EFIGE IS A PROJECT DESIGNED TO HELP IDENTIFY THE INTERNAL POLICIES NEEDED TO IMPROVE EUROPE'S EXTERNAL COMPETITIVENESS

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Technological Change, Trade in Intermediates and the Joint Impact on Productivity*

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Abstract

This paper examines the interdependence between innovation and imports of inter- mediates, and their joint impact on productivity. We do so by developing a quantitative model with heterogeneous firms and international trade where firms can invest in R&D and source inputs internationally. Innovating firms on average become more productive, thereby enabling them to cover the fixed costs of sourcing foreign inputs, which in turn also has a benign impact on measured productivity. Using Norwegian firm-level data on R&D and trade in intermediates, we structurally estimate the model and find that both imports and R&D investment play a key role in explaining firm-level productivity growth. Moreover, the estimated returns to R&D are significantly lower after controlling for the complementarity between R&D investments and imports. We exploit the introduction of an R&D tax credit scheme in Norway in 2002, which lowered the marginal cost of R&D substantially. The estimated structural model can explain most of the observed increase in trade in intermediates as more firms started to innovate, underscoring the quantitative importance of our theoretical mechanism. Moreover, one fifth of measured productivity growth among new innovators came from increased foreign sourcing, rather than technology upgrading, illustrating how trad can amplify productivity gains. An implication of our work is that lower input trade barriers pro- mote technological change. Hence, our work offers a new mechanism through which imports increase productivity, which may help explain why a number of studies find firm-level productivity gains associated with input trade liberalization.

JEL: F10, F12, F14, O30, O33.

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1 Introduction

Understanding the role of international trade in explaining aggregate productivity remains a key question in economics. Recent empirical research has documented a strong positive impact of access to imported intermediates on firm performance. A different strand of the literature has highlighted how productivity evolves endogenously and responds to firms' investment in knowledge and technology. In this paper, we argue that technology upgrading and imports of intermediates are determined jointly, and that we need to model the interdependence between trade in intermediates and innovation, and their combined impact on measured productivity.

We build a quantitative model with heterogeneous firms to analyze the relationship between investment in knowledge and imports of intermediate goods. Innovating and importing intermediates are subject to fixed costs, consistent with the stylized fact that only a subset of firms innovate and import, and that these firms are considerably larger than than other firms (see Section 2.3. In equilibrium, firm-level innovation and imports of intermediates are complementary activities. Complementarity arises since R&D on average increases future profits and revenue, thereby making it more profitable to cut costs by sourcing inputs internationally.

We emphasize three main implications of the model. First, since both innovation and foreign sourcing reduces marginal costs, and the two activities are complementary, we need to control for both factors when estimating the impact of R&D or imports on measured productivity. Second, our model delivers a novel channel by which trade affects technological change. Input trade liberalization stimulates both imports and innovation, bringing about productivity gains both at the firm and aggregate level. In the model, declining input trade barriers lower marginal production costs and raise firm revenue. That in turn increases the returns to incurring a fixed R&D cost, since a one percent productivity gain translates into more sales in dollars when revenue is high. Hence, our work offers a new mechanism through which imports increase productivity, which may help explain why a number of studies find large firm-level productivity gains associated with input trade liberalization, e.g. Amiti and Konings (2007), Goldberg et al. (2010) and Khandelwal and Topalova (2011). Third, lower innovation costs, e.g. due to R&D tax credits, raise the returns to both R&D and imports of intermediate inputs, thereby promoting not only technology upgrading but also imports.

We first build a structural estimator, in the spirit of Doraszelski and Jaumandreu (2011) and Aw et al. (2011) among others, where we estimate the impact of R&D and imports on productivity. We explicitly control for the fact that input costs are heterogeneous across firms, since innovating firms reduce costs by importing foreign varieties. We confront the model with data on Norwegian firms' innovation activities and their sourcing of imported inputs. Our structural estimates show that both investment in knowledge and foreign sourcing drive down marginal cost. A firm that performs R&D in every period has on average 30 percent higher revenue compared to a firm that never invests in R&D. A firm in the upper quartile in terms of the number of products sourced from abroad has roughly twice the revenue compared to a firm in the lowest quartile.[1] This translates into substantial measured productivity differences across firms.[2] Furthermore, omitting the cost saving effect of imports when estimating the model generates a substantial upward bias in the returns to R&D. This occurs since, in the data, starting R&D is positively correlated with importing more varieties.

Second, we proceed by analyzing the impact of reduced costs of innovation. In the early 2000s, a tax credit for R&D projects was introduced in Norway, lowering the marginal cost of R&D by 20 percent. This policy reform lends itself as a natural experiment. We use a simple difference-in-differences methodology, exploiting the fact that the R&D tax credit only lowered marginal R&D costs for a subset of firms. Reduced form evidence suggests that lower marginal R&D costs had a large impact on both investment in knowledge and imports of foreign intermediates, consistent with our model.[3]

Third, we simulate the estimated model, asking how much international sourcing of inputs the model predicts in response to the actual surge in innovation that occurred due to the policy change. We compare the import growth in the simulation with our reduced form estimates. This enables us to evaluate the importance of the theoretical mechanism proposed in this paper, relative to competing hypotheses. We find that a majority of the import surge that occurred in the aftermath of the policy change can be attributed to the proposed theoretical mechanism. This suggests that complementarity is also quantitatively important. Moreover, one fifth of average measured productivity growth among new innovators came from sourcing more products, while the remaining 4/5 came from technical change, illustrating how trade can amplify productivity gains. The import channel alone contributed to a 12 percent increase in sales (and a corresponding decrease in costs). In our view, that a government R&D policy can give cost savings of this magnitude due to imports is indeed an important finding.

The paper makes three main contributions. First, we document novel firm-level facts on the relationship between R&D activity and imports of intermediates. Innovating firms are

[1] I.e. importing the number of products between the 3rd quartile and up, compared to importing the number of products between 0 and the 1st quartile.

[2] In the model we build, productivity is proportional to revenue.

[3] Our results on the impact of the policy reform on R&D are in line with the findings of Hægeland and Møen (2007).

larger, import more varieties and have a higher import share. Firms that start to innovate increase their portfolio of imported varieties relative to all other firms. Second, we develop a new model that highlights the complementarity between innovating and other cost saving activities such as imports of intermediates. According to the model, R&D policy impacts not only on innovation but also on imports, while trade policy affects measured productivity both due to changes in import prices and due to changes in the incentive to innovate. Hence, our work offers a mechanism for why trade in intermediates affects technological change and productivity. Third, we build both a reduced form and a structural estimator and quantify the interdependence between innovation and importing and their joint impact on productivity.

Our analysis brings together three strands of the literature. First, our work relates to the literature on R&D and productivity. Doraszelski and Jaumandreu (2011) build and estimate an empirical model of endogenous productivity to examine the impact of investment in knowledge on the productivity of firms, extending the knowledge capital model pioneered by Griliches (1979). Aw et al. (2011) estimate the returns to R&D and exporting for the Taiwanese electronics industry. Both of these papers assume that input costs are homogeneous across firms, ruling out the possibility of further cost reductions as innovation takes place.

Second, our work relates to the literature on foreign sourcing and productivity. The importance of intermediate inputs for productivity growth has been emphasized in several theoretical papers, e.g. Ethier (1979, 1982), Romer (1987, 1990) and Markusen (1989). Halpern et al. (2011) estimate a model of importers using Hungarian micro data and find that importing more varieties leads to large measured productivity effects. Recent work by Gopinath and Neiman (2011) also find large negative measured productivity effects from a collapse in imports following the Argentine crisis in 2001-2002. The empirical studies of Amiti and Konings (2007); Goldberg et al. (2010); Khandelwal and Topalova (2011) all find that declines in input tariffs are associated with sizable measured productivity gains. Compared to our work, these papers do not consider the role of investment in knowledge. As a consequence they are unable to disentangle the effects of imports relative to R&D investments on productivity.[4]

Third, our work relates to the literature on complementarities between trade and technology adoption. Empirical work by Bustos (2011) and Lileeva and Trefler (2010) show that trade integration can induce exporters to upgrade technology. Compared to our work, these

[4] Goldberg et al. (2010) find that lower input tariffs are associated with increased R&D expenditures, although the coefficient is imprecisely estimated, which is consistent with our framework. But the authors do not disentangle the direct impact of tariffs on productivity relative to the indirect impact of tariffs on R&D and productivity.

papers do not model the import side, so that complementarities only arise due to market size effects. Bloom et al. (2011) focus on the effect of imports from developing countries on technology upgrading and productivity in OECD countries. But while we investigate the role of intermediates import, they examine the impact of import competition. Theoretical work by Atkeson and Burstein (2011) and Costantini and Melitz (2007) also emphasize the impact of market size on innovation, and highlight the general equilibrium and dynamic effects of trade shocks on innovation. But the connection between imports and innovation has received scant attention in the literature. Three exceptions are Glass and Saggi (2001), Goel (2012) and Rodriguez-Clare (2010). While these papers are primarily concerned with the wage effects of offshoring, our paper focuses on complementarity and the returns to imports and innovation in terms of productivity.

The remainder of this paper is organized as follows. In Section 2 we document a set of stylized facts about R&D, imports, and labor productivity. Section 3 introduces the model, while in Section 4 we proceed by structurally estimating it. In Section 5 we turn to a set of difference-in-differences regressions and estimate the effect on the number of imported varieties from lower marginal R&D costs. Section 6 discusses alternative mechanisms that may explain the complementarity between R&D and imports and examines their relevance. Section 7 presents a simple counterfactual exercise, allowing us to quantify the effect of the proposed complementarity between imports and R&D, while Section 8 concludes.

