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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. Export market profits are a substantial source of the expected return to R&D. R&D spending is found to have a larger impact on firm productivity in the export market than in the domestic market. 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 10 percent tariff on Swedish exports reduces the expected benefits of R&D for the median firm by 18.6 percent and lowers the amount of R&D spending by 7.6 percent in the high-tech industries. The corresponding reductions in the low-tech industries are 20.6 and 5.5 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

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domestic firms. This can be due to the larger market size, an ability to learn from knowledge 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 endogenously invest more in innovation activities such as R&D which then generate higher productivity and profit gains relative to their nonexporting counterparts.[1]

While it has been well-established that exporting firms are more likely to innovate than nonexporters, the underlying causal mechanism establishing how firm investment in innovation is affected by export market conditions, such as the size of the foreign market or the cost of exporting, is less well studied. To assess the dynamic impacts of trade policies that affect the size of the export market, either through trade liberalization or imposition of tariffs, it is necessary to understand how they impact firm decisions on whether or not to invest in innovation and how much to spend on these investments. In addition, innovation policies, such as R&D subsidies, are used in many countries to promote specific investment goals, such as the EU's desired three percent R&D-to-sales ratio (European Commission, 2010; OECD, 2021). Because trade and innovation policies are often used in concert, predicting the impact of policy changes requires an understanding of how each policy tool impacts the underlying benefits and costs of innovation investments to the firm.

This article estimates a dynamic structural model of a firm's optimal R&D expenditure and quantifies both the long-run expected rate of return to R&D and the cost of innovation. The model is estimated using data for Swedish manufacturing firms and quantifies how each firm's export market participation affects its decision on whether to invest in R&D and how much. The model is used to simulate how trade restrictions and innovation subsidies affect the proportion of firms that invest in R&D (extensive margin) and shift the distribution of R&D expenditures across firms (intensive margin).

The framework and estimates contribute to our understanding of the relationship between exporting and R&D investment in several ways. First, unlike the previous literature, the model endogenizes the firm R&D investment as a mixed discrete-continuous choice. It accounts for differences in the level of R&D spending across firms resulting from underlying differences in industry, firm size, and both domestic and export market productivity. In the Swedish manufacturing industries, R&D investment is dominated by firms with continual expenditures over time and changes in aggregate R&D investment are driven by adjustments by these firms on the intensive margin. Quantifying shifts in the distribution of R&D expenditure across firms is necessary to understand how trade policy affects innovation.

Second, in our framework, the firm's choice of R&D impacts the path of future revenue productivity, sales, and profits separately in the domestic and export markets. The two markets differ in size, cultural factors, consumer preferences, and information access resulting in differences in the products and services sold, that can drive differences in revenue productivity and profitability between markets. The existence and magnitude of these differences are an empirical issue and, for this reason, the model allows R&D to have different impacts on the future path of domestic and export productivity and sales. This provides a flexible structure that allows us to measure how endogenous R&D investment contributes to performance

[1] Melitz and Redding (2021) and Akcigit and Melitz (2022) provide recent reviews of the theoretical and empirical literature on trade and innovation. They emphasize the linkages between exposure to trade and endogenous firm decisions on innovation.

differences between domestic and exporting firms.

Third, the model provides estimates of two underlying structural components that are difficult, if not impossible, to quantify without a structural model: the expected long-run return to R&D and the innovation cost function. The expected return is the change in long-run firm value resulting from R&D investment and will depend on the firm's size, the endogenous evolution of productivity in both markets, and export market activity. The innovation cost function includes both variable costs, that allow for diminishing returns to R&D spending, and fixed costs that differ between firms that are starting or maintaining an R&D program. These factors are the key to understanding the heterogeneous patterns of firm investment in R&D and to simulating firm responses to innovation and trade policy.

Fourth, by modeling the dynamic decision rule for R&D expenditure at the firm level, the model allows us to simulate the response to innovation or trade policies across the whole distribution of firms. In general, innovation policies such as R&D subsidies are designed to lower the costs of innovation. In contrast, export market policies, such as reduction in trade costs or imposition of tariffs, often affect the size of the export market which impacts the firm by changing the long-run expected benefits of exporting. The structural model allows the separate impacts of these two policy channels on R&D expenditure to be distinguished.

The analysis recognizes that many Swedish manufacturing industries are dominated by high-tech, R&D intensive products, and high levels of export sales. Given the small domestic market, export sales account for more than 47 percent of the total sales in manufacturing. Overall R&D spending equals 3.7 percent of GDP, with a government-stated goal of increasing it to 4.0 percent (European Commission, 2010; OECD, 2021). Many firms combine both substantial export sales with significant investment in R&D and it is important to study the two forces simultaneously. Our data show clear patterns in the firm-level relationship between exporting and R&D investment. 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 export market sales and profits raising the return to R&D, so that trade policy may have a significant impact on overall R&D investment. The data also show that the vast majority of R&D spending comes from firms with long-term ongoing R&D programs, rather than from startups, so that stimulating additional investment on the intensive margin by these experienced firms will likely be the most effective channel to increase total R&D spending.

The empirical results show that a firm's R&D investment raises its future revenue 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 nonexporters 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 0.549 to 3.428 for the nonexporting firms but from 7.951 to 52.863 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 exporting firm in the high-tech industries, this increase varies from 4.7 percent to 95.9 percent across industries with four of the six industries having a value greater than 39.8 percent. In contrast, the impact for the median nonexporting firm does not exceed 2.3 percent in any industry. In the low-tech industries the returns are much lower. The impact at the median firm varies from 0.9 percent to 1.4 percent for the exporters and is always less than 0.4 percent for the nonexporters.

Counterfactual simulations are implemented to study the effects of both trade and innovation policies. For trade policy, the simulations show that a 10 percent tariff on Swedish exports reduces the expected net benefits of R&D by 18.6 percent for the median firm in high-tech industries and 20.6 percent in low-tech industries. Consequently, it reduces the amount of R&D spending by 7.6 percent and 5.5 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 10 percent tariff on inputs. The decline in the expected net benefits of R&D is at least 25 percent 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, reflecting subsidy rates recently implemented in Sweden. This reduces the cost of innovation and raises both the expected net benefits to R&D, by 4.2 percent, and the amount of R&D spending, by 7.4 percent, for the high-tech industries. The corresponding numbers in the low-tech industries are 1.1 and 2.2 percent. The median ratio between benefits and cost of implementing the R&D policy is 5.67 and 3.12 across high-tech and low-tech sectors, respectively. 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 of particular interest 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. Our findings are relevant for other countries similar to Sweden that use innovation policy to promote investment goals but rely on export markets for much of their profits. In these cases, 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. Section eight draws conclusions.

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 heterogeneous 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.[2]

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.

Many empirical studies have shown that exporting firms are more likely to invest in innovation, but the direction of causation is generally not clear.[3] 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. One empirical approach uses exogenous export market shocks, often from a trade liberalization episode, to identify a causal effect of exporting on firm innovation. 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.

Alternatively, dynamic structural models of the firm's export and R&D decisions have been used to measure linkages between export market profits and endogenous innovation investments by the firm. Aw, Roberts, and Xu (2011) study the Taiwanese electronics industry, which is characterized by substantial firm adjustment on the extensive margin of R&D investment. The authors find that, conditional on current productivity, exporting firms have larger productivity gains than nonexporters and that a trade liberalization that expands the export market substantially increases the proportion of firms that invest in R&D.[4] Peters, Roberts, and Vuong

[2]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.

[3]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).

[4]Using a similar framework with Spanish firm data, Máñez, Rochina-Barrachina, and Sanchis-Llopis (2015)

(2018) also treat R&D as a discrete decision and study the extensive margin of adjustment for German high-tech manufacturing firms. They find that, if a firm undertakes R&D, it raises the probability they realize a new product or process innovation which, in turn, raises future productivity. The productivity impacts are larger for exporting firms, so they have higher expected returns to R&D and thus a higher probability of investing. Lim, Trefler, and Yu (2018) use a calibrated structural model for Chinese manufacturing firms and find that export 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.

In this paper we estimate a structural model of R&D investment that extends the existing frameworks in several ways. It endogenizes both the firm's discrete decision to undertake R&D (extensive margin) and the optimal expenditure (intensive margin) along with the endogenous decision to export. It estimates both a variable cost and a fixed cost of innovation, where both costs include separate firm-time cost shocks that generate heterogeneity in the firms' R&D decisions. We provide conditions for uncovering two unobserved firm productivity shocks using data on the firm's export sales, domestic sales, investment, and number of export destinations. The process of productivity evolution is estimated separately for export and domestic market productivity and depends on the interaction between the level of R&D spending by the firm and its past productivity. The estimates provide a rich framework for measuring how the distribution of R&D investment across firms is impacted by trade restrictions and innovation subsidies, such as tax credits, that vary with the level of R&D expenditure by the firm.

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 are important in the specification of the structural model.

The data set we constructed 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 A.

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.

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 presents evidence on the sources of adjustment in total R&D spending in our sample between each pair of years from 2003 to 2010. It summarizes the importance of the extensive margin, the change in total R&D spending by firms that start or stop R&D investment, and the intensive margin, expansions or contractions of spending by firms that invest in both years. The top panel summarizes the firms in the high-tech industries and the bottom panel the firms in the low-tech industries. The first column reports the total growth in R&D spending over the firms present in our sample in each pair of years. The year-to-year fluctuations are often substantial, more than a 12 percent increase or decrease occurs in three of the time periods for each of the industry groups, but the overall trend is clearly different for the two groups. The high-tech industries average an 8.2 percent annual increase in R&D expenditure, while the low-tech industries average a 4.6 percent decrease.

