Internal and External R&D: An analysis of costs and benefits

[PRELIMINARY - PLEASE DO NOT CITE/CIRCULATE] *

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January 31, 2024

Abstract

This paper analyzes the costs and benefits of internal and external R&D activities. Using Dutch production and innovation surveys between 2000 and 2020 focusing on the IT industry, I document an increasing trend of R&D activities across industries and present evidence suggesting that internal and external R&D are complementary. To rationalize these findings, I build and estimate a dynamic discrete choice model of R&D, which explicitly includes specific investment costs of R&D. I find that the cost of doing external R&D is ≈ 4 times higher than the internal R&D, reflecting the transaction costs of such contract and explaining the observed small share of external R&D firms in the data. To mimic the Dutch Tax Incentives for Innovation scheme, I simulate the effect of two types of R&D subsidization programs. I find that if the government has no preference for any particular R&D activity, the share of R&D-active firms increases the most and leads to higher welfare change. On the other hand, if the government prefers the firms only to perform internal R&D, the share of R&D-active firms is practically unchanged and leads to lower change in welfare.

Keywords: Research and Development, Complementarity, Innovation, Productivity, Internal R&D, External R&D, Outsourcing

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*This paper is based on my MPhil thesis. I would like to thank my supervisors, Sabien Dobbelaere and José-Luis Moraga-González, for their constant guidance and support. I would also like to thank Bettina Peters and Mark Roberts for their helpful comments and suggestions. I am grateful to seminar discussants and audiences in JEI-Gran Canaria (2022), Penn State IO/Applied Micro Brownbag Seminar (2023), VU Amsterdam Internal Seminar (2023), Tinbergen Institute PhD Seminar (2023), EARIE (2023), DKIIS-Valencia (2023), CAED-Penn State (2024), and SED Meeting-Barcelona (2024) for their comments. The views expressed in this paper are mine and do not reflect the views of the Statistics Netherlands (CBS). All errors are mine.

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1 Introduction

In practice, R&D is usually done in-house or through contracting out to other strategic partners within or outside the country. This paper proposes a structural model that captures the costs and benefits of such R&D activities, estimates it using Dutch microdata between 2000 and 2020 focusing on the Dutch I(C)T industry, quantifies whether these activities are complementary, asks and simulates whether this complementarity plays an important role in the R&D subsidization program.

First, I document that the share of firms performing at least one type of R&D activity in the economy increases over time. Most of these firms perform their R&D in-house or both in-house and contract out part of their R&D to other partners. In particular, I observe that the share of firms performing only in-house R&D increases over time. Meanwhile, the share of firms performing R&D though only contracting out to other entities is constant over time. I also find that the share of firms performing no R&D at all decreases, but increases after 2016. My reduced-form evidence also indicates that these R&D activities are complementary.

To rationalize these stylized facts, I build a model that captures the costs and benefits of in-house R&D (i.e., internal R&D) and contracting out R&D to other entities (i.e., external R&D). My model consists of two parts: a static and a dynamic part. In the static part, both the demand and supply sides follow a standard assumption of monopolistic competition. The dynamic part follows a standard single-agent dynamic discrete choice model of R&D and incorporates firms' R&D decisions by specific investment costs for each R&D activity. In this part, I introduce a parameter that captures whether internal and external R&D activities are cost-complementary. In the model, firms' R&D decisions on which type of R&D they want to pursue are considered as inputs, and in turn, these will yield different productivity evolution for the firm. Furthermore, a firm's productivity influences its profitability.

There are several steps in estimating the model. In the static part, the first step is to estimate the demand elasticity. Then, the second step is to perform semiparametric productivity estimation to get parameters related to the firm's productivity evolution. In the dynamic part, using the estimates obtained from the static part and a nested-fixed point algorithm as in Rust (1987), I recover the structural parameters of the model; that is, the internal R&D investment costs, the external R&D investment costs, and the cost-complementarity parameter.

My main findings from the estimated parameter of the model can be briefly summarized as follows. From the static part, I find that the types of R&D the firm pursues are important productivity determinants. From the dynamic part, I find that the average cost of internal R&D is 0.13 million EUR, while the average cost of external R&D is 2.45 million EUR. The ratio of the costs of external to internal R&D is ≈ 4; that is, the external R&D costs are significantly higher than the costs of performing internal R&D. I argue that this high cost is the primary reason for an observed small share of firms performing only external R&D and reflects the high transaction cost of performing such contract. Furthermore, for firms in the Dutch I(C)T industry, the benefits of performing both internal and external R&D outweighs the costs; that is, both R&D are complementary.

