbol{\beta},\boldsymbol{\alpha},\boldsymbol{\delta})$ together (13 parameters) or sequentially (one parameter, i.e., for a given β_k get $(\boldsymbol{\alpha},\boldsymbol{\delta})$ 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 one parameter. This is preferable given optimization errors when there is a large state space.

function is given for all firms, the export demand shocks for non-exporters are then constructed as the fitted value of μ_{jt} using the non-exporters' information on $(k_{jt}, i_{jt}, \omega_{jt})$.

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 the firm's variable cost for the R&D investment as:

$$VC(rd_{jt}) = rd_{jt} + \theta rd_{jt}^2. \tag{24}$$

This specification recognizes that the actual expenditure on R&D is playing a major role in the magnitude of the variable cost. 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:

$$FC(I(rd_{jt-1})) \sim \exp(\gamma^m I(rd_{jt-1} > 0) + \gamma^s(1 - I(rd_{jt-1} > 0)) \tag{25}$$

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. The variable cost of R&D investment affects the firm's investment decision on the intensive margin, while the fixed cost does so on the extensive margin.

We also estimate the distribution of exporting cost faced by the firms when making their export decision. The export cost is assumed to be firm-time specific draw from an exponential distribution with mean parameter γ^f : $c_{jt}^z \sim \exp(\gamma^f)$. Therefore, according to the equation (6), the probability of exporting is

$$P_{jt}^f = 1 - \exp(-\pi_{jt}^f/\gamma^f) \tag{26}$$

and the mean export cost, conditional on exporting is

$$E(c_{jt}^z|\pi_{jt}^f > c_{jt}^z) = \gamma - \pi_{jt}^f[(1 - P_{jt}^f)/P_{jt}^f] \tag{27}$$

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

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

where $\boldsymbol{c}_0$ and $\boldsymbol{c}_1$ are vectors of approximation parameters that differ for firms that do and do not choose to do R&D. The functions $\Phi(k, g^\omega, g^\mu)$ are the 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:

$$V(k_{jt}, \omega_{jt}, \mu_{jt}, I(rd_{jt-1})) = (1 - I(rd_{jt-1}))\Phi(k_{jt}, \omega_{jt}, \mu_{jt})\boldsymbol{c}_0 + I(rd_{jt-1})\Phi(k_{jt}, \omega_{jt}, \mu_{jt})\boldsymbol{c}_1 \quad (28)$$

This equation denotes that the value function for the state $(k_{jt}, \omega_{jt}, \mu_{jt})$ is either $\Phi(k_{jt}, \omega_{jt}, \mu_{jt})\boldsymbol{c}_0$ or $\Phi(k_{jt}, \omega_{jt}, \mu_{jt})\boldsymbol{c}_1$ depending on the state variable $I(rd_{jt-1})$. The value function approximation parameters $\boldsymbol{c}_0$ and $\boldsymbol{c}_1$ are found by solving equation (11) for optimal R&D choices in all states.

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 the moments of the data generated by the policy functions of the model $\tilde{\boldsymbol{\delta}}(\boldsymbol{\theta})$ with the moments of the observed data $\overline{\boldsymbol{\delta}}$. The moments generated by the model denoted $\tilde{\boldsymbol{\delta}}(\boldsymbol{\theta})$ depend on the structural parameters $\boldsymbol{\theta}$ and are computed using R&D investments, probability to invest in R&D conditional on previous R&D decision, and the probability to be an exporter.

To identify the coefficient of the R&D variable cost function, we match the quantiles of the logarithm of R&D investments for firms that do R&D in the data. The startup costs γ^m

and γ^s are identified by matching the means (from the model and data) of the discrete R&D decision conditional on the previous R&D decision. Similar, the export cost γ^f is identified by matching the means of the discrete export decision. The criterion function minimizes the distance between the moments $\tilde{\boldsymbol{\delta}}(\boldsymbol{\theta})$ and $\overline{\boldsymbol{\delta}}$

$$J(\boldsymbol{\theta}) = [\overline{\boldsymbol{\delta}} - \tilde{\boldsymbol{\delta}}(\boldsymbol{\theta})]' \boldsymbol{A} [\overline{\boldsymbol{\delta}} - \tilde{\boldsymbol{\delta}}(\boldsymbol{\theta})], \tag{29}$$

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

[5] However, the identity matrix can be also used.

[6] These 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).

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 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

[7] Swedish 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.

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 six manufacturing industries: food and beverages (SNI 15,16), textiles (SNI 17-19), and plastics (SNI 25).

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 0.0021 at the 10th percentile to 0.1442 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 non-exporters 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 0.0099 across the export groups. At the 90th percentile the R&D intensity varies from 0.0414 to 0.0686 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 (19), across firms and time. Table 3 reports estimates of the structural parameters η_d, η_f, β_k, and the revenue function intercepts for each of the nine 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 -2.854 to -3.600 in the domestic market and -2.939 to -3.581 in the export market. The coefficient β_k is negative in both sectors, implying that increases in the capital stock lower the short-run marginal cost of production. 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 (19).

Table 4 reports estimates of the parameters in the evolution process for productivity and the export demand shock, equations (22) and (23). Estimates of the parameters for the productivity processes for high-tech firms that have positive R&D expenditures are reported in column 2 and for firms that have zero R&D expenditures in column 3. Column 4 and 5 show the corresponding estimates for the low-tech firms. The top panel reports the parameters for the evolution of ω. The parameter estimates on lagged productivity, α_1, α_2 and α_3 show significant differences in the persistence of productivity between low-tech and high-tech firms. They also differ between firms with and without positive R&D spending. Overall, the estimates indicate a highly persistent and nonlinear productivity process for all firms. Using $\hat{\alpha_1}, \hat{\alpha_2}$ and $\hat{\alpha_3}$ we constructed an estimate of the persistence of productivity $\frac{\partial \omega_{it}}{\partial \omega_{it-1}}$ for each observation. The median value of $\frac{\partial \omega_{it}}{\partial \omega_{it-1}}$ is 0.941 for high-tech and 0.751 for low-tech firms with R&D investment. Firms without R&D investment have in the high-tech industries a median level of persistence of 0.886 and 0.67 in low-tech. The distribution of these estimates is more concentrated among R&D investing firms versus non-investors and more concentrated in high-tech than in low-tech sector. In high-tech the difference in the 90th and 10th percentiles relative to the median is 0.087 for R&D investors and 0.136 for non - investors, whereas the corresponding numbers in the low-tech sector is 0.815 and 0.981 respectively. The high variation of productivity persistence for non-investor indicate high uncertainty in the productivity evolution process, but R&D investment lowers the degree of uncertainty. This effect is stronger for high-tech firms than low-tech firms, not least because of the stronger impact of R&D investment on productivity. We will get to this later.

