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The Dynamic Impact of Exporting on Firm R&D Investment

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The Dynamic Impact of Exporting on Firm R&D Investment*

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Abstract

This article estimates a dynamic structural model of firm R&D investment in twelve Swedish manufacturing industries and uses it to measure rates of return to R&D and to simulate the impact of trade restrictions on the investment incentives. R&D spending is found to have a larger impact on firm productivity in the export market than in the domestic market. Export market profits are a substantial source of the expected return to R&D. Counterfactual simulations show that trade restrictions lower both the expected return to R&D and R&D investment level, thus reducing an important source of the dynamic gains from trade. A 20 percent tariff on Swedish exports reduces the expected benefits of R&D by an average of 32.2 percent and lowers the amount of R&D spending by 13.9 percent in the high-tech industries. The corresponding reductions in the low-tech industries are 30.4 and 8.9 percent, respectively. R&D adjustments in response to export tariffs mainly occur on the intensive, rather than the extensive, margin.

1 Introduction

The theoretical literature on growth and trade, as developed by Grossman and Helpman (1993, 1995), is built on a framework of endogenous innovation where a firm's incentives to undertake costly innovation expenditures are impacted by their exposure to international markets. For exporting firms, the expected return on investments in innovation can be larger than for pure domestic firms. This can be due to the larger market size, an ability to learn from knowledge

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spillovers in the foreign country, or because of competitive pressure from exporting firms based in other countries. Regardless of the source, this higher expected return should motivate exporting firms to invest more in innovation activities such as R&D which help them realize higher productivity and profit gains relative to their non-exporting counterparts.

While it has been well-established that exporting firms are more likely to innovate than others, the underlying causal mechanism linking export market conditions, such as the size of the export market or the cost of exporting, and firm innovation is less well studied. Yet, when assessing the dynamic impacts of trade policy, it is important to understand how opening to trade, or, as more applicable in the present policy environment, imposition of tariffs, impacts firm investment in innovation.

Two empirical approaches have been used to quantify the impact of trade exposure on innovation. The first uses exogenous export market shocks to identify an impact of exporting on firm innovation. The second approach estimates a dynamic structural model of the firm's export and R&D investment decisions. The advantage of the structural model is that, by quantifying the pathways linking R&D investment and long-run profits, it can measure the expected return to R&D for both exporting and non-exporting firms. This framework provides a natural measure of the return to R&D: the change in long-run firm value resulting from R&D investment. Also, by estimating the dynamic decision rule for R&D, the model can analyze counterfactuals including the response of firm R&D investment to changes in export market profits or to R&D subsidies.

In this article we use Swedish firm-level data to estimate a dynamic, structural model of a firm's R&D investment while allowing the investment to interact with the firm's export participation. We generalize the discrete choice models of Aw, Roberts, and Xu (2011) and Peters, Roberts, and Vuong (2018) by treating R&D investment as a continuous decision and analyze both the intensive and extensive margin of the investment process. In our framework, the firm's optimal choice of R&D is based on comparing the expected long-run payoff with the incurred cost of innovation. For an exporting firm, the payoff to R&D investment comes from its impact on the path of future productivity, sales, and profits separately in the domestic and export markets. In addition to these sales and profit impacts, R&D-induced productivity improvements can raise the likelihood a non-exporting firm enters the foreign market. In our model, the return to R&D can differ in the export and domestic market, not just because one market is larger than the other, but because the R&D investment differentially impacts productivity in the two markets. We estimate the innovation cost function which consists of both variable and fixed cost components. The variable cost depends on the firm's actual R&D expenditure and allows for adjustment costs or diminishing returns to R&D spending. The fixed cost can vary with the firm's R&D history to reflect differences in the cost of starting or maintaining an R&D program.

Both trade policy and innovation policy can alter the amount of innovation in a country by altering the incentives of firms to invest in R&D. The structural model we estimate allows us to quantify the effects of policy changes on R&D investment and long-run firm value. We simulate how firm R&D investments, including the proportion of firms investing and the level of expenditure, respond to several counterfactual policy environments including tariff changes and R&D subsidies. Changes in tariffs affect the size and profitability of the export market, and impact the firm's R&D decisions on the intensive and extensive margins. The magnitude of these effects depends on the firm's productivity and size. By simulating the effect of export market tariffs, we measure one source of dynamic losses from trade restrictions. R&D subsidies are often used to promote innovation and these can be granted proportionately to the firm's actual R&D spending or as lump-sum payments directed at R&D startups. Changes in subsidies alter the firm's cost of innovation and can have direct effects on both investment margins.

With a relatively small domestic market, Swedish firms rely heavily on sales in foreign markets. In manufacturing, export sales account for more than 47 percent of the sector's total sales. Many Swedish firms produce high-tech products and are significant investors in R&D. Overall R&D spending equals 3.7 percent of GDP. This combination of reliance on high-tech products and export markets makes the linkage between exporting and R&D investment particularly important for the future success of these firms. Our data also show clear patterns in the relationship between exporting and R&D investment within industry. Both the probability a firm invests in R&D (extensive margin) and the R&D-sales ratio (intensive margin) rise with the firm's export share. These patterns are consistent with an increase in the incentive to invest in R&D as export participation increases.

The empirical results show that a firm's R&D investment raises its future productivity in both the domestic and export market with a larger impact in the export market. Productivities in both markets are highly persistent, implying that R&D expenditures will have a long-lasting impact on firm profitability. The expected long-run payoff to R&D, measured as the increase in firm value per krona spent on R&D, is substantially higher for exporting firms than non-exporters in each industry and higher in the high-tech industries when compared with the low-tech industries. For the median firm in each high-tech industry, this payoff varies from 0.526 to 3.867 for the non-exporting firms but 10.174 to 56.595 for the exporting firms. The return to R&D can also be measured as the proportional increase in firm value resulting from the total R&D investment. For the median firm in the high-tech industries, this increase varies from a low of 3.4 percent in the metals industry to 82.7 percent in chemicals, with virtually all of the impact coming from exporting firms. In the low-tech industries the returns are much lower. The impact at the median firm varies from 0.6 percent to 1.3 percent, with a larger impact for exporting firms.

Counterfactual simulations show that a 20 percent tariff on Swedish exports reduces the expected net benefits of R&D by an average of 32.2 percent in high-tech industries and 30.4 percent in low-tech industries. Consequently, it reduces the amount of R&D spending by 13.9 percent and 8.9 percent in the high-tech and low-tech industries, respectively. Most of the adjustment occurs on the intensive margin with firms continuing to invest in R&D, but reducing their R&D spending in response to the reduction in export market profits that results from the tariff. Additionally, we simulate the joint effect of the output tariff and a retaliatory 20 percent tariff on inputs. The decline in the expected net benefits of R&D is at least three times larger than from the output tariff alone. The addition of the input tariff has a particularly large negative impact on the firms with low foreign-market productivity. These are firms that are heavily committed to the domestic market. The impact of direct innovation policy is analyzed in a counterfactual that simulates a 20 percent R&D subsidy. This reduces the cost of innovation and raises both the expected net benefits to R&D, by 3.8 percent, and the amount of R&D spending, by 11.2 percent, for the high-tech industries. The corresponding numbers in the low-tech industries are 4.2 and 6.0 percent. Overall, the counterfactual simulations show that not only innovation policy but also trade policy can have significant effects on the R&D investment by Swedish manufacturing firms.

The findings are important for policy discussions because they show that restrictions on free trade will undermine efforts to use innovation policies to increase R&D and innovation activity. For countries such as Sweden, that are both export-oriented and innovative, trade and innovation policies cannot be implemented or analyzed in isolation from each other.

The next section briefly reviews the literature that focuses on the causal linkage between exporting and innovation. The third section summarizes some empirical patterns between exporting and R&D investment in the Swedish manufacturing industries. The fourth and fifth sections develop the theoretical and empirical model of firm's R&D investment and export participation. Sections six and seven discuss the empirical results and counterfactual exercises.

2 The Impact of Trade on Investment in Innovation

A large theoretical literature, much of it based on the framework developed by Melitz (2003), has shown how firms that differ in their productivity will face different payoffs to selling in export markets, importing material inputs, or making foreign direct investments of production facilities. This leads to the self-selection of more productive firms into these activities. Shu and Steinwender (2018) review a large number of empirical studies that document productivity differences between exporting and domestic firms as well as firms that source their inputs domestically or import them. These studies generally support the theoretical predictions that more productive firms are more likely to be engaged in international trade. While these heterogenous productivity models do not incorporate endogenous firm-level productivity dynamics, they have been used to explain dynamic changes in the composition of trading firms in response to trade liberalizations, and cost or demand shocks in foreign markets.[1]

A second line of research focuses on the source of these firm-level productivity differences. The theoretical literature on growth and trade is built on models of endogenous investment in innovation activities where the incentives to invest are affected by whether the firm is engaged in trade. Theoretical models in this literature include Grossman and Helpman (1993, 1995), Constantini and Melitz (2008), Atkeson and Burstein (2010), Van Long, Raff, and Stähler (2011), Burstein and Melitz (2013) and Akcigit, Ates, and Impullitti (2018). These models emphasize the role of firm investment in innovation activities such as R&D, patenting, new product introduction, process innovations, quality improvements, or adoption of new technologies as the source of firm dynamics. The interesting issue is to what extent participation in international markets, through either exporting output or importing inputs, leads firms to increase their innovation efforts and thus generates dynamic gains that are not fully captured by static models of trade. Of particular relevance to this article, Burstein and Melitz (2013) analyze models in which firms make decisions about entry/exit, exporting, and investment in innovation. One implication is that trade liberalizations lead to differential response of innovation investments between exporting and non-exporting firms which then amplifies the productivity differences between the two groups.

[1] Syverson (2011, Section 4.2.2) reviews the literature linking changes in trade competition to within-firm changes in productivity and changes in the composition of firms in an industry because of selection effects.

Many empirical studies have shown that exporting firms are more likely to invest in innovation, but the direction of causation is generally not clear.[2] The questions we address in this article are related to the small empirical literature that focuses on the causal impact of changes in export market conditions on the firm's investment in innovation. The first group of studies in this literature uses exogenous export market shocks, often from a trade liberalization episode, to identify a causal effect of exporting on firm innovation.[3] Bustos (2010) documents a positive effect of a tariff reduction facing Argentine firms on their expenditure on technology upgrading. Lileeva and Trefler (2010) find that Canadian firms that were induced to expand exporting in response to U.S tariff reductions, also increased product innovation and had higher rates of technology adoption. Coelli, Moxnes, and Ultveit-Moe (2015) use data from 60 countries and find a positive effect of the trade liberalization in the 1990s on firm patenting. Aghion, Bergeaud, Lequien, and Melitz (2018) find that high-productivity French firms increase their patenting activity in response to positive export market shocks while low productivity firms decrease their patenting. They explain this with a combination of an expansion of the export market, which differentially benefits high-productivity firms, and an increase in competition in the destination markets, which disadvantages low-productivity firms.

Alternatively, dynamic structural models of the firm's export and R&D decisions have been used to measure the impact of exporting on the return to R&D investment. Aw, Roberts, and Xu (2011) model R&D investment as a discrete decision that increases firm productivity and study the extensive margin of firm R&D investment. The authors analyze firm data for Taiwanese electronics producers and find that, conditional on current productivity, exporting firms have larger productivity gains than non-exporters and that an expansion of the export market substantially increases the probability of investing in R&D. This mechanism contributes to the productivity gap between exporting and domestic firms.[4] Peters, Roberts, and Vuong (2018) also treat R&D as a discrete decision but allow a more flexible relationship between R&D and the impact on export and domestic productivity. They estimate the investment model using data on German high-tech manufacturing firms and find that an increase in firm R&D raises the probability that the firm realizes new product or process innovations and these innovations raise future productivity. Both effects are larger for export market productivity, so that exporting firms will have substantially higher expected returns to R&D and thus a higher probability of investing. Simulating contractions in the foreign markets due to tariffs, they find

[2]The empirical literature showing that exporting is positively correlated with measures of innovation includes Bernard and Jensen (1997), Aw, Roberts, and Winston (2007), Van Beveren and Vandenbussche (2010), Altomonte, Aquilante, Bekes, and Ottaviano (2013), Becker and Egger (2013), and Damijan, Kostevc, and Rojec (2017).