2 Facts on R&D, imports and labor productivity

2.1 Data

Our data is a biannual panel of Norwegian manufacturing firms with more than 50 employees during 1997 to 2005. The data is gathered from three different sources. Balance sheet data is from Statistics Norway's capital database, which is an annual unbalanced panel of all non-oil manufacturing joint-stock firms, with approximately 8,000 firms per year, which amount to 90 percent of all manufacturing firms.[5] The panel provides information about revenues, costs of intermediates, value added, employment, and capital stock. Information about firm level imports is assembled from customs declarations. These data make up an unbalanced panel of each firm's annual import value for each HS 4 digit product. Finally, innovation data is from Statistics Norway's R&D statistics, which is based on a biannual survey of all manufacturing firms with more than 50 employees. The panel provides information about firm level R&D investment and R&D personnel. We merge all three sources based on a unique firm identifier.

[5] Statistics Norway's capital database is described in Raknerud et al. (2004).

After dropping firms with either zero employment, missing capital stocks or missing value added, we get an unbalanced panel of roughly 850 firms per year. Further details on the data set and the construction of variables are provided in the appendix.

2.2 Trends in innovation and importing

A major reform of Norway's innovation policy was introduced in January 2002. The tax credit reform, "Skattefunn", enabled firms to deduct 20 percent of their R&D costs from their tax bill, effectively reducing marginal costs of R&D by 20 percent. The final details of the reform was announced only months earlier, which limited the scope for anticipation effects and strategic behavior.[6] The tax credit was only applied to R&D expenditures less than NOK 4 mill (0.5 mill USD using the 2002 exchange rate).[7] In Section 5, we will exploit this feature of the scheme in order to estimate the impact of reduced marginal costs of R&D on R&D investments and imports. Except for purchases from a few pre-approved domestic R&D institutions, only in-house R&D investment was eligible for the tax credit, so that e.g. the price of imported products or services was not affected by the reform.[8]

Figure 1 illustrates the substantial changes that occurred in the manufacturing sector during our sample period. The share of innovating firms increased from 42 to 57 percent from 1997 to 2005, while the share of importers increased from 89 to 97 percent.[9] Most of the change took place between 2001 (pre-reform) and 2003 (post-reform). At the same time, there was a surge in the average number of imported products, with an 18 percent increase over the period.[10] Almost all manufacturing industries experienced an increase in both import and R&D participation. In 21 out of 26 industries the share of importers rose, while in 25 industries the share of innovating firms increased.[11] One objective of this paper is to explain how these large shifts in innovation and importing are jointly determined, and that, as a consequence, both R&D investments and imports responded to the fall in R&D

[6] The Norwegian government constituted a committee on March 23 1999 to evaluate different measures to increase private sector investments in R&D. The committee handed in their Official Norwegian Report (NOU 2000:7) on March 8 2000, in which it recommended that 25 percent of firms' R&D expenses up to NOK 4 mill should be tax deductible. This was then subject to political treatment and in a proposition presented on September 22 2000 regarding the national budget, the government announced the introduction of a fund to which firms could apply for grants covering up to 25 percent of R&D expenditures. The fund of NOK 200 mill was established on July 1 2001, and the maximum amount one firm could be rewarded was NOK 1 mill. It was replaced by the tax credit reform "Skattefunn" on January 1 2002, which ensured that all projects satisfying the requirements had the right to tax deduction.

[7] Originally, only smaller firms (SMEs) with less than 100 employees were eligible for the scheme, but already in 2003 large enterprises were included as well.

[8] In 2003, 80 percent of total R&D investment was classified as in-house.

[9] Importers and innovators are defined as firms with positive imports and R&D expenditure respectively.

[10] We define a product as a unique HS 4-digit variety.

[11] NACE 2 digit industries.

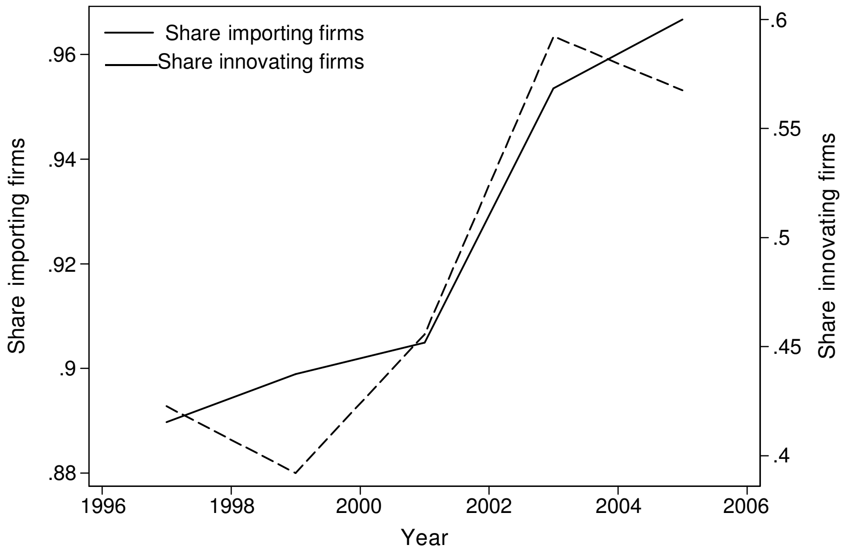

Figure 1: Share of innovating and importing firms.

costs that occurred in 2002.

2.3 Facts on innovators and importers

We start by documenting a few basic facts about innovating firms and their sourcing behavior, which will guide our theory and econometric model. Three facts are worth noting.

Fact 1: Only a subset of firms innovate. Among innovating firms, almost all firms import. This is illustrated in Table 1. More than 40 percent of the firms do not invest in R&D. Among those who do invest in R&D, as much as 98 percent source inputs from abroad. As for those who do not invest in R&D, 13 percent are non-importers.

Fact 2: Innovating firms are larger, source more foreign products, have a higher import share and labor productivity. Importers are also larger and have higher labor productivity. Table 2 gives average numbers for innovators (firms with positive R&D investment) and non-innovators (firms with no R&D investment). Innovators have more that 50 percent as many employees, import twice as many products, have a 60 percent higher import share of intermediates, and a 13 percent labor productivity advantage compared to non-innovators.

We also run a set of simple regressions with log firm characteristics as left hand side variables, and a dummy indicating whether a firm has positive or zero R&D investment as the right hand side variable, while controlling for industry and size effects (NACE 2 digit). The results indicate that the correlation between positive R&D investment and import

Table 1: R&D investment and import participation, 2003, %

	R&D investment		
Importing	No	Yes	Total
No	5.34	1.21	6.55
Yes	37.01	56.43	93.45
Total	42.35	57.65	100

Notes: % of firms importing or innovating in 2003.

R&D and importing = yes whenever positive R&D or importing occur.

Table 2: Innovators vs. Non-innovators, 2003.

	Innovators	Non-Innovators
Employees	198	127
# imported products	45	22
Import share	.21	.13
Labor productivity	606	537
No. of obs.	480	349

Notes: Imported products refer to unique HS 4-digit products. Innovators are firms with positive R&D investment. Import share is defined as firm import value relative to operating costs.

Labor productivity is defined as real value added relative to employees in 1000 NOK. All numbers are simple averages across the two groups.

Table 3: R&D premia, 2003.

Dependent variable	Employees	Import dummy	No of imported products	Import share	Labor productivity	Import dummy	No of imported products	Import share	Labor productivity
R&D	.549*** (.098)	.064** (.026)	.600*** (.099)	.571*** (.146)	.118 ** (.034)	.041* (.021)	.298*** (.090)	.418*** (.147)	.082** (.035)
Size						.043*** (.016)	.642*** (.047)	.325*** (.099)	.071*** (.018)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	824	824	770	770	817	824	770	770	817

Notes: R&D=1 if R&D investment is positive. Standard errors in parentheses clustered by 2 digit industry.

*** = p-val<.01, ** = p-val<.05, * = p-val<.1. All firm characteristics except import dummy are in logs.

Imported products refer to unique HS 4-digit products. Import share is defined as firm import value relative to operating costs.

Table 4: Starting to innovate.

Dependent variable	D Employees	D No of imported products	D Import value	D Import share	D Employees	D No of imported products	D Import value	D Import share
Starting R&D	.066**	.111*	.354***	.320**	.065**	.111*	.354***	.321**
	(.030)	(.060)	(.127)	(.134)	(.031)	(.060)	(.127)	(.134)
No R&D	.044*	.065	.141*	.109	.052**	.067	.139*	.106
	(.024)	(.042)	(.080)	(.072)	(.024)	(.043)	(.078)	(.070)
Continuing R&D	.030	.041	.130	.099	.015	.037	.133	.107
	(.023)	(.047)	(.086)	(.077)	(.023)	(.047)	(.090)	(.080)
Size					.034***	.007	-.007	-.018
					(.007)	(.014)	(.022)	(.021)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	2730	2442	2442	2442	2730	2442	2442	2442

Notes: Standard errors in parentheses clustered by 2 digit industry. *** = p-val<.01, ** = p-val<.05, * = p-val<.1. The dependent variable is annual log change. Imported products refer to unique HS 4-digit products. Import share is defined as firm import value relative to operating costs.

participation, import share, number of imported products as well as labor productivity, also holds within a given industry and after controlling for firm size.

Similarly, importers are roughly three times larger and 30 percent more productive (labor productivity) than non-importers. This also remains true when comparing firms within industries.

Fact 3: Firms that start to innovate, grow faster, increase their import share and the number of imported varieties, compared to all other firms. We categorize firms in 4 different groups, starting R&D (startRD), no R&D (noRD), continuing R&D (contRD) and stopping R&D, depending on whether they innovate in $t-1$ and t. We then estimate the following regression

$$\Delta \ln y_{it} = \alpha + \gamma_j + \beta_1 startRD_{it} + \beta_2 noRD_{it} + \beta_3 contRD_{it} + \ _{it}$$

where γ_j is an industry fixed effect, and $\Delta \ln y_{it}$ is the annual log change in our firm outcome variable, such as import share. Table 4 illustrates that, within each industry, R&D starters grow faster than the other three groups. Furthermore, R&D starters clearly shift their sourcing strategy - in an absolute sense and relative to non-innovators - as they start to import a larger number of products, increase the value of imports as well as the share of imports relative to total costs.