The lower panel of Table 4 reports the parameter estimates for the evolution of the export market shock μ.

Estimates of the persistence of the foreign demand shock $\frac{\partial \mu_{it}}{\partial \mu_{it-1}}$ indicate high level of persistence in the export market shock as well with a median value of 0.979 for firms with positive R&D expenditure and 0.945 for firms without R&D expenditure. In high-tech sector, 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 0.183 across firms with R&D expenditures and 0.818 for the group of firms without R&D. The dispersion in μ for low-tech firms is fairly similar between firms with and without R&D expenditures. They are 0.365 for firms with positive R&D spending and 0.324 for firms without R&D, respectively. While both productivity and foreign demand shocks are highly persistent, higher degree of heterogeneity in the persistence of the foreign demand shocks than those of productivity is consistent with greater volatility in export market sales relative to domestic sales observed in the data.

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 the 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. We include a linear and squared term of log R&D investment in the productivity and export demand shock evolution processes to allow for more heterogeneity in the marginal effect of R&D. Specifically, the marginal effect of R&D varies across firms according to their R&D investment level. In the high-tech industries, the coefficients on the log of lagged R&D expenditure, α_4 and α_5, indicate that R&D has a positive but diminishing effect on productivity, while this effect is positive and increasing for low-tech industries. Similarly, the coefficients δ_4 and δ_5 indicate an increasing and diminishing marginal effect of R&D on export demand shock in both low-tech and high-tech sectors. Although, the individual coefficients are not statistically significant. Overall, the estimates show that the evolution of productivity and export demand is positively impacted by the firm's investment in R&D across all industries.

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 0.0096. A one-percent increase in R&D expenditure increases productivity by slightly under 1 percent. The 10th and 90th percentile of the distribution are 0.0074 and 0.0147, respectively. The impact of R&D on the foreign demand shock in the high-tech industries is slightly smaller at the median but is more heterogeneous across firms. The elasticity of foreign demand shock with respect to R&D equals 0.0001, 0.0076, and 0.0257 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 the domestic and export market, and its impact on export demand. We report the effect of a change in R&D on the revenues in each market in the last three rows of table 5. In the domestic market, R&D affects the firm's revenue through its impact on productivity scaled by the demand elasticity: $\frac{\partial \ln R^d_{jt}}{\partial ln(rd_{jt-1})} = -(\eta^d + 1)\frac{\partial \omega_{jt}}{\partial ln(rd_{jt-1})}$. Correspondingly, the impact on foreign market sales depends on the R&D impact through both ω and μ and can be constructed as: $\frac{\partial \ln R^f_{jt}}{\partial ln(rd_{jt-1})} = -(\eta^f + 1)\frac{\partial \omega_{jt}}{\partial ln(rd_{jt-1})} + \frac{\partial \mu_{jt}}{\partial ln(rd_{jt-1})}$. Summing the two revenue elasticities gives the effect of R&D on total firm sales. In the high-tech industries, an expansion of R&D always raises domestic, foreign, and total firm revenue. At the median, the revenue elasticity with respect to R&D is 0.0198 for domestic sales, 0.0288 for foreign sales, and 0.0497 for total firm sales. The latter figure implies that a one percent expansion in R&D increases total firm sales by almost 5 percent with more than half of the increase resulting from the impact on export sales. This total sales elasticity increases from 0.0265 at the 10th percentile to 0.0864 at the 90th percentile implying substantial revenue effects from R&D investment for many firms. R&D investment thus increases firm revenues about three times more at the 90th percentile than at the 10th. The contribution of R&D through the export demand channel is substantial. The heterogeneity in the magnitudes of R&D effect across firms as well as between domestic and export revenue emphasizes the importance of distinguishing the different channels of R&D impact for the understanding of the observed heterogeneity in firm investment decisions.

In the low-tech industries, the median observation has an elasticity of productivity with respect to R&D expenditures of 0.0064. A one-percent increase in R&D expenditure raises productivity by 0.64 percent, which is lower than the productivity elasticity in the high-tech industries. There is little heterogeneity across firms with 0.0064 in the 10th percentile and 0.0073 in the 90th percentile. The impact of R&D on export demand shock is smaller but is more heterogeneous across firms. The elasticity of μ with respect to R&D equals 0.0036 for the median observation, 0.0001 in the 10th percentile and 0.0109 in the 90th percentile. The elasticity of productivity ω for the median observation is double the elasticity of μ in the low-tech industries. The corresponding difference in elasticities of productivity and of foreign demand shock with respect to R&D is much smaller in the high-tech industries.

One percent increase in R&D expenditure raises domestic revenue by 1.52 percent, the export revenue by 1.88 percent and 3.31 percent of total revenue. Compared to the high-tech industries, the revenue elasticities at the median are thus 1 percentage point lower for foreign sales and 1.6 percentage points lower for total sales. The corresponding difference for domestic sales is only 0.5 percentage point. This implies that differences in revenue effects from R&D investments between high-tech and low-tech industries mainly arise from foreign sales. In other words, the contribution of R&D to firm's profit coming from export sales is more substantial in the high-tech than in low-tech industries. The most pronounced differences in magnitudes are found in the upper tail of the elasticity distributions, where revenue elasticities in the 90th percentiles of the high-tech industries are twice the level of those in the low-tech industries. Because revenue elasticities are short-run gain from R&D investment, low elasticities in the low-tech sector is consistent with lower export and R&D intensities in this sector in comparison to high-tech.

5.2 The Firm's R&D Investment Decision

The results reported in Table 4 and 5 indicate that firm expected productivity ω and export demand μ will improve over time if the firm invests in R&D. This provides the firm with positive incentives to invest in 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 assess the importance of ω and μ in explaining the firm's R&D investment and export market participation by estimating the reduced-form policy functions for the three choice variables: the discrete R&D decision, the log expenditure on R&D, and the discrete export decision. We specify each of the policy functions as a quadratic function of the three state variables. The results for the high-tech industry are reported in the second, third, and fourth columns of Table 6. Columns labeled "discrete" report estimates of logit regressions using a discrete indicator of exporting or R&D. Columns labeled "log expend" report OLS estimation results with log R&D expenditure as the dependent variable.

Overall, the policy function estimates for the high-tech industries demonstrate that ω, μ, and the firm's capital stock are all important determinants of the firm's export and R&D decisions. For each of the three state variables, either the first-order or squared term are statistically significant in the regressions. 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 and show that the null hypothesis that one of the state variables is not important is rejected in every case.