[3]A related literature has studied how exogenous import market shocks, often from China's expansion into new markets after it joined the WTO, affected innovation. Bloom, Draca, and Van Reenen(2016) find a positive effect on firm patents, IT spending, and R&D spending for 12 European countries. In contrast, Autor, Dorn, Hanson, Pisano, and Shu (2017) find a negative effect on patenting and R&D expenditure for U.S. firms. Using U.S. data, Xu and Gong (2017) find a negative effect on R&D spending for low-productivity firms but a positive impact for high-productivity firms.

[4]Using a similar framework with Spanish firm data, Máñez, Rochina-Barrachina, and Sanchis-Llopis (2015) find that two activity variables, exporting and R&D, increase both productivity and the probability of undertaking the complementary activity in future periods. An exception to the finding of a positive relationship between trade exposure and technology upgrading is the study by Santos (2017). He finds that reductions in trade costs increase competition among domestic firms and reduce their incentives to adopt new technologies.

that a 20 percent output tariff on German exports reduces the long-run payoff to R&D by 24.2 to 46.9 percent for the median firm across five high-tech manufacturing industries. This leads to a reduction in the probability of investing in R&D by between 5.0 and 16.0 percentage points. In both cases the payoff to R&D investment is significantly impacted by the profitability of the export market.

Two other empirical studies also utilize a structural framework to quantify the effect of trade exposure on the firm's incentive to innovate. Lim, Trefler, and Yu (2018) use a calibrated structural model to focus on the roles of export market expansion and competition on the patterns of patenting, R&D spending, and new product sales for Chinese manufacturing firms. They find that market expansion positively impacts innovation measures and competition negatively impacts them, but firms can escape the competition effects if they are able to innovate into less-competitive niche markets. Using a general equilibrium model calibrated to U.S. data, Akcigit, Ates, and Impullitti (2018) find that import tariffs provide small welfare gains in the short run, but reduce the incentives to innovate which results in large welfare losses in the long run. They also find that R&D subsidies are effective in promoting R&D investment for new and incumbent firms.

The empirical model developed in sections 4 and 5 will be used to analyze differences in the rate of return to R&D between exporting and non-exporting firms and measure how each will respond, on both the intensive and extensive margin of R&D investment, to changes in export market profitability and R&D subsidies.

3 R&D Investment and Exporting by Swedish Manufacturing Firms

In the Swedish manufacturing sector, high-tech products account for a substantial fraction of output, and many industries are both export and R&D intensive. Firm export and innovation strategies are closely linked and firm-level decisions in these two dimensions must be analyzed in concert. This is particularly true when using counterfactual simulations to analyze the impact of innovation and trade policies. This section describes some patterns of R&D investment and exporting among Swedish manufacturing firms that will be important in the specification of the structural model.

The data set we construct contains firm-level observations for the years 2003-2010 on domestic and export sales, input use, and R&D investment for a sample of Swedish manufacturing firms. We aggregate the firms into twelve industries, and categorize six of them as high-tech and six as low-tech industries based on the R&D-sales ratios in the industry. A detailed description of the data set construction is given in the Appendix.

Table 1 summarizes R&D intensity, measured as industry R&D expenditure relative to total industry sales, and export intensity, industry exports as a share of total industry sales. There is a marked difference in R&D investment between the high-tech and low-tech groups. In the high-tech industries R&D expenditure equals 6.5 percent of sales, on average across the years, while in the low-tech industries it equals 0.9 percent of sales. Both industry groups are dependent on export market sales. 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. The structural model developed in the next section allows for a different impact of R&D in the two industry groups and between export and domestic market sales.

Table 2 looks within the industry groups and 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 industry group and the bottom half summarizes it for the low-tech group. 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 investment. 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 distribution of R&D intensity.

The table shows that there is substantial variation within each group in both the extensive and intensive margin of R&D investment and both margins are correlated with export intensity. Focusing on the high-tech industries, the first column shows that the fraction of firms investing in R&D, the extensive margin, 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 expenditure that is less than two-tenths of one percent of sales (0.0017). The median firm has an expenditure 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 R&D 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 table also documents a clear positive relationship between R&D intensity and export intensity among exporting firms.

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.

These simple summary statistics indicate a positive correlation between exporting and R&D investment on both the extensive and intensive margin but the strength of the correlation differs between the low-tech and high-tech industry groups. There are also a substantial group of firms that invest in R&D but do not export and still others that export at a high rate but do not invest in R&D. The dynamic model of R&D investment developed in the next sections contains two sources of firm-level heterogeneity, an export market productivity and a domestic market productivity, that can each be impacted by the firm's R&D expenditure. These two productivity shocks will help to explain the observed relationship between exporting and R&D investment on both the extensive and intensive margin. The large difference in R&D investment rates between the two industry groups also suggests substantial differences in the benefits or costs of R&D and the model will be estimated separately for the two industry groups as a result.

4 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. We begin by deriving the firm's revenue functions in the domestic and export market and its static profit function. In each period t, firm j observes its capital stock, productivity in domestic and export market sales, and past R&D investments. The firm maximizes its period t profits by choosing its optimal output prices, production quantity, and whether or not it sells to foreign markets. The firm then chooses its R&D investment which acts to improve the expected future values of its productivities and profits at home and abroad. We develop the firm's dynamic decision rule for R&D incorporating both the intensive and extensive margin of investment.

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

In period t, firm j produces output at constant, short-run marginal cost

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

where k_{jt} is the firm capital stock, w_t contain the prices of variable inputs, which are assumed to be equal across all firms, and ψ_{jt} is the firm's production efficiency, which is 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

$$q^d_{jt} = \tilde{\Phi}^d_t (p^d_{jt})^{\eta_d} \exp(\phi^d_{jt}), \tag{1}$$

where $\tilde{\Phi}^d_t$ denotes the industry aggregate demand for this product, p^d_{jt} is the price for firm j's product in the domestic market, η_d is the constant elasticity of demand ($\eta_d < 0$), and ϕ^d_{jt} is a firm-specific domestic demand shock. The latter represents differences in consumer demand across firms and is known to the firm but not the researcher.

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

$$q^f_{jt} = \tilde{\Phi}^f_t (p^f_{jt})^{\eta_f} \exp(\phi^f_{jt}) \tag{2}$$

where $\tilde{\Phi}^f_t$ is the aggregate component of demand in the aggregate export market, p^f_{jt} is the price firm j charges in the export market, and η_f is the constant elasticity of demand. ϕ^f_{jt} is a firm-specific export demand shifter that captures differences in the total demand for the firm j's output in the export market due to consumers' taste for firm j's product or the firm's export scope. Because firms can export to a different number of destinations, firms with a large number of export destination will tend to have larger values for ϕ^f_{jt}. This demand representation abstracts from 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 ϕ^f_{jt}. Similar to ψ_{jt} and ϕ^d_{jt}, ϕ^f_{jt} is known to the firm but is not observed by the researcher.

In the domestic market, the firm chooses its output price to maximize its domestic profit. The firm's revenue in the domestic market at the optimal price is:

$$\ln R^d_{jt} = \beta^d_0 + \Phi^d_t + (\eta_d + 1)(\beta_k \ln k_{jt} - \omega_{jt}) + \varepsilon^d_{jt} \tag{3}$$

where $\beta^d_0 = (\eta_d + 1)\left[\ln \frac{\eta_d}{1+\eta_d} + \beta_0\right]$ captures all constant terms, and $\Phi^d_t = \ln \tilde{\Phi}^d_t + (1 + \eta_d)\beta_w \ln w_t$ incorporates all time-varying demand and cost factors that are common across firms. The term $\omega_{jt} = \psi_{jt} - (\frac{1}{\eta_d+1})\phi^d_{jt}$ captures all variation in domestic revenue for firm j arising from unobserved cost and demand factors. We refer to ω_{jt} as the firm's domestic productivity and differences across firms can arise from differences in production efficiency, product quality, or markups. Domestic productivity will be a key state variable in the firm's dynamic choice of R&D. The error term ε^d_{jt} captures transitory shocks to domestic revenue that are unknown to the firm when it maximizes profits.

Not all firms participate in the export market. When deciding to export firms observe an export cost c^z_{jt} that contains, for instance, transaction costs related to the export activities, sunk costs, and adjustment costs when firms alter their set of export destinations.[5] Given knowledge of ψ_{jt}, ϕ^f_{jt}, and c^z_{jt}, firm j maximizes its foreign market profits by choosing its optimal foreign market prices and whether or not to export. If the firm chooses to export, its export revenue at the optimal output price is:

$$\ln R^f_{jt} = \beta^f_0 + \Phi^f_t + (\eta_f + 1)(\beta_k \ln k_{jt} - \mu_{jt}) + \varepsilon^f_{jt} \tag{4}$$

where $\beta^f_0 = (\eta_f + 1)\left[\ln \frac{\eta_f}{1+\eta_f} + \beta_0\right]$ and $\Phi^f_t = \ln \tilde{\Phi}^f_t + (1 + \eta_f)\beta_w \ln w_t$. All the firm-specific unobserved cost and demand factors are captured in $\mu_{jt} = \psi_{jt} - (\frac{1}{\eta_f+1})\phi^f_{jt}$ which we will label the firm's unobserved foreign revenue productivity. The error term ε^f_{jt} captures transitory shocks to export revenue that are unknown to the firm when it maximizes profits.

If firm j competes in monopolistically competitive markets and has the cost and demand structure specified, their 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:

$$\begin{aligned} \pi^d_{jt} &= -\tfrac{1}{\eta_d} R^d_{jt}(\Phi^d_t, k_{jt}, \omega_{jt}) \\ \pi^f_{jt} &= -\tfrac{1}{\eta_f} R^f_{jt}(\Phi^f_t, k_{jt}, \mu_{jt}). \end{aligned} \tag{5}$$

Because exporting firms also have to incur export costs, 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

$$P^f_{jt} = \Pr(e_{jt} = 1) = \Pr(\pi^f_{jt} > c^z_{jt}), \tag{6}$$

[5] We do not distinguish fixed costs of exporting from sunk entry costs because very few firms in our data switch their export status. Das, Roberts, and Tybout (2007) discuss how switches in export status are used to identify fixed and sunk costs. Export choice is endogenous in this model but it is not treated as a dynamic decision.

where e_{jt} takes the value 1 if firm j exports to any destination and zero otherwise. The expected short-run total profit of the firm is

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

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 its capital stock, market level factors in both the domestic and export market, the cost of exporting, and the firm-specific revenue productivities ω_{jt} and μ_{jt}.

4.2 The Role of R&D

The two key factors that capture unobserved firm heterogeneity in the domestic and export market 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 R&D expenditure. We specify the firm's domestic 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 R&D expenditure 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 firms and time with $\mathbb{E}[\xi_{jt}] = 0$ and $Var[\xi_{jt}] = \sigma_\xi^2$. The productivity shocks ξ_{jt} are realized in t and are not correlated with ω_{jt-1} or rd_{jt-1}. This allows for firms with the same previous period productivity and R&D expenditure to differ in their current productivity through luck or other sources of randomness in the innovation process.