3 A Model of R&D and international sourcing

Motivated by the facts presented in Section 2, we build a model of innovation and international sourcing of intermediates. Marginal costs fall as a result of investment in R&D and the use of imported inputs, but due to the presence of fixed costs of innovating and importing, only the largest and most productive firms are able to undertake both activities (facts 1 and 2). Investment in knowledge raises the endogenous productivity of the firm, thereby increasing firm size and the equilibrium number of imported products (fact 3).

The R&D side of the model builds on Griliches' (1979) knowledge capital model, as well as more recent work by Aw et al. (2011) and Doraszelski and Jaumandreu (2011). Firms may choose to invest in R&D which on average will increase their future productivity. The returns to R&D are subject to uncertainty, reflecting the fact that some R&D projects ultimately fail.

Firms may choose to source intermediate inputs from the domestic or foreign market, as in Goldberg et al. (2010) and Halpern et al. (2011). Imported inputs lower marginal costs through two channels emphasized in the theoretical as well as the empirical literature. First, their quality-adjusted price is potentially lower. Second, following product-variety models with intermediate inputs, a larger set of imported inputs means more specialized intermediates which are complementary to domestically sourced input varieties. Since firms are heterogeneous in productivity, and innovation as well as international sourcing is costly, only a subset of firms finds it profitable to invest in R&D or to import intermediates.[12]

3.1 Costs and revenue

Firm i's short-run marginal cost function at time t is given by

$$\ln c_{it} = \beta_0 - \beta_k \ln k_{it} + \beta_w \ln w_t + \sum_j \gamma_j \ln q_{ijt} - \omega_{it}$$

where k_{it} is capital stock, w_t is labor costs common to all firms, q_{ijt} is the price of intermediate input j, and ω_{it} is a Hicks neutral productivity term. As we describe below, intermediate j has a domestic and an imported component that are potentially combined according to a CES aggregator. Importantly, both input prices and productivity are endogenous, since the firm may change the value of these variables by either importing or innovating.

The market is characterized by monopolistic competition, and the demand curve faced

[12] As in Melitz (2003), higher productivity may also be thought of as producing a higher quality variety at equal cost. In the model, either type of productivity difference is isomorphic.

by firm i is of the standard Dixit-Stiglitz form. Hence demand is $\Phi_t p_{it}^{-\eta}$, where p_{it} is firm i's price, Φ_t is a demand shifter, and η is the constant elasticity of demand.

Given these assumptions, the firm charges a price that is a constant mark-up over marginal costs. Inserting the optimal price into the demand function yields the log of revenue

$$\ln r_{it} = \kappa + \ln \Phi_t - (\eta - 1)\left(\beta_0 - \beta_k \ln k_{it} + \beta_w \ln w_t + \sum_{j=1}^{J} \gamma_j \ln q_{ijt} - \omega_{it}\right) \quad (1)$$

where $\kappa = (1-\eta)\ln[\eta/(\eta-1)]$. In the empirical model in Section 4, we estimate the revenue function and quantify the returns to innovation and sourcing of foreign products. As is standard in this class of models, variable profits are proportional to revenue, $\pi_{it} = r_{it}/\eta$.

3.2 Intermediate inputs

The J intermediate inputs are either sourced from the domestic market or assembled from a combination of a foreign and a domestic variety. Specifically, if both the domestic and foreign varieties are purchased, the quantity of intermediate j is

$$\left[(b_j x_{ijtF})^{(\theta-1)/\theta} + x_{ijtH}^{(\theta-1)/\theta}\right]^{\theta/(\theta-1)}$$

where x_{ijtF} and x_{ijtH} are the quantities of foreign and domestic inputs, $\theta > 1$ is the elasticity of substitution, and b_j is a quality shifter for the foreign variety. The prices of domestic and foreign varieties are $\tilde{q}_{jtH}$ and $\tilde{q}_{jtF}$, and by choosing the domestic price to be the numeraire, we set $\tilde{q}_{jtH} = 1$. Given the CES structure, the price of the composite intermediate is

$$q_{ijt} = \begin{cases} 1 & \text{if } j \text{ is a pure domestic input} \\ \left[1 + (\tilde{q}_{jtF}/b_{jt})^{1-\theta}\right]^{1/(1-\theta)} < 1 & \text{if } j \text{ is a composite of domestic and foreign inputs} \end{cases}$$

Importing reduces unit costs for two reasons. First, the production technology implies that firms gain from variety, and that imports and domestic inputs are imperfect substitutes. Second, the quality-adjusted price of imports $\tilde{q}_{jtF}/b_{jt}$ may be lower than the domestic price (but not necessarily). In the following, we assume that the relative price of the composite input under importing, $a_{jt} \equiv \ln\left[1 + (\tilde{q}_{jtF}/b_{jt})^{1-\theta}\right]^{1/(1-\theta)}$, is identical across all products, i.e. that $a_{jt} = a$. This amounts to assuming that the quality-adjusted price of imports relative to that of domestic inputs is the same for all intermediate products and years. This assumption greatly simplifies the empirical analysis, which otherwise would be intractable. In the empirical analysis, a therefore captures the average price advantage of imports.

Following Halpern et al. (2011), we define $G(n)$ as the Cobb-Douglas share of intermediate inputs using imports relative to all intermediate inputs, $G(n) = \sum_{j \in M} \gamma_j / \gamma$, where n is the number of imported products, M denotes the set of intermediates with imports, and $\gamma = \sum_j^J \gamma_j$. Without loss of generality, order products with the highest expenditure shares first. Then $G(n) \in [0, 1]$ is increasing and concave in n (but not continuous). Substituting, we can now express the input prices in the revenue function as a function of the import share:

$$\sum_j \gamma_j \ln q_{ijt} = a \sum_{j \in M} \gamma_j + \sum_{j \notin M} \gamma_j \ln 1 = a\gamma G(n). \tag{2}$$

We proceed by determining the optimal number of imported products. Importing a variety of product j is associated with a fixed cost f_i per product. We allow f_i to vary across firms. As emphasized in the previous literature (e.g Halpern et al. (2011) and Gopinath and Neiman (2011)), the dominant role of the extensive margin in explaining aggregate import growth, i.e. the importance of new importers and new products in total imports, as well as the high level of churning of imported products, suggests that imports entail per-period per-product fixed costs. The firm faces a discrete choice problem of finding the optimal n that maximizes profits. Since the cost savings per product is larger for products with a high expenditure share γ_j, but the fixed cost f is constant, the firm is more likely to outsource the high γ_j products. The optimal number of products n^* satisfy

$$\begin{aligned} \pi(n^*) - \pi(n^* - 1) &> f; \quad n^* = 1, 2, .., J \\ \pi(n^* + 1) - \pi(n^*) &\leq f; \quad n^* = 0, 1, .., J - 1 \end{aligned} \tag{3}$$

In words, the firm finds it optimal to increase n as long as the change in variable profits $\Delta\pi$ from importing one more product is larger than the additional fixed cost f.[13] Next, we turn to the decision about whether or not to innovate. We emphasize that our structural estimator simply conditions on the observed choice of imports and innovation, so that our estimator is not sensitive to how we model these discrete decisions to import and innovate.

3.3 Innovation

Define $\Pi(\omega_{it}; \Theta)$ as the firm's net profits after paying its fixed costs of importing. Net profits are determined by firms' productivity (ω_{it}) and Θ, which is a vector of aggregate variables, such as relative import prices, a, that affects net profits and total number of imported

[13] The problem is identical to $n^* = \arg\max_n \{\pi(n) - nf\}$.

products, n^*.

Following Doraszelski and Jaumandreu (2011) and Aw et al. (2011), we assume that productivity evolves over time following a controlled first-order Markov process that depends on whether the firm innovates or not, as well as a random shock,

$$\begin{aligned}\omega_{it} &= g(\omega_{it-1}, d_{it-1}) + \xi_{it} \\ &= \alpha_0 + \alpha_1 \omega_{it-1} + \alpha_2 d_{it-1} + \xi_{it}, \end{aligned} \tag{4}$$

where d_{it-1} is a dummy taking the value 1 if the firm innovates in period $t-1$. The uncertain nature of productivity is captured by the term ξ_{it}, which is mean independent of all information known at $t-1$. Importantly, ξ_{it} is not anticipated by the firm, and is therefore uncorrelated with the remaining right hand side variables.

Innovating is subject to a cost f_d. Since innovating firms reap the benefits of R&D investments in future periods, the decision to innovate is a dynamic problem. The Bellman equation for the firm is

$$V(\omega_{it}) = \Pi(\omega_{it}; \Theta) + \max_{dit} \{\delta E[V(\omega_{it+1}|\omega_{it}, d_{it} = 1)] - f_d, \delta E[V(\omega_{it+1}|\omega_{it}, d_{it} = 0)]\} \tag{5}$$

The firm chooses to innovate if the net present value of future profit flows, minus the cost of innovating f_d, is higher when performing R&D, compared to not performing R&D.

For expositional purposes, all economy-wide variables are assumed to be constant, so that only productivity enters the firm's state space. We also treat the firm's capital stock as fixed over time. In the empirical application, we condition on time-varying capital stock, aggregate demand and cost shocks (by fixed effects), as well as the firm's innovation and import choices. Hence, there is nothing substantive to be gained by modeling additional endogenous state variables here.

Given an assumption about the distribution of ξ_{it}, $F()$, the expected future value of the firm can be written

$$E[V(\omega_{it+1}|\omega_{it}, d_{it})] = \int V(\omega_{it+1}|\omega_{it}, d_{it})\, dF(\omega_{it+1}|\omega_{it}, d_{it})$$

As is common in this class of problems, the policy function takes a simple form, with $d_{it} = 1$ if $\omega > \underline{\omega}(\Theta)$. Hence, only firms above a certain productivity threshold innovate, and the threshold depends on the economic environment. In particular, since lower quality-adjusted import prices, a, boost profits, the hurdle $\underline{\omega}$ is increasing in a, so that e.g. lower input trade barriers make more firms innovate. Moreover, reduced costs of innovation f_d make investing in R&D more profitable and therefore lower the threshold $\underline{\omega}(\Theta)$ as well. We summarize this in the following proposition.