The remaining columns disaggregate the annual growth in R&D expenditure into the component arising from each of the four categories of adjustment. The second and third columns report the percentage growth arising from the extensive margin of firm adjustment. In the high-tech industries, firms that begin to invest in R&D contribute, on average, a 1.9 percent increase in total R&D, while firms that stop investing lower total spending growth by 1.5 percent, on average. The annual changes never exceed 3.8 percent from beginners and -2.5 percent for quitters and the net adjustment on this margin is actually negative in four of the seven years. The last two columns report the contribution from the intensive margin captured by firms that expand or contract their spending from year-to-year. On average, firms that expand their R&D increase the industry total by 21.8 percent, while firms that reduce their spending lower it by 14.1 percent. The net contribution from the intensive margin is 7.7 percent, which is substantially larger than the net change on the extensive margin, and accounts for virtually all of the total growth in R&D spending for the high-tech industries.[5]

The adjustment pattern is slightly different for the low-tech industries. There is a larger role for adjustment on the extensive margin. Firms that begin investing in R&D contribute, on average, a 7.2 percent increase in the industry total while firms that stop investing lower it by 5.5 percent, a 1.7 percent net increase. The decrease in R&D investment comes on the intensive margin where firms scale back their R&D spending. On average, the expanding firms raise the industry total by 15.7 percent but this is outweighed by the 22.0 percent average decrease by firms that contract their spending.

[5] The share of observations in each of the expansion and contraction categories over all pairs of years are: begin R&D 0.080, expand R&D 0.331, contract R&D 0.243, exit R&D 0.084, do not invest in R&D in either year 0.262, in the high-tech industries. The corresponding shares in the low-tech industry are: begin 0.107, expand 0.199, contract 0.164, exit 0.104, never invest 0.426.

While the intensive margin is the main source of year-to-year changes in the amount of R&D spending in both industry groups, the extensive margin plays a larger role in the low-tech industries. To conduct counterfactual analysis of R&D or trade policies on R&D investment in the Swedish manufacturing sector, it is important for the underlying structural model to incorporate the discrete decision to start or stop R&D investment, but, even more important, to capture the firm's decision on the level of R&D spending.

Table 3 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 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 nonexporting firms. 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 that 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 nonexporters, 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 nonexporters, 10 percent of the observations have R&D expenditure that is less than two-tenths of one percent of sales (0.002). The median firm has an expenditure equal to 1.5 percent of sales and the firm at the 90th percentile has R&D expenditure equal to 13.8 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 0.002 at the 10th percentile to 0.144 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 nonexporters to 0.464 for firms with an export intensity above the median. Only 46.4 percent of the highest-intensity exporters invest in R&D in low-tech industries, compared with 77.6 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 0.007 to 0.010 across the export groups. At the 90th percentile the R&D intensity varies from 0.041 to 0.069 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. However, there are also firms that invest in R&D but do not export (17.5 and 16.2 percent in the high-tech and low-tech industries, respectively) and still others that have export intensity above the industry median but do not invest in R&D (22.4 and 53.6 percent in the high-tech and low-tech industries, respectively). The dynamic model of R&D investment developed in the next sections contains two sources of firm-level heterogeneity, an export market productivity shock and a domestic market productivity shock, 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

$$\ln c_{jt} = \beta_0 + \beta_k \ln k_{jt} + \beta_{\tilde{\mathrm{w}}} \ln \tilde{\mathrm{w}}_t - \psi_{jt},$$

where k_{jt} is the firm capital stock, $\tilde{\mathrm{w}}_t$ contains 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.

Both the domestic and export markets are assumed to be monopolistically competitive and segmented from each other. This rules out strategic interaction between firms in each market, but does allow firms to charge markups that differ in the two markets. The demand curves faced by firm j in each market are assumed to have the CES form. The demand curve in the domestic market is:

$$q_{jt}^d = \frac{M_t^d}{P_t^d}(\frac{p_{jt}^d}{P_t^d})^{\eta_d} \exp(\phi_{jt}^d) = \tilde{\Phi}_t^d (p_{jt}^d)^{\eta_d} \exp(\phi_{jt}^d), \tag{1}$$

where M_t^d is total market size, P_t^d is an aggregate price index, p_{jt}^d 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_{jt}^d is a firm-specific domestic demand shock. The latter represents differences in consumer demand across firms, that can arise from differences in product quality, and the mix of products produced by the firms. It is known to the firm but not the researcher. The aggregate price index and market size are combined into the industry aggregate demand, denoted $\tilde{\Phi}_t^d$.

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

$$q_{jt}^f = \frac{M_t^f}{P_t^f}(\frac{p_{jt}^f}{P_t^f})^{\eta_f}\exp(\phi_{jt}^f) = \tilde{\Phi}_t^f(p_{jt}^f)^{\eta_f}\exp(\phi_{jt}^f), \tag{2}$$

where $\tilde{\Phi}_t^f$ captures the aggregate component of demand in the export market resulting from market size, M_t^f, and the aggregate industry price index, P_t^f. The price firm j charges in the export market is p_{jt}^f, and η_f is the constant elasticity of demand. ϕ_{jt}^f is a firm-specific export demand shifter representing heterogeneity in the total demand for each firm's output in the export market. This captures a number of factors including differences across firms in the quality of their product, the mix of products they produce, consumers' taste for the firm's product, and the breadth of the firm's export network. In particular, firms that export on a global scale will tend to have larger values of ϕ_{jt}^f than firms that export to a smaller number of regional destinations. This demand representation abstracts from differences in a firm's demand across destinations, but allows us to represent the heterogeneity in total firm export demand across firms and time which will be an important source of heterogeneity in export profits and firm investment in R&D. Similarly to ψ_{jt} and ϕ_{jt}^d, ϕ_{jt}^f 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 logarithm of revenue in the domestic market at the optimal price is:

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

where $\beta_0^d = (\eta_d + 1)\left[\ln \frac{\eta_d}{1+\eta_d} + \beta_0\right]$ captures all constant terms, and $\Phi_t^d = \ln \tilde{\Phi}_t^d + (1+\eta_d)\beta_{\tilde{\mathrm{w}}} \ln \tilde{\mathrm{w}}_t$ incorporates all time-varying demand and cost factors that are common across firms. The term $\omega_{jt} = \psi_{jt} - (\frac{1}{\eta_d+1})\phi_{jt}^d$ 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_{jt}^d 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_{jt}^f that contains, for instance, transaction costs related to the export activities, sunk costs, and adjustment costs when firms alter their set of export destinations.[6] Given knowledge of ψ_{jt}, ϕ_{jt}^f, and c_{jt}^f, 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 logarithm of

[6] 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. All firms in our data sell in the domestic market.

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 Φ^f_t =ln $\tilde{\Phi}^f_t + (1+\eta_f)\beta_{\tilde{w}}$ln $\tilde{w}_t$. 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. This will be treated as an indicator of the firm's overall success in the export market and will be a state variable that the firm can affect by investing in R&D. The error term ε^f_{jt} captures transitory shocks to export revenue that are unknown to the firm when it maximizes profits.

Given this structure, firm $j's$ short-run profits in the domestic and export markets are fractions of their sales in the respective market. Specifically, the gross profits in domestic (π^d) and export (π^f) markets are:

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

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

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

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 before observing c^f_{jt} is

$$\pi(k_{jt}, \omega_{jt}, \mu_{jt}) = \pi^d(\Phi^d_t, k_{jt}, \omega_{jt}) + P^f_{jt}[\pi^f(\Phi^f_t, k_{jt}, \mu_{jt}) - E(c^f_{jt}|\pi^f_{jt} > c^f_{jt})], \tag{7}$$

where $E(c^f_{jt}|\pi^f_{jt} > c^f_{jt})$ 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 the revenue productivities ω_{jt} and μ_{jt}. Productivity in each market can evolve persistently and stochastically over time, but can also be affected by the firm's R&D expenditure. The productivity processes in the two markets are modeled as:

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

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

where the previous-period productivity level allows for firm-level persistence over time. The firm's current period R&D expenditure, rd_{jt}, can shift the path of future productivity in each market. Because of the persistence in the productivity processes, the impact of R&D investment will be carried forward in time and allow the gain from R&D to be long-lived. The stochastic components of the processes, ξ_{jt+1} and ν_{jt+1}, are assumed to be iid across firms and time with $E[\xi_{jt+1}] = E[\nu_{jt+1}] = 0$, $Var[\xi_{jt+1}] = \sigma^2_\xi$, $Var[\nu_{jt+1}] = \sigma^2_\nu$, and $Cov(\xi_{jt+1}, \nu_{jt+1}) = \sigma_{\xi\nu}$. The productivity shocks are realized in period $t+1$ and are not correlated with ω_{jt}, μ_{jt}, or rd_{jt}. The two shocks can be contemporaneously correlated to allow for common cost shocks or correlated demand shocks across the two markets. The stochastic components in productivity evolution allow firms with the same current-period market productivity and R&D expenditure to differ in their future productivity through luck or other sources of randomness in the innovation process.[7]

The processes of foreign and domestic market productivity evolution are allowed to differ for reasons 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. 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 will lead to differences in the profitability path between exporting firms and those that focus solely on the domestic market and thus lead to differences in the incentive to invest in R&D.

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

[7] Several studies have generalized the original model of exogenous productivity evolution by Olley and Pakes (1996) to incorporate endogenous investments in innovation. Doraszelski and Jaumandreu (2013) allow a firm's productivity index to evolve endogenously with investments in R&D. Peters, Roberts, Vuong, and Fryges (2017) and Peters, Roberts and Vuong (2018) model revenue productivity as evolving endogenously with realizations of product and process innovations by the firm. Aw, Roberts, and Xu (2011) model productivity evolution as affected by the firm's discrete investment in R&D and discrete participation in the export market. The latter allows for learning-by-exporting which is important in their developing country context.