Similarly, we model the firm's export market productivity 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 $\mathbb{E}[\nu_{jt}] = 0$ and $Var[\nu_{jt}] = \sigma_\nu^2$. There is both persistence and randomness in the export market productivity, captured by the presence of lagged μ_{jt-1} and ν_{jt}. The process of foreign market productivity evolution is allowed to differ from the process for domestic market productivity as discussed in the trade and endogenous growth literature. Grossman and Helpman (1993, 1995) point out that firms operating in international markets may have access to a broader set of opportunities for innovation, be exposed to new products or production processes by their foreign competitors, or be better able to exploit innovations that they develop as a result of their R&D investment. This will be captured in our framework by different processes for productivity evolution in each market. These processes specify the impact of R&D on firm productivity, a crucial component of the return to R&D investment and thus the firm's incentives to invest.[6]

[6]Several studies have generalized the original model of exogenous productivity evolution by Olley and Pakes

Our framework allows for two underlying sources of persistent heterogeneity and each of them can be affected in a different way by the firm's choice of R&D expenditure. If R&D investment has a larger impact on μ than on ω, it can induce new firms to enter the export market but also lead to differences in the profitability path between exporting firms and those that focus solely on the domestic market.

4.3 Dynamic R&D Investments

In this section we model the firm's dynamic decision to invest in R&D. In this framework, the firm uses R&D investment to buy improvements in expected future productivity. How much it costs the firm to achieve the desired level of improvement depends on the returns to scale in the innovation process, adjustment costs, and any startup costs that the firm must occur when it begins to invest in R&D. The cost of a productivity improvement is specified with an innovation cost function that is the sum of a variable cost and a fixed cost:

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

The variable cost of innovation $VC(\cdot)$ is a function of the firm's current spending on R&D, rd_{jt}, and a firm-time specific shock υ_{jt}. The shock captures, for example, differences in the firm's cost efficiency in producing productivity improvements, differences in the portfolio of investment projects, or differences in subsidies or tax treatment of the firm's R&D spending. The shock is observed by the firm at the time it chooses rd_{jt} but is not observed by the econometrician. This specification recognizes that the variable cost is endogenous because of the endogenous choice of R&D expenditure. Since the dynamic choice of R&D depends on the firm's productivities ω and μ, which evolve with some persistence over time, this will introduce a source of persistence in the firm's variable cost of innovation.[7] The fixed cost $FC(\cdot)$ captures any differences in the cost of innovation that are not related to the amount of R&D spending and can include its past experience and expertise in innovation. Denoting $I(rd_{jt-1})$ as a discrete indicator of prior period expenditure, fixed costs will differ between firms that are paying a start-up cost to begin R&D investment $I(rd_{jt-1}) = 0$ or a maintenance cost for ongoing operations $I(rd_{jt-1}) = 1$. FC is treated as a draw from a known distribution that differs depending on $I(rd_{jt-1})$.

In this environment, the firm chooses the optimal R&D expenditure to maximize the discounted sum of future profits. The firm's value function, before the R&D fixed cost and variable cost shock is realized, is given by:

(1996) to incorporate endogenous firm choices. Doraszelski and Jaumandreu (2013) allow a firm's productivity index to evolve endogenously with investments in R&D. Peters, Roberts, Vuong, and Fryges (2017) model revenue productivity as evolving endogenously with realizations of product and process innovations by the firm. Aw, Roberts, and Xu (2011) extend the stochastic productivity framework to interrelated export and domestic markets where productivity evolution is affected by the firm's discrete investment in R&D and discrete participation in the export market. The latter allows for learning-by-exporting that is potentially important in their developing country context. Foreign revenue productivity evolves exogenously and is not affected by the firm's R&D investment. Peters, Roberts and Vuong (2018) allow R&D to differentially affect productivity in the export and domestic market where productivity evolution depends on indicators of product and process innovation.

[7] The models by Aw, Roberts, and Xu (2011) and Peters, Roberts, and Vuong (2018) treat the total cost of innovation as a stochastic shock which does not allow for persistence in a firm's innovation cost over time.

$$V(k_{jt},\omega_{jt},\mu_{jt},I(rd_{jt-1})) \;=\; \pi(k_{jt},\omega_{jt},\mu_{jt})+\int \max\{V^0(k_{jt+1},\omega_{jt+1},\mu_{jt+1}), \tag{11}$$
$$\max_{rd>0}\left[V^1(k_{jt+1},\omega_{jt+1},\mu_{jt+1})-C_I(rd_{jt},\upsilon_{jt},I(rd_{jt-1}))\right]\}d\upsilon dFC$$

where $V^0(\cdot)$ and $V^1(\cdot)$ 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

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

and

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

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 ν. The firm that invests in R&D at the optimal, positive level, has its future value additionally affected by the shifts in the ω and μ processes that result from R&D investment. The optimal choice of R&D rd^*_{jt} is a function of the state variables and satisfies the first-order condition:

$$\frac{\partial V(k_{jt},\omega_{jt},\mu_{jt},I(rd_{jt-1}))}{\partial rd_{jt}}=0 \tag{14}$$

5 Estimation

5.1 The Evolution of Domestic and Foreign Market Productivity

The first goal of the empirical model is to estimate the parameters of the revenue functions, equations (3) and (4), the parameters of the productivity processes, equations (8) and (9), and to construct estimates of firm domestic and foreign-market productivity ω_{jt} and 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).[8]

Though not explicitly modelled in our framework, we assume a firm makes capital investment decision in each period based on its current capital stock, and levels of domestic and foreign revenue productivity

$$i_{jt}=i_t(k_{jt},\omega_{jt},\mu_{jt}). \tag{15}$$

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 log of the number of destination markets nd_{jt} then depends on the state variables

$$nd_{jt}=nd_t(k_{jt},\omega_{jt},\mu_{jt}). \tag{16}$$

[8] Jaumandreu and Yin (2018) estimate a production model with both unobserved demand and cost shocks. They use data on the revenue of Chinese firms in the domestic and export market to recover the two shocks.

The variable nd_{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.[9] Under certain regularity conditions (monotonicity and supermodularity, Pakes (1994)), the two policy functions can be inverted to express the unobserved productivities as functions of the observable capital stock, investment, and number of export destinations:[10]

$$\begin{aligned} \omega_{jt} &= i_t^{-1}(k_{jt,}i_{jt}, nd_{jt}) \\ \mu_{jt} &= nd_t^{-1}(k_{jt,}i_{jt}, nd_{jt}) \end{aligned} \tag{17}$$

Substituting these expressions into the domestic and export revenue functions, equations (3) and (4), allows us to write sales in each market as a function of observable variables. Replacing ω_{jt} in the domestic revenue function with a general function of k_{jt}, i_{jt} and nd_{jt} gives:

$$\ln R_{jt}^d = \gamma_I + \gamma_t + h_t(k_{jt,}i_{jt}, nd_{jt}) + u_{jt}^d \tag{18}$$

where the function $h_t(k_{jt,}i_{jt}, nd_{jt}) = (\eta_d + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt,}i_{jt}, nd_{jt}))$, γ_I is an industry intercept, γ_t captures common, time-varying factors in $\ln \Phi_t^d$, and u_{jt}^d is a transitory error. Similarly, replacing μ_{jt} in the export revenue function gives:

$$\ln R_{jt}^f = \rho_I + \rho_t + b_t(k_{jt,}i_{jt}, nd_{jt}) + u_{jt}^f \tag{19}$$

where the function $b_t(k_{jt,}i_{jt}, nd_{jt}) = (\eta_f + 1)(\beta_k \ln k_{jt} - \mu_{jt}(k_{jt,}i_{jt}, nd_{jt}))$, ρ_I is an industry intercept, ρ_t captures common, time-varying factors in $\ln \Phi_t^f$, and u_{jt}^f is a transitory error.

We approximate $h_t(k_{jt,}i_{jt}, nd_{jt})$ and $b_t(k_{jt,}i_{jt}, nd_{jt})$ by polynomial functions in their arguments and estimate equations (18) and (19) using ordinary least squares.[11] We can then express the lagged unobserved domestic and foreign productivities as functions of these fitted values $\hat{h}$ and $\hat{b}$ and the unknown parameters η_d, η_f, and β_k:

[9] Recent empirical studies have shown that several dimensions of firm heterogeneity are important in explaining patterns of export participation, 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. Roberts, Xu, Fan, and Zhang (2018) find that productivity, demand, and entry cost differences are important in explaining pricing, output, and entry decisions across destination markets for Chinese exporters.

[10] See also Maican and Orth (2020) for a detailed discussion of the properties of policy functions in complex dynamic programming problems with endogenous states.

[11] Relying solely on export revenues of exporting firms to uncover the foreign revenue productivity μ_{jt}, 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 foreign productivity:

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

The probability of exporting is estimated as $P_{jt}^f = \lambda(i_{jt-1}, k_{jt-1}, nd_{jt-1})$, where the nonparametric function $\lambda(\cdot)$ is approximated by a second-order polynomial. This estimate of the probability of exporting does not take full advantage of the structure of the export decision outlined in section 4.2, but rather is a reduced-form approximation that controls for the endogenous choice of exporting when estimating the process for the foreign revenue productivity μ_{jt}. The results show that the terms that include P_{jt}^f are not statistically significant in the foreign revenue productivity process, which implies that our estimates are not affected by export selection bias.

$$\omega_{jt-1} = -\frac{1}{(\eta_d+1)}\hat{h}_{jt-1} + \beta_k \ln k_{jt-1} \tag{20}$$
$$\mu_{jt-1} = -\frac{1}{(\eta_f+1)}\hat{b}_{jt-1} + \beta_k \ln k_{jt-1}$$

To estimate the processes for productivity evolution, we specify the functions $g_\omega(\cdot)$ and $g_\mu(\cdot)$ as:

$$\omega_{jt} = \alpha_1\omega_{jt-1} + \alpha_2\omega_{jt-1}^2 + \alpha_3 rd_{jt-1} + \alpha_4 rd_{jt-1}^2 + \alpha_5\omega_{jt-1}rd_{jt-1} + \xi_{jt} \tag{21}$$
$$\mu_{jt} = \delta_1\mu_{jt-1} + \delta_2\mu_{jt-1}^2 + \delta_3 rd_{jt-1} + \delta_4 rd_{jt-1}^2 + \delta_5\mu_{jt-1}rd_{jt-1} + \nu_{jt.} \tag{22}$$

Substituting equations (20), (21), and (22) into the revenue functions, equations (3) and (4) gives domestic and foreign market revenue in terms of observables and the structural parameters $\beta_k, \eta_d, \eta_f, \alpha_1...\alpha_5, \delta_1, ...\delta_5$:

$$\begin{aligned} \ln R_{jt}^d &= -(\eta_d+1)\left[\alpha_1\omega_{jt-1} + \alpha_2\omega_{jt-1}^2 + \alpha_3 rd_{jt-1} + \alpha_4 rd_{jt-1}^2 + \alpha_5\omega_{jt-1}rd_{jt-1}\right]) \\ &\quad +(\eta_d+1)\beta_k k_{jt} + \gamma_I + \gamma_t - (\eta_d+1)\xi_{jt} + u_{jt}^d \end{aligned} \tag{23}$$

$$\begin{aligned} \ln R_{jt}^f &= -(\eta_f+1)\left[\delta_1\mu_{jt-1} + \delta_2\mu_{jt-1}^2 + \delta_3 rd_{jt-1} + \delta_4 rd_{jt-1}^2 + \delta_5\mu_{jt-1}rd_{jt-1}\right]) \\ &\quad +(\eta_f+1)\beta_k k_{jt} + \rho_I + \rho_t - (\eta_f+1)\nu_{jt} + u_{jt}^f \end{aligned} \tag{24}$$