Proposition 1. Reduced R&D costs f_d, as well as lower foreign sourcing costs, a, increase the profitability of R&D and therefore lower the innovation threshold $\underline{\omega}(\Theta)$.

3.4 Scale Complementarity

We have developed a model where complementarity between imports and innovation occurs due to scale: Innovating firms gain market share, so that it becomes easier to cover the fixed costs of undertaking further cost reductions such as to start or expand importing. In the same way, importing firms reduce costs and increase their sales, so that it becomes easier to cover the fixed costs of innovating.

We show this theoretically: declining R&D costs f_d lower the innovation hurdle $\underline{\omega}(\Theta)$, so that more firms innovate and, on average, future productivity rises. In the appendix, we show that

$$\frac{\partial\left[\pi(n)-\pi(n-1)\right]}{\partial\omega}>0.$$

In other words, higher productivity raises the returns to importing the marginal product. Hence, from equation (3) follows that the the rise in productivity encourages an increase in the number of imported products.

Conversely, declining trade costs, captured by the price of the intermediate composite a, lower the innovation hurdle $\underline{\omega}(\Theta)$ due to the benign impact of reduced trade costs on the value of future profits (see Proposition 1). Consequently more firms innovate, and on average, future productivity rises. The number of products imported goes up due to a direct effect and an indirect effect. The direct effect is simply the static impact of lower a. In the appendix, we show that

$$\frac{\partial\left[\pi(n)-\pi(n-1)\right]}{\partial a}<0.$$

Hence, lower import costs a raises the returns to importing the marginal product, and from equation (3) it follows that lower a leads to an increase in the number of imported products. The indirect effect of lower trade costs relates to the impact on future imports since innovation on average raises productivity which in turn encourages increased importing. In sum, lower R&D costs lead to more innovation and sourcing of more foreign products. Lower trade costs on foreign intermediates lead to sourcing of more foreign products, as well as more innovation, and, on average, higher firm-level productivity. We summarize this in the following proposition.

Proposition 2. Lower foreign sourcing costs, a, raise the returns to imports of the marginal product, and therefore increase the optimal number of imported products n^*_{it}. Moreover, lower

R&D costs f_d raise average productivity for firms induced to innovate, which in turn increase the optimal number of imported products n^*_{it}.

4 Empirical Model and Estimation

4.1 The empirical model

Now we proceed by taking the model introduced in Section 3 to the data. The empirical facts on R&D investment and sourcing behavior presented in Section 2 showed that starting R&D and importing new products are positively correlated. Provided that imports have a benign effect on costs, an estimator based on the assumption of homogeneous prices of intermediates will thus tend to overstate the impact of R&D on productivity. A key feature of our model is that intermediate input prices vary across firms as some inputs are imported and others are not. Hence, compared to the previous literature on R&D and productivity, our approach controls specifically for the interdependence between R&D investment and international sourcing.

In order to estimate the impact of R&D investment and international sourcing on revenue and productivity, we proceed in two steps. First, we estimate the revenue function in equation (1). Second, we estimate the Markov process governing the evolution of productivity from equation (4). As is well known, OLS estimates of the revenue function suffer from simultaneity bias, since productivity ω_{it} is likely to affect the demand for inputs. We therefore use the insights from Olley and Pakes (1996) and Levinsohn and Petrin (2003) that demands for static inputs such as materials can be used to recover unobserved productivity.

Following Levinsohn and Petrin (2003), let total demand for intermediates m_{it} be a function of the state variables productivity, ω_{it}, and capital, k_{it}.[14] In addition, and departing from the previous literature, demand depends on intermediate prices, which varies across firms due heterogeneity in the number of imported products n_{it}. n_{it} is defined, as in Section 5, as the number of imported HS products at the 4 digit level. We therefore write intermediate demand as $m_{it} = f_t(\omega_{it}, k_{it}, n_{it})$. Given monotonicity in ω_{it} for all relevant k_{it} and n_{it}, we can invert $f_t()$ to yield ω_{it} as a function of intermediates, capital and the number of imported inputs, i.e. $\omega_{it} = \omega_t(m_{it}, k_{it}, n_{it})$.[15] Hence, we can use these variables to control for productivity in the revenue function. Using equation (2) to substitute for input prices in

[14] Alternatively, we could have used investment as our proxy, as in Olley and Pakes (1996). Using investment would reduce the sample size since a non-negligible number of firms has zero investment.

[15] Recall that the fixed cost of importing f_i is firm-specific. Hence, conditional on ω_{it} and k_{it}, we have variation in $m_{it} = f_t(\omega_{it}, k_{it}, n_{it})$ since some firms have low fixed costs, and as a consequence lower inter-
mediate prices and higher n_{it}. With no heterogeneity in f_i, the relationship between ω_{it} and n_{it} would be deterministic, and we would not be able to identify the impact of n_{it}.

the revenue function (1) , we can then write

$$\ln r_{it} = \kappa + \delta_t + h(m_{it}, k_{it}, n_{it}) + {}_{it} \tag{6}$$

where $h(k_{it}, m_{it}, n_{it}) = (\eta - 1)[\beta \ln k_{it} - \gamma a G(n_{it}) + \omega_t(k_{it}, m_{it}, n_{it})]$, and δ_t is a year fixed effect capturing labor costs common to all firms w_t, as well as the demand shifter Φ_t. We have added an i.i.d. error term ${}_{it}$ that reflects measurement error in revenue.

In the 1st stage, we estimate equation (6) by OLS. In order to allow for heterogeneity in production technology across manufacturing sectors, we estimate the revenue function separately for each NACE 2-digit sector in our sample (industry subscripts are suppressed for clarity).[16] Since the G() function is unobserved, we replace $\gamma a G(n_{it})$ with 3 dummies D_{qit}, $q = 2, 3, 4$, that indicate which quartile n_{it} belongs to. By using dummies, we allow for G() to be nonlinear.[17] The h() function is approximated by a 2nd order polynomial in m_{it}, k_{it} and D_{qit}. Note that the 1st stage estimation is unable to identify the effect of imports on revenue since the contribution of imported products enters both directly (as $\gamma a G(n_{it})$) and through the productivity term $\omega_t()$.

In the 2nd stage, we first use the definition of h() to rewrite productivity

$$\omega_{it} = \frac{h_{it}}{\eta - 1} - \beta_k \ln k_{it} + \gamma a G(n_{it}). \tag{7}$$

Using (7) to substitute for ω_{it} and ω_{it-1} into the Markov process from equation (4) then yields

$$h_{it} = \alpha_0^* + \beta_k^* \ln k_{it} - \gamma^* a G(n_{it}) + \alpha_1 [h_{it-1} - \beta_k^* k_{it-1} + \gamma^* a G(n_{it-1})] + \alpha_2^* d_{it-1} + \xi_{it}^* \tag{8}$$

where superscript * denotes that the variable is multiplied by $(\eta - 1) > 0$. R&D investment is captured by the binary variable d_{it-1} which takes the value one if the firm makes positive R&D investments, and zero otherwise.

We proceed by estimating this relationship by GMM. Since capital k_{it} is determined in $t-1$, and since ξ_{it} is the unanticipated part of productivity in year t, ξ_{it} and k_{it} are orthogonal. By the same logic, h_{it-1}, k_{it-1} and d_{it-1} are orthogonal to the error term. The number of imported products n_{it}, however, responds to the error term. The lagged n_{it-1}, on the other hand, was chosen before ξ_{it}, and is therefore uncorrelated with the shock. In our baseline specification, we therefore instrument the number of imported inputs with

[16] We estimate on every NACE 2 digit sector with more than 20 firms present. They are NACE 15, 20, 21, 22, 24, 25, 26, 27, 28, 29, 31, 32, 33, 34, 35, and 36.

[17] The quartiles are $n = 7, 25$ and 50. The 1st quartile is the omitted group.

lagged values. As in the 1st stage, we allow for a non-linear response of the number of imported products on marginal costs, and replace $\gamma^* aG(n_{it-1})$ with the three dummies D_{qit-1}, $q = 2, 3, 4$. In sum, we form the empirical counterparts to the moments $E[z_{it}\xi_{it}] = 0$, with $z_{it} = \ln k_{it-1} \ \ln k_{it} \ \ h_{it-1} \ \ d_{it-1} \ \ \{D_{qit-1}\}_{q=2}^{4} \ \ 1$. This gives us 8 moments and 7 unknowns (α^*_0 α_1, α^*_2 β^*_k and the three product dummies). Our estimates are then found by minimizing the sum of squared sample moments. We use equal weights for every moment (one-step estimator) since two-step estimators are found to have finite-sample bias in short panels (Altonji and Segal, 1996). We estimate the Markov process for the entire manufacturing sector and include year and industry (NACE 2-digit) fixed effects.[18]

The 2nd stage enables us to identify the impact of R&D investments and imports of intermediate inputs on revenue and productivity. Given that outsourcing reduces marginal costs, we expect that $\gamma^* aG(n_{it})$ is negative and increasing in n_{it}. Given that R&D investment positively shifts the productivity process, we expect that α^*_2 is positive. Given knowledge about the elasticity of substitution η, which is not identified in our framework, we can back out productivity ω_{it} from equation (7).

Identification. In the 1st stage revenue function, the number of imported products n_{it} enters both in the proxy function $\omega()$, since input prices vary according to sourcing strategy, and directly in $G(n_{it})$. Hence, the impact of imports on revenue is not identified in the 1st stage. This is reminiscent of the methodology in Ackerberg et al. (2006), where identification occurs exclusively in the 2nd stage. The role of the 1st stage is therefore to isolate and eliminate the portion of output that is determined by either unanticipated shocks or by measurement error. In the 2nd stage (equation (8)), we identify the impact of R&D on productivity by using exogenous variation in d_{it-1} conditional on lagged productivity ω_{it-1} and imports $\gamma aG(n)$. Similarly, the impact of imports on marginal costs/revenue is identified by using exogenous variation in lagged imports conditional on lagged productivity and R&D. The control function approach allows us to isolate productivity and compare revenue of two equally productive firms that only differ in the number of foreign sourced varieties n_{it}. Conditional on productivity, n_{it} varies across firms due to variation in the fixed cost f_i. Note that the way we model the discrete R&D and importing decision is not essential for identification, since we condition on the observed R&D and importing choice in the data. Hence, our estimator is robust to alternative models of the R&D and import decision.