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.[8] 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 $I(rd_{jt-1}) = 1$. The value of the fixed cost for each firm and time period, FC_{jt}, 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:

$$\begin{aligned} V(k_{jt}, \omega_{jt}, \mu_{jt}, I(rd_{jt-1})) \quad &= \quad \pi(k_{jt}, \omega_{jt}, \mu_{jt}) + \int_{FC_{jt}} \int_{\upsilon_{jt}} \max\{V^0, \\ &\max_{rd_{jt}>0} \left[V^1 - C_I(rd_{jt}, \upsilon_{jt}, I(rd_{jt-1}))\right]\} d\upsilon_{jt} dFC_{jt}, \end{aligned} \tag{11}$$

where V^0 and V^1 are the discounted expected future value of the firm if it chooses to not invest in R&D or invest in R&D, respectively. They are defined as

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

and, for positive investment level:

$$V^1 = \beta \int_{\xi_{jt+1}} \int_{\nu_{jt+1}} V(k_{jt+1}, g^{\omega}(\omega_{jt}, rd_{jt}) + \xi_{jt+1}, g^{\mu}(\mu_{jt}, rd_{jt}) + \nu_{jt+1}) d\nu_{jt+1} d\xi_{jt+1}, \tag{13}$$

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

[8] 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.

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).[9]

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

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

Investment demand is strictly increasing in productivities as a consequence of the assumptions that the Markov productivity processes, equations (8) and (9), are stochastically increasing in ω_{jt} and μ_{jt} and the marginal product of capital increases in both arguments (Pakes, 1994; Olley and Pakes, 1996). Firms with higher productivities invest more because they have higher expected marginal products of capital in the future.

Firms with higher foreign productivity are more likely to export to a larger number of destinations. As defined in equation (4), foreign productivity μ_{jt} is an aggregate index of revenue productivity in all export markets the firm participates in and captures all unobserved demand and cost factors that reflect the firm's product quality and cost efficiency. Firms with high foreign productivity can be more profitable in destinations with higher entry costs or lower demand than their lower productivity counterparts, and will develop a larger export network. While we do not explicitly model the set of destination countries for a firm, or the destination-specific export sales, the number of destination markets contains information on the firm's size and export efficiency and we treat the log of the number of destinations nd_{jt} as function of the state variables

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

This is consistent with empirical studies in the trade literature that show that several dimensions of firm heterogeneity are important in explaining patterns of export participation, the number of markets a firm serves, and the specific destinations a firm enters. In particular, Eaton, Kortum, and Kramarz (2011) and Roberts, Xu, Fan, and Zhang (2018) find that productivity, demand, or entry cost differences are important in explaining the number and pattern of destination markets for French and Chinese exporting firms, respectively. Firms that export to a larger number of destinations also export to less popular destinations, reflecting their ability to enter less profitable markets because of their underlying efficiency. In our data set, nd_{jt} and $\ln R_{jt}^{f}$ are positively correlated with a value of 0.724 in high-tech and 0.670 in low-tech industries. This suggests that nd_{jt} will be a good proxy for firm-level variation in foreign sales that arises from μ_{jt}.

We use the investment and export destination policy functions (15) and (16) in the estimation by inverting them to express the unobserved productivities ω and μ as functions of k, i, and nd. In the case with a single policy function and unobservable factor, strict monotonicity guarantees the inversion. In the case with two equations and two unobservables, the invertibility condition is satisfied when the determinant of the Jacobian of the two equation system, (15) and (16), is not zero. In this application, this is satisfied when

[9] 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.

$(\partial i/\partial \omega)/(\partial i/\partial \mu) \neq (\partial nd/\partial \omega)/(\partial nd/\partial \mu)$. This implies that the relative impact of productivity changes on investment and the number of export destinations must be different for domestic and foreign productivities. Appendix B and Maican and Orth (2021a, 2021b) provide additional details and discussion. This requirement is not restrictive and holds empirically in our estimated reduced-form policy functions.

In this case, 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:

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

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 observed variables. Replacing ω_{jt} in the domestic revenue function with a general function of k_{jt}, i_{jt} and nd_{jt} gives:

$$\ln R_{jt}^d = \beta_I^d + \rho_t^d + h_t(k_{jt,} i_{jt}, nd_{jt}) + \varepsilon_{jt}^d, \tag{18}$$

where the function $h_t(k_{jt,} i_{jt}, nd_{jt}) = (\eta_d + 1)(\beta_k \ln k_{jt} - \omega_{jt}(k_{jt,} i_{jt}, nd_{jt}))$, ρ_t^d captures common, time-varying factors in $\ln \Phi_t^d$ and we model the intercept β_I^d with a set of two-digit industry dummies. Similarly, replacing μ_{jt} in the export revenue function gives:

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

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_t^f captures common, time-varying factors in $\ln \Phi_t^f$, and the intercept is a set of two-digit industry dummies.

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.[10] By definition of $h_t(\cdot)$ and $b_t(\cdot)$, we can 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:

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

[10] Relying solely on export revenues of exporting firms to uncover the foreign revenue productivity μ_{jt} might induce 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}. We accurately predict the probability of exporting using the variables in firm's information set in $t-1$. However, the results show that the terms that include predicted $\hat{P}_{jt}^f$ are not statistically significant in the foreign revenue productivity process. This implies that our estimates are not affected by export selection bias.

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

$$\omega_{jt} = \alpha_1\omega_{jt-1} + \alpha_2\omega_{jt-1}^2 + \alpha_3 rd_{jt-1} + \alpha_4 rd_{jt-1}^2 + \alpha_5\omega_{jt-1}rd_{jt-1} + \xi_{jt} \quad (21)$$

$$\mu_{jt} = \delta_1\mu_{jt-1} + \delta_2\mu_{jt-1}^2 + \delta_3 rd_{jt-1} + \delta_4 rd_{jt-1}^2 + \delta_5\mu_{jt-1}rd_{jt-1} + \nu_{jt}. \quad (22)$$

Substituting equations (21) and (22) into equations (3) and (4) gives the domestic and foreign market revenue functions:

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

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

The intercepts in each equation are modeled as a set of industry dummies, β_I^d and β_I^f, and the common, time-varying factors are modeled with time dummies, ρ_t^d and ρ_t^f. Finally, substituting equation (20) for the values of ω_{jt-1} and μ_{jt-1} gives the revenue functions in terms of observables and the structural parameters $\beta_k, \eta_d, \eta_f, \alpha_1 ... \alpha_5, \delta_1 ... \delta_5$. The error terms are $-(\eta_d+1)\xi_{jt} + \varepsilon_{jt}^d$ and $-(\eta_f+1)\nu_{jt} + \varepsilon_{jt}^f$ 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 quantities, marginal cost is equal to marginal revenue in each market, such that

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

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.[11]

[11] The measure $\hat{b}_{jt}$ is estimated from the export revenue equation. Thus, equation (20) only gives us μ_{jt} for exporting firms. To impute the revenue productivity for nonexporting 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 nonexporters is then constructed as the fitted value of μ_{jt} using the nonexporters' 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.[12] 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 $I(rd_{jt-1})$:

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

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: $c_{jt}^f \sim \exp(\gamma^f)$.[13] 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 $E(c_{jt}^f|\pi_{jt}^f > c_{jt}^f) = \gamma^f - \pi_{jt}^f[(1-P_{jt}^f)/P_{jt}^f]$. The expressions for P_{jt}^f and $E(c_{jt}^f|\pi_{jt}^f > c_{jt}^f)$ can be substituted into the firm's short-run profit function, equation (7) to complete the specification of the model parameters.

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

[13] By treating exporting as a static decision we do not distinguish sunk entry costs from fixed costs of exporting. The distribution of the export cost c_{jt}^f will reflect both types of costs. The parameter that we estimate γ^f is the mean of this mixed distribution. It will likely be larger than the mean fixed cost and smaller than the mean entry cost. We do not think this is a serious restriction since we have very few firms entering or exiting exporting and find very little impact of R&D on the decision to export.

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:

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

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 $\Phi(\cdot)$ 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 moments (Hansen, 1982; Hall, 2005). 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 weighted distance between the moments $\tilde{\boldsymbol{Q}}(\boldsymbol{\Gamma})$ and $\mathbf{Q}$

$$\mathbf{J}(\boldsymbol{\Gamma}) = [\mathbf{Q} - \tilde{\boldsymbol{Q}}(\boldsymbol{\Gamma})]' \left[Var[\boldsymbol{Q}]^{-1}\right] [\mathbf{Q} - \tilde{\boldsymbol{Q}}(\boldsymbol{\Gamma})]. \quad (31)$$

6 Empirical Results

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

6.1 Productivity Evolution and the Profit Function

Table 4 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 correlation between the shocks to productivity evolution in the domestic and export markets is positive in both industries.

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 5 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, $\frac{\partial \omega_{jt}}{\partial ln(rd_{jt-1})}$, varies from 0.004 at the 10th percentile to 0.013 at the 90th. The median value is 0.008. The elasticity of foreign market productivity is larger, with a value of 0.010 at the median and 0.017 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 0.018 and 0.021, in the domestic and foreign markets, respectively. In the low-tech industries the medians are 0.004 and 0.008. 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]

[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

The last two rows of the table report the persistence in each market's productivity. These elasticities are uniformly high, between 0.883 and 0.980 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 are more heavily affected by the elasticities of R&D.

6.2 The Firm's R&D Investment Decision

The results reported in Table 5 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 dynamic programming model, the firm's optimal choice of R&D and exporting are both functions of the productivities ω_{jt}, μ_{jt}, capital stock k_{jt}, and lagged R&D indicator $I(rd_{jt-1})$. Before estimating the firm's dynamic demand for R&D, we assess the importance of these state variables in explaining the firm's endogenous decisions 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 function of the four state variables using b-splines to provide a flexible non-parametric specification that is consistent with the dynamic programming framework. The results for the high-tech industry are reported in the second, third, and fourth columns of Table 6. Columns labeled "Discrete" report estimates of logit regressions using a discrete indicator of exporting or R&D. Columns labeled "Log Expend" report OLS estimates with log R&D expenditure as the dependent variable.