The error terms are $-(\eta_d+1)\xi_{jt} + u_{jt}^d$ and $-(\eta_f+1)\nu_{jt} + u_{jt}^f$ which consist of the period t transitory shocks to productivity evolution and the revenue functions. The moment conditions specify that these errors are uncorrelated with Z_{jt} =($\hat{h}_{jt-1}$, $\hat{h}_{jt-1}^2$, $\hat{b}_{jt-1}$, $\hat{b}_{jt-1}^2$, k_{jt}, k_{jt-1}, rd_{jt-1}, rd_{jt-1}^2, ($rd_{jt-1}\cdot$ $\hat{h}_{jt-1}$), ($rd_{jt-1}\cdot$ $\hat{b}_{jt-1}$), D_t, D_I) where the latter two arguments are year and industry dummies. To identify the demand elasticities η_d and η_f, we rely on the static demand and short-run marginal cost assumptions. At profit maximizing prices and quantity, marginal cost is equal to marginal revenue in each market, such that

$$tvc_{jt} = q_{jt}^d c_{jt} + q_{jt}^f c_{jt} = R_{jt}^d(1+\frac{1}{\eta_d}) + R_{jt}^f(1+\frac{1}{\eta_f}) + u_{jt}, \tag{25}$$

where the error term u_{jt} is the measurement error in total variable cost. We add two additional moment conditions specifying that u_{jt} is uncorrelated with R_{jt}^d and R_{jt}^f. This gives a total of 40 moment conditions. Minimizing the sum of the weighted moment conditions, using $Z'Z$ as the weighting matrix, provides estimates of the structural parameters of the profit function and productivity processes.[12]

[12]The measure $\hat{b}_{jt}$ is estimated from the export revenue equation. Thus, the equation (20) only gives us μ_{jt} for exporting firms. To impute the revenue productivity μ_{jt} for non-exporting observations, we invert the capital investment equation (15) and regress the obtained μ_{jt} for exporters on their $(k_{jt}, i_{jt}, \omega_{jt})$. Because the investment policy function is given for all firms, the foreign revenue productivity for non-exporters is then constructed as the fitted value of μ_{jt} using the non-exporters' information on $(k_{jt}, i_{jt}, \omega_{jt})$.

5.2 R&D and Export Cost Functions

The second goal of the empirical model is to estimate the dynamic parameters for the innovation and export cost. The variable cost of innovation is specified as:

$$VC(rd_{jt}, \upsilon_{jt}) = \theta_1 rd_{jt} + \theta_2 rd_{jt}^2 + rd_{jt}\upsilon_{jt}. \tag{26}$$

The parameter $\theta_2 > 0$ reflects the adjustment cost or increasing marginal cost of innovation. The deviations υ_{jt} are stochastic and we assume $\upsilon \sim N(0, \sigma_\upsilon^2)$. The structural error term υ_{jt} allows for differences in the variable and marginal costs of innovation across firms and will account for heterogeneity in the level of R&D expenditure across firms. The parameter σ_υ reflects the dispersion in the marginal cost of innovation across firms.[13] The shocks are rescaled as $\upsilon = \sigma_\upsilon \upsilon^*$ where $\upsilon^* \sim N(0,1)$ and the variable cost function becomes

$$VC(rd_{jt}, \upsilon_{jt}^*) = \theta_1 rd_{jt} + \theta_2 rd_{jt}^2 + \sigma_\upsilon rd_{jt}\upsilon_{jt}^*. \tag{27}$$

The fixed cost of innovation is modeled as a firm-time specific shock. It is specified as a draw from an exponential distribution where the mean of the distribution depends on the firm's prior period R&D experience $I(rd_{jt-1})$:

$$FC(I(rd_{jt-1})) \sim \exp(\gamma^m I(rd_{jt-1} > 0) + \gamma^s(1 - I(rd_{jt-1} > 0))) \tag{28}$$

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 specify the distribution of exporting cost faced by the firms when making their export decision. The export cost is assumed to be a 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

$$P_{jt}^f = 1 - \exp(-\pi_{jt}^f/\gamma^f) \tag{29}$$

and the mean export cost, conditional on exporting is $E(c_{jt}^z|\pi_{jt}^f > c_{jt}^z) = \gamma - \pi_{jt}^f[(1 - P_{jt}^f)/P_{jt}^f]$. The expressions for P_{jt}^f and $E(c_{jt}^z|\pi_{jt}^f > c_{jt}^z)$ can be substituted into the firm's short-run profit function, equation (7) to complete the specification of the model parameters.

5.3 The Firm Value Function and R&D Policy Function

The sources of firm-level heterogeneity in long-run profits and R&D investment at the extensive and intensive margin are the state variables $k_{jt}, \omega_{jt}, \mu_{jt}, I(rd_{jt-1})$. To estimate the dynamic parameters for innovation and export costs, we approximate the value function for each firm at a given value of the dynamic parameters using basis functions. We approximate the two value functions, equations (12) and (13) as:

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

[13] Barwick, Kalouptsidi, and Bin Zahur (2019) and Ackerberg, Benkard, Berry, and Pakes (2007) develop dynamic models with shocks that affect the continuous part of the firm's choice variable.

where $\boldsymbol{c}_0$ is a vector of approximation parameters for firms that do not do R&D, $\boldsymbol{c}_1$ is a vector of approximation parameters for firms that do R&D, and the basis functions $\Phi(k, g^{\omega}, g^{\mu})$ are Chebyshev polynomials. The left hand side of the value function equation (11) can be approximated as either V^0 or V^1 depending on the firm's past R&D:

$$V(k_{jt}, \omega_{jt}, \mu_{jt}, I(rd_{jt-1})) = (1 - I(rd_{jt-1}))\Phi(k_{jt}, \omega_{jt}, \mu_{jt})\boldsymbol{c}_0 + I(rd_{jt-1})\Phi(k_{jt}, \omega_{jt}, \mu_{jt})\boldsymbol{c}_1 \quad (30)$$

The full set of parameters estimated in the dynamic stage is $\Gamma = (\theta_1, \theta_2, \sigma_{\upsilon}, \gamma^f, \gamma^m, \gamma^s, \mathbf{c}_0, \mathbf{c}_1)$. For given values of the parameters Γ, we solve the first-order condition, equation (14) to find the optimal R&D level at each state and draw of the cost shock υ. Using the optimal R&D investment, we find the value function approximation parameters $\mathbf{c}_0$ and $\mathbf{c}_1$ by solving the Bellman equation (11) at a set of approximation nodes. Since the fixed costs of innovation and exporting are assumed to follow exponential distributions, we obtain analytical expressions for their integrals as functions of the parameters γ^m, γ^s, and γ^f. We use numerical quadrature to integrate over the variable cost shocks υ and productivity shocks ξ and ν in the domestic and foreign markets, respectively.

The structural parameters Γ are estimated using the method of indirect inference (Gourieroux, Monfort, and Renault (1993), Gourieroux and Monfort (1996), and Li(2010)). For firms that invest in R&D, the estimator matches the percentiles of the observed log R&D distribution Q_x, where $x = (0.05, 0.10, 0.15, 0.20, \cdots, 0.95)$, with percentiles of average R&D generated by the model. It also matches the mean probability of investing in R&D (conditional on past R&D) and the mean probability of exporting. Thus, the coefficients of the R&D variable cost function, $\theta_1, \theta_2, \sigma_{\upsilon}$, are estimated from the percentiles of the distribution of log R&D expenditure for firms that invest in R&D. The fixed costs γ^m and γ^s are identified by matching the mean of the discrete R&D decision conditional on the previous R&D decision, and the export cost γ^f is identified by matching the mean of the discrete export decision. In each case, denote the vector of moments generated by the model as $\tilde{\boldsymbol{Q}}(\boldsymbol{\Gamma})$, and $\mathbf{Q}$ as the corresponding vector of data moments. The criterion function minimizes the distance between the moments $\tilde{\boldsymbol{Q}}(\boldsymbol{\Gamma})$ and $\mathbf{Q}$

$$\mathbf{J}(\boldsymbol{\Gamma}) = [\mathbf{Q} - \tilde{\boldsymbol{Q}}(\boldsymbol{\Gamma})]'\boldsymbol{A}[\mathbf{Q} - \tilde{\boldsymbol{Q}}(\boldsymbol{\Gamma})], \quad (31)$$

where $\boldsymbol{A}$ is the weighting matrix $\boldsymbol{A} = Var[\boldsymbol{Q}]^{-1}$.

6 Empirical Results

In this section we summarize the parameter estimates for the productivity processes, profit function, and costs function for innovation. We then use the estimates to summarize the distribution of expected benefits from R&D investment and show how this differs between exporting and non-exporting firms.

6.1 Productivity Evolution and the Profit Function

Table 3 reports the estimates of the structural parameters for the profit functions and productivity processes. The qualitative patterns in the coefficients are similar across the four industry-market pairs. The coefficient on lagged productivity is positive and large. This means firm productivity is highly persistent, therefore productivity gains resulting from R&D will be long lived. The coefficient on the squared value of lagged productivity is negative, indicating that the degree of persistence will be smaller for high-productivity firms. The positive coefficient on R&D and the negative coefficient on R&D squared indicate that R&D has a positive but diminishing effect on productivity in the four industry-market pairs. The interaction term between R&D and lagged productivity is positive, showing that the return to R&D is increasing in the firm's own productivity. The magnitude of the R&D coefficients do differ across industry and market groups. The first-order coefficient on R&D is larger in the high-tech industries relative to the low-tech industries and in the export markets relative to the domestic markets, implying a larger impact of R&D on productivity and profits in the export market relative to the domestic market.

The elasticities of productivity with respect to R&D expenditure and lagged productivity depend on the current R&D expenditure and productivity and therefore vary across firms. Table 4 summarizes the distribution of these elasticity estimates across the firm-year observations. The top two lines report elasticities with respect to R&D. In the high-tech industries, the elasticity of domestic market productivity with respect to R&D, $\frac{\partial \omega_{it}}{\partial ln(rd_{it-1})}$, varies from 0.004 at the 10th percentile to 0.0130 at the 90th. The median value is 0.0082. The elasticity of foreign market productivity is larger, with a value of 0.0104 at the median and 0.0165 at the 90th percentile. Both elasticities are smaller in the low-tech industries but the foreign market elasticity remains larger than the domestic market elasticity.

The elasticity of market x revenue $(x = d, f)$ with respect to R&D is a measure of the short-run return to R&D, and is calculated by multiplying the productivity elasticity by $-(1 + \eta^x)$. For the high-tech industries, the median values are 0.0180 and 0.0206, in the domestic and foreign markets, respectively. In the low-tech industries the medians are 0.0040 and 0.0084. The larger values for the foreign market revenue imply that an increase in R&D spending will have a larger impact on total firm profits through their foreign market sales than their domestic market sales. This means that firms with a larger share of sales in the foreign market will have a higher return to R&D investment. Within each market, there is substantial heterogeneity in the R&D elasticity across firms - the 90th percentile is about three times larger than the 10th percentile in high-tech which implies different returns to R&D across firms.[14]

The last two rows of the table report the persistence in each market's productivity. These elasticities are uniformly high, between 0.88 and 0.98 across all firms in both markets. This implies that the productivity gains from R&D expenditure depreciate slowly, so that current investments have a long-lasting impact on future firm profits and thus firm value. The similarity in elasticities within each market implies that differences in productivity depreciation rates are not a major source of across-firm differences in the return to R&D. The across-firm differences

[14]These estimates are in line with the results of related studies. In their review of the literature, Hall, Mairesse, and Mohnen (2010) report that revenue elasticity estimates vary across studies from 0.01 to 0.25 and are centered around 0.08. Doraszelski and Jaumandreu (2013, Table 7) report estimates of the elasticity of output, not revenue, for ten Spanish manufacturing industries. The average value over all firms is 0.015, and the average at the industry level varies from -0.006 to 0.046 across the ten industries, with half of the industries falling between 0.013 and 0.022. Peters, Roberts, Vuong, and Fryges (2017, Table 11) report estimates based on the extensive margin of R&D investment, comparing the revenue of firms that invest in R&D and firms that do not, for German manufacturing industries. The average value of the revenue elasticity is 0.122 for a group of five high-tech industries and 0.061 for seven low-tech industries.

are more heavily affected by the elasticities of R&D.