Standard errors. Standard errors are obtained by a bootstrap with 250 repetitions. We sample firms with replacement, keeping their entire time path together. This is similar to

[18] Allowing the coefficients of the Markov process to vary by industry as well yields the same qualitative results, although the precision of the estimates are greatly reduced, since some industries consist of relatively few firms.

Table 5: GMM Estimates.

	(1) Baseline	(2) n exogenous	(3) No imports	(4) Continuous R&D
β_k^*	.26***	.28**	.61***	.25***
	(.03)	(.04)	(.03)	(.06)
D_2 (2nd quartile)	-.15**	-.11***		-.23
	(.08)	(.03)		(.16)
D_3 (3rd quartile)	-.48***	-.25***		-.78***
	(.13)	(.04)		(.27)
D_4 (4th quartile)	-.95***	-.48***		-1.52***
	(.19)	(.06)		(.38)
α_1	.90***	.91***	.54***	.87***
	(.01)	(.01)	(.04)	(.02)
α_2^*	.03**	.03**	.10***	.02**
	(.01)	(.01)	(.02)	(.01)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	2495	2495	2495	1203

Notes: Bootstrapped standard errors in parentheses. *** = p-val<.01, ** = p-val<.05, * = p-val<.1. R&D is a binary variable in (1)-(3), and log R&D expenditure in (4).

clustering standard errors by firm.

4.1 Results

The parameter estimates from the estimation of equations (6) and (8) are reported in Table 5, and give the effects of imports and R&D investment on revenue. The contribution of imports is reflected by the estimated coefficients for the dummy variables, D_{qit-1}, representing $\gamma^* aG(n_{it-1})$ according to the quartile to which a firm belongs in terms of the number of imported products.

Column 1 reports the baseline results, where we instrument D_{qit} with lagged values (see the instrument vector z_{it} in the previous section). Column 2 instruments D_{qit} with itself which would be our preferred specification if the number of imported products were uncorrelated with the shock ξ_{it}. This is equivalent to estimating equation (8) by OLS. Column 3 is estimated under the restriction that intermediate input prices are homogeneous and the number of imported products does not have any impact on revenues. Formally, this amounts to ignoring the term $\gamma^* aG(n)$, in the 1st as well as the 2nd stage. Column 4 reports results using the log of R&D expenditure instead of a R&D binary dummy as the independent variable.

The capital coefficient β_k^* is positive and significant in all specifications, implying that variable costs are lower and revenue is higher for firms with higher capital stock. Building on estimates from Broda and Weinstein (2006),[19] we assume an elasticity of demand of $\eta = 4$, which allows us to calculate the elasticity of capital with respect to marginal costs of -0.09.

The coefficients on D_q measure the effect of the 4 quartiles of imported products on revenue. In the baseline case (see column (1)), importing n products, where n is in between the 1st and 2nd quartile, boosts revenue by 15 percent, relative to importing a number of products below the threshold of the 1st quartile. Importing n products, where n is in between the 3rd and 4th quartile, doubles revenue. The specifications reported in column (2) and (4) show the same pattern, although the magnitude is more muted when we instrument D_{qit} with itself.

In all four specifications, the impact on lagged productivity on current productivity, measured by α_1, is strong and precisely estimated, indicating that serial correlation in ω_{it} is strong.

The short run impact of R&D investment on revenue, captured by α^*_2 is 3 percent. This estimate is fairly similar across all specifications, except for the case where intermediate input prices are assumed to be homogeneous (column (3)). In the latter case, the R&D effect is more than three times as strong. We view this as additional empirical evidence for the complementarity between R&D and trade in intermediates that we emphasize in this paper. Since R&D and other cost saving activities such as imports of intermediates go together, failing to account for this channel will overstate the impact of R&D on productivity.

However, the estimate of α^*_2 only captures the one period impact of innovation, while our dynamic model predicts a potentially different response in the long run. We therefore calculate the mean long run impact of R&D on productivity based on the estimates from the base line case (column (1)). Iterating on the Markov process in equation (4), using (7) and assuming an elasticity of demand of $\eta = 4$, we find that a firm performing R&D in every period on average has 10.5 percent higher productivity compared to a firm that never invests in R&D (i.e. setting $d_{it-1} = 0$ in every period for a perpetual non-innovator and $d_{it-1} = 1$ in every period for a perpetual innovator). Since revenue is proportional to productivity, see equation (6), firm revenue is $10.5\,(\eta - 1) = 31.5$ percent higher for innovators relative to non-innovators. Of course, the total impact of R&D on marginal costs is higher than this, since R&D enables the firm to reduce costs by sourcing more foreign varieties. We calculate the magnitude of this indirect effect in the counterfactual in Section 7.

Our results on the long run impact of R&D are in line with existing empirical evidence on the returns to R&D (see e.g. Hall et al. (2010) for an overview), most of which range from returns of 10 to 20 percent. There is, nevertheless, significant variation. Doraszelski

[19] The 1990-2001 mean at the SITC-3 level.

and Jaumandreu (2011), who also base their estimates on a dynamic model find rates of return to R&D of on average 35 percent but with substantial differences across industries, ranging from very modest values near 10% to 50%. In general, the rates of return to R&D are typically found to exceed those for physical capital. Comparing our estimates on returns to capital to the long run returns to R&D, we see that this is also true for our analysis.

5 A Natural Experiment: Analyzing the impact of an R&D policy reform

Above we have provided structural results on the benign and joint impact of imports and R&D investments on productivity and revenue. According to the theoretical model developed in section 3, we expect that lower costs of innovation boost R&D as well as sourcing of intermediate inputs. In this section, we provide reduced form evidence of the complementarity between innovation and imports. Finally, in Section 7, we compare the reduced form evidence with a counterfactual based on the estimated structural model. This allows us to quantify the importance of our proposed theoretical mechanism.

5.1 A difference-in-differences model

To analyze the impact of reduced costs of innovation, we exploit an R&D tax credit scheme introduced in Norway in 2002. The tax credit enabled firms to deduct 20 percent of their R&D costs from their tax bill, but only up to a threshold of NOK 4 mill in R&D expenditures (0.5 mill USD using the 2002 exchange rate). In essence, therefore, the marginal cost of R&D declined by 20 percent, but only for firms with less than NOK 4 mill in R&D costs. We exploit this feature of the tax credit in a simple difference-in-differences (DID) framework. In a nutshell, we identify the impact of lower R&D costs on R&D investment and imports by using the fact that only firms ex-ante below the threshold were exposed to the policy change (that their marginal costs were affected).

We proceed as follows. We split firms into two groups, a treatment group and a control group, according to their pre-reform R&D investment, and examine subsequent R&D and imports of intermediates. Define $H_{1i} = 1$ if average pre-reform R&D in 1999 and 2001 was less than NOK 4 mill. Let $H_{1i} = 0$ if pre-reform R&D in 1999 and 2001 was more than NOK 4 mill. In 2001, 17 percent of the firms were classified in the control group. Additional descriptives about the treatment and control groups are presented in Table 11 in the appendix. In Figure 2, we plot average R&D investment for the two groups of firms. The means are normalized so that 1997=1. The trend in R&D investment is relatively similar across the two groups, with the exception of the shift occurring for the treatment group between 2001 and 2003. In Figure 3, we plot the average number of products imported for the same two groups, again indexed so that 1997=1. The pattern is roughly similar here, with a large increase in the number of products imported for the treatment group post reform. Hence, simple descriptives suggest that those firms whose marginal costs of innovation were affected due to the introduction of the tax credit, increased both R&D investment and their imports of intermediates relative to the control group.

Consider the following difference-in-differences model,

$$y_{it} = \alpha_i + \delta_t + \beta_t (H_{1i} \times \delta_t) + \gamma X_{it} + {}_{it}, \tag{9}$$

where the outcome variable y_{it} is either R&D investment, R&D personnel relative to total employment, revenue, or the number of imported HS 4-digit products, for firm i in year t (all in logs).[20] α_i and δ_t are firm and year fixed effects and X_{it} is a vector of controls: employment, capital stock, labor productivity (all in logs), and a firm exit and entry indicator.[21] Importantly, β_t is a vector of coefficients for the interaction between H_{1i} and δ_t. We expect that β_{1999} and β_{2001} are zero, while β_{2003} and β_{2005} are positive (1997 is the omitted year dummy), which would indicate that growth in e.g. R&D in the years prior to reform was similar for the treatment and control group, but that growth was higher post reform for the treatment group (all conditional on the vector of controls X_{it}). Intuitively, we are comparing the growth of e.g. R&D pre to post reform, for two firms that have the same level of employment and labor productivity, etc., but that differ according to their assignment to treatment and control group.

A potential concern is that β may be biased due to mean reversion. For example, a firm may be classified as $H_{1i} = 0$ in year t due to a positive idiosyncratic R&D shock. If the shock is transitory, we should expect lower R&D in $t + 1$. Hence, growth for $H_1 = 0$ firms may be lower than for $H_1 = 1$ firms, even in the absence of the introduction of the R&D policy. In practice, however, mean reversion is most likely negligible in our particular case. First, R&D investment is highly autocorrelated. The correlation for R&D spending and R&D employment is 0.91 and 0.95 respectively, suggesting that idiosyncratic shocks are small. Second, since the definition of H_1 is based on R&D spending averaged over 1999-2001, transitory shocks should be averaged out. Third, as we will see in the results section, we perform a placebo test which does not produce mean reversion.

[20] In all specifications except the Poisson maximum likelihood case, outcome variables that take the value zero are lost due to the log transformation.

[21] Specifically, $Entry_{it} = 1$ if the firm is present in t but not in $t-1$, and $Exit_{it} = 1$ if the firm is present in t but not in $t+1$. Since we have balance sheet data for both 1996 and 2006, we can calculate these indicators for all the years with R&D data (1997, 1999, 2001, 2003 and 2005).