The estimated parameters of the model allow me to perform several counterfactual exercises that mimic a reduced-form version of the R&D subsidization program done by the Dutch government. I define the subsidy as a reduction in cost for one or all types of associated R&D costs. In the first exercise, I consider the case of whether the government discriminates against one particular type of R&D activity. For example, suppose the government does not prefer any particular R&D activity (i.e., uniform subsidy). In this case, a 5% subsidy of all costs yields the most significant change in the share of firms performing at least one type of R&D, and results in the highest welfare improvement (in terms of producer surplus). I also find that the next best scenario is for the government to provide 5% subsidy only the external R&D cost. Finally, the case of 20% subsidy only for the internal R&D cost yields the least change in the share of R&D-active firms and has the lowest welfare improvement. My counterfactual exercise also yields an important insight regarding the complementarity between internal and external R&D; in particular, without this complementarity, we would see a significant drop in firms performing both types of R&D. The welfare-improving impact of the subsidy is also significantly reduced. Overall, without this complementarity, to achieve the same welfare-improving impact of the subsidy, the government would have to spend more euros on the subsidy.

Related Literature.—Moving to the discussion of related literature. First, let me discuss the general structure of the model. The static part of my model has a similar structure to Aw et al. (2011), Boler et al. (2015), and Peters et al. (2017). The main deviation from their model is that my model has a different dynamic part and assumes different distributional assumptions. The dynamic part of my model is related to Igami (2017) and Igami and Uetake (2019). As in their model, the dynamic part of my model utilizes the notion of specific investment costs to illustrate the general and organization-specific costs related to R&D activities. However, unlike their model, I do not specifically model the strategic interaction between firms, which is impossible due to unavailable price data. It is also important to note that in Igami (2017) or Igami and Uetake (2019), they do not model complementarity. I borrow insights from the static model of Miravete and Pernias (2006) to explicitly incorporate the complementarity parameter in the cost-side of the dynamic part of my model. Moreover, unlike my paper, Miravete and Pernias (2006) discuss the complementarity of product and process innovations.

Let me now move to the discussion of the reduced-form evidence. First, it is related to Cassiman and Veugelers (2006) where they use insights from Arora (1996) and Athey and Stern (1998) to test whether internal and external R&D are complementary to each other. The main difference with my reduced-form evidence is that I extend their findings while exploiting the panel structure of the data. Moreover, Cassiman and Veugelers (2006) only consider reduced-form evidence. Their empirical exercises are also limited to one wave of the CIS survey. Another related paper in this context is the one from Mohnen and Roeller (2005). However, in this paper, I only consider dichotomous activities (internal and external R&D), while they consider more than three activities. My approach of using the Panel (Random Error) Tobit model for accounting for the censored dependent variable while exploiting the panel structure of the data is quite similar to Hagedoorn and Wang (2012) and Love et al. (2014).

The mainstream literature of productivity estimation usually relies on the value-added output rather than the gross output. For example, estimation approaches and identification issues discussed in De Loecker and Warzynski (2012), Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). However, their proposed estimations might encounter identification issues whenever brought to the gross output settings. Some have resolved the issue using a nonparametric approach for identification (see Gandhi et al. (2021)). For estimating productivity, I follow a similar semiparametric approach as in Aw et al. (2011), Doraszelski and Jaumandreu (2013), and Peters et al. (2017).

On the theoretical side, this paper is related to the discussion of hybrid R&D in Goyal et al. (2008). They derive a necessary and sufficient condition on the firm's profit function such that all projects the firm currently undertakes are complementary. In essence, complementarity can arise solely from market advantages due to the lower cost of the firm. The condition holds even in the case of no technological spillovers from outside the firm. My results establish that internal and external R&D complementarity stems from the cost side. The result of the high cost of external R&D also supports the notion of high financial constraints faced by the firms to perform external R&D, as discussed by the recent theory paper by Brunner et al. (2023) on the relation between research joint venture and financial constraints. We can also think of the high transaction costs as a hold-up problem (as suggested by the classic Grossman and Hart (1986) model), or reflects haggling and friction due to the complexity of the R&D contract between the firm and other third parties (as suggested by Bajari and Tadelis (2001) and Tadelis (2002)).