6.2 The Firm's R&D Investment Decision

The results reported in Table 4 indicate that both domestic and export productivities ω and μ 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 productivities ω_{jt}, μ_{jt}, and capital stock k_{jt}. Before estimating the firm's dynamic demand for R&D, we assess the importance of these state variables 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 5. Columns labeled "Discrete" report estimates of logit regressions using a discrete indicator of exporting or R&D. Columns labeled "Log Expend" report OLS estimates with log R&D expenditure as the dependent variable.

Overall, the policy function estimates for the high-tech industries demonstrate that ω_{jt}, μ_{jt}, and k_{jt} are all important determinants of the firm's export and R&D decisions. In the case of the R&D reduced forms, some of the individual coefficients are not statistically significant, while most of the individual coefficients are significant for the export decision. More importantly, 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 estimates of the parameters characterizing the cost of innovation and exporting are reported in Table 6**.** The parameter estimates satisfy 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_1, θ_2, and σ_v in the variable cost function of R&D, γ^m and γ^s, which are the unconditional means of the fixed maintenance and fixed startup cost distributions of R&D, and γ^f the unconditional mean of the fixed cost distribution for exporting. The parameter θ_2 is positive in all industries, indicating rising marginal cost of innovation as the firm increases its R&D expenditure. In the electrical machinery industry θ_2 is virtually zero, implying constant marginal cost of innovation. The parameter σ_v measures the dispersion in the marginal cost of innovation, holding the level of R&D expenditure fixed. The estimates are between 0.1345 and 0.5622 in the high-tech industries and between 0 and 0.2024 in the low-tech industries. These estimates indicate substantial dispersion in the marginal cost of innovation across firms and time, which also implies substantial dispersion in the expected benefits of R&D investment across firms and time.

The R&D maintenance cost parameter γ^m is always smaller than the startup cost γ^s. This implies that firms with positive R&D investment in the previous year 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. The fixed cost of exporting is a measure of the level of export profits needed to induce the firm to export. In the high-tech industries the export cost parameter γ^f implies that average export costs are less than 2.5 million SEK in five out of six industries.[15] This reflects the fact that the export participation rates in our sample are high, with only a few firms not exporting. In contrast, the fixed cost parameters in the low-tech industries are higher, ranging between 1.6 and 13.6 million SEK, indicating that fewer Swedish firms in these industries will find it profitable to export.

Table 7 summarizes the distribution of the expected marginal cost of innovation (EMC) across observations where the expectation is taken over the random shock υ. In the high-tech industries it shows substantial heterogeneity arising from differences in the level of R&D expenditure. Both the level of EMC and its dispersion within-industry differs across industries. The level is particularly large in the metal and vehicle industries indicating that all firms in those industries face high costs of innovation. In low-tech industries, the marginal cost of innovation is high in the upper percentiles of the distribution, indicating that for a substantial number of firms the long-run payoff to R&D will have to be high in order to make R&D investment profitable for them.

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 two and three, versus paying a startup cost to begin investing, columns four and five. Overall, the mean frequencies of the maintenance cost of R&D and the start up cost of R&D are matched well for all industries. The mean frequencies of the export cost are also matched almost perfectly. Table 9 reports the fit of the model with respect to the level of R&D expenditure for observations with positive R&D investment. In each industry the ability of the model to replicate the distribution of R&D expenditures across firms and over time is very good.

6.3 The Long-Run Return to R&D Investment

Measuring the private rate of return to R&D has been a goal of productivity researchers for many years. The most commonly used measure of the gross rate of return is constructed from production function estimates of the marginal product of knowledge capital, measured as a depreciated sum of past R&D expenditures, on output. In their comprehensive review of the literature, Hall, Mairesse, and Mohnen (2010) summarize a wide range of estimates that are generally in the 20 to 30 percent range, but can be as high as 75 percent. The model we develop here provides an alternative measure based on the increase in firm value resulting from R&D spending. As part of our estimation, we solve for the value functions and construct the expected payoff to R&D at each state. We define the long-run expected benefit of R&D as the difference between the value function when investing at the optimal level of R&D minus the value function when not investing in R&D: $EB = V^1 - V^0$. It is normalized in two ways. First,

[15] In 2010, 1 USD=7.2 SEK and 1 EUR=9.54 SEK

as $EB/R\&D$, which summarizes the total payoff to the R&D investment per krona spent, and, second, as EB/V^0, which summarizes the proportional gain in long-run firm value from the optimal R&D investment.

Table 10 summarizes the 25th, 50th, and 75th percentiles of the distribution of $EB/R\&D$ across firm observations for both the non-exporting and exporting firms. Three patterns stand out. First, the distribution of expected benefits for exporters stochastically dominates the distribution for non-exporters in every industry. For example, in the chemical industry, the 25th and 75th percentiles among the non-exporters are 1.006 and 1.712, while the values for the exporters are 4.477 and 110.797. The median values among the non-exporters vary from 0.526 to 5.372 across industries. For two industries, electrical machinery and instruments, the values are less than one, implying that the total benefits to R&D investment would not exceed the expenditure. Second, there is also substantially more heterogeneity among the exporting firms. The fourth and last columns report the interquartile range relative to the median. The dispersion among exporting firms is, in general, larger than for non-exporting firms. The difference in dispersion is largest for the metals, vehicles, plastics, and miscellaneous industries. This reflects the role played by the heterogeneity in export market productivity μ among the exporters.

Third, among the non-exporters, the benefits of R&D are larger in several of the low-tech industries than in the high-tech industries. For example, in the paper, ceramics, and miscellaneous industries, the benefits at the 75th percentile of the distribution are larger than the corresponding percentiles in all the high-tech industries. This finding does not extend to the exporting firms. Among exporting firms the benefits at the 25th percentile are not substantially different between the high- and low-tech industries, but at the median and 75th percentile the benefits from the optimal R&D expenditure in the high-tech sectors are substantially higher in most industries. Overall, the table demonstrates that there are large differences in the benefits of R&D across firms within the same industry. The upper tails of the payoff distribution are particularly large for exporting firms in the high-tech industries, emphasizing the positive relationship between exporting and incentives to invest in innovation.

The median value of the proportional gain in firm value resulting from R&D investment, EB/V^0, is reported in Table 11 for each industry. This clearly illustrates the differences in the gain from R&D between the high-tech and low-tech industries and between firms with different export status. For the non-exporting firms, the median gain is less than 2.2 percent in all but one high-tech industry and less than 0.7 percent in all low-tech industries. Non-electrical machinery is the one outlier in this pattern. For the exporting firms, the proportional gains are much higher in the high-tech industries, exceeding 38.6 percent in four of the six industries. In contrast, they never exceed 1.4 percent in the low-tech industries. R&D investment clearly has the largest impact on long-run firm value among the exporting firms in the high-tech industries, particularly chemicals, nonelectrical and electrical machinery and instruments.

The patterns reported in Tables 10 and 11 indicate that across-firm variation in the long-run payoff to R&D is substantial and arises from differences in domestic and foreign market productivity and firm size. This firm-level heterogeneity in long-run benefits is an important factor contributing to the differences in R&D investment across industries and between exporting and non-exporting firms that were seen in Table 2. In the next section we simulate how R&D investment on both the extensive and intensive margin responds to changes in the export market conditions and innovation costs.

7 Counterfactual Analysis of Tariffs and R&D Subsidies

While Sweden has long advocated free trade policies, policy makers have recently noted that, because of increasing threats to free trade, the role of innovation is particularly important to maintaining the international competitiveness of Swedish exports and have focused efforts on improving Sweden's position in world markets (Swedish government, 2012, 2019). However, the Organization for Economic Co-operation has emphasized the lack of accurate evaluations of the role of R&D investment across sectors that can help guide policy choices (OECD, 2013).

The structural model of R&D investment developed in this article provides the necessary framework to analyze the impact of trade and innovation policies that impact the benefits or costs of R&D investment. Export tariffs on Swedish manufactured products will impact the profitability of export market sales, which, as shown in the previous section, contributes substantially to the return on R&D. Import tariffs that raise the cost of imported materials will also reduce the profitability of Swedish producers in both domestic and export markets and affect the payoffs to R&D investment. Subsidies to firms that invest in R&D, either through direct payments or through beneficial tax treatment of R&D expenditures, impact the cost of innovation and can affect the amount of R&D investment undertaken. In this section we use the estimated model to simulate the effect of tariffs and R&D subsidies on the intensive and extensive margin of R&D investment.[16]

7.1 Output and Input Tariffs

Most of the empirical literature summarized in section 2 has focused on the impact of trade liberalizations on the incentives of firms to invest in innovation-related activities and generally find that openness encourages innovation investments. In this section we simulate how restrictions in international markets due to output and input tariffs affect both the probability of investing in R&D (the extensive margin) and the amount of R&D spending (the intensive margin) by Swedish manufacturing firms. Countries like Sweden, that are technologically advanced but have small domestic markets, rely heavily on export markets for their sales and the return to R&D can be substantially affected by access to those markets.[17]

Table 12a reports the results from a simulation of a permanent 20 percent tariff on Swedish exports. In the model this is equivalent to reducing the intercept of the export market revenue function. This results in a change in the optimal amount of R&D spending and thus affects both the total benefits and total costs of the investment. To summarize the total impact on the firm we define the expected net benefits of R&D as the expected benefits net of the total cost of innovation: $ENB = V^1 - V^0 - C_I(rd)$. The table reports five dimensions in

[16] In the counterfactual analysis we change one or more of the structural parameters and resolve the model for the optimal R&D spending in the new environment. Changes in the optimal R&D yield changes in future productivities and short- and long-run profits.

[17] In practice, export and import tariffs are set by the European Union and Sweden is not free to vary tariffs independently. These counterfactuals are designed to show how restrictions in the export or import markets affect long-run firm value and the return to R&D.

which the tariff affects the endogenous variables for firm choices and outcomes. The first two columns report the percentage change in the continuous variables, ENB and the optimal R&D expenditure, respectively. The last three columns report the impacts on the extensive margins: the probability of a firm continuing to invest in R&D, beginning to invest in R&D, and exporting. The values reported are the median values across firms in each industry.[18] For the six high-tech industries, the net benefit of investing in R&D falls by between 27.06 and 42.05 percent. This leads to a reduction in expenditure on R&D of between 10.47 and 18.02 percent for the median firm across industries. The largest impacts are in the instruments industry and the smallest in the vehicle industry. There is also a large impact on the intensive margin of R&D investment in five of the six low-tech industries. With the exception of the food industry, the net benefit of R&D investment falls between 25.45 and 40.76 percent, resulting in a decline in R&D expenditure in these industries of between 7.25 and 12.03 percent. Reductions in the profitability of the export market lead to significant downward adjustments in the amount of R&D spending.