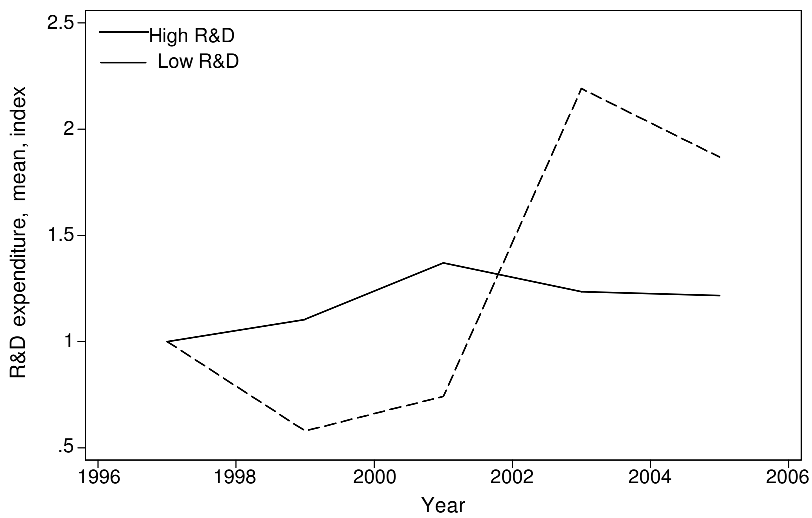

Figure 2: Average R&D investment. Index, 1997=1.

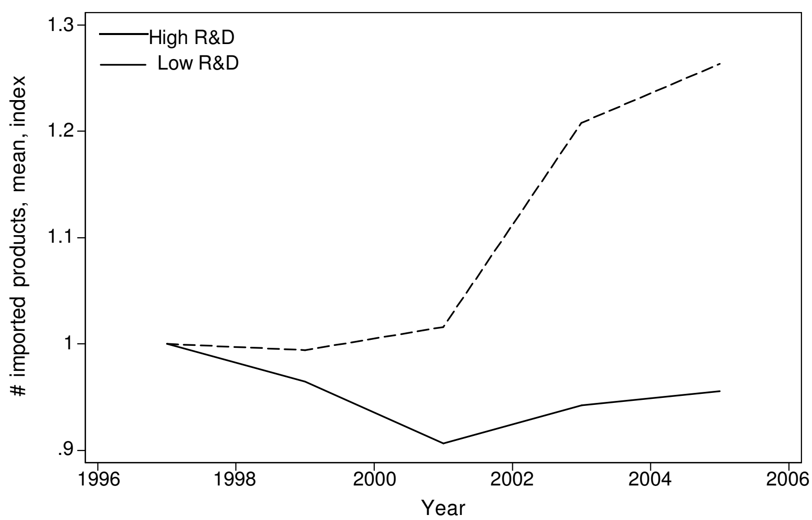

Figure 3: Average # of products imported. Index, 1997=1

Nevertheless, we proceed by defining two alternative treatment groups, which will alleviate any remaining concerns. Our first approach is to estimate $e_{it} = \alpha_i + \delta_t + {}_{it}$, where e_{it} is the outcome variable (e.g. R&D expenditure), and α_i and δ_t are firm and year fixed effects, and then define the treatment group based on predicted R&D in 2001, $\hat{r}_{i2001}$. Formally, we define $H_{2i} = I\,[\hat{r}_{i2001} < 4$ mill]. Hence, transitory shocks are eliminated from the determination of H_{2i}. Our second approach is to define the treatment group based on industry rather than firm characteristics. We proceed by calculating the share of firms within each NACE 5 digit sector with less than 4 mill in R&D spending. We then define $H_{3i} = 1$ if this share is more than half on average in 1999-2001. The autocorrelation in the share variable is 0.75, showing that some industries are inherently big R&D spenders while others are not. Our treatment and control groups are therefore determined by arguably exogenous technological characteristics of the industry.

Another potential concern is that our DID estimator may pick up differential trends across the treatment and control group, even after controlling for firm size and the other variables in X_{it}. We therefore also estimate a model with firm-specific random trends, sometimes referred to as a correlated random trend model. Let

$$y_{it} = \alpha_i + \delta_t + g_i t + \beta\,(H_{i1} \times t \geq 2002) + \gamma X_{it} + {}_{it}$$

where g_i is a firm-specific trend coefficient. Here, the treatment $(H_{i1} \times t \geq 2002)$ may be arbitrarily correlated with either α_i or the firm-specific trend g_i. Differencing this yields a triple differences model

$$\Delta y_{it} = \Delta\delta_t + g_i + \beta\Delta\,(H_{i1} \times t \geq 2002) + \gamma\Delta X_{it} + \Delta\ {}_{it} \tag{10}$$

which we estimate by fixed effects.

Finally, since the number of imported product n_{it} features prominently in our theory, we tweak our regressions to accommodate the fact that n_{it} is a non-negative discrete variable. Specifically, we estimate a fixed effects Poisson pseudo-MLE model, following Wooldridge (2010).[22] n_{it} is assumed to be a realization from the Poisson distribution, $n_{it} \sim Possion\,(\mu_{it})$, where the conditional expectation is μ_{it} is

$$E\,[n_{it}] = \exp\,[\alpha_i + \delta_t + \eta\,(H_{1i} \times \delta_t) + \gamma X_{it}] \tag{11}$$

Note that differencing n_{it} is not feasible in the Poisson framework (since Δn_{it} would then take negative values). We do, however, allow for group specific trends by including the term

[22] See also Silva and Tenreyro (2006) for an application of the Poisson model for estimating gravity models.

$t \times H_{1i}$. The conditional expectation is then

$$E[n_{it}] = \exp[\alpha_i + \delta_t + g(t \times H_{1i}) + \beta(H_{i1} \times t \geq 2002) + \gamma X_{it}] \tag{12}$$

The Poisson model yields a straightforward interpretation of the coefficients: e.g. $\exp(\beta)$ measures the percent change in n_{it} due to the reform.

5.1 Results

Employing the DID framework developed above, we now estimate the impact of reduced R&D costs on R&D expenditure, R&D employment relative to total employment, revenue, and number of imported intermediate products.[23] We report estimates from equation (9) in columns (1) - (3) and estimates from equation (10) in columns (4) - (7) in Tables 6 and 7. The empirical results on firms' R&D expenditure and R&D employment suggest that the R&D policy reform had a large and significant impact on R&D investment. In the specifications without firm-specific trends, the interaction between the year dummy and H_i is always close to zero prior to the reform and turns positive after the reform, showing that firm-level growth in R&D investment picked up after 2002, but only for the treatment group. Since trends in R&D spending may be different across groups even in the absence of reform, we include firm-specific trends in columns (4) - (6), which are our preferred specifications. They show that the R&D policy raised R&D investment by 0.30 to 0.54 log points (Table 6), and raised the share of R&D employees by 0.23-0.30 log points (Table 7). Finally, column (7) presents results from a placebo test. Here we instead compare outcomes for firms with ex ante R&D investment between NOK 4 and 8 million (placebo treatment) with firms with ex ante R&D spending more than NOK 8 million (placebo control). Irrespective of outcome variable and specification, we always find a coefficient near zero. This suggests that our methodology delivers unbiased estimates, and in particular that mean reversion is not affecting our results. Moreover, in every specification and for every outcome variable, dropping the control variables X_{it} only changes the estimates slightly, underscoring the robustness of the results.

Next, we estimate the impact of the reform on firm revenue. In this case, in our preferred specification with firm trends (equation (10)), the point estimate varies from .01 to .14, depending on the choice of treatment/control group, but the estimates are less precise, so we cannot reject the null hypothesis of a zero impact on revenue.[24] A possible explanation for the less robust results is that our DID framework only captures potential revenue gains

[23] n_{it} is defined, as in Section 4, as the number of imported HS products at the 4 digit level.
[24] The full set of results is available upon request.

Table 6: log R&D expenditure.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1999×H	-.08	-.13	.11				
2001×H	-.06	-.06	.03				
2003×H	.40***	.26*	.24*				
2005×H	.24*	.09	.08				
>2002×H				.54***	.35**	.29**	-.03
Control group	H_1	H_2	H_3	H_1	H_2	H_3	H_1
Firm trends	No	No	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Threshold	4 mill	4 mill	4 mill	4 mill	4 mill	4 mill	8 mill
N	1635	1635	1625	963	963	963	386
Firms	597	597	596	414	414	414	140

Notes: Standard errors in parentheses clustered by firm. *** = p-val<.01, ** = p-val<.05, * = p-val<.1. Columns 1-3 refer to equation (5), while columns 4-7 refer to equation (10).

Table 7: log R&D employment share.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1999×H	-.04	.09	-.02				
2001×H	-.08	-.04	-.05				
2003×H	.21***	.10	.10				
2005×H	.27**	.20*	.15				
>2002×H				.30***	.23**	.23**	-.04
Control group	H_1	H_2	H_3	H_1	H_2	H_3	H_1
Firm trends	No	No	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Threshold	4 mill	4 mill	4 mill	4 mill	4 mill	4 mill	8 mill
N	1636	1636	1626	963	963	963	386
Firms	600	600	599	414	414	414	140

Notes: Standard errors in parentheses clustered by firm. *** = p-val<.01, ** = p-val<.05, * = p-val<.1. Columns 1-3 refer to equation (5), while columns 4-7 refer to equation (10).

Table 8: # imported HS4 products, Poisson pseudo-MLE.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1999×H	-.00	.01	-.00				
2001×H	.06	.11*	.04				
2003×H	.17***	.22***	.15***				
2005×H	.17***	.22***	.16***				
>2002×H				.08**	.08*	.14***	.03
Control group	H_1	H_2	H_3	H_1	H_2	H_3	H_1
Group trends	No	No	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Threshold	4 mill	4 mill	4 mill	4 mill	4 mill	4 mill	8 mill
N	3411	3411	3399	3411	3411	3399	411
Firms	859	859	858	859	859	858	142

Notes: Standard errors in parentheses clustered by firm. *** = p-val<.01, ** = p-val<.05, * = p-val<.1. Columns 1-3 refer to equation (11), while columns 4-7 refer to equation (12).

from R&D in one to three periods after the reform was implemented in 2002. As emphasized in the structural framework, which utilizes the entire sample from 1997 to 2005, the short run gains from R&D investment are significantly smaller than long run gains.