The next step of the estimation estimates the parameters characterizing the R&D and export costs. Embedded in this stage are three conditions on the firm's choices: (i) the firm chooses the R&D expenditure that satisfies the first-order condition implicit in the second line of equation (11), (ii) the net payoff to this expenditure is greater than the payoff to not investing in R&D, and (iii) the firm chooses to export if the current period profits from exporting are greater than a fixed cost. The parameters to be estimated are θ in the variable cost function of R&D, equation (24), γ^m and γ^s which are the means of the fixed maintenance and fixed startup cost distributions of R&D, and γ^f the mean of the fixed cost distribution to participate in the export market.

The cost parameter estimates are reported in Table 7. The estimate of θ is 0.001 for most of the industries, indicating that there are increasing marginal costs from investing in R&D. The mean of the startup cost distribution γ^s varies from 20.69 to 153.45 million Swedish kronor (SEK) across the high-tech industries and from 36.73 to 49.84 across the low-tech industries. [8]

These parameters are the unconditional mean of an exponential distribution. Firm that start investing in R&D will have a cost draw that is less than the payoff from investing in R&D

[8] 1 Euro is approximately 10 SEK.

at the optimal level. The startup cost is important in explaining firm's investment decision in year $t+1$ given they were not investing in year t. The maintenance cost parameter γ^m is always smaller than the startup cost. This implies that firms with positive R&D investment in previous period face lower fixed costs if they continue their investment than firms without previous R&D spending. Because their fixed cost is drawn from an exponential distribution with lower mean, they also face less uncertainty in their total R&D cost. In the high-tech industries, firms with prior R&D experience incur on average fixed costs that vary between 0.20 and 19.27. These costs are between 11.99 and 16.23 for firms in the low-tech industries. The final parameter estimates measure the fixed cost of exporting. These cost estimates are rather small across all industries. In five out of six high-tech industries the export costs average to less than 160 thousands SEK and to less than 1 million SEK in two of the low-tech industries. The lower cost estimates in the high-tech sector result from high export participation rates in our sample with only a few less profitable firms not exporting, whereas in low-tech we have relatively more big firms that do not export.

After estimating the structural parameters of the model we assess the ability of our model to explain the R&D and exporting patterns in the data. Table 8 summarizes the fit of the model with respect to the discrete R&D and export decisions for high-tech and low-tech industries. In the case of the discrete R&D decision, we distinguish between firms that are paying a maintenance cost to continue investing, columns 2 and 3, versus paying a startup cost to begin investing, columns 4 and 5. Focusing on the probability of investing in R&D when facing a maintenance cost, the sample frequencies vary from 0.821 to 0.916 for high-tech, implying that firms with positive previous R&D investments are likely to continue. The predicted probabilities are close to observed data with deviations from the data by at most 3.4 percentage points (chemical industry). For low-tech industries, the R&D maintaining frequencies are lower than in high-tech and they vary from 0.532 to 0.724, and the model predictions are almost identical. Overall, the frequency of continued R&D investment is replicated by the model well. For the firms that are paying a startup cost, the model predictions are virtually identical to the sample frequencies, which vary from 0.151 to 0.340 for high-tech and from 0.107 to 0.264 for low-tech. The model is able to predict the lower rate of R&D investment for firms that are paying a startup cost for both groups of industries. Finally, we can replicate the export frequencies with the model closely. The frequency of exporting is very high in the sample, varying from 0.809 to 0.985, with five of the six industries above 0.90 in high-tech. This pattern contributes to the low estimated fixed export costs. For low-tech industries, the frequency of exporting is lower than in high-tech, varying from 0.393 to 0.961.

We also assess the ability of the model to replicate the pattern of R&D expenditure in the data. Table 9 reports the 25th, 50th, and 75th percentiles of the distributions of actual and predicted log R&D expenditures, among the firms that invest. In the estimation we match 20 different percentiles of the log R&D distribution with reasonable fit overall. [9]

5.3 The Return to R&D Investment

The long-run expected marginal benefit of R&D investment is the increment in future firm value resulting from one additional krona spent on R&D, $\partial V^1/\partial rd$. This measure will differ across firms and time as a function of the state variables. We refer to this as the marginal return to investment on the intensive margin. Table 10 summarizes the regression results of the marginal return on the state variables. The results show that the marginal return is increasing in both ω and μ and the coefficients are statistically significant for all industries. For the high-tech industries, the magnitude of the coefficients for ω are larger than for μ implying that heterogeneity in the marginal benefits of R&D across firms arises more from differences in domestic productivity than from export demand factors. The coefficient on capital is negative implying lower returns to R&D for larger firms, holding productivity and export demand shock fixed. One important pattern in the table is seen by comparing the high-tech and low-tech industries. In the latter, while there is still significant variation in $\partial V^1/\partial rd$ due to ω and μ, the coefficients however are considerably smaller than those in the high-tech industries. This pattern indicates less heterogeneity in the return to R&D across low-tech than high-tech firms.

At the optimal R&D level, $\partial V^1/\partial rd$ equals the marginal cost of additional SEK investment which is $\partial VC/\partial rd = 1 + 2\theta rd_{jt}$ from equation (24). The marginal cost increases with the firm's R&D expenditure and differs across industries because of the differences in θ. Table 11

[9] This compares percentiles of the actual and predicted distribution of log R&D expenditure for the sample observations with positive R&D expenditure.

summarizes the within-industry distribution of $\partial V^1/\partial rd$ at the optimal R&D level. For most of the industries the lower quartile of the distribution is approximately 1 reflecting low expenditure on R&D by these firms. Above the median, the marginal return rises as R&D expenditure increases. At the 90th percentile in the high-tech industries, the return to investment on the intensive margin varies from 1.021 to 1.181 krona per krona spent on R&D. In the low-tech industries, the return on an additional krona is generally close to 1.0 and rises to 1.01 in the textile industry.

5.4 Exporting and the Return to R&D

In this section we examine the differences in the return to R&D and their relationship to the firm's export participation. The return to R&D is a combination of its impact on domestic productivity and foreign demand. In Table 4 we reported the contribution of R&D to firm's short-run profit and separated the impact of R&D into revenue effects coming through domestic and export channels. Similarly, to consider the long-run marginal return to R&D, we disaggregate the marginal impact of R&D on firm's value into a component that describes the effect of R&D on the firm's value working through ω and another component describing the effect of R&D working through μ

$$\frac{\partial V^1}{\partial rd} = \frac{\partial V^1}{\partial \omega} * \frac{\partial \omega}{\partial rd} + \frac{\partial V^1}{\partial \mu} * \frac{\partial \mu}{\partial rd}. \tag{30}$$

Table 12 summarizes the share of the marginal return that is due to the foreign demand component μ : $sf = (\frac{\partial V^1}{\partial \mu} * \frac{\partial \mu}{\partial rd})/\frac{\partial V^1}{\partial rd}$. In almost all industries the 10th percentile of the sf distribution exceeds 0.60 implying that the marginal benefit of R&D comes mainly from its impact on sales and profits in the export markets. At the median, between 65.9 and 87.7 percent of the marginal benefit of R&D comes through the foreign market sales and this number rises to a minimum of 84.3 percent at the 90th percentile across all industries. The impact of R&D on μ, combined with the persistence in the μ process, imply that the profitability in the export market is an extremely important source of the return to R&D.