On the extensive margin the changes are much smaller. For the high-tech industries, there is no impact on the probability that a firm that is investing in R&D will stop completely and there is a small reduction, between 0.6 and 2.1 percentage points, in the probability that a firm will begin investing in R&D. There is also a reduction in the probability of exporting in two industries, metals and instruments, which contributes to the reduction in the expected payoff to R&D. The impact on the extensive margins in the low-tech industries are larger than in the high-tech industries, with three of the industries showing a reduction in the number of firms that continue R&D of a least one percentage point, and four of the industries showing at least a one percentage point reduction in the probability of starting to invest in R&D. Export participation is reduced by between 2.39 and 13.42 percent in five of the six industries. Overall, the reduction in export market profitability due to the output tariff discourages some firms from undertaking R&D but the larger impact occurs on the intensive margin where the reduction in the amount of R&D spending by the investing firms is substantial. The export market is a significant source of the firms' overall return to R&D and restrictions on exporting lead to less investment in R&D, thus reducing a source of the dynamic gains from exporting.

While Table 12a reports impacts for the median firm in the sample, Table 12b summarizes impacts across the distribution of firms. In this case, firms are distinguished by their level of domestic and foreign market productivity ω and μ. Each firm is assigned to a cell based on the industry quartile in which its productivities lie. Moving across each row, the foreign market productivity μ increases, and moving down each column domestic productivity ω increases. The table reports the percentage change in expected net payoff to R&D, ENB, at the median within each cell.

Focusing on the high-tech industries, the tariff has a larger negative impact on firms with larger foreign productivities. The reduction in net benefits is between -31.12 and -60.62 percent for the most productive foreign-market firms. This is consistent with the fact that firms with high foreign productivity will tend to have larger foreign sales and thus be more heavily impacted by the export market tariff. However, there is a more heterogeneous pattern when both μ and

[18] We also construct the total reduction in R&D spending over all sample firms and this number is very similar to the reduction for the median firm that is reported in Tables 12a-14a. For clarity we will focus on the impact on the median firm, but this is a good estimate of the impact on total R&D investment in the industry.

ω vary. The loss in benefits is increasing with ω when μ is low, but decreasing with ω when μ is high. The former pattern implies that high productivity domestic firms that export little are affected as options to expand exports are reduced, while the latter pattern implies that the firms with high foreign productivity are less impacted by the tariff if they are simultaneously good in the domestic market.

The counterfactual reported in Table 13a maintains the 20 percent output tariff on Swedish exports and adds a 20 percent tariff on imported materials.[19] This represents the case where a retaliatory tariff is imposed to protect domestic suppliers of intermediate materials. This input tariff raises the cost of the Swedish manufacturers and impacts sales in both the domestic and export markets. The results in Table 13a show the same qualitative pattern as the export tariff alone, but the magnitudes of the effects are magnified. Across all the high- and low-tech industries, the expected net benefit of investing in R&D falls by between 37.89 and 56.89 percent with the largest impacts in the low-tech industries. This reduction generates reductions in the amount of R&D spending by between 15.99 and 24.80 percent, with the largest reductions in spending in the high-tech industries. The dual tariffs also have a larger impact on the probability of maintaining R&D investment in the low-tech industries. The probability of maintaining R&D falls by 2.64 to 7.7 percent in five of the industries (and by 25.22 percent in the remaining industry). The probability of starting R&D investment falls by a magnitude that is approximately twice as large as what was observed with just the output tariff, with reductions between 1.38 and 4.55 percent in all but one industry. Finally, the reduction in the probability of exporting is approximately equal to what was observed with just the output tariff.

Focusing on the distribution of the reduction in benefits across firms with different productivities in Table 13b, the reduction in the expected benefits, relative to the output tariff alone, is much larger. The decline in net benefits is particularly large for the firms with lower levels of foreign productivity μ. For the firms in the lowest quartile of μ, the median percentage decline in ENB varies from 25.39 to 48.96 percent across industries. This decline is at least three times larger than was observed with the output tariff alone. Penalizing all firms with the additional tariff impacts the firms least exposed to the foreign market most heavily.

7.2 Subsidies to R&D expenditure

Firm R&D investments can be below the socially desired level. Reasons for this include R&D investments being costly to firms that are financially constrained; the outcome of the R&D process being subject to high level of uncertainty; and firms not internalizing the full benefits of innovations resulting from their R&D undertakings. To encourage R&D investment, governments often promote policies designed to lower the R&D cost incurred by firms, such as applying tax credits or accelerated depreciation. Relying on our model estimates, we assess the effectiveness of policies that subsidize innovation costs in terms of their impact on firm's

[19] In the data we do not observe the fraction of materials that are imported by each firm. We impute the fraction of imported materials using the average value in the industry. These account for approximately half of input expenditures in Swedish industries.

investment and export activities.[20] In particular, we simulate the firm's R&D investment and export decisions for a 20 percent reduction in the variable cost of innovation.

To simulate the effect of a 20 percent subsidy of the firm's R&D expenditure, we set $\theta_1 = 0.80\hat{\theta_1}$ in the variable cost function equation (27) which reduces the marginal cost of investment but does not affect the slope of the marginal cost curve by leaving the adjustment cost component θ_2 unaffected. We simulate the effect of this cost change on the same five firm-level outcomes as the tariff counterfactuals. Table 14a summarizes the median of these measures for firms in the high-tech and low-tech industries, respectively.

With a 20 percent subsidy, lower marginal cost leads to a higher optimal R&D investment level. Across industries, the percentage change in R&D investment is heterogeneous. The R&D level increases between 1.84 (chemical) and 28.57 percentage points (electrical machinery). A substantial increase in R&D spending, such as the rise observed in electrical machinery, reflects a marginal benefit curve $\partial V^1/\partial rd$ that is fairly flat, so that cost reductions generate significant increases in the intensive margin of R&D investment.

The second column reports the growth in the total net benefits ENB to the firm from the expansion in its R&D. The results show that the 20 percent subsidy increases firm's total benefits from R&D between 0.79 (chemical) and 5.91 percent (vehicle) in high-tech industries. For example, the median firm in the chemical industry has an R&D net benefit that amounts to 82.7 percent of firm value (see Table 11); an increase of 0.79 percent in R&D benefit is therefore non-negligible. The growth in firm's net benefit is a multiple of the innovation cost saving firms receive from the subsidy because the growth reflects the impact of additional R&D investment on two sources: the increase in marginal benefits from improved future (ω, μ) paths and the reduction in future marginal costs due to the subsidy.

The change in the marginal cost has little impact on increasing R&D participation rates for both firms continuing and starting R&D. At the median, the change in R&D at the extensive margin for continuing firms amounts to zero while it is below 1 percent for firms starting new R&D investments. One reason for the small impact of the subsidy is that 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 same pattern can be observed for the export market participation. The median change in export participation is zero for most of the industries. While an expansion in R&D investment has a positive impact on firm productivity (ω, μ), increases its export sales, and enhances its chance of exporting, this gain does not sufficiently offset the fixed cost for exporting to make exporting profitable for the firm.

A similar pattern characterizes the low-tech industries. The reduction in firm's R&D variable cost generates positive gains in R&D investment levels and R&D net benefits. The gains are smaller and have smaller variation than those of the high-tech industries. Except for the food industry, the percentage change in R&D spending across industries is below 5.48 percent

[20]The empirical literature on the effects of R&D subsidies on investment and innovation is vast. Hall and Van Reenen (2000) provide a survey. Recent works by González, Jaumandreu, and Pazó (2005) and Arqué-Castells and Mohnen (2015) using Spanish firm data, and Takalo, Tanayama, and Toivanen (2013, 2017) using Finnish data, estimate structural models of firm R&D investment and use them to conduct counterfactuals on the level of subsidies.

and below 2.86 percent in the R&D net benefit. The cost reduction also shows little impact on the extensive margin in the low-tech industries. The change in R&D participation and the export participation rate is positive but close to zero.

Focusing on the percentage change of R&D benefit by their productivity levels ω and μ reported in Table 14b, firms in the high-tech industries enjoy a higher percentage gain in R&D benefit than those in the low-tech industries. The percentage gain ranges between 25.16 percent in the lowest (ω, μ) quartile and 1.08 percent in the highest productivity quartile in high-tech. In low-tech those numbers range between 6.45 and 0.33 percent. As productivity levels (ω, μ) increase the percentage gain decreases monotonically in high-tech, whereas no clear pattern emerges in the low-tech industries.

In an alternative policy experiment, we simulate firms' responses to a 20 percent reduction in the startup cost for R&D investment, and find that this cost reduction causes between 1 and 3 percent more firms to start investing in R&D. At the same time there is virtually zero change in the industry level of R&D investment. This indicates that a startup cost subsidy creates incentives for firms to invest in R&D, which would not have done so without the cost reduction; however, these firms invest only a small amount.

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. However, it has little impact on inducing new R&D participation in Swedish manufacturing industries.

8 Conclusion

This article develops an empirical model of the firm's dynamic decision to invest in R&D, where the decision is both whether or not to invest and how much to spend on R&D. The firm's investment choice impacts the path of future productivity in both domestic and export market sales. The model provides a measure of the expected long-run gain from investing in R&D that depends on the firm's export and domestic market productivities. It also estimates the cost function for innovation, which includes the actual expenditure on R&D, 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 domestic and export productivity channels and increase expected future firm value substantially. Investment in R&D is found to have a larger impact on revenue and profits in export markets than in the domestic market. At the median across firms in a group of high-tech industries, the elasticity of revenue with respect to R&D expenditure is 0.018 for domestic sales and 0.0206 for foreign market sales. This difference will contribute to a higher return on R&D for firms that are substantial exporters and act as a source of dynamic productivity gains for exporters relative to non-exporting firms.

The model provides a direct measure of the return to R&D as the increase in long-run firm value resulting from the R&D investment. This return is much larger in a group of six high-tech industries than in a group of six low-tech industries, and a large premium for exporting firms is also found. The median of the expected gain in firm value from investing in R&D is less than 0.7 percent and 1.4 percent for non-exporters and exporters, respectively, in the low-tech industries. The expected gain is generally less than 2.2 percent for non-exporting firms in the high-tech industries but is substantially larger for the exporting firms. Across the six high-tech industries the median gain varies from 5.1 to 84.7 percent, with four of the industries having values above 38 percent.

The estimated decision rules for R&D investment and export market participation allow us to study counterfactual environments where profitability in both markets is impacted by export and import tariffs and the cost of innovation is reduced by R&D subsidies. The results show that a 20 percent export tariff on Swedish high-tech exports reduces the expected net payoff to R&D by between 27.06 to 42.05 percent across the six high-tech industries. This decline in benefit of R&D generates a reduction in R&D spending on the intensive margin of between 10.47 and 18.02 percent in the high-tech industries. A similar decline is seen in five of the six low-tech industries. These results indicate that the ability to export to a larger world market has a substantial effect on the return to R&D and the level of R&D spending in the Swedish manufacturing industries. More modest effects of the export tariff on the extensive margin of R&D investment are observed in the counterfactual results. The output tariff has virtually no impact on the decision of firms to stop investing in R&D and reduces the probability of a firm to begin invest in R&D by one to two percentage points. Another set of counterfactuals finds that a 20 percent subsidy to R&D spending increases R&D expenditure by 1.84 to 28.57 percent across the high-tech industries with three of the industries having an increase of more than 10 percent.

This study has explored the differences in long-run benefits of R&D investment between exporting and non-exporting firms and how this impacts their decisions to undertake R&D investment, how much to spend on R&D, and whether or not to export. The underlying mechanism is that R&D spending can have a different impact on the productivity of a firm in each market. The export market is shown to be an important source of profits for Swedish manufacturing firms and high productivity in export market sales substantially increases the payoff to R&D investment. Policies that reduce export market profitability or reduce innovation costs do impact the amount of R&D spending that firms undertake on the intensive margin but have relatively small effects on the extensive margin decisions to begin investing in R&D or begin exporting.

Our results are relevant to recent policy concerns about promoting innovation in an environment with increasing restrictions to free trade. In particular, we find that the imposition of tariffs that reduce export market profitability will significantly reduce the amount of R&D spending that firms will undertake, and will offset innovation policies designed to stimulate R&D investment. The linkages between the firm's trade exposure and innovation decisions are important for policy makers to recognize when attempting to stimulate investment in innovation.