The discussion of R&D subsidies is an essential point in this paper. Galaasen and Irarrazabal (2021) finds that a uniform subsidy to Norwegian firms stimulates investment, growth, and welfare. However, the size-dependent subsidy increases only aggregate R&D but reduces growth and welfare. My counterfactual exercises also point out that a uniform, non-discriminatory subsidy leads to a higher share of R&D-active firms in the economy. On the contrary, the discriminatory subsidy might not lead to a higher share of R&D-active firms in the economy. Gonzalez et al. (2005) find that for Spanish firms that previously do not invest in R&D, half of the large ones would begin investing if they were given a 10% subsidy, and one-third of the small ones would begin investing if they were given a 40% subsidy. I find that a 20% reduction of all costs, i.e., internal and external investment costs, leads to a decrease in the share of R&D-inactive firms in the Dutch I(C)T industry.

Structure of the Paper.—This paper has the following structure. The next section describes the data, information on the Dutch Tax Incentive for Innovation scheme, and reduced-form evidence. In Section 3, I present my model, which consists of two parts; a static and a dynamic part. Section 4 outlines the empirical implementation of the structural model and briefly discusses sources of identification. The result of the model is presented in Section 5. I then proceed with some counterfactual exercises in Section 6. Section 7 concludes the paper.

2 Institutional Setting, Data, and Motivating Evidence

This section will outline the motivation regarding the Dutch Tax Incentives for Innovation, information regarding the data that I used, and certain stylized facts as motivating evidence.

2.1 Dutch Tax Incentives for Innovation

To promote research and development in the Netherlands, the Dutch government introduced a comprehensive innovation program that provides tax incentives for Dutch companies. This comprehensive innovation program consists of two sides: profit and cost sides. From the cost side, if eligible, the firms' wage taxes on the R&D performed in the Netherlands will be greatly reduced. From the profit side, if eligible, the firms will face a special corporate income tax regime or any profit generated with the associated R&D. In turn, these incentives will lead firms to face a lower Effective Tax rate.

On the cost side, the program is called WBSO (NL: *Wet Bevordering Speuren Ontwkkelingswerk*, EN: The Promoting Research and Development Act) administered by the RVO (NL: *Rijksdienst voor Ondernemend Nederland*, EN: the Dutch Enterprise Agency). We can think of WBSO as an R&D remittance reduction of the wages tax and contribution to the national insurance scheme. To be eligible for this cost-side benefit, firms need to apply for the WBSO statement to the RVO, showcasing the following: 1. Firms need to demonstrate that they develop a technically new product or new production process, write software programs, or perform scientific research; 2. These projects that the firms deal with need to contain necessary technical bottlenecks that known techniques cannot solve and require them to perform R&D[1]. After the RVO assessment, firms will receive the WBSO statement

[1]Example of projects assessed by the RVO: Suppose Firm A submits a project that aims to create a machine learning model using certain well-known libraries like Tensorflow. In this case, the RVO will not approve the application since Firm A is using existing libraries/technologies to solve certain technical issues. Should the project be about building a machine learning model from scratch and, on the way, solving certain technical bottlenecks, the RVO might grant Firm A with the WBSO statement. In summary, the main

and the granted R&D hours for which the firms can calculate their "R&D base". With this statement, firms are now eligible for the remittance reduction.

In 2022, this remittance reduction is 32% of the so-called "R&D base" of up to 350,000 EUR and 16% for more than 350,000 EUR. There is also a special rate of 40% up to 350,000 EUR for new entrants, i.e., firms that employ people for less than five years and were granted the WBSO statement by the agency less than three calendar years. There are two ways to calculate this "R&D base": Either based on the number of R&D hours done by the workers or the actual costs and expenses related to R&D activities[2].