Table 13 summarizes the variation in the marginal return to R&D across industries and firm's export intensity. The table reports the average marginal return on the intensive margin for four firm types in the high-tech and low-tech industries, categorized based on their export-sales ratio. In the first category are firms that do not export, in the second firms with export intensity less than the 25th percentile of their industry, the third and fourth category identify firms that lie between the 25th and 50th percentile and then above the 50th percentile, respectively. On average, the firms that do not export have an expected return to a one krona additional investment in R&D equal to one krona. This is true across all nine industries. As the firm's export intensity rises, the return to an additional krona increases for firms in the high-tech industries. For example, in the chemical industry the return on the intensive margin rises, on average, to 1.009, 1.011, and 1.029 krona across the export categories. Firms with a larger share of their sales in foreign markets have larger expected returns (and larger marginal costs) from increased R&D spending. For the firms that have export-sales ratios greater than the median in their high-tech industry, the average return varies from 1.007 in electrical machinery to 1.029 in chemicals. In contrast, the return to an additional krona of R&D in the low-tech industries never exceeds 1.004 krona, and barely increases with the export intensity of the firm.

This difference in the marginal return to R&D across firms with different export intensities reflects the differences in R&D investment between exporting and non-exporting firms, which in turn results from the underlying variation in the state variables ω and μ. The model allows us to directly study the impact of these state variables on the three key firm decisions in this study: whether or not to invest in R&D, if investing, the optimal level of R&D investment, and whether or not to export. Table 14 divides ω and μ into quartiles and reports the probability of positive R&D investment $Pr(rd > 0)$, R&D-sales ratio, and the probability of export $\Pr(e = 1)$.[10] The top panel reports the probability that firm's in the high-tech industries invest in R&D. The probability increases monotonically in both ω and μ. Firms that lie in the upper half of the μ and ω distributions invest in R&D with a probability higher than 90 percent. This implies that policy instruments attempting to increase firm R&D participation will be more successful if they impact the investment incentive of firms with μ and ω lying in the lower half of these distributions. The second panel reports these probabilities for firms in the low-tech industries. While the probabilities of investing are also increasing in ω and μ, their magnitude is lower than

[10]The firm values of ω and μ are normalized by the industry mean value before assigning the firms to quartiles.

in the high-tech industries reflecting the lower participation rates in the low-tech industries. For firms with μ level above the median, moving from the 3rd to 4th quartile of the ω distribution does not result in further increases in the probability of investment. The probability of investing in R&D caps out at about 0.74 in the low-tech while it reaches 1.0 in the high-tech industries.

The next two blocks in Table 14 report the predicted R&D intensity, measured as the R&D-sales ratio. In the high-tech industries, the ratio is increasing in ω and μ, however not monotonically. R&D intensity increases in both state variables across the first three quartiles, but then declines slightly for firms in the highest quartile. Previous literature on R&D and firm size found similar patterns, where R&D effort is increasing in firm size up to a certain threshold. In our model this pattern is driven by the fact that revenue increases exponentially in ω and μ, whereas the increase in R&D investment due to changes in these state variables are modest resulting from the rather flat marginal benefit curve $\partial V1/\partial rd$. The table shows that the average R&D-sales ratio peeks around 4.0 percent even for firms with productivity and foreign demand shocks in the highest two quartiles of the respective distributions. For firms with lower levels of ω and μ, R&D intensity does increase with these variables. The bottom two blocks in Table 14 reports the probability of firm exporting. Firms in both high-tech and low-tech industries have high probabilities of participating in the export market. The magnitude of the probabilities are higher in the high-tech than in the low-tech sector. This is consistent with the pattern observed in our data. Furthermore, the probabilities are increasing in both state variables ω and μ. Because firm chooses to export when its export profit exceeds the export cost, higher probabilities of exporting at higher values of ω and μ comes from the positive impacts of ω and μ on the firm's export profit.

Overall, the patterns in Table 14 provide strong evidence on the linkages between firm's export, R&D decisions and the underlying state variables that measure firm productivity and demand in the domestic and export markets. Firms with high productivity ω and high foreign demand μ have larger sales in each market, are more likely to export, are more likely to invest in R&D and invest at a higher intensity than firms with low ω and μ. High R&D investments from high (ω, μ) firms leads to further improvements in their underlying (ω, μ) paths, these in turn increase future firm profits and reinforce the differences in the profitability between low and high (ω, μ) firms.

5.5 Simulating the Impact of R&D Subsidies

The structural model of R&D investment developed in this article provides a useful framework to analyze the impact of policies that facilitate firm R&D investment. R&D investments are costly to firms and the outcome of the R&D process is subject to high level of uncertainty. Furthermore, firms often cannot fully internalize the full benefit of the innovations resulting from their R&D undertakings. These factors cause firm R&D investment often to be below the socially desired level without government interventions. Many governments promote policies designed to lower the R&D cost incurred by firms to encourage investments, such as tax credits or accelerated depreciation. Relying on our model we can assess the effectiveness of R&D cost reducing policies in terms of their impact on firm's investment and export decisions. Our assessment does not account for externalities of R&D investment arising from spillover effects. It is rather showing how firm would respond to changes in its investment incentives. In particular, we simulate the firm's R&D investment and export decisions for three alternative policies that affect the R&D cost function. In the first two cases we consider policies that reduces the variable cost of R&D spending. Consider the variable cost function $VC(rd_{jt}) = \alpha_s rd_{jt} + \theta rd_{jt}^2$, we set $\alpha_s = 0.90$ and 0.75 to simulate policies that subsidize 10 percent and 25 percent of firm's R&D expenditures. Both cases lower the marginal cost of investment but does not affect the slope of the marginal cost curve by leaving the adjustment cost component θ unaffected. In the third policy experiment we alter the fixed cost function $FC(I(rd_{jt-1})) \sim \exp(\gamma^m I(rd_{jt-1} > 0) + \alpha_s \gamma^s (1 - I(rd_{jt-1} > 0))$ by reducing the mean of the startup cost distribution γ^s. This is the fixed amount firms must pay when they begin to invest in R&D. We set $\alpha_s = 0.8$ to simulate a 20 percent reduction in the startup cost. We simulate the effect of these cost changes on four different firm-level outcomes: the growth in the level of R&D spending, the probability of investing in R&D, the growth in total benefits that accrue to the firm from their R&D investment, and the growth in export volume. Table 15 summarizes the impact of these cost subsidies in three of the high-tech industries that have the highest overall levels of R&D

spending, chemicals, electrical machinery, and vehicles.[11]