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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

Table 3: Revenue Functions and Productivity Evolution (standard errors)

Parameter (variable)	High-Tech Industries	Low-Tech Industries
	Domestic Market Revenue	
$\alpha_1(\omega_{t-1})$	0.9944 (0.0296)	1.0376 (0.0060)
$\alpha_2(\omega_{t-1}^2)$	-0.0309 (0.0006)	-0.0322 (0.0030)
$\alpha_3(ln(rd_{t-1}))$	0.0173 (0.0024)	0.0050 (0.0006)
$\alpha_4(ln(rd_{t-1}))^2$	-0.0011 ($2.4{\cdot}10^{-5}$)	-0.0005 ($2.4{\cdot}10^{-5}$)
$\alpha_5(ln(rd_{t-1})\omega_{t-1})$	0.0058 ($7.0{\cdot}10^{-5}$)	0.0027 (0.0001)
β_k	-0.1081 (0.0004)	-0.079 (0.0008)
η_d	-3.1965 ($2.0{\cdot}10^{-6}$)	-3.235 ($3.0{\cdot}10^{-6}$)
	Export Market Revenue	
$\delta_1(\mu_{t-1})$	0.9968 (0.0207)	0.9791 (0.0005)
$\delta_2(\mu_{t-1}^2)$	-0.0221 (0.0001)	-0.0006 ($6.1{\cdot}10^{-5}$)
$\delta_3(ln(rd_{t-1}))$	0.0229 (0.0029)	0.0098 ($6.1{\cdot}10^{-5}$)
$\delta_4(ln(rd_{t-1}))^2$	-0.0016 ($2.6{\cdot}10^{-5}$)	-0.0003 ($4.3{\cdot}10^{-5}$)
$\delta_5(ln(rd_{t-1})\mu_{t-1})$	0.0062 ($6.3{\cdot}10^{-5}$)	0.0004 (0.0002)
β_k	-0.1061 (0.0004)	-0.249 (0.0060)
η_f	-2.9697 ($7.0{\cdot}10^{-6}$)	-2.574 ($1.0{\cdot}10^{-6}$)
sample size	3374	1834

All models include industry and year dummies

Table 4: Elasticities of Productivity						
	High-Tech Industries			Low-Tech Industries		
	10th	Median	90th	10th	Median	90th
Impact of R&D						
Domestic Market Productivity: $\frac{\partial \omega_{it}}{\partial ln(rd_{it-1})}$	0.0040	0.0082	0.0130	0.0002	0.0018	0.0028
Export Market Productivity: $\frac{\partial \mu_{it}}{\partial ln(rd_{it-1})}$	0.0052	0.0104	0.0165	0.0042	0.0053	0.0067
Impact of Lagged Productivity						
Domestic Market Productivity: $\frac{\partial \omega_{it}}{\partial \omega_{it-1}}$	0.883	0.919	0.957	0.906	0.937	0.961
Export Market Productivity: $\frac{\partial \mu_{it}}{\partial \mu_{it-1}}$	0.883	0.922	0.959	0.975	0.978	0.980

Table 5: 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	-1.259	4.903**	127.359**	0.490	1.521	-5.485
	(1.325)	(0.645)	(15.700)	(2.103)	(1.553)	(3.919)
ω_t	-0.995	-0.119	-46.888**	-3.958	1.785	0.356
	(1.546)	(0.681)	(8.727)	(3.054)	(1.932)	(7.778)
ω_t^2	0.090	0.093	4.893**	-0.172	-0.533	17.281**
	(0.508)	(0.218)	(1.654)	(1.262)	(0.664)	(5.176)
k_t	0.656	.687**	37.268**	0.539	0.0004	3.309*
	(0.351)	(0.196)	(4.109)	(0.563)	(0.346)	(1.576)
k_t^2	-0.004	0.025	2.477**	-0.051	-0.0008	1.013**
	(0.036)	(0.024)	(0.294)	(0.049)	(0.024)	(0.224)
μ_t	-0.958	-0.210	-116.97**	0.605	0.837	3.914
	(0.527)	(0.309)	(12.983)	(0.670)	(0.467)	(2.590)
μ_t^2	0.580**	0.348**	26.216**	-0.033	0.073	6.642**
	(0.104)	(0.067)	(2.850)	(0.116)	(0.086)	(0.815)
$\mu_t \times \omega_t$	0.413	0.152	21.332**	0.796	0.169	-22.509**
	(0.320)	(0.171)	(3.109)	(0.527)	(0.329)	(3.666)
$k_t \times \omega_t$	0.205	0.011	-6.581**	0.438	0.227	-7.705**
	(0.227)	(0.111)	(1.113)	(0.477)	(0.232)	(2.072)
$k_t \times \mu_t$	-0.445	-0.216**	-16.304**	-0.197	-0.107	3.383**
	(0.100)	(0.072)	(1.738)	(0.114)	(0.081)	(0.691)
Goodness of fit[a]	0.285	0.625	0.825	0.225	0.540	0.716
Sample Size	3374	2260	3374	1834	888	1834
Test Statistics (P-value)[b]						
H_0: coefficients on ω =0	16.91 (0.00)	3.53 (0.01)	82.21 (0.00)	13.57 (0.01)	2.27 (0.06)	109.97 (0.00)
H_0: coefficients on μ =0	155.92 (0.00)	83.07 (0.00)	492.78 (0.00)	62.89 (0.00)	17.83 (0.00)	220.86 (0.00)
H_0: coefficients on k =0	41.53 (0.00)	14.51 (0.00)	471.54 (0.00)	31.80 (0.00)	1.76 (0.10)	108.68 (0.00)

All models contain industry and year 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 4 restrictions.

Table 6: Estimates of Structural Cost Parameters (bootstrap standard errors)

	R&D Variable Cost			R&D Maint	R&D Startup	Export Cost
	θ_1	θ_2	σ_υ	γ^m	γ^s	γ^f
High-Tech Industries						
Chemicals	0.0855 (0.0013)	0.0089 (0.0001)	0.3450 (0.0066)	4.309 (0.305)	84.542 (10.010)	0.822 (0.048)
Metals	0.9075 (0.0094)	0.0126 (0.0002)	0.4371 (0.0042)	10.897 (0.589)	121.040 (6.566)	6.221 (0.265)
Non elect machinery	0.2830 (0.0047)	0.0076 (0.0001)	0.4839 (0.0088)	7.484 (0.705)	55.636 (3.096)	2.309 (0.146)
Electrical machinery	0.4146 (0.0090)	$6.89 \cdot 10^{-4}$ ($9.77 \cdot 10^{-6}$)	0.1345 (0.0022)	5.298 (0.303)	62.095 (3.574)	1.088 (0.077)
Instruments	0.0831 (0.0012)	0.0155 (0.0002)	0.1773 (0.0022)	4.622 (0.241)	15.714 (0.993)	2.506 (0.109)
Vehicles	0.6587 (0.0129)	0.0108 (0.0002)	0.5622 (0.0093)	14.439 (1.084)	98.709 (8.700)	1.566 (0.095)
Low-Tech Industries						
Food	0.7984 (0.0116)	0.0411 (0.0006)	0.2024 (0.0027)	23.022 (0.563)	59.786 (3.262)	13.562 (0.477)
Textiles	0.1740 (0.0019)	0.3957 (0.0057)	0.1607 (0.0019)	7.287 (0.244)	23.021 (1.871)	1.647 (0.088)
Paper	0.0396 (0.0008)	0.7093 (0.0115)	0.0503 (0.0007)	19.048 (1.260)	99.678 (5.556)	8.416 (0.375)
Plastics	0.1479 (0.0025)	0.2154 (0.0032)	0.1324 (0.0019)	12.350 (0.607)	39.239 (1.731)	2.127 (0.092)
Ceramics	0.1661 (0.0025)	0.4711 (0.0064)	$1.14 \cdot 10^{-5}$ ($1.69 \cdot 10^{-7}$)	13.383 (0.849)	93.633 (4.581)	3.315 (0.155)
Miscellaneous	0.4055 (0.0054)	0.2440 (0.0037)	0.0839 (0.0012)	12.673 (0.509)	48.420 (1.955)	2.979 (0.108)

Table 7: Expected Marginal Cost of Innovation

	Percentiles of the Distribution of $EMC(\omega, \mu, k)$				
	10th	25th	50th	75th	90th
High-Tech Industries					
Chemicals	0.538	0.553	0.618	0.741	0.985
Metals	1.165	1.180	1.258	1.362	1.653
Non elect machinery	0.839	0.850	0.908	0.998	1.086
Electrical machinery	0.458	0.459	0.466	0.476	0.494
Instruments	0.313	0.328	0.366	0.449	0.503
Vehicles	1.170	1.182	1.222	1.316	1.402
Low-Tech Industries					
Food	0.839	0.860	0.953	1.022	1.121
Textiles	0.494	0.561	0.737	1.090	1.580
Paper	0.421	0.722	1.176	2.136	3.249
Plastics	0.356	0.508	0.778	1.107	1.487
Ceramics	0.440	0.678	0.953	2.088	2.316
Miscellaneous	0.511	0.644	1.046	1.397	1.583

Table 8: Model Fit - Actual and Predicted Probabilities (mean)						
	Maintain R&D		Start R&D		Export	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
High-Tech Industries						
Chemicals	0.903	0.904	0.340	0.341	0.984	0.987
Metals	0.806	0.803	0.152	0.152	0.802	0.804
Non elect machinery	0.887	0.889	0.296	0.294	0.936	0.938
Electrical machinery	0.863	0.863	0.212	0.213	0.918	0.918
Instruments	0.880	0.880	0.333	0.333	0.870	0.870
Vehicles	0.804	0.804	0.264	0.264	0.935	0.937
Low-Tech Industries						
Food	0.517	0.517	0.104	0.104	0.420	0.420
Textiles	0.537	0.537	0.125	0.125	0.903	0.903
Paper	0.523	0.524	0.125	0.126	0.774	0.775
Plastics	0.636	0.635	0.246	0.246	0.960	0.959
Ceramics	0.589	0.589	0.157	0.157	0.813	0.813
Miscellaneous	0.639	0.639	0.219	0.219	0.898	0.897

Table 9: Model Fit - Distribution of log R&D Expenditures (thousands of SEK)						
	10th Percentile		Median		90th Percentile	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
High-Tech Industries						
Chemicals	6.907	6.478	9.321	9.815	11.229	10.265
Metals	5.991	5.490	8.292	8.597	10.571	10.553
Non elect machinery	6.684	6.312	9.210	9.549	11.708	11.466
Electrical machinery	6.397	6.393	8.987	8.796	10.714	11.356
Instruments	6.404	6.518	8.780	8.654	9.851	9.986
Vehicles	6.331	5.951	8.578	8.804	11.127	11.030
Low-Tech Industries						
Food	4.605	4.928	6.955	7.028	8.239	8.158
Textiles	5.298	5.348	6.397	6.620	7.400	7.416
Paper	5.298	5.794	6.895	6.705	7.601	7.615
Plastics	5.298	5.724	7.313	7.263	8.307	7.979
Ceramics	5.962	6.100	6.908	6.790	7.972	7.753
Miscellaneous	5.298	5.683	7.090	7.058	7.824	7.797