The top panel in the table reports the degree of approximation for each of the state variables. These are determined based on the Akaike Information Criterion test. The bottom panel in the table provides the test statistics and p-values for the hypothesis tests that the four state variables are individually not significant in the reduced form regressions. The test statistics reject the hypotheses in 22 of the 24 cases. The only exceptions are for the domestic productivity in the R&D decisions in the low-tech industries. Overall, the policy function estimates demonstrate that the state variables ω_{jt}, μ_{jt}, k_{jt} and $I(rd_{jt-1})$ are important determinants of the firm's export and R&D decisions.

The structural estimates of the parameters characterizing the cost of innovation and exporting are reported in Table 7. 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 estimated are θ_1, θ_2, and σ_v for the variable cost function of R&D, γ^m and γ^s, the unconditional means of the fixed maintenance and fixed startup cost distributions of R&D, and γ^f the unconditional mean of

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.

the 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 two machinery industries, θ_2 is virtually zero, implying constant marginal cost of innovation. The parameter σ_υ measures dispersion in the firm's marginal cost of innovation, holding the level of R&D expenditure fixed. The estimates are between 0.1381 and 0.5705 in the high-tech industries and between 0 and 0.2057 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 a 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. (In 2010, 1 USD=7.2 SEK and 1 EUR=9.54 SEK). 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. It indicates that a high fixed cost of exporting, and not just insufficient demand, contributes to the lower export intensity among Swedish low-tech firms.

Table 8 summarizes the distribution of the expected marginal cost of innovation (EMC) across observations where the expectation is taken over the random shock υ. EMC is in millions of SEK and measures the increase in the variable cost of innovation needed to generate the improvement in productivity consistent with the first-order condition for R&D choice, equation (14). The findings in the high-tech industries show 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 9 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 10 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, 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 11 summarizes the 25th, 50th, and 75th percentiles of the distribution of $EB/R\&D$ across firm observations with positive R&D investment for both the nonexporting and exporting firms. Three patterns stand out. First, the distribution of expected benefits for exporters stochastically dominates the distribution for nonexporters in every industry. The median values among the nonexporters vary from 0.549 to 5.662 across industries and, for four industries, chemicals, non-electrical and electrical machinery, and instruments, the values are less than one, implying that the total benefits to R&D investment would not exceed the expenditure. The median values among the exporters vary from a low of 4.758 in textiles to a high of 52.863 in chemicals. 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 nonexporting 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 nonexporters, 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 75th percentile in all the high-tech industries. In contrast, among exporting firms at the median and 75th percentile, the benefits from the optimal R&D expenditure in the high-tech industries are substantially higher than in most low-tech 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 percentiles of the distribution for the proportional increase in firm value from R&D investment, EB/V^0, is reported in Table 12 for each industry. The patterns reinforce the importance of exporting in determining the gains from R&D investment. The 25th percentile gain among the exporters exceeds the 75th percentile gain among the nonexporters in five of the six high-tech and four of the six low-tech ones. The across-firm heterogeneity in returns is also fairly small for the nonexporting firms, even in the high-tech industries. Among the nonexporting firms the increase in firm values at the 75th percentile never exceeds 3.3 percent in any of the industries and is generally less than 2.0 percent in the high-tech industries and 1.0 percent in the low-tech ones. In contrast, among the exporting firms the returns are larger, there is substantially greater heterogeneity within industry, and very high returns for the top half of the distributions in the high-tech industries. Among the high-tech exporters, the increase in firm value resulting from R&D investment is greater than 39.8 percent for the median firm in four of the six industries and exceeds 83.9 percent at the 75th percentile for all the industries. Another way to interpret this finding is that, for these high-return firms, at least half of their firm value is derived from the combination of R&D investment and export market profits. 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, policymakers 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, 2019a). 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 counterfactual analysis explores both trade policies and innovation policies. In recent years, protectionism has gained attention, and policymakers debate trade restrictions world-wide. Notable examples are the Trump administration's imposition of tariffs and the retaliatory tariffs imposed by several countries, including China and the European Union (Amiti, Redding, and Weinstein, 2019). Against this background, our first two counterfactual scenarios investigate trade restrictions regarding increased export and import tariffs. The third counterfactual regime evaluates innovation policies by implementing R&D tax credits that are commonly used for stimulating investments in research and development. Nearly all countries in the OECD provide tax generosity toward investments in R&D and the effectiveness of such policy tools are of great concern to policymakers, which make our policy experiments relevant in a broader context (OECD, 2018, 2021).

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 and R&D benefits. Because of the substantial heterogeneity across firms in both the high and low-tech sectors, we will emphasize the distributional effects of the changes.

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. Export and import tariffs vary substantially by product and country and the average tariff for Swedish exports to the world was 9.43 percent in 2003 and declines slightly over time (Worldbank, 2022). To tie the counterfactual scenario closely to the tariff rates faced by Swedish firms, we implement a 10 percent export tariff, corresponding to a doubling of the existing (average) tariff rates during our time period.[15]

Table 13a reports the results from a simulation of a permanent 10 percent tariff on Swedish exports, which implies a change in firm profits in foreign markets by -3.36 percent and -3.89 percent for the high-tech and low-tech sectors, respectively. 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 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 for the firms with positive investment, 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 10th, 50th, and 90th percentiles of the distribution across firm-year observations. Across the observations in the high-tech industries, the net benefit of investing in R&D changes by between -39.7 and -4.3 percent. This leads to a change in expenditure of firm R&D between -12.7 and -1.9 percent at the extreme percentiles. The median firm changes its R&D expenditure by -7.6 percent. In the low-tech industries, the change in the expected benefit of R&D is similar, varying from a -35.9 percent for the most heavily-affected firms to -3.5 percent for the least affected. The corresponding changes in R&D spending are smaller, varying from -8.7 to -1.1 percent across firms. The median change is -5.5 percent. The implication is that the reduction in export market profitability resulting from the tariff has a considerable negative effect on the intensive margin of R&D spending, although the magnitude differs substantially across firms.

[15] 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.

To get an industry-level measure of the changes in firm benefits, we aggregate the heterogeneous responses and calculate the total change in the expected benefit of R&D, EB, resulting from the tariff. In this scenario, EB changes by -18.2 and -23.4 percent in the high and low-tech industries, respectively. This reduction in the payoff to R&D changes total R&D spending in our sample by -8.2 percent in the high-tech sector and by -6.2 percent in the low-tech sector.

On the extensive margin, the impact of the tariff is much smaller. For the most heavily impacted firms in the high-tech industries (10th percentile), the probability that an investing firm will stop its R&D investment completely changes by -4.5 percentage points, the probability that a firm will begin investing in R&D changes by -7.0 percentage points, and the probability they will export changes by -9.4 percentage points. While these extensive margin effects are sizeable for some firms, they do not characterize the impact for most firms in the industry. At the median, there is no impact on the probability of continuing to invest in R&D or to export, and a -0.7 percentage point change in the probability of beginning R&D investment in the high-tech industries. In general, firms in the low-tech industries have lower profits than those in the high-tech industries, which can explain why the tariffs more heavily affect them on the extensive margin.

Overall, the reduction in export market profitability due to the output tariff discourages some firms from undertaking R&D but the major 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.

Table 13b summarizes which firms, distinguished by their level of domestic and foreign market productivity ω and μ, are most heavily affected. 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 negatively affects the payoff to R&D for all firms regardless of their productivity levels, but has a larger negative impact on firms with larger foreign productivities. The change in net benefits is between -18.4 and -38.4 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 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 have simultaneously high productivity in the domestic market.

The counterfactual reported in Table 14a maintains the 10 percent output tariff on Swedish exports and adds a 10 percent tariff on imported materials.[16] This represents the case where a retaliatory tariff is imposed to protect domestic suppliers of intermediate materials. This

[16] 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.

input tariff raises the cost of the Swedish manufacturers and impacts sales in both the domestic and export markets. The results in Table 14a show the same qualitative pattern as the export tariff alone, but the effects are magnified and the negative impacts extend across the whole distribution of firms. In particular, the least affected firms, those at the 90th percentile have larger negative effects. For example, in the high-tech sector, the expected net benefit changes by -16.2 percent and the intensive margin of R&D spending by -7.5 percent. These reductions are four times larger than for the export tariff alone. A similar pattern occurs in the low-tech industries but the differential is seven times larger for the least affected firms. The extensive margin is less impacted. While the most heavily affected firms continue to reduce the probability they invest in R&D, that does not propagate across the whole distribution of firms. Just like with the export tariff increase alone, the negative impact on the extensive margin of trade and exporting is limited to a subset of firms.

Focusing on the distribution of the reduction in benefits across firms with different productivities in Table 14b, 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 change in ENB varies from -14.4 to -29.9 percent across industries. This decline is at least three times larger than what 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. The combination of export and import tariffs harm firms with low domestic productivity and low foreign productivity proportionally more than just the export tariff. When combining the import and export tariff, the expected net benefit realized by firms in the lowest quartile of both domestic and foreign productivity declines by seven times in the high-tech industries and five times in the low-tech industries.

A final interesting pattern is that there is less dispersion in the decline in expected net benefits across firms in different quartile groups under the combined tariff scheme than under the export tariff alone. Firms in the low-tech industries experience fairly similar reductions in expected net benefits regardless of their domestic productivity. Firms in low-tech industries still reduce their expected benefits more the higher the foreign market productivity, although the magnitude of the differences across firms in the quartile groups are smaller under the combined tariff than under the export tariff only.

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 investment and export activities.[17] As noted above, R&D tax credits are a frequently used

[17] The empirical literature on the effects of R&D subsidies on investment and innovation is vast. Hall and Van Reenen (2000) and Bloom, Van Reenen, and Williams (2019) survey the literature. Recent works by

policy tool for stimulating investments in innovation. In 2020, 32 out of 37 OECD countries offer R&D tax incentive support at the central government level. While the U.S. federal R&D tax credit is approximately 5 percent, countries like France, Portugal, and Chile have tax credit rates above 20 percent (OECD, 2018).