On the profit side, the program is called the Dutch Innovation Box policy. This program provides firms with a reduced corporate income tax rate. Historically, this program used to be called the Patent Box Policy, and as of 2010, it has greatly expanded to become the Dutch Innovation Box policy. As of 2022, firms' profit that is deemed to be under the guideline of the policy will be subject to a corporate income tax rate of 9% instead of the usual rate of 25.8%[3]. Note that not all of the firms' profits are eligible for the Innovation Box policy, only those which are deemed attributable to R&D activities. The main requirement for applying this policy is the WBSO statement from RVO. If the size of the firms is deemed 'large,' then they are also required to have a patent or plant breeders' right (NL: *Kwekersrecht*). Firms are deemed 'small' if they satisfy the following two conditions: 1. The sum of the gross margin of the firms related to the intangible asset for the past five years is less than 37.5 million EUR, 2. The sum of the turnover/sales of the firms for the

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factor for the RVO approval is whether the project the firm pursues is solving any technical problems that any known methods cannot solve.

[2]For the first method (based on the number of R&D hours), we can use the average hourly wage of 29 EUR for every R&D hour granted. For the first 1800 of the granted R hours, firms are also eligible for an additional 10 EUR for every hour. More than 1800 of the granted R&D hours, firms can add 4 EUR for every additional hour.

[3]Since the introduction of this Dutch Innovation Box policy in 2010, the corporate income tax rate has changed from initially set to be 5% to the current rate of 9%. In the Netherlands, there are two corporate income tax bracket. For the first bracket -that is, the first firms' profit below the 395,000 EUR threshold, then the profit is taxed at the 15% tax rate. Meanwhile, the profit beyond 395,000 EUR will be taxed at 25.8% rate. For example, if Firm A has profit of 500,000 EUR in one fiscal year, the first 395,000 EUR will be taxed at 15%. The remaining 105,000 EUR will be taxed at 25.8%.

past five years is less than 250 million EUR.

Four methods exist to determine the taxable profit under the Dutch Innovation Box policy. The Dutch Tax Authority will then use one of these methods to determine the profit attributable to R&D. The first method, which is the most popular, is the peel-off method (NL: *Afpelmethode*) which is attributing certain parts of the earnings before interest and tax (EBIT) to entrepreneurship, sales, production, and those coming from R&D[4]. The second method is the cost-plus method, in which the Dutch Tax Authority adds a mark-up between 8% to 15% on all costs related to R&D. The third method is the single intangible asset method is quite similar to the peel-off method, but instead of using EBIT as the initial point, this method relies only takes the development/R&D expenses/costs and the related benefits to the intangible asset[5]. In the case where the previous three methods are deemed not feasible, the Dutch Tax Authority will use the fourth method which is the flat rate method of imposing 25% of the profit will fall under the Dutch Innovation Box[6].

The Dutch government has adopted the OECD "Nexus Approach" for the Innovation Box Policy, under which only qualifying income relating to intangible assets developed by firms "in-house" will be eligible for the application. This decision effectively prevents firms from benefiting from the tax benefits of the policy if they do not have a substantial economic presence in the Netherlands or if they are not engaged in any research or innovative activities in the country. Furthermore, the decision implies that only innovation developed in-house by firms will be eligible for the tax benefits[7].

[4]The Dutch Tax Authority is the one responsible in assessing the the share of profits that can be attributed to the parts explained above. Example: 20% to entrepreneurship, 10% to sales, 30% to production, and this leaves 40% attributable to R&D. The Dutch Tax Authority will also assess whether R&D is an essential party of day-to-day activity of the firm. The Tax Authority also has the hurdle for development costs, in which the costs of the R&D should be compensanted by the profits attributable to R&D.

[5]The single intangible asset method is usually used by the Tax Authority in royalty structures. In this case, it is more straightforward to identify the revenue generated from specific intangible asset. For example, we can think of the royalty revenue from a single patent from Firm A.

[6]The benefit is capped at maximum of 25,000 EUR for each year. The fourth method is usually used for small-sized firms.

[7]Technically, R&D outsourcing to an affiliated entity is feasible as long as the R&D costs and risks are

Throughout the paper, I try to capture both WBSO and Dutch Innovation Box Policy in the counterfactual simulation as some forms of reduction in the tax rate that affects the static profit of the firm and increase in the subsidy rate to innovation costs.

2.2 Data

I employ several datasets from various sources. The first dataset is the Production Statistics survey (PS) from the Statistics Netherlands (NL: *Centraal Bureau voor Statistiek*, CBS). This dataset contains information on the firm's characteristics, such as capital, intermediate inputs, and revenue of the firm. This survey is conducted annually by CBS. The dataset covers all large firms in the Netherlands. As for the smaller firms, CBS performs a randomization[8]. For firms with fewer than ten workers, the tax registration data is used as much as possible to fill out the PS survey. Businesses with fewer than 50 workers receive a questionnaire from CBS on a sample basis. For firms with workers larger than 50, all are included in the PS survey.