Table 10: Percentiles of Distribution of R&D Benefits $(V^1 - V^0)/R\&D$

	Non-exporters				Exporters			
	P_{25}	P_{50}	P_{75}	IQR/P_{50}	P_{25}	P_{50}	P_{75}	IQR/P_{50}
High-Tech Industries								
Chemicals	1.006	1.085	1.712	0.651	4.477	56.595	110.797	1.879
Metals	2.431	3.867	5.726	0.852	3.551	10.174	161.685	15.54
Non elect machinery	1.219	1.894	3.534	1.222	5.483	45.127	103.844	2.180
Electrical machinery	0.213	0.526	0.967	1.433	2.063	21.294	47.711	2.144
Instruments	0.429	0.573	0.802	0.631	3.501	25.145	57.251	2.138
Vehicles	1.237	1.707	3.167	1.131	3.345	11.718	90.606	7.447
Low-Tech Industries								
Food	1.798	2.924	4.173	0.812	6.536	9.985	19.095	1.258
Textiles	1.925	2.124	4.046	0.999	2.687	4.628	8.711	1.302
Paper	2.987	5.372	10.469	1.393	5.585	11.126	22.394	1.511
Plastics	1.167	2.180	2.451	0.589	4.310	8.795	79.705	8.572
Ceramics	1.811	2.912	6.385	1.571	7.555	16.498	31.469	1.450
Miscellaneous	2.003	3.347	6.490	1.341	4.581	9.939	54.469	5.019

Table 11: Proportional Increase in Firm Value $(V^1 - V^0)/V^0$ (median)

	All Firms	Non-exporters	Exporters
High-tech Industries			
Chemicals	0.827	0.015	0.847
Metals	0.034	0.022	0.051
Non elect machinery	0.543	0.119	0.667
Electrical machinery	0.229	0.004	0.386
Instruments	0.401	0.010	0.547
Vehicles	0.069	0.008	0.089
Low-tech Industries			
Food	0.006	0.003	0.013
Textiles	0.009	0.004	0.009
Paper	0.009	0.007	0.010
Plastics	0.013	0.004	0.013
Ceramics	0.013	0.003	0.014
Miscellaneous	0.012	0.003	0.013

Table 12a: Change in Variables in Response to 20% Export Tariff (Median)					
	Percentage Change		Change in Probability		
	ENB	R&D	Maintain R&D	Start R&D	Export
High-Tech Industries					
Chemicals	-0.3018	-0.1303	0.0000	-0.0210	-0.0000
Metals	-0.3512	-0.1402	0.0000	-0.0154	-0.0843
Non elect machinery	-0.3025	-0.1383	0.0000	-0.0119	-0.0002
Electrical machinery	-0.2857	-0.1429	0.0000	-0.0062	-0.0003
Instruments	-0.4205	-0.1802	0.0000	-0.0107	-0.0339
Vehicles	-0.2706	-0.1047	0.0000	-0.0135	-0.0003
Average - High-Tech	**-0.3221**	**-0.1394**	**0.0000**	**-0.0131**	**-0.0198**
Low-Tech Industries					
Food	-0.0550	-0.0178	-0.0113	-0.0004	-0.0770
Textiles	-0.3994	-0.1203	-0.0317	-0.0116	-0.0717
Paper	-0.3725	-0.1013	-0.0192	-0.0078	-0.1342
Plastics	-0.4076	-0.1185	-0.0079	-0.0266	-0.0042
Ceramics	-0.2545	-0.0725	-0.0041	-0.0214	-0.0343
Miscellaneous	-0.3327	-0.1040	-0.0074	-0.0153	-0.0239
Average - Low-Tech	**-0.03036**	**-0.0891**	**-0.0136**	**-0.0139**	**-0.0576**

Table12b: Percentage Change in ENB from 20% Export Tariff (Median)				
	$P_0 \leq \mu \leq P_{25}$	$P_{25} < \mu \leq P_{50}$	$P_{50} < \mu \leq P_{75}$	$P_{75} < \mu \leq P_{100}$
HighTtech Industries				
$P_0 \leq \omega \leq P_{25}$	-0.0334	-0.4421	-0.5942	-0.6062
$P_{25} < \omega \leq P_{50}$	-0.0853	-0.3790	-0.4329	-0.4143
$P_{50} < \omega \leq P_{75}$	-0.1346	-0.3023	-0.3448	-0.3515
$P_{75} < \omega \leq P_{100}$	-0.1329	-0.2286	-0.2596	-0.3112
Low-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	-0.0816	-0.3376	-0.4158	-0.4975
$P_{25} < \omega \leq P_{50}$	-0.1436	-0.2762	-0.4322	-0.5178
$P_{50} < \omega \leq P_{75}$	-0.1882	-0.2875	-0.3788	-0.4986
$P_{75} < \omega \leq P_{100}$	-0.2014	-0.3030	-0.3379	-0.4120

Table 13a: Change in Variables in Response to 20% Export and Import Tariffs (Median)					
	Percentage Change		Change in Probability		
	ENB	R&D	Maintain R&D	Start R&D	Export
High-Tech Industries					
Chemicals	-0.3789	-0.1818	0.0000	-0.0367	0.0000
Metals	-0.5287	-0.2349	0.0000	-0.0268	-0.0849
Non elect machinery	-0.3843	-0.2016	0.0000	-0.0225	-0.0002
Electrical machinery	-0.4705	-0.2480	0.0000	-0.0185	-0.0003
Instruments	-0.5295	-0.2379	0.0000	-0.0251	-0.0342
Vehicles	-0.4743	-0.1919	0.0000	-0.0275	-0.0003
Average - High-Tech	**-0.4610**	**-0.2160**	**0.0000**	**-0.02618**	**-0.0200**
Low-Tech Industries					
Food	-0.4368	-0.1785	-0.0770	-0.0043	-0.0773
Textiles	-0.5689	-0.1964	-0.0622	-0.0192	-0.0719
Paper	-0.5580	-0.1756	-0.0446	-0.0138	-0.1344
Plastics	-0.5652	-0.1892	-0.0264	-0.0378	-0.0042
Ceramics	-0.4981	-0.1599	-0.0331	-0.0455	-0.0344
Miscellaneous	-0.5452	-0.2098	-0.0252	-0.0308	-0.0224
Average - Low-Tech	**-0.5287**	**-0.1849**	**-0.0447**	**-0.0252**	**-0.0574**

Table13b: Percentage Change in ENB from 20% Export and Import Tariffs (Median)				
	$P_0 \leq \mu \leq P_{25}$	$P_{25} < \mu \leq P_{50}$	$P_{50} < \mu \leq P_{75}$	$P_{75} < \mu \leq P_{100}$
High-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	-0.2539	-0.6032	-0.6826	-0.6803
$P_{25} < \omega \leq P_{50}$	-0.3731	-0.5434	-0.5702	-0.4702
$P_{50} < \omega \leq P_{75}$	-0.4402	-0.5201	-0.4395	-0.4101
$P_{75} < \omega \leq P_{100}$	-0.4686	-0.4730	-0.3771	-0.3772
Low-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	-0.4566	-0.5465	-0.5893	-0.6224
$P_{25} < \omega \leq P_{50}$	-0.4498	-0.5138	-0.5861	-0.6239
$P_{50} < \omega \leq P_{75}$	-0.4478	-0.5172	-0.5555	-0.6287
$P_{75} < \omega \leq P_{100}$	-0.4896	-0.5257	-0.5323	-0.5775

Table 14a: Change in Variables in Response to 20% Variable R&D Cost Reduction (Median)

	Percentage Change		Change in Probability		
	ENB	R&D	Maintain R&D	Start R&D	Export
High-Tech Industries					
Chemicals	0.0079	0.0184	0.0000	0.0015	0.0000
Metals	0.0539	0.1777	0.0000	0.0020	0.0003
Non elect machinery	0.0443	0.0527	0.0000	0.0060	0.0000
Electrical machinery	0.0457	0.2857	0.0000	0.0017	0.0000
Instruments	0.0211	0.0312	0.0000	0.0022	0.0001
Vehicles	0.0591	0.1074	0.0000	0.0046	0.0000
Average - High-Tech	**0.0387**	**0.1122**	**0.0000**	**0.0030**	**0.0001**
Low-Tech Industries					
Food	0.0686	0.2338	0.0021	0.0007	0.0004
Textiles	0.0186	0.0318	0.0017	0.0005	0.0001
Paper	0.0019	0.0038	0.0001	0.0001	0.0000
Plastics	0.0123	0.0228	0.0004	0.0006	0.0000
Ceramics	0.0080	0.0142	0.0006	0.0003	0.0000
Miscellaneous	0.0286	0.0548	0.0009	0.0010	0.0000
Average - Low-Tech	**0.1380**	**0.0602**	**0.0010**	**0.0005**	**0.0001**

Table 14b: Percentage Change in ENB from 20% Variable R&D Cost Reduction (Median)

	$P_0 \leq \mu \leq P_{25}$	$P_{25} < \mu \leq P_{50}$	$P_{50} < \mu \leq P_{75}$	$P_{75} < \mu \leq P_{100}$
High-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	0.2516	0.1264	0.0551	0.0392
$P_{25} < \omega \leq P_{50}$	0.1816	0.0652	0.0382	0.0148
$P_{50} < \omega \leq P_{75}$	0.0909	0.0489	0.0244	0.0146
$P_{75} < \omega \leq P_{100}$	0.0459	0.0293	0.0193	0.0108
Low-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	0.0645	0.0230	0.0067	0.0141
$P_{25} < \omega \leq P_{50}$	0.0174	0.0208	0.0090	0.0167
$P_{50} < \omega \leq P_{75}$	0.0033	0.0048	0.0159	0.0063
$P_{75} < \omega \leq P_{100}$	0.0178	0.0056	0.0070	0.0034

9 Appendix: Construction of the Swedish Firm Data

Estimation of this 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 data from four censuses or surveys that are administered by Statistics Sweden. All the sources use a common firm id which allows very accurate matching of the firm observations across the four data sources.

The first data source is the Financial Statistics (FS), a census of all Swedish manufacturing firms belonging to the Swedish Standard Industrial Classification (SNI) codes 15 to 37.[21] 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 and third data sources are the R&D survey (SCB-RD) and the Community Innovation Survey (CIS), which together provide information on R&D spending. Each SCB-RD survey is sent to a representative sample of 600-1000 manufacturing firms including all firms with more than 200 employees. The SCB-RD is administered in the odd years (1999, 2001, 2003, 2005, 2007, 2009), but also collects R&D information for the even years (2000, 2002, 2004, 2006, 2008, 2010). The CIS survey collects information on own R&D expenditure, outsourced R&D expenditure, and product and process innovations. It is administered in the even years (2004, 2006, 2008, 2010), and the design follows the common standard across countries in the EU.[22] The survey covers approximately 2000 manufacturing firms, including all firms with more than 250 employees. In order to be included in SCB-RD or CIS surveys the minimum number of full-time adjusted employees per firm is 3-5. Since large manufacturing firms account for a disproportionate share of economic activity, the CIS and SCB-RD surveys include the firms that are responsible for the majority of total R&D, exports, and sales in Sweden. For smaller firms, the SCB-RD and CIS samples are not identical, but combining data from both surveys gives us broader coverage of the population of small manufacturing firms.

The final data source, Industrins Varuproduktion (IVP), contains firm-level information on imports and exports. In particular, it contains annual 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.

After merging the data sources, we aggregate the firms into two industry groups based on the average intensity 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: chemicals (SNI 23,24), basic and fabricated metals (SNI 27,28), non-electrical machinery (SNI 29), electrical machinery (SNI 30-32), instruments (SNI 33) and motor vehicles (SNI 34-35). The low-tech industry group includes: food and beverages(SNI 15,16), textiles (SNI 17-19), wood and paper (SNI 20-22), plastics (SNI 25), ceramics (SNI 26) and miscellaneous (SNI 36-37).

[21]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).

[22]Swedish firms are obliged to answer. In 2010 the response rate was over 85 percent, which is substantially higher than many other European countries.