During our data period from 2000 to 2010, Sweden did not have an R&D tax credit. In order to lower the cost of innovation, a 10 percent tax credit on R&D expenditure was implemented in 2014 and this was increased to 19.59 percent in 2020 (Swedish government, 2019b).[18] Apart from its undoubted policy relevance in OECD countries, an accurate evaluation of the distributional effects of the R&D tax credit is possible in our dynamic setting, which endogenizes both extensive and intensive R&D margins and highlights the tradeoff between short-run innovation costs and the long-run benefits. In order to replicate the current policy environment in Sweden, we simulate the effect of a 20 percent subsidy of the firm's R&D expenditure by setting $\theta_1 = 0.80\hat{\theta_1}$ in the variable cost function, equation (27). This 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 15a summarizes the impact of the R&D subsidy across the distribution of firms. With a 20 percent subsidy, lower marginal cost leads to a higher optimal R&D investment level. Not surprisingly, the percentage change in R&D investment is positive but heterogeneous across firms. The increase in the expected payoff to R&D varies from 0.6 to 27.7 percent across the distribution of high-tech firms. The growth in firm's net benefit is a multiple of the innovation cost-saving that 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. In the high-tech industries, this change in the net payoff to R&D generates an increase in R&D spending on the intensive margin that is highly skewed across firms. In the high-tech industries, the 10th percentile firm increases its R&D spending by 2.0 percent, the median firm by 7.4 percent, and the 90th percentile firm by 25.6 percent increase. This is an indicator that R&D subsidies will have substantial impact on a subset of firms. While the magnitudes of the increases are smaller in the low-tech industries, the pattern of substantial heterogeneity is also present.

The change in the marginal cost of innovation has little impact on the extensive margin decisions of firms to either continuing or start R&D. In the high-tech industries there is a small increase in the probability that firms invest in R&D at the top end of the distribution, 2.1 percentage points for firms to continue investing and 0.8 percentage points for firms to begin. 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 has 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

González, Jaumandreu, and Pazó (2005) and Arqué-Castells and Mohnen (2015) using Spanish firm data, Takalo, Tanayama, and Toivanen (2013, 2022) using Finnish data, and Akcigit, Hanley, and Stantcheva (2022) using U.S. data, estimate structural models of firm R&D investment and use them to conduct counterfactuals on the level of subsidies.

[18] There is an upper monetary bound of 14.7 million SEK per year on the R&D tax credit (Swedish government, 2021).

in case of investment. The same pattern can be observed for the export market participation. The median change in export participation is zero in both sectors. 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.[19]

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 but the impact is even more highly skewed. It is only at the 90th percentile of the firm distribution that the subsidy generates a substantial increase in spending on the intensive margin.

Focusing on the percentage change of R&D benefit by their productivity levels ω and μ reported in Table 15b, 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 25.2 percent in the lowest (ω, μ) quartile and 1.1 percent in the highest productivity quartile in high-tech. In low-tech those numbers range between 6.5 and 0.3 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. This implies that firms in the lowest quartile of domestic and foreign market productivity increase the expected net benefits of R&D the most after introduction of the tax credit. Firms in high-tech industries with low domestic and foreign productivity experience the most pronounced gains from the tax credit. These firms benefit from additional R&D investments through higher future productivity growth in the domestic and foreign markets while also experiencing lower costs of innovating in R&D. As compared to previous work on R&D tax credits, our findings add heterogeneous responses to policy interventions along two firm-specific dimensions in terms of domestic and foreign market productivity.

From a policy perspective, it is helpful to evaluate the welfare effects of R&D tax credits. Our framework allows us to calculate benefit-cost ratios where total long-run benefits are obtained by summing the expected net benefit across all sample firms and total costs are calculated by actual R&D spending times the subsidy rate. The results from the counterfactual policy that impose a 20 percent tax credit show that benefits are larger than the cost of the R&D policy. The ratio of total firm benefits to the cost of implementing the R&D policy is 5.67 and 3.12 in high-tech and low-tech industries, respectively. The subsidy has a higher benefit-cost ratio in the high-tech industries. By quantifying the effect on firm profits (producer surplus) and the cost of the government subsidy, this analysis provides a lower bound on the net welfare gain of the innovation policy. It is likely only a lower bound on the total welfare gain because it does not capture possible gains in consumer surplus due to the entry of new products or interfirm spillovers in the productivity improvements from R&D. 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.

[19] Previous work on R&D subsidies by Dechezleprêtre, Einiö, Martin, Nguyen, and Van Reenen (2022) has found most adjustment on the intensive margin. In their simulation exercises of one-shot R&D subsidies, Arqué-Castells and Mohnen (2015) find relative large effects on both the share of firms that invest in R&D and average R&D spending.

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 revenue 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 0.021 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 nonexporting 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. Across the industries, the median expected gain in firm value from investing in R&D is less than 0.4 percent and 1.4 percent for nonexporters and exporters, respectively, in the low-tech industries. The expected gain is generally less than 2.3 percent for nonexporting 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 4.7 to 95.9 percent, with four of the industries having values above 39 percent.

In the counterfactual environment where firms face a 10 percent export tariff, we find that the expected payoff to R&D is reduced substantially and leads to significant reductions in the R&D spending on the intensive margin. On the contrary, export tariffs have little impact on the extensive margin. The median firm in the high-tech industries changes its R&D spending by -7.6 percent, while its counterpart in the low-tech industries change it by -5.5 percent. The tariff changes total R&D spending in our sample of firms by -8.2 percent in the high-tech sector and -6.2 percent in the low-tech sector. In contrast, when we simulate firm responses to a 20 percent subsidy on their R&D expenditure, there are significant increases in R&D spending. As with the export tariff, most of the response is on the intensive margin as firms already investing in R&D increase their spending, but the response is more heavily concentrated among the high-tech firms. At the median firm response, R&D spending increases by 7.4 percent in the high-tech sector and 2.2 percent in the low-tech sector. The proportional increase in the expected net benefit of R&D is highly skewed within the high-tech sector and is substantially higher for firms that have relatively low domestic and foreign productivity. Overall in the sample, the median ratio of the total gain in firm value to the total cost of the R&D subsidies is 5.67 and 3.12 in the high-tech and low-tech industries, respectively. We can only measure benefits that accrue to the firms investing in R&D and cannot quantify gains to consumers or spillovers to other firms. Thus, these ratios would be a lower bound on the benefit-cost ratio for the R&D subsidy policy.

This paper shows that export market profits are an essential component of the expected benefits of R&D investment by Swedish manufacturing firms. Tariffs that reduce export market profitability negatively impact the amount of R&D investment at the firm level and the magnitude of the effect is very heterogeneous across firms. Both patterns are consistent with other empirical studies, discussed in section 2, that attempt to measure a causal link between openness to trade and innovation. Our structural framework allows us to draw new insights on the source of the firm level adjustment in R&D spending by distinguishing changes on the intensive versus extensive margin. We find that tariff increases lead to substantial contraction of R&D spending on the intensive margin as firms respond to the reduction in export market profits but, in contrast, have relatively little impact on the extensive margin decision to stop R&D investment.

This combination of effects likely reflects that, in general, Sweden specializes in exports of high-tech products and innovation through R&D investment has long been a critical component of many exporting firms' strategies. This contrasts with the trade environment in the Taiwanese electronics industry studied by Aw, Roberts, and Xu (2011). While they do not model the intensive margin of investment, they do find that firms adjust on the extensive margin in response to both changes in export market profits and innovation costs. Not surprisingly, the industry they study has a different structure than the Swedish manufacturing industries. It is characterized by many small producers and the export market acts as a channel for knowledge flows that facilitate their own investment in innovation activities. While there is clearly a positive linkage between exporting and R&D investment in both environments, the underlying mechanism is dependent on the nature of R&D and exporting activities specific to the country or industry.

We moreover find that R&D subsidies also act primarily on the intensive margin of R&D investment. For Sweden, the success of trade and innovation policies that attempt to generate an increase in total R&D investment in the manufacturing sector will depend on how the policies impact the spending decisions of firms that are already committed to R&D investment. Since exporting firms play a major role in overall R&D investment and their spending is sensitive to export market profits, policymakers must recognize the linkages between trade and innovation policy when attempting to stimulate investment in innovation.

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Table 1: R&D and Export Intensity by Industry Groups

	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
Sample Size	5286		3083	

NOTES: The high-tech group includes chemicals, metals, non-electrical machinery, electrical machinery, instruments, and motor vehicles. The low-tech group includes food and beverages, textiles, wood and paper, plastics, ceramics, and miscellaneous. R&D intensity is measured as industry R&D expenditure relative to total industry sales. Export intensity is measured as industry exports as a share of total industry sales.

Table 2: The Decomposition of Growth in R&D Expenditure by Extensive and Intensive Margins

Year-to-Year		Extensive Margin		Intensive Margin	
	R&D Growth	Begin	Stop	Expand	Contract
	(1)	(2)	(3)	(4)	(5)
High-Tech					
2003-2004	0.517	0.023	-0.012	0.570	-0.064
2004-2005	-0.154	0.025	-0.005	0.164	-0.337
2005-2006	-0.008	0.007	-0.016	0.100	-0.099
2006-2007	0.220	0.038	-0.012	0.306	-0.111
2007-2008	0.014	0.010	-0.015	0.135	-0.117
2008-2009	0.042	0.009	-0.021	0.184	-0.131
2009-2010	-0.057	0.023	-0.025	0.070	-0.125
Average	0.082	0.019	-0.015	0.218	-0.141
Low-Tech					
2003-2004	0.132	0.088	-0.029	0.149	-0.075
2004-2005	-0.019	0.062	-0.032	0.278	-0.327
2005-2006	-0.035	0.024	-0.062	0.190	-0.186
2006-2007	-0.186	0.059	-0.074	0.165	-0.336
2007-2008	0.003	0.179	-0.057	0.098	-0.217
2008-2009	-0.095	0.019	-0.042	0.125	-0.197
2009-2010	-0.121	0.074	-0.090	0.096	-0.201
Average	-0.046	0.072	-0.055	0.157	-0.220

NOTES: Column 1 reports the growth in total R&D for the firms in our sample that are present in each pair of years. Columns (2)-(5) disaggregate this total into four categories based on whether the firm adjusted on the extension margin (begin and stop doing R&D) or the intensive margin (expand and contract their R&D expenditure), i.e., (1)=(2)+(3)+(4)+(5).