Table 8 presents results with the number of imported products as the dependent variable. Since n_{it} is a non-negative discrete variable, we exploit the full variation in the data by estimating the fixed effects Poisson pseudo-MLE model. Importantly, the Poisson model also utilizes the zeros of n_{it}, which are lost if using a log transformation. In our preferred specifications with group-specific trends (columns (4) to (6)), the R&D policy generated an 8 to 14 percent increase in the number of imported products. Again, the falsification test presented in column (7) produces an insignificant estimate close to zero.

In sum, by exploiting the natural experiment of the policy change, we find evidence of more R&D spending and employment as a consequence of lower marginal R&D costs. Perhaps more surprisingly, we find that innovation was accompanied by more sourcing of foreign inputs, consistent with our theoretical model.

Recent research by Bloom et al. (2011) has shown that import competition from low cost countries affects innovation rates in developed countries. From 2001 to 2005, the Chinese import share in Norway increased from 3.0 to 5.6 percent.[25] A potential concern is therefore that our results may confound the effect of the R&D policy with import competition effects. Note that our DID approach is robust to any such concern if the effect of low cost competition is uniform across our treatment and control group. Nevertheless, we investigate this issue by

[25] Imports from China relative to total imports, from www.ssb.no/muh.

Table 9: Robustness: Low cost import competition.

	log R&D	log R&D employment share	# of imported products
>2002×H	.61***	.27**	.08**
	(.15)	(.12)	(.04)
Firm FE & trends	Yes	Yes	Yes
Control group	H_1	H_1	H_1
N	806	806	2819

Notes: Standard errors in parentheses clustered by firm. *** = p-val<.01, ** = p-val<.05, * = p-val<.1. Column 3 is based on Poisson pseudo-MLE as in Table 8.

estimating the DID model only on industries that were relatively unaffected by the rise in low cost imports. Specifically, we order NACE 2 digit industries according to their percentage point increase in the Chinese import share from 2001 to 2005. We then estimate the model only on industries below the 75th percentile in terms of import share growth.[26] The details about matching of industries to trade data are presented in the appendix. Column 1 in Table 9 shows the result on log R&D expenditure, when including firm trends. We see that the coefficient estimate is roughly similar to the estimate in column 4 in Table 6. We also report the estimate on the R&D employment share and the number of imported products in columns 2 and 3. Again, the estimates are very similar to the baseline estimates. We therefore conclude that low cost import competition does not seem to affect our results.

6 Alternative mechanisms explaining the complementarity between R&D and imports

In this section, we explore some additional moments of the data. In particular, we explore whether the R&D cost shock shifted imports toward certain sourcing countries or product varieties. First, we investigate whether the cost shock shifted imported products towards low wage countries. Second, we investigate whether the cost shock raised imports of capital goods in particular. Third, we investigate whether the R&D content of imports was affected by the policy change. This helps us to assess the relevance of our theory versus alternative hypotheses in explaining the trends in R&D and imports. In sum, we find that the R&D shock raised the number of imported products across all products varieties. We find no evidence that the policy increased sourcing from low wage countries. This is consistent with our model of scale complementarity, which predicts a broad based increase in imports.

[26] The industries with Chinese import share growth above the 75th percentile are: NACE 17, 35, 19, 18, 32 and 30, with NACE 30 the industry with the highest percentage point change in the import share.

Table 10: Imported HS4 products and imported R&D intensity.

	OECD	Non-OECD	Capital	Non-capital	Import R&D intensity
>2002×H	.08**	.01	.09**	.07*	-.03
	(.04)	(.09)	(.02)	(.04)	(.05)
Firm trends	Yes	Yes	Yes	Yes	Yes
Control group	H_1	H_1	H_1	H_1	H_1
N	3411	2686	3339	3369	2318

Notes: Standard errors in parentheses clustered by firm. *** = p-val<.01, ** = p-val<.05, * = p-val<.1. Columns 1-4 based on Poisson pseudo-MLE as in Table 8. Column 5 based on OLS.

Imports from low-wage countries. We decompose imported products into the number of imported HS4 products from OECD countries n_{it}^{OECD} and non-OECD countries $n_{it}^{\sim OECD}$. In 2001, average n_{it}^{OECD} was almost 13 times higher than $n_{it}^{\sim OECD}$, primarily reflecting the importance of the EU as the main trading partner. We then estimate the same Poisson model as presented in Table 8, but with n_{it}^{OECD} and $n_{it}^{\sim OECD}$ as dependent variables. Columns (1) and (2) in Table 10 show the results for the interaction variable defined above, >2002×H (similar to column (4) in Table 8). We identify an increase in the number of imported OECD products for the treatment group as a consequence of the R&D cost-shock, and no impact on the number of non-OECD products. This suggests that the R&D policy did not induce substitution towards inputs from low wage countries.

Imports of capital goods. We decompose imported products into the number of imported HS4 capital goods n_{it}^{cap} versus non-capital goods $n_{it}^{\sim cap}$. Capital goods are classified according to the BEC nomenclature.[27] In 2001, the average number of imported non-capital goods was roughly roughly 50 percent higher than the number of imported capital goods. Columns (3) and (4) show the regression results, using the same methodology as columns (1) and (2). The results suggest that the reform in R&D policy affected imports of both capital and non-capital goods, and almost to the same extent.

R&D intensity in imports. Finally, we create a firm-level measure of R&D intensity embodied in imports. We hypothesize that the firm's R&D activities may be complementary with R&D that is embodied in its imports (see e.g. Coe and Helpman (1995)). We proceed by calculating industry-specific R&D intensities for the OECD, and then assigning every imported HS product an R&D intensity according to sector. Firm-level R&D import intensity

[27] Specifically, we define capital goods if they belong to BEC digits 4 or 5. BEC codes are matched to HS 6 digit codes using the UN correspondence. Since the analysis is performed at the HS 4 digit level, we classify a given HS 4 digit code as capital if more than half of the 6 digit products (within a 4 digit product) are capital goods.

for firm i is then the weighted mean across firm i's imported products.[28] For our sample as a whole, the average import R&D intensity increased from 2.5 percent in 1997 to 3.2 percent in 2005. However, as shown in column 5, we do not find evidence that embodied R&D in imports was affected by the R&D policy change.

7 A counterfactual

In this paper, we have emphasized one particular mechanism that gives rise to complementarity between innovation and trade in intermediates. In this section, we evaluate the empirical importance of this particular mechanism. We know from our reduced form results in Section 5 that the decline in R&D costs due to the tax credit introduced in 2002 raised the average number of imported products per firm by around 10 percent (see Table 8 columns (4)-(6)). Here we ask what the increase in imports would have been according to the structural model we developed and estimated above, see sections 3 and 4. We find that our model produces a 6 percent increase in the number of imported inputs. This suggests that the lion's share of the observed increase can be explained by our proposed theoretical mechanism.

We proceed as follows. First, we approximate $\gamma^* aG(n)$, which is estimated non-parametrically, with the smooth concave function $G(n) = c(1 - \exp(-\mu n)$, where c and μ are parameters.[29] The limit of $G(n)$ is c, so we set c equal to the estimate of the 4th quartile impact (0.95, see Section 4, Table 5). μ is a parameter determining the shape of the function. Halpern et al. (2011) estimate this function, and we use their point estimate of 0.20. We discretize the number of imported products n in ten bins, 0-10, 11-20, and so forth until 90-. Second, we calculate predicted 2001 revenue conditional on n_{it}, that is, $\hat{r}_i(n)$ from equation 6 and the expression for h(). Given a value for the elasticity of substitution η, this also gives us predicted gross profits $\hat{\pi}_i(n)$. In our baseline, we use $\eta = 4$, as in Section 4. Third, conditional on an initial guess of the per product fixed import cost f, we find the firm's optimal number of imported inputs n_i^* from equation 3. Since f is unknown, we calibrate it to match the actual share of firms belonging to the $n \in [0 - 10]$ bin. In the data, this share is 0.29. Setting $f = 690,000$ USD per 10 products matches the simulated and actual share.

We can now shock our economic environment. Using the population of firms that are operating both pre and post reform (2001 and 2005), we identify the firms that were not innovating in 2001 but were innovating in 2005. 18 percent of the firms are classified as R&D starters. We then ask what the level of revenue for the R&D starters would have been in 2005 according to our theoretical model, if they had been innovating in every period from

[28] More details about the procedure is presented in the appendix.

[29] Recall from Section 3 that G() by definition is concave, due to our ordering of the products.

2002 onwards. In other words, we calculate counterfactual revenue and profits $\hat{r}^{cf}_i(n)$ and $\hat{\pi}_i^{cf}(n)$ for the R&D starters by adding the long run revenue gains from R&D, estimated in the previous section (from equation (8)), keeping all else constant.[30] Finally, we recalculate the R&D starters' optimal number of imported inputs n_i^{*cf} under the counterfactual. We can then compare the change in foreign sourcing in the data with the change occurring according to the model.

We evaluate the fit of the model by comparing the counterfactual outcomes n_i^{*cf} versus the reduced form results. The results in Section 5 indicated that the R&D policy raised the average number of imported products per firm by 10 percent (see Table 8). The corresponding counterfactual increase, $\hat{n} \equiv \sum_i n_i^{*cf} / \sum_i n_i^*$, is 6 percent, suggesting that our model can explain the lion's share of the import surge. As a simple robustness check, we calculate $\hat{n}$ for a range of values of the fixed cost f. It turns out that $\hat{n}$ is relatively insensitive to our calibration of f. Note that we never estimated a relationship between innovation and imports in the structural model. Rather, we estimated revenue conditional on imports and innovation. As a consequence, there is nothing in the model that mechanically produces a counterfactual growth in n close to the actual growth in n.