We focus first on the 10 and 25 percent R&D expenditure subsidies. The upper panel in Table 15 summarizes the mean growth rate in R&D spending across all firms with positive investment in the industry. With 10 percent subsidy the median firm increases its R&D spending by approximately 11 percent and with 25 percent subsidy this increase is between 29 and 30 percent. These substantial rises in R&D spending indicate a rather flat R&D marginal benefit curve $\partial V^1/\partial rd$,, allowing for cost reductions to generate significant quantity increases. The second panel shows the average increase in the probability of conducting R&D. This varies between firms that pay a fixed maintenance cost to continue an R&D program and those paying a startup cost to begin. The subsidies do not have a large impact on these probabilities. The impact of 25 percent subsidy is slightly higher than those of 10 percent subsidy. The former generates increases between 0.16 and 0.34 percentage points in the R&D continuation rates and increases between 0.39 and 0.56 percentage point in the startup rates. One reason for the small impact of subsidy is a large proportion of firms in these industries already invest in R&D and have a high probability of continuing even without the subsidy. Another reason is the subsidies do not generate sufficient additional R&D spending and hence sufficient additional benefit to cover the maintenance and startup costs that would occur in case of investment.

The third panel reports the growth in the total benefits to the firm from the expansion in its R&D. The firm's total benefit is measured as $(V(rd) - C(rd)) - V(rd = 0)$, this is the net long-run payoff to the firm from undertaking R&D at the optimal level rd minus the long-run payoff from choosing $rd = 0$. We calculate the growth rate by comparing the firms' total benefits resulting from their optimal R&D investments in environments with and without R&D subsidies. We find that 10 percent subsidy increases firm's total benefits by 2.38 to 4.54 percent. This results from roughly 11 percent expansion in R&D spending through the subsidy as reported in the first panel of the table. With 25 percent subsidy, firms expand their R&D investment such that, depending on the industry, on average 7.42 to 16.82 percent additional total benefit can be generated. The growth rate in firm's total benefit is the multiple of the R&D cost saving firms receive through R&D subsidy. This is due to the fact that the growth

[11] The patterns are very similar for the other three high-tech industries and, as a result, we do not report them in the table.

in total benefit not only captures the marginal benefit coming from improved (ω, μ) paths due to the current additional R&D investment, but it also include the gain from facing reduced marginal cost in future periods and the additional R&D investment resulting therefrom.

The bottom panel in Table 15 reports the short-run growth in export volumes in year $t+1$ that results from the subsidy and expansion of R&D in year t. Expansion in R&D leads to improvements in ω_{t+1} and μ_{t+1} , which in turn lead to increases in export sales in $t+1$. Under the 25 percent subsidy regime the average growth in firm exports varies from 0.29 to 0.66 percent across industries. These results are driven by the export sales elasticity with respect to R&D investment reported previously in Table 5. Alternatively, we can simulate firm R&D investment and their resulting export volumes under different subsidy schemes over a longer time period to capture the effects of additional R&D spending and the persistence in (ω, μ) on firm's export.[12]

The third subsidy policy lowers the startup cost faced by firms that are not investing in R&D. The last two columns of each panel in the table report the impact of the startup cost reduction on these firms. The top panel reports the R&D-sales ratio of the firms that only start to invest in R&D because of the cost subsidy. On average, their R&D - sales ratio varies from 1.6 to 3.1 percent across industries. These numbers correspond to R&D intensities of rather high (ω, μ) firms in the high-tech industries reported in Table 14. This suggests that a firm might be productive in the R&D process, the high startup cost however is a substantial barrier to firm R&D activities. The second panel shows an increase in the probability of investing by these firms that varies from 3.5 to 5.6 percentage points. The startup cost subsidy directly encourages entry, has a bigger impact on R&D participation than variable cost subsidy. The third panel estimates the growth in the total benefit that accrue to these firms from their total R&D investment. It is calculated as the growth from V^0 to $(V^1 - C(rd))$ where V^1 and $C(rd)$ are calculated under the subsidy and V^0 is calculated assuming the firm does not invest in R&D. The growth in net firm value is approximately 26 percent, on average for the firms in each industry. While this is a substantial amount of additional benefit resulting from altered R&D decision, the amount is partly driven by the level of startup cost reduction. Firm net

[12]The calculations for this exercise are not completed.

benefit $V^1 - C(rd)$ not only contains the impact of optimal R&D spending on the firm value, but also include the savings coming from paying low startup cost.

Overall, the counterfactual simulations show that subsidies reducing the variable cost of R&D investment have significant impacts on R&D expenditure by firms that are already investing. It has positive impact on inducing new R&D participation, however this impact is rather small. Startup cost reduction on the other hand has higher impact on inducing new investment, though the absolute number of new entrants is small.

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 and time-varying firm characteristics. We infer their magnitudes using information on the firm's domestic and export market revenues. The firm's investment in R&D impact its profitability 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. The empirical model estimates the firm's dynamic decision to invest in R&D and provides a measure of both the expected long-run gain from investing in R&D and the cost of investing in R&D, which includes adjustment costs, fixed costs of maintaining an R&D program, and startup costs for firms beginning to invest.

The empirical results show that R&D expenditures operate through both the productivity and export demand channels and increase expected future firm value substantially. The impact of R&D expenditure is much larger in a group of six high-tech industries than in a group of three low-tech industries. The higher impact of R&D leads to a much higher expected return to R&D investment, and more investment in the high-tech industries. The median value of the expected return to an additional one krona investment in R&D varies from 0.3 to 2.3 percent across the six high-tech industries. In contrast the corresponding values in the low-tech industries are between 0.1 and 0.3 percent. While the expected marginal return values in the low-tech industries are similar across firms, they are substantially higher for some firms in the high-tech industries. For instance, in the chemicals, industry the firm at the 90th percentile of the distribution of expected returns has a return of approximately 18 percent. We further disaggregate the expected long-run marginal return to R&D into impacts on firm value that come from productivity and export demand shock. At the median, over 66 percent of the marginal return comes from export demand μ. This share increases further to above 84 percent at the 90th percentile of the marginal return distribution, emphasizing the importance of export to the firm's return on R&D. Much of the difference in the return to R&D can be traced to underlying differences in productivity and export demand across firms in the same industry. The model allows us to link these differences in productivity and export demand to differences in the firm's decisions. The probabilities of the firm's R&D and export participation increase in both variables, with R&D participation rate rises above 90 percent for firms with productivity and export demand in the upper half of the respective distributions. R&D intensity among investing firms also rises in ω and μ, however only up to a threshold.