Table 3: Firm 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	0.002	0.015	0.138
Export Intensity $\leq P_{25}$	0.393	0.002	0.017	0.144
$P_{25} <$ Export Intensity$\leq P_{50}$	0.582	0.003	0.019	0.111
Export Intensity $> P_{50}$	0.776	0.004	0.033	0.143
Low-Tech Industries				
No Exports	0.162	0.001	0.009	0.090
Export Intensity$\leq P_{25}$	0.259	0.001	0.008	0.069
$P_{25} <$ Export Intensity $\leq P_{50}$	0.292	0.001	0.007	0.041
Export Intensity $> P_{50}$	0.464	0.001	0.010	0.047

NOTES: The figures show the share of the firms that invest in R&D and the 10th, 50th, and 90th percentiles of the R&D intensity (columns) for the firms in one of the following export categories: nonexporters, below the 25th percentile of the export intensity distribution, between 25th and 50th, and above the 50th percentiles (rows). Export intensity is defined as the firm's sales in foreign markets divided by total sales. R&D intensity is defined as the firm's R&D expenditure divided by total sales for firms with positive R&D expenditure.

Table 4: The Estimation of the Revenue Functions and Productivity Evolution					
Panel A: Domestic Market Revenue			Export Market Revenue		
Parameter	High-Tech	Low-Tech	Parameter	High-Tech	Low-Tech
$\alpha_1(\omega_{t-1})$	0.9944	1.0376	$\delta_1(\mu_{t-1})$	0.9968	0.9791
	(0.0296)	(0.0060)		(0.0207)	(0.0005)
$\alpha_2(\omega_{t-1}^2)$	-0.0309	-0.0322	$\delta_2(\mu_{t-1}^2)$	-0.0221	-0.0006
	(0.0006)	(0.0030)		(0.0001)	(6.1E-5)
$\alpha_3(ln(rd_{t-1}))$	0.0173	0.0050	$\delta_3(ln(rd_{t-1}))$	0.0229	0.0098
	(0.0024)	(0.0006)		(0.0029)	(6.1E-5)
$\alpha_4(ln(rd_{t-1}))^2$	-0.0011	-0.0005	$\delta_4(ln(rd_{t-1}))^2$	-0.0016	-0.0003
	(2.4E-5)	(2.4E-5)		(2.6E-5)	(4.3E-5)
$\alpha_5(ln(rd_{t-1})\omega_{t-1})$	0.0058	0.0027	$\delta_5(ln(rd_{t-1})\mu_{t-1})$	0.0062	0.0004
	(7.0E-5)	(0.0001)		(6.3E-5)	(0.0002)
β_k	-0.1081	-0.0790	β_k	-0.1061	-0.2490
	(0.0004)	(0.0008)		(0.0004)	(0.0060)
η_d	-3.1965	-3.2352	η_f	-2.9697	-2.5740
	(2.0E-6)	(3.0E-6)		(7.0E-6)	(1.0E-6)
Sample Size	3374	1834		3374	1834
Panel B: Recovered domestic and export shocks and their correlations					
	High-Tech	Low-Tech			
σ_ξ	0.2303	0.2013			
σ_ν	0.4317	0.3713			
$Corr(\xi, \nu)$	0.2991	0.3662			
$Corr(\omega, \mu)$	0.4921	0.5132			

NOTES: Panel A shows the estimated coefficients of the domestic and foreign revenue functions (equations (23) and (24)) and the evolution of productivities for high and low tech groups. All specifications include industry and year dummies. Standard errors are reported in parentheses (note that nE-$m = n \times 10^{-m}$). Panel B shows descriptive statistics of the recovered distributions of domestic and export shocks using the estimated coefficients in Panel A. σ_ξ and σ_ν measure empirical standard deviation.

Table 5: Elasticities of Productivity	High-Tech Industries			Low-Tech Industries		
	10th	Median	90th	10th	Median	90th
Impact of R&D						
Domestic Market Productivity: $\frac{\partial \omega_{jt}}{\partial ln(rd_{jt-1})}$	0.004	0.008	0.013	0.000	0.002	0.003
Export Market Productivity: $\frac{\partial \mu_{jt}}{\partial ln(rd_{jt-1})}$	0.005	0.010	0.017	0.004	0.005	0.007
Impact of Lagged Productivity						
Domestic Market Productivity: $\frac{\partial \omega_{jt}}{\partial \omega_{jt-1}}$	0.883	0.919	0.957	0.906	0.937	0.961
Export Market Productivity: $\frac{\partial \mu_{jt}}{\partial \mu_{jt-1}}$	0.883	0.922	0.959	0.975	0.978	0.980

NOTES: The 10th, 50th and 90th percentiles are computed using the distributions of elasticities of productivity with respect to R&D expenditure and lagged productivity across firm-year observations derived from the estimated productivity evolution in Table 4.

Table 6: Reduced Form Policy Functions for R&D and Exporting Using B-Splines Approximation

	High-Tech Industries			Low-Tech Industries		
	R&D Discrete	R&D Log Expend	Export Discrete	R&D Discrete	R&D Log Expend	Export Discrete
Degree approx. ω	6	3	8	3	4	6
Degree approx. μ	5	3	8	3	11	6
Degree approx. k	5	3	8	3	11	6
Degree approx. $I(rd_{jt-1} > 0) \times \omega$	3	3	3	3	3	3
Degree approx. $I(rd_{jt-1} > 0) \times \mu$	3	3	3	3	3	3
Degree approx. $I(rd_{jt-1} > 0) \times k$	3	3	3	3	3	3
Goodness of fit[a]	0.373	0.985	0.534	0.209	0.986	0.572
Test Statistics (p-value)[b]						
H_0: coefficients on $I(rd_{jt-1} > 0)$ =0	655.295	8.398	111.214	175.352	2.867	48.599
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
H_0: coefficients on ω =0	16.988	3.873	45.040	7.464	1.494	73.517
	(0.049)	(0.001)	(0.000)	(0.28)	(0.168)	(0.000)
H_0: coefficients on μ =0	53.475	37.736	67.888	22.791	3.230	85.927
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
H_0: coefficients on k =0	21.520	15.493	148.957	23.496	2.185	67.595
	(0.006)	(0.000)	(0.000)	(0.001)	(0.008)	(0.000)

NOTES: The optimal policy function $a_{jt} = \tilde{a}_t(I(rd_{jt-1} > 0), \omega_{jt}, \mu_{jt}, k_{jt})$ is approximated using b-splines, i.e., $a_{jt} = \rho^{rd} I(rd_{jt-1} > 0) + bs(\omega_{jt}, df^{\omega})\boldsymbol{\rho}^{\omega} + bs(\mu_{jt}, df^{\mu})\boldsymbol{\rho}^{\mu} + bs(k_{jt}, df^{k})\boldsymbol{\rho}^{k} + bs(I(rd_{jt-1} > 0) \times \omega_{jt}, 3)\boldsymbol{\rho}^{i\omega} + bs(I(rd_{jt-1} > 0) \times \mu_{jt}, 3)\boldsymbol{\rho}^{i\mu} + bs(I(rd_{jt-1} > 0) \times k_{jt}, 3)\boldsymbol{\rho}^{ik} + \epsilon_{jt}$, where the degrees df^{ω}, df^{ν}, and df^{k} gives the number of columns of generated basis matrix bs for each state variable. Logit and OLS estimators are used. For each policy the degrees of b-spline approximation (i.e., best specification) are choosen based on Akaike Information Criterion test (AIC). p-values for test statistics are reported in parentheses. All specifications 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. The tests have 4,(df^{ω}+3), (df^{ν}+3), and (df^{k}+3) restrictions.

Table 7: Estimates of Structural Cost Parameters

	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	0.0139 (0.0002)	0.0058 (0.0001)	0.1566 (0.0022)	3.789 (0.198)	87.017 (3.862)	0.096 (0.059)
Metals	0.5860 (0.0107)	0.0244 (0.0003)	0.5298 (0.0076)	12.224 (0.550)	127.789 (4.242)	6.273 (0.164)
Non elect machinery	0.5109 (0.0079)	2.94E-4 (5.69E-6)	0.1505 (0.0024)	5.052 (0.230)	46.925 (2.863)	2.242 (0.107)
Electrical machinery	0.4235 (0.0045)	7.27E-4 (1.06E-5)	0.1381 (0.0019)	5.404 (0.194)	63.079 (4.582)	1.088 (0.044)
Instruments	0.1189 (0.0020)	0.0136 (0.0002)	0.1675 (0.0028)	4.539 (0.306)	15.647 (0.908)	2.506 (0.118)
Vehicles	0.6641 (0.0123)	0.0111 (0.0002)	0.5705 (0.0079)	14.733 (0.603)	100.231 (4.621)	1.567 (0.078)
Low-Tech Industries						
Food	0.8241 (0.0118)	0.0403 (0.0006)	0.2057 (0.0032)	23.542 (1.356)	61.027 (2.757)	13.562 (0.523)
Textiles	0.1835 (0.0028)	0.4052 (0.0051)	0.1615 (0.0019)	7.502 (0.249)	23.696 (1.340)	1.646 (0.067)
Paper	0.0579 (0.0008)	0.7769 (0.0133)	0.1119 (0.0020)	19.682 (1.164)	101.966 (5.725)	8.427 (0.461)
Plastics	0.4768 (0.0007)	0.0292 (0.0005)	0.1782 (0.0029)	12.670 (0.711)	40.521 (2.241)	2.111 (0.115)
Ceramics	6.21E-7 (9.08E-9)	0.5651 (0.0076)	7.85E-8 (1.21E-9)	13.975 (0.945)	96.011 (4.839)	3.317 (0.138)
Miscellaneous	0.4529 (0.0071)	0.2349 (0.0037)	0.0833 (0.0012)	12.975 (0.476)	49.407 (2.216)	2.975 (0.115)

NOTES: The figures show the estimates of the structural cost parameters for the variable cost of R&D (equation (27)), the fixed maintenance and fixed startup costs of R&D (equation (28)), and the fixed cost of exporting (equation (29)). Standard errors were calculated via subsampling (50 subsamples). Note that nE-$m = n \times 10^{-m}$). The cost is measured in million SEK (1 USD = 7.2 SEK, 1 EUR = 9.54 SEK).