Next, we decompose the growth in revenue. R&D starters sell more since innovation on average makes them more productive, but also since higher productivity makes them import more products, which lowers costs and increases revenue. In our counterfactual, roughly one fifth of average productivity growth among the R&D starters stems from sourcing more products, while the remaining 4/5 stems from innovation, illustrating how trade can amplify productivity gains. The import channel alone contributed to a 12 percent increase in sales (and a corresponding decrease in costs). In our view, that a government R&D policy can give cost savings of this magnitude due to imports is indeed remarkable.

While R&D is a binary decision in the model, it is clearly continuous in the data. Presumably, the R&D policy affected both the intensive and extensive margin of R&D investment, whereas the theoretical model only includes the extensive margin. Adding the intensive margin to the model would in all likelihood give a stronger counterfactual increase in foreign sourcing $\hat{n}$. Hence, we interpret our results as a lower bound on the complementarity effect between R&D and imports.

Finally, we also explore the change in the distribution of n^*_i. In Figure 4, we plot the actual 2001 and 2005 distributions versus the counterfactual 2001 and 2005 distributions. The horizontal axis denotes the bins 0-10, 11-20, and so forth, while the vertical axis denotes the shares of firms belonging to each bin. The actual distribution changed quite dramatically pre and post reform. In particular, the share of firms in the lowest bin dropped from 0.29 to

[30] Specifically, $\hat{r}_i^{cf} = \hat{r}_i + .105\,(\eta - 1)$ for R&D starters and $\hat{r}_i^{cf} = \hat{r}_i$ for all other firms.

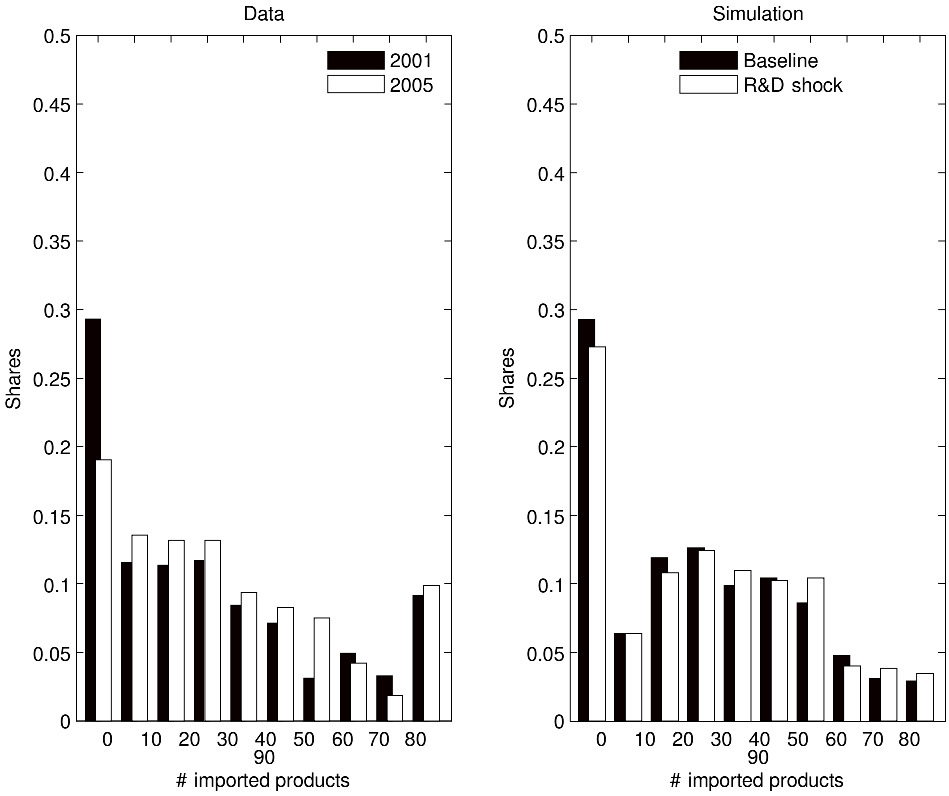

Figure 4: Distribution of the number of imported inputs. Data and simulation.

0.19. Note that the actual change in n_i^* is determined by a host of factors other than R&D, so we do not expect our model to match our data perfectly. Nevertheless, our counterfactual displays some similar patterns as in the data, most notably that the bulk of the adjustment occurs in the [0-10] and [60-70] bins, i.e. that the R&D shock had a strong impact on non-importers or firms with few imported inputs pre reform, and that the shock had a non-linear effect over the distribution.

8 Conclusions

The returns to R&D investments are well documented. There is moreover substantial empirical evidence on the impact of imported intermediates on firms' productivity. What we know less about is the relationship between R&D investment and international sourcing. This paper attempts to close the gap. We have developed a theoretical model proposing a mechanism for complementary between R&D investment and trade in intermediates. We propose a straightforward and novel mechanism by which input trade liberalization fosters technical change. In the model, declining input trade barriers lower marginal production costs and raise firm revenue. That in turn increases the returns to incurring a fixed R&D cost, since a one percent productivity gain translates into more sales in dollars when revenue is high. We develop a structural estimator and quantify the returns to foreign sourcing and innovation. We estimate substantial returns to both activities. Furthermore, estimates are severely biased if not accounting for the complementarity between them. An R&D tax reform lends itself as a natural experiment in order to test predictions in a difference-in-differences framework. We find that, in line with our theoretical predictions, initiatives lowering R&D costs not only have a benign impact on R&D but also on trade in intermediates. Finally, by comparing our reduced form estimates with a simulation of the estimated structural mode, we evaluate the importance of the theoretical mechanism proposed in this paper, relative to competing hypotheses. We find that a majority of the import surge that occurred in the aftermath of the policy change can be attributed to the proposed theoretical mechanism. Moreover, one fifth of measured productivity growth among R&D starters stems from sourcing more products, while the remaining 4/5 stems from technical change. An important implication of our work is therefore that R&D policies have ramifications beyond innovation, such as for international trade.

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Appendix

A Derivation of marginal profits

In this section, we show that higher productivity ω_{it} and lower foreign sourcing costs a increase the marginal return from foreign sourcing, as shown in Section 3.4.

Using the expression for revenue in equation (1) as well as the expression for the G() function in equation (2), we can write variable profits as

$$\begin{aligned} \pi(n_{it}) &= (1/\eta)\exp[\kappa + \ln\Phi_t - (\eta+1)(\beta_0 - \beta_k \ln k_{it} + \beta_w \ln w_t + a\gamma G(n_{it}) - \omega_{it})] \\ &= K e^{(1-\eta)[a\gamma G(n_{it}) - \omega_{it}]} \end{aligned}$$

where $K \equiv (1/\eta)\exp[\kappa + \ln\Phi_t - (\eta+1)(\beta_0 - \beta_k \ln k_{it} + \beta_w \ln w_t)]$. The marginal change in profits from sourcing one more variety from the foreign market is then

$$\pi(n_{it}) - \pi(n_{it}-1) = K e^{(\eta-1)\omega_{it}} \quad e^{(1-\eta)a\gamma G(n_{it})} - e^{(1-\eta)a\gamma G(n_{it}-1)} \quad .$$

Differentiating with respect to a yields

$$\frac{\partial[\pi(n_{it}) - \pi(n_{it}-1)]}{\partial a} = K(1-\eta)e^{(\eta-1)\omega_{it}}\gamma \quad G(n)\,e^{(1-\eta)a\gamma G(n)} - G(n-1)\,e^{(1-\eta)a\gamma G(n-1)} < 0,$$

which is negative since $K > 0$, $\eta > 1$, $a < 0$ and $G(n)$ is increasing in n. Hence, a decline in the cost of foreign sourcing increases profits from foreign sourcing, on the margin.

Differentiating with respect to ω_{it} yields

$$\frac{\partial[\pi(n_{it}) - \pi(n_{it}-1)]}{\partial\omega} = K(\eta-1)e^{(\eta-1)\omega_{it}} \quad e^{(1-\eta)a\gamma G(n_{it})} - e^{(1-\eta)a\gamma G(n_{it}-1)} \quad > 0.$$

Hence, higher productivity increases profits from foreign sourcing, on the margin.

B Data : Identifying import competing sectors

To order the industries according to the degree of import competition from China, we use data gathered from Statistics Norway on Norwegian sector level Chinese imports, as a fraction of total imports. The data is based on the 2 digit SITC code, which cannot easily be matched to the 2 digit NACE code in the capital database. Based on the correspondence table from Eurostat, we count the number of 5 digit SITC sectors corresponding to each 2 digit NACE

Table 11: Treatment and control groups, average, 2001.

	$H_{1i} = 1$	$H_{1i} = 0$
Employees	134	377
# imported products	26	73
Import share	0.18	0.28
Labor productivity	512	633
R&D expenditure	592	47,054
No. of obs.	668	136

Notes: Imported products refer to unique HS 4-digit products. R&D expenditure is measured in 1000 NOK. Import share is defined as firm import value relative to operating costs. Labor productivity is defined as real value added relative to employees in 1000 NOK. All numbers are simple averages across the two groups.

sector. We match the 2 digit SITC sectors to the 2 digit NACE sector with the most 5 digit matches.

C Data : Import R&D intensity

Using data gathered from the OECD's iLibrary, we generate a measure of R&D intensity for each manufacturing sector, given by the number of persons employed as R&D personnel relative to the total number of employees. The R&D intensity used in the empirical analysis is a yearly average over OECD countries.

The OECD data is based on the 2 digit International Standard Industrial Classification (ISIC). The trade data follows the Harmonized System (HS) and the Standard International Trade Classification (SITC). To be able to match the intermediate inputs to the ISIC structure, we use a correspondence table from Eurostat, the statistical office of the European Union. Each HS number is matched at the 5 digit SITC level to the 2 digit ISIC code.

The imports for each firm are then aggregated to the 2 digit sector level and matched with the average R&D intensities. Finally, the firm level import R&D intensity is constructed as an average of the sector level R&D intensities, weighted by each sector's share of the firm's total imports.