The estimated decision rules for R&D investment and export market participation allow us to simulate the impact of cost reducing R&D policies on the firm's decisions. The results show that a 25 percent subsidy in the R&D spending generates on average 30 percent more R&D by firms on the intensive margin and also induces more R&D on the extensive margin, though the latter is rather small. Higher level of R&D investment resulting from lower marginal cost through subsidy improves the firm's productivity and export demand and in turn their future profits. This amounts to an average of 7.4 to 16.8 percent higher total benefit from investment for the investing firm. A 20 percent startup cost reduction has a positive impact on R&D investment on the extensive margin. It raises the probability of investment among non-investing firms by approximately 4 percentage points. Firms starting R&D investment due to startup cost subsidy yield on average a total benefit from investment that amounts to 26 percent of their firm value.

In this article we demonstrate that it is possible to infer the expected long-run return to R&D from a model that utilizes the first-order condition for R&D choice. R&D can work through many channels including creating new products that have substantial value in anew or existing markets or developing new production processes that can reduce costs or improve product quality. We focused on two channels, the first affecting the firm's domestic sales, which we designate as productivity, and the second that is unique to the firm's demand in foreign markets. For Sweden, a country that depends heavily on the export channel for its manufactured products, we find that the effect of R&D on export sales is particularly important. Firms that have high export sales resulting from the demand shock have a higher return to R&D and thus a greater incentive to invest. There is a reinforcing effect in which firms with high productivity and favorable export demand have a higher return to R&D, will choose to invest more, and will have greater future improvements in both dimensions. R&D is an important endogenous source of differences in firm values.

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Table 1: R&D and Export Intensity (share of value of shipments)

	High-Tech Industries		Low-Tech Industries	
Year	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 ≤P(25)	0.393	0.0021	0.0167	0.1442
P(25)<Export Intensity≤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≤P(25)	0.259	0.0010	0.0081	0.0686
P(25)<Export Intensity≤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)=

Table 3: Revenue Function Parameter Estimates					
Parameter	High-Tech Industries		Parameter	Low-Tech Industries	
	Domestic Revenue	Export Revenue		Domestic Revenue	Export Revenue
β_k	-0.131		β_k	-0.213	
η_d - chemicals	-2.523	-2.547	η_f - food	-2.854	-2.939
η_d - metals	-2.875	-2.966	η_f- textiles	-2.899	-2.944
η_d - non el machine	-2.853	-2.926	η_f - plastics	-3.600	-3.581
η_d - el machine	-4.395	-4.427			
η_d - instruments	-2.015	-2.052			
η_d - vehicles	-3.324	-3.429			
γ_0 - chemicals	2.763 (0.108)**	0.755 (0.218)**	ρ_0 - food	3.073 (0.121)**	1.362 (0.215)**
γ_0 - metals	2.951 (0.101)**	0.690 (0.216)**	ρ_0 - textiles	2.468 (0.140)**	1.456 (0.217)**
γ_0 - non el machine	3.211 (0.100)**	0.816 (0.214)**	ρ_0 - plastics	2.533 (0.127)**	1.362 (0.209)**
γ_0 - el machine	3.257 (0.103)**	0.778 (0.211)**			
γ_0 - instruments	2.822 (0.106)**	0.742 (0.214)**			
γ_0 - intercept	3.261 (0.107)**	1.067 (0.218)**			

All models include a full set of year dummies.

Table 4: Structural Parameters - Evolution of Productivity and Export Demand				
Parameter (variable)	High-Tech, $rd_{t-1} > 0$	High-Tech, $rd_{t-1} = 0$	Low-Tech $rd_{t-1} > 0$	Low-Tech, $rd_{t-1} = 0$
		Productivity ω		
α_0 intercept	-0.0752 (0.0330)*	0.0110 (0.0037)**	-0.0503 (0.0412)	-0.0130 (0.0038)**
$\alpha_1(\omega_{t-1})$	0.9176 (0.0117)**	0.8762 (0.0174)**	0.6449 (0.0513)**	0.6622 (0.0257)**
$\alpha_2(\omega^2_{t-1})$	0.0421 (0.0154)**	0.1125 (0.0193)**	0.8449 (0.1561)**	0.8756 (0.1146)**
$\alpha_3(\omega^3_{t-1})$	-0.0075 (0.0052)	-0.0420 (0.0120)**	-0.4862 (0.1035)**	-0.4876 (0.1102)**
$\alpha_4(ln(rd_{t-1}))$	0.0147 (0.0072)*		0.0065 (0.0104)	
$\alpha_5(ln(rd_{t-1}))^2$	-0.0003 (0.0004)		0.0001 (0.0006)	
adj R^2	0.952	0.872	0.860	0.752
sample size	2329	1107	895	1003
		Export Demand μ		
δ_0 intercept	0.3115 (1.2252)	-0.4854 (0.4579)	0.0837 (0.3183)	0.3704 (0.2653)
$\delta_1(\mu_{t-1})$	0.5273 (0.1769)**	0.1635 (0.1833)	0.6876 (0.0437)**	0.7397 (0.0730)**
$\delta_2(\mu^2_{t-1})$	0.1827 (0.0781)*	0.3754 (0.0897)**	0.1986 (0.0207)**	0.1345 (0.0591)**
$\delta_3(\mu^3_{t-1})$	-0.0235 (0.0107)*	-0.0515 (0.0131)**	-0.0354 (0.0029)**	-0.0205 (0.0128)
$\delta_4(ln(rd_{t-1}))$	0.0258 (0.0205)		0.0110 (0.0299)	
$\delta_5(ln(rd_{t-1}))^2$	-0.0011 (0.0010)		-0.0005 (0.0019)	
$\delta_6(Pr(export_{t-1}))$	0.0122 (7.4451)	3.5137 (3.0281)	-0.2294 (2.1254)	-2.2929 (2.0390)
$\delta_7(Pr(export_{t-1})^2)$	-2.4207 (11.982)	-6.9322 (5.4643)	-1.0039 (3.9658)	2.6876 (3.6380)
$\delta_8(Pr(export_{t-1})^3)$	2.3539 (5.8517)	4.4299 (2.9981)	1.2470 (2.1953)	-0.6544 (1.8890)
adj R^2	0.920	0.870	0.954	0.892
sample size	2280	859	839	690

Table 5: Elasticities With Respect to R&D						
	High-Tech Industries			Low-Tech Industries		
	10th	Median	90th	10th	Median	90th
Productivity: $\frac{\partial \omega_{it}}{\partial ln(rd_{it-1})}$	0.0074	0.0096	0.0147	0.0064	0.0064	0.0073
Export Demand: $\frac{\partial \mu_{it}}{\partial ln(rd_{it-1})}$	0.0001	0.0076	0.0257	0.0001	0.0036	0.0109
Domestic Revenue: $-(\eta^d + 1)\frac{\partial \omega_{it}}{\partial ln(rd_{it-1})}$	0.0112	0.0198	0.0351	0.0111	0.0152	0.0180
Export Revenue: $-(\eta^f + 1)\frac{\partial \omega_{it}}{\partial ln(rd_{t-1})} + \frac{\partial \mu_{it}}{\partial ln(rd_{t-1})}$	0.0147	0.0288	0.0566	0.0124	0.0188	0.0249
Total Revenue: $-(\eta^d + \eta^f + 2)\frac{\partial \omega_{it}}{\partial ln(rd_{t-1})} + \frac{\partial \mu_{it}}{\partial ln(rd_{t-1})}$	0.0265	0.0497	0.0864	0.0244	0.0331	0.0406