Table 8: Expected Marginal Cost of Innovation: Percentiles of the Distribution of $EMC(\omega, \mu, k)$

	10th	25th	50th	75th	90th
High-Tech Industries					
Chemicals	0.238	0.255	0.326	0.446	0.669
Metals	1.084	1.107	1.236	1.405	1.856
Non elect machinery	0.549	0.550	0.555	0.565	0.575
Electrical machinery	0.468	0.470	0.476	0.488	0.506
Instruments	0.318	0.332	0.368	0.446	0.496
Vehicles	1.183	1.196	1.237	1.333	1.420
Low-Tech Industries					
Food	0.864	0.884	0.976	1.044	1.141
Textiles	0.505	0.576	0.758	1.123	1.628
Paper	0.484	0.794	1.272	2.281	3.464
Plastics	0.563	0.592	0.652	0.737	0.846
Ceramics	0.384	0.651	0.962	2.225	2.479
Miscellaneous	0.551	0.677	1.071	1.415	1.597

NOTES: Units are millions of SEK. EMC measures the increase in the variable cost of innovation needed to generate an improvement in productivity. It satisfies the first-order condition with respect to R&D in the firm's dynamic optimization problem.

Table 9: Model Fit – Mean of Actual and Predicted Probabilities						
	Maintain R&D		Start R&D		Export	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
High-Tech Industries						
Chemicals	0.903	0.903	0.340	0.338	0.984	0.999
Metals	0.806	0.803	0.152	0.152	0.802	0.803
Non elect machinery	0.887	0.885	0.296	0.296	0.936	0.940
Electrical machinery	0.863	0.862	0.212	0.212	0.918	0.918
Instruments	0.880	0.880	0.333	0.333	0.870	0.869
Vehicles	0.804	0.803	0.264	0.264	0.935	0.936
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	0.522	0.125	0.125	0.774	0.775
Plastics	0.636	0.633	0.246	0.245	0.960	0.959
Ceramics	0.589	0.590	0.157	0.157	0.813	0.813
Miscellaneous	0.639	0.639	0.219	0.219	0.898	0.898

Table 10: 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	7.217	9.321	9.990	11.229	11.013
Metals	5.991	5.655	8.292	8.785	10.571	10.446
Non elect machinery	6.684	6.534	9.210	9.402	11.708	11.910
Electrical machinery	6.397	6.390	8.987	8.792	10.714	11.347
Instruments	6.404	6.494	8.780	8.622	9.851	9.997
Vehicles	6.331	5.956	8.578	8.811	11.127	11.025
Low-Tech Industries						
Food	4.605	4.931	6.955	7.028	8.239	8.158
Textiles	5.298	5.358	6.397	6.618	7.400	7.411
Paper	5.298	5.672	6.895	6.653	7.601	7.585
Plastics	5.298	5.331	7.313	7.559	8.307	8.769
Ceramics	5.962	6.183	6.908	6.803	7.972	7.713
Miscellaneous	5.298	5.664	7.090	7.058	7.824	7.806

Table 11: Percentiles of Distribution of R&D Benefits $(V^1 - V^0)/R\&D$								
	Nonexporters				Exporters			
	P_{25}	P_{50}	P_{75}	IQR/P_{50}	P_{25}	P_{50}	P_{75}	IQR/P_{50}
High-Tech Industries								
Chemicals	0.494	0.711	0.821	0.460	4.059	52.863	97.617	1.770
Metals	2.131	3.428	5.212	0.899	2.710	7.951	154.813	19.130
Non elect machinery	0.189	0.687	2.064	2.729	4.294	49.130	75.596	1.451
Electrical machinery	0.241	0.549	0.993	1.370	2.126	22.104	49.805	2.157
Instruments	0.416	0.568	0.809	0.692	3.480	25.717	53.361	1.940
Vehicles	1.266	1.726	2.889	0.940	3.475	12.423	93.942	7.282
Low-Tech Industries								
Food	1.876	3.028	4.298	0.800	6.719	10.210	19.365	1.239
Textiles	1.653	2.100	4.016	1.125	2.771	4.758	9.010	1.311
Paper	3.153	5.662	11.071	1.398	5.710	11.700	23.552	1.525
Plastics	0.997	1.758	1.972	0.555	3.121	6.002	51.268	8.022
Ceramics	1.618	2.678	6.308	1.751	7.612	17.184	33.127	1.485
Miscellaneous	2.174	3.528	6.709	1.285	4.725	10.146	54.686	4.924

NOTES: The V^1 and V^0 are value functions when the firm invests and does not invest in R&D and are obtained directly from the estimated model. The ratio $(V^1 - V^0)/R\&D$ is reported for firms with observed positive R&D investments. The interquartile range IQR is defined as $IQR = P_{75} - P_{25}$.

Table 12: Proportional Increase in Firm Value Due to R&D: Percentiles of $(V^1 - V^0)/V^0$

	Nonexporters			Exporters		
	P_{25}	P_{50}	P_{75}	P_{25}	P_{50}	P_{75}
High-Tech Industries						
Chemicals	0.009	0.012	0.016	0.064	0.959	1.310
Metals	0.017	0.023	0.033	0.018	0.047	0.859
Non elect machinery	0.001	0.004	0.022	0.045	0.772	1.116
Electrical machinery	0.001	0.004	0.009	0.029	0.398	0.963
Instruments	0.006	0.009	0.015	0.068	0.566	0.956
Vehicles	0.003	0.009	0.015	0.028	0.090	0.839
Low-Tech Industries						
Food	0.002	0.003	0.006	0.009	0.014	0.022
Textiles	0.002	0.004	0.005	0.005	0.009	0.016
Paper	0.005	0.003	0.011	0.006	0.010	0.014
Plastics	0.002	0.003	0.004	0.006	0.013	0.079
Ceramics	0.001	0.003	0.007	0.010	0.014	0.019
Miscellaneous	0.001	0.003	0.007	0.006	0.013	0.058

NOTES: The V^1 and V^0 are value functions when the firm invests and does not invest in R&D and are obtained directly from the estimated model. The ratio $(V^1 - V^0)/V^0$ is reported for firms with observed positive R&D investments.

Table 13a: Policy Experiment: The Impact of a 10% Export Tariff					
	Proportional Change		Change in Probability		
	ENB	R&D	Maintain R&D	Start R&D	Export
High-Tech Industries					
10th Percentile	-0.397	-0.127	-0.045	-0.070	-0.094
Median	-0.186	-0.076	-0.000	-0.007	-0.000
90th Percentile	-0.043	-0.019	-0.000	-0.000	-0.000
Low-Tech Industries					
10th Percentile	-0.359	-0.087	-0.074	-0.050	-0.088
Median	-0.206	-0.055	-0.007	-0.005	-0.035
90th Percentile	-0.035	-0.011	-0.000	-0.000	-0.000

NOTES: The 10th, 50th, and 90th percentile change in the firm variables are based on simulations from the estimated model. $ENB = V^1 - V^0 - C_I(rd)$, where $C_I(rd)$ is the total cost of innovation (fixed and variable). It is the firm's expected net benefit of investing in R&D.

Table 13b: Policy Experiment: The Proportional Change in Expected Net Benefit of R&D Investment (ENB) across Domestic and Foreign Productivity Distributions (ω and μ) from a 10% Export Tariff

	$P_0 \leq \mu \leq P_{25}$	$P_{25} < \mu \leq P_{50}$	$P_{50} < \mu \leq P_{75}$	$P_{75} < \mu \leq P_{100}$
High-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	-0.022	-0.285	-0.381	-0.384
$P_{25} < \omega \leq P_{50}$	-0.058	-0.234	-0.265	-0.246
$P_{50} < \omega \leq P_{75}$	-0.084	-0.187	-0.205	-0.208
$P_{75} < \omega \leq P_{100}$	-0.083	-0.136	-0.154	-0.184
Low-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	-0.054	-0.213	-0.269	-0.318
$P_{25} < \omega \leq P_{50}$	-0.091	-0.174	-0.274	-0.330
$P_{50} < \omega \leq P_{75}$	-0.117	-0.180	-0.236	-0.306
$P_{75} < \omega \leq P_{100}$	-0.123	-0.187	-0.203	-0.256

NOTES: Productivity bins are defined based on the 25th, 50th, and 75th percentiles of the estimated domestic productivity ω (rows) and foreign productivity μ (columns) distributions.

Table 14a: Policy Experiment: The Impact of 10% Export and Import Tariffs					
	Proportional Change		Change in Probability		
	ENB	R&D	Maintain R&D	Start R&D	Export
High-Tech Industries					
10th Percentile	-0.492	-0.157	-0.085	-0.100	-0.095
Median	-0.259	-0.108	-0.000	-0.014	-0.000
90th Percentile	-0.162	-0.075	-0.000	-0.000	-0.000
Low-Tech Industries					
10th Percentile	-0.455	-0.118	-0.115	-0.072	-0.089
Median	-0.332	-0.097	-0.017	-0.010	-0.035
90th Percentile	-0.244	-0.076	-0.000	-0.001	-0.000

NOTES: The 10th, 50th, and 90th percentile change in the firm variables are based on simulations from the estimated model. ENB is the firm's expected net benefit of investing in R&D. $ENB = V^1 - V^0 - C_I(rd)$, where $C_I(rd)$ is the total cost of innovation (fixed and variable).