Table 6: Reduced Form Policy Functions for R&D and Exporting

	High-Tech Industries			Low-Tech Industries		
	R&D Discrete	R&D Log Expend	Export Discrete	R&D Discrete	R&D Log Expend	Export Discrete
Intercept	-1.286**	5.815**	3.012**	-2.051**	5.934**	0.502
	(0.225)	(0.196)	(0.564)	(0.341)	(0.362)	(0.479)
ω_t	0.748	1.504**	-14.42**	-0.176	4.068**	5.977*
	(0.626)	(0.402)	(3.540)	(1.733)	(1.399)	(3.103)
ω_t^2	-1.425**	0.042	32.61**	-19.80**	-3.834	-3.639
	(0.383)	(0.144)	(8.005)	(4.990)	(3.468)	(7.378)
k_t	0.408**	.291**	7.399**	1.146**	0.233	-0.624
	(0.127)	(0.100)	(0.782)	(0.239)	(0.240)	(0.555)
k_t^2	-0.081*	0.073**	2.402**	-0.234**	-0.027	1.890**
	(0.033)	(0.018)	(0.365)	(0.056)	(0.045)	(0.301)
μ_t	0.069	0.514**	-10.18**	0.807*	0.578	-4.093**
	(0.163)	(0.105)	(1.177)	(0.462)	(0.362)	(1.529)
μ_t^2	0.198**	0.051	6.709**	0.910**	0.0007	4.096*
	(0.046)	(0.028)	(0.727)	(0.352)	(0.243)	(1.788)
$\mu_t \times \omega_t$	-0.142	-0.031	26.25**	-0.154	-2.456*	-0.349
	(0.248)	(0.123)	(4.329)	(1.612)	(1.209)	(10.02)
$k_t \times \omega_t$	0.698**	-0.200*	-17.49**	2.360*	0.205	-4.620*
	(0.220)	(0.101)	(3.242)	(1.168)	(0.782)	(2.196)
$k_t \times \mu_t$	-0.027	-0.054	-8.198**	-0.508*	0.126	-4.917**
	(0.061)	(0.038)	(1.000)	(0.228)	(0.147)	(1.271)
Goodness of fit[a]	0.296	0.642	0.813	0.253	0.536	0.722
Sample Size	3436	2313	3436	1898	897	1898
Test Statistics (P-value)[b]						
H_0: coefficients on ω =0	43.36 (0.00)	9.46 (0.00)	112.5 (0.00)	38.99 (0.01)	4.675 (0.00)	38.90 (0.01)
H_0: coefficients on μ =0	182.00 (0.00)	67.34 (0.00)	387.4 (0.00)	75.62 (0.00)	9.476 (0.00)	75.60 (0.00)
H_0: coefficients on k =0	16.54 (0.00)	90.14 (0.00)	312.2 (0.00)	71.86 (0.00001)	7.420 (0.00)	71.81 (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.

Table 7: Estimates of Structural Cost Parameters (million of SEK)				
	R&D Variable Cost (θ)	R&D Maintenance (γ_m)	R&D Startup (γ_s)	Export Cost (γ)
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
High-Tech Industries				
chemicals	1.005e-3	0.434	114.026	0.060
metals	1.039e-3	19.272	153.448	3.978
non elect machinery	1.020e-3	10.512	62.784	0.158
electrical machinery	1.032e-3	4.560	51.083	0.816
instruments	1.020e-3	0.202	20.695	0.025
vehicles	1.005e-3	18.670	117.180	0.084
Low-Tech Industries				
food	2.618e-3	16.237	49.838	5.246
textiles	1.350e-3	11.997	36.729	0.862
plastics	1.398e-3	13.044	43.955	0.509

Bootstrapped standard errors are forthcoming.

Table 8: Model Fit - Actual and Predicted Probabilities						
	Maintain R&D		Startup R&D		Export	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
High-Tech Industries						
chemicals	0.905	0.939	0.340	0.340	0.985	0.999
metals	0.821	0.810	0.151	0.143	0.809	0.809
non elect machinery	0.887	0.888	0.296	0.296	0.936	0.999
electrical machinery	0.863	0.891	0.211	0.215	0.918	0.924
instruments	0.916	0.947	0.333	0.333	0.901	0.999
vehicles	0.825	0.825	0.263	0.262	0.937	0.999
Low-Tech Industries						
food	0.532	0.535	0.107	0.107	0.393	0.395
textiles	0.724	0.728	0.163	0.163	0.908	0.910
plastics	0.711	0.718	0.264	0.264	0.961	0.961

Table 9: Model Fit - Distribution of log R&D Expenditures (thousands of SEK)						
	25th Percentile		Median		75th Percentile	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
High-Tech Industries						
chemicals	8.216	7.846	9.375	9.484	10.217	10.607
metals	7.244	7.276	8.487	8.898	9.798	10.428
non elect machinery	7.696	7.678	9.210	9.349	10.404	10.441
electrical machinery	7.313	6.445	8.987	8.110	10.027	8.829
instruments	8.006	7.684	9.414	8.940	10.564	9.720
vehicles	7.549	7.497	8.909	8.902	10.944	10.379
Low-Tech Industries						
food	5.548	5.866	6.907	6.6438	7.833	7.201
textiles	6.214	6.160	7.696	7.223	8.189	8.161
plastics	6.214	6.349	7.600	7.033	8.541	7.755

Table 10: Regression Coefficients for Marginal Benefit of R&D $\partial V_1/\partial rd$ (standard errors)					
	ω	μ	lnk	$Intercept$	R^2
High-Tech Industries					
chemicals	0.2022 (0.0167)**	0.0519 (0.0041)**	-0.0309 (0.0067)**	0.8829 (0.0127)**	0.736
metals	0.2420 (0.0202)**	0.0203 (0.0037)**	-0.0216 (0.005)**	0.9640 (0.0084)**	0.646
non electrical machinery	0.1909 (0.0088)**	0.0322 (0.0018)**	-0.0220 (0.0024)**	0.9504 (0.0042)**	0.753
electrical machinery	0.1105 (0.0075)**	0.0079 (7e-04)**	-0.0019 (7e-04)**	0.9504 (0.0042)**	0.631
instruments	0.0984 (0.0046)**	0.0263 (0.0014)**	-0.0303 (0.0024)**	0.9792 (0.003)**	0.820
vehicles	0.3167 (0.0311)**	0.0282 (0.0049)**	-0.0175 (0.0057)**	0.9470 (0.0098)**	0.578
Low-Tech Industries					
food	0.0042 (5e-04)**	0.0022 (2e-04)**	-1e-04 (1e-04)	1.0011 (3e-04)**	0.765
textiles	0.0062 (0.001)**	0.0013 (3e-04)**	0.0014 (2e-04)**	0.9963 (5e-04)**	0.718
plastics	0.0082 (9e-04)**	0.0017 (2e-04)**	5e-04 (2e-04)	0.9962 (6e-04)**	0.565