Table 14b: Policy Experiment: The Proportional Change in Expected Net Benefit of R&D investment (ENB) across Domestic and Foreign Productivity Distributions (ω and μ) from 10% Export and Import Tariffs

	$P_0 \leq \mu \leq P_{25}$	$P_{25} < \mu \leq P_{50}$	$P_{50} < \mu \leq P_{75}$	$P_{75} < \mu \leq P_{100}$
High-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	-0.144	-0.389	-0.443	-0.426
$P_{25} < \omega \leq P_{50}$	-0.220	-0.333	-0.348	-0.273
$P_{50} < \omega \leq P_{75}$	-0.263	-0.316	-0.256	-0.240
$P_{75} < \omega \leq P_{100}$	-0.287	-0.283	-0.218	-0.220
Low-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	-0.266	-0.342	-0.381	-0.406
$P_{25} < \omega \leq P_{50}$	-0.270	-0.318	-0.373	-0.405
$P_{50} < \omega \leq P_{75}$	-0.283	-0.321	-0.349	-0.391
$P_{75} < \omega \leq P_{100}$	-0.299	-0.325	-0.332	-0.364

NOTES: Productivity bins are defined based on the 25th, 50th, and 75th percentiles of the estimated domestic productivity ω (rows) and foreign productivity μ (columns) distributions.

Table 15a: Policy Experiment: The Impact of 20% Variable R&D Cost Reduction

	Proportional Change		Change in Probability		
	ENB	R&D	Maintain R&D	Start R&D	Export
High-Tech Industries					
10th Percentile	0.006	0.020	0.000	0.001	0.000
Median	0.042	0.074	0.000	0.003	0.000
90th Percentile	0.277	0.256	0.021	0.008	0.001
Low-Tech Industries					
10th Percentile	0.001	0.003	0.000	0.000	0.000
Median	0.011	0.022	0.000	0.000	0.000
90th Percentile	0.076	0.208	0.004	0.002	0.000

NOTES: The 10th, 50th, and 90th percentile change in the firm variables are based on simulations from the estimated model. ENB is the firm's expected net benefit of investing in R&D. $ENB = V^1 - V^0 - C_I(rd)$, where $C_I(rd)$ is the total cost of innovation (fixed and variable).

Table 15b: Policy Experiment: The Proportional Change in Expected Net Benefit of R&D investment (ENB) across Domestic and Foreign Productivity Distributions (ω and μ) from a 20% Variable R&D Cost Reduction

	$P_0 \leq \mu \leq P_{25}$	$P_{25} < \mu \leq P_{50}$	$P_{50} < \mu \leq P_{75}$	$P_{75} < \mu \leq P_{100}$
High-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	0.252	0.126	0.055	0.039
$P_{25} < \omega \leq P_{50}$	0.182	0.065	0.038	0.015
$P_{50} < \omega \leq P_{75}$	0.091	0.049	0.024	0.015
$P_{75} < \omega \leq P_{100}$	0.046	0.029	0.019	0.011
Low-Tech Industries				
$P_0 \leq \omega \leq P_{25}$	0.065	0.023	0.007	0.014
$P_{25} < \omega \leq P_{50}$	0.017	0.021	0.009	0.017
$P_{50} < \omega \leq P_{75}$	0.003	0.005	0.016	0.006
$P_{75} < \omega \leq P_{100}$	0.018	0.006	0.007	0.003

NOTES: Productivity bins are defined based on the 25th, 50th, and 75th percentiles of the estimated domestic productivity ω (rows) and foreign productivity μ (columns) distributions.

Online Appendix
The Dynamic Impact of Exporting on Firm R&D Investment

Florin G. Maican, Matilda Orth, Mark J. Roberts, and Van Anh Vuong

Appendix A: 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.[20] 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.[21] 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

[20] 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).

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

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). Overall, in our estimating sample, there are 5286 observations on 1926 unique firms in the high-tech industries and 3083 observations on 1249 unique firms in the low-tech industries. While some firms are dropped from the estimating sample over time because of the rotation of small firms in the survey years, this is not related to firm exit from production. The true exit rate of these firms averages 2.7 percent per year in the high-tech industries and 3.2 percent in the low-tech industries. Sample selection based on firm exit is not a serious issue in our sample.

Appendix B: Identification of the Productivity Processes and Inversion of the Policy Functions

Identification. Identification pertains to the system of revenue functions for domestic and export sales, equations (3) and (4), and the processes of productivity evolution for the two unobservables, domestic and foreign productivity, equations (8) and 9), where each unobservable is in only one equation. Control functions for investment and the number of export destinations, that are based on the firm's optimal policy functions, are used to proxy for ω_{jt} and μ_{jt}. Ackerberg, Benkard, Berry, and Pakes (2007) (Section 2.4.3) and Matzkin (2008) discuss identification of such a system of equations. Ackerberg, Benkard, Berry, and Pakes (2007) show that we cannot identify one production function equation with two correlated unobservables even if we have two controls. To restore identification, they suggest the introduction of another equation, which they label an index function, that contains only one unobservable. Maican and Orth (2021a, 2021b) also analyze identification in this case. Identification in our model is actually more straightforward than the case they analyze, because we have two controls and two revenue equations and the two correlated unobservables enter in a parametric form in the Markov processes (equations (21) and (22)). This satisfies the conditions Ackerberg, Benkard, Berry, and Pakes (2007) specify for identification.

Invertibility conditions with two unobservables. The general functions for investment and log of the number of destinations that arise from the firms' dynamic optimization problem are given by the two equations:

$$\begin{aligned} i_{jt} &= i_t(k_{jt}, \omega_{jt}, \mu_{jt}) \\ nd_{jt} &= nd_t(k_{jt,}\omega_{jt}, \mu_{jt}). \end{aligned} \tag{32}$$

The aim is to recover ω_{jt} and μ_{jt} using this system of equations. The conditions required for identification follow the arguments in (Maican and Orth 2021a, 2021b). To invert these equations and express ω_{jt} and μ_{jt} in terms of i_{jt}, nd_{jt}, and k_{jt}, certain conditions on the partial derivatives and determinant of the 2x2 Jacobian $\partial(i, nd)/\partial(\omega, \mu)$ must be satisfied. The partial derivatives must be continuous and the Jacobian determinant is not zero. In other words, the ratios between the impact of ω and μ on the investment and number of destinations should not be the same, i.e., $(\partial i/\partial\omega)/(\partial i/\partial\mu) \neq (\partial nd/\partial\omega)/(\partial nd/\partial\mu)$. This condition requires that domestic and foreign productivities have a different impact on investment and the number of destinations, and the relative impact is not the same. In other words, the tradeoff between changes in the domestic and foreign productivities must be different for investment and the number of export destinations.

The proof of the invertibility of the system of equations under these conditions is an application of the implicit function theorem. In our case, points in $(2+3)$-dimensional space $\mathbb{R}^{2+3}$ can be written in the form of $(\mathbf{x};\mathbf{b})$, where $\mathbf{x}=(\omega,\mu)$ and $\mathbf{b}=(i,nd,k)$. We can rewrite the system as $f_1(\mathbf{x};\mathbf{b})=0$ and $f_2(\mathbf{x};\mathbf{b})=0$ or simply as an equation $F(\mathbf{x};\mathbf{b})=0$. Invertibility of the policy functions requires that the relation $F(\mathbf{x};\mathbf{b})=0$ is also a function. In other words, under what conditions can $F(\mathbf{x};\mathbf{b})=0$ be solved explicitly for $\mathbf{b}$ in terms of $\mathbf{x}$, obtaining a unique solution. The following theorem provides the conditions that, for a given point $(\mathbf{x}_0,\mathbf{b}_0)$ such that $F(\mathbf{x}_0,\mathbf{b}_0)=0$, there exists a neighborhood of $(\mathbf{x}_0,\mathbf{b}_0)$ where the relation $F(\mathbf{x};\mathbf{b})=0$ is a function.

Theorem (Implicit Function Theorem): *Let $\mathbf{f}=(f_1,f_2)$ be a vector of functions defined on the open set S in $\mathbb{R}^{2+3}$ with values in $\mathbb{R}^2$. Suppose $\mathbf{f}\in C'$ on S (i.e., components in $\mathbf{f}$ have continuous first-order partials). Let $(\mathbf{x}_0;\mathbf{b}_0)$ be a point in S for which $\mathbf{f}(\mathbf{x}_0,\mathbf{b}_0)=\mathbf{0}$ and for which the 2×2 Jacobian determinant $\partial(f_1,f_2)/\partial(\omega,\mu)$ is not zero at $(\mathbf{x}_0,\mathbf{b}_0)$. Then there exists a 3-dimensional open set B_0 that includes $\mathbf{b}_0$ and one and only one vector based functions $\mathbf{g}$ defined on B_0 and having values in $\mathbb{R}^2$ such that*
(i) $\mathbf{g}\in C'$ *on* B_0
(ii) $\mathbf{g}(\mathbf{b}_0)=\mathbf{x}_0$
(iii) $\mathbf{f}(\mathbf{g}(\mathbf{b});\mathbf{b})=\mathbf{0}$ *for every* $\mathbf{b}$ *in* B_0.
PROOF: The general proof of the theorem can found on pp. 373-375 in Apostol(1974).

References

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[2] Matzkin, Rosa L. (2008), "Identification in Nonparametric Simultaneous Equation Models," Econometrica, Vol. 76, No. 5, pp. 945-978.