Table 11: The Distribution of Marginal Benefits at Optimal R&D					
	Percentiles of the Distribution of $\partial V^1/\partial rd$				
	10th	25th	50th	75th	90th
High-Tech Industries					
chemicals	1.002	1.005	1.023	1.068	1.181
metals	1.001	1.001	1.004	1.023	1.069
non elect machinery	1.001	1.002	1.014	1.057	1.097
electrical machinery	1.001	1.001	1.003	1.011	1.021
instruments	1.001	1.004	1.012	1.029	1.053
vehicles	1.001	1.002	1.008	1.040	1.088
Low-Tech Industries					
food	1.000	1.001	1.002	1.004	1.006
textiles	1.000	1.001	1.001	1.004	1.010
plastics	1.001	1.001	1.003	1.005	1.008

Table 12: Share of Marginal Benefits Arising from Foreign Markets					
	Percentiles of the Distribution of sf				
	10th	25th	50th	75th	90th
High-Tech Industries					
chemicals	0.605	0.623	0.659	0.715	0.843
metals	0.631	0.663	0.723	0.845	0.940
non elect machinery	0.627	0.658	0.709	0.826	0.902
electrical machinery	0.790	0.824	0.877	0.929	0.961
instruments	0.558	0.612	0.665	0.753	0.885
vehicles	0.678	0.706	0.775	0.848	0.944
Low-Tech Industries					
food	0.680	0.716	0.760	0.831	0.910
textiles	0.708	0.729	0.781	0.886	0.945
plastics	0.708	0.744	0.781	0.832	0.883

Table 13: The Relationship Between Export Intensity and Benefits of R&D				
Industry	No Exports	Export Intensity		
		$\leq P(25)$	$P(25) - P(50)$	$\geq P(50)$
High-Tech Industries Intensive Margin: $\partial V^1/\partial rd$				
chemicals	1.001	1.009	1.011	1.029
metals	1.000	1.002	1.004	1.016
non elect machinery	1.001	1.007	1.016	1.028
electrical machinery	1.000	1.001	1.003	1.007
instruments	1.000	1.008	1.009	1.020
vehicles	1.001	1.006	1.006	1.011
Low-Tech Industries Intensive Margin: $\partial V^1/\partial rd$				
food	1.001	1.003	1.003	1.003
textiles	1.000	1.000	1.000	1.003
plastics	1.001	1.001	1.002	1.004

Table 14: R&D and Exporting Outcomes by ω and μ (mean)				
	$\omega \leq P(25)$	$P(25) \leq \omega < P(50)$	$P(50) \leq \omega < P(75)$	$\omega \geq P(75)$
High-Tech Industries: $Pr(rd > 0)$				
$\mu \leq P(25)$	0.100	0.203	0.561	0.724
$P(25) \leq \mu < P(50)$	0.375	0.646	0.832	0.962
$P(50) \leq \mu < P(75)$	0.617	0.626	0.908	0.980
$\mu \geq P(75)$	0.755	0.745	0.959	0.999
Low-Tech Industries: $Pr(rd > 0)$				
$\mu \leq P(25)$	0.030	0.085	0.138	0.260
$P(25) \leq \mu < P(50)$	0.077	0.176	0.397	0.518
$P(50) \leq \mu < P(75)$	0.140	0.460	0.640	0.587
$\mu \geq P(75)$	0.178	0.501	0.744	0.735
High Tech Industries: R&D Intensity				
$\mu \leq P(25)$	0.011	0.014	0.023	0.027
$P(25) \leq \mu < P(50)$	0.018	0.026	0.035	0.032
$P(50) \leq \mu < P(75)$	0.021	0.028	0.046	0.038
$\mu \geq P(75)$	0.018	0.026	0.039	0.031
Low-Tech Industries: R&D Intensity				
$\mu \leq P(25)$	0.008	0.010	0.012	0.012
$P(25) \leq \mu < P(50)$	0.008	0.010	0.010	0.012
$P(50) \leq \mu < P(75)$	0.006	0.006	0.008	0.010
$\mu \geq P(75)$	0.004	0.007	0.008	0.009
High-Tech Industries: $Pr(e = 1)$				
$\mu \leq P(25)$	0.807	0.862	0.955	0.947
$P(25) \leq \mu < P(50)$	0.879	0.974	0.996	0.999
$P(50) \leq \mu < P(75)$	0.981	0.972	0.999	1.000
$\mu \geq P(75)$	0.993	0.996	1.000	1.000
High-Tech Industries:$Pr(e = 1)$				
$\mu \leq P(25)$	0.129	0.364	0.442	0.514
$P(25) \leq \mu < P(50)$	0.741	0.921	0.888	0.804
$P(50) \leq \mu < P(75)$	0.979	0.966	0.990	0.868
$\mu \geq P(75)$	1.000	0.805	0.961	0.918

Table 15: Counterfactual Simulations of R&D Subsidies

	10% R&D Subsidy		25% R&D Subsidy		20% Reduction in Startup Cost	
	Growth in Firm R&D Spending (mean)				R&D-Sales Ratio (mean)	
chemicals	0.105		0.284		0.031	
electrical machinery	0.113		0.307		0.016	
vehicles	0.108		0.291		0.021	
	Change in Probability R&D >0 (mean)					
	Maintenance	Startup	Maintenance	Startup	Maintenance	Startup
chemicals	0.0	0.0021	0.0016	0.0056	0.0	0.0563
electrical machinery	0.0013	0.0014	0.0034	0.0039	0.0	0.0352
vehicles	0.0011	0.0017	0.0031	0.0045	0.0	0.0466
	Growth in Total Benefits from R&D (mean)					
chemicals	0.0238		0.0814		0.261	
electrical machinery	0.0454		0.1682		0.264	
vehicles	0.0266		0.0742		0.259	
	Growth in Exports - One Year (mean)					
chemicals	0.0011		0.0029		0.0	
electrical machinery	0.0024		0.0066		0.0	
vehicles	0.0017		0.0046		0.0	