The second dataset is the biennial Community Innovation Survey (CIS). This dataset contains information about the mode of R&D. Let us first discuss the mode of R&D captured in this survey. The definition of the mode of R&D in this paper closely follows the definition outlined by Cassiman and Veugelers (2006). For example, suppose a firm performs in-house R&D with its own staff. In that case, I define this R&D activity as internal R&D. If a firm decides to contract out its R&D to other firms, universities, or other strategic partners, I define this activity as external R&D. The survey only contains information on the extensive margin, i.e., whether firms perform a certain type of R&D or not in a given year[9].

owned by the firm in which it has a significant domestic presence. However, the benefit of doing such a strategy is greatly reduced. Only a maximum of 30% of the R&D expenses can be outsourced to an affiliated entity to be eligible for the Innovation Box benefits.

[8]The detailed information about how the survey is conducted can be found in the following link here: https://www.cbs.nl/en-gb/onze-diensten/methods/surveys/korte-onderzoeksbeschrijvingen/production-statistics

[9]From the CIS, the indicator of R&D type must be filled in by the firm. However, the information on

In this paper, I focus on the Dutch Information, Communication, and Technology/I(C)T industry. This industry consists of several sub-industries, such as software, IT, and data processing, including telecommunications, and other sub-industries with significant presence in these sub-industries[10]. I also use deflators data for output, capital, and intermediate inputs from OECD's STAN. The final dataset that I have is an unbalanced panel dataset of the join PS and CIS from 2000 to 2020 (for even years).

Table 1: Firm Characteristics of Dutch I(C)T Industry

Variables	**Average**
Output/Revenue	59822.95
Capital	7899.39
Intermediate Inputs	28810.87
Value Added	30353.23
FTE Workers	229.55
Energy	247.57
Share of New Products	11.01%
No R&D	37%
Internal-only R&D	32%
External-only R&D	3%
Both R&D	28%
Observations	2883
Number of Firms	750

Notes.—The unit for firms' output, capital, intermediate inputs, value-added, and energy is in the 1000 EUR (real). The unit for FTE workers is the number of people employed by a firm.

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how much R&D expenses for each activity is not mandatory and is not always available or asked in the survey questionnaire in every wave of the survey.

[10]The operationalization of the ICT industry in this paper is the following. I choose firms that are active in these two or three digits SBI (NL: *Standaard Bedrijsindeling*, EN: Standard Business Classification); 61 (telecommunications), 62 (support activities in the field of information technology), 63 (information service activities), 582 (software publishing).

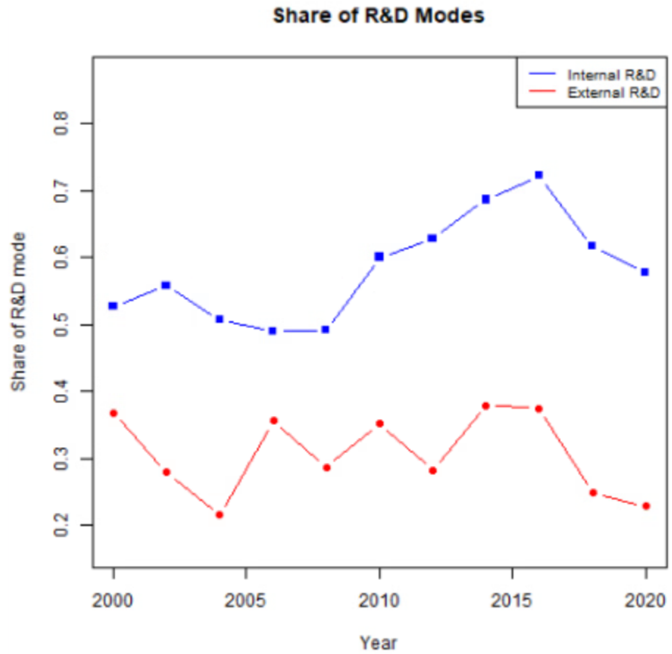
Table 1 provides information on several variables that I use throughout the paper. As we can see from Table 1, among 750 firms in the sample, on average, firms' revenue is around 59 million EUR with a capital of 7.8 million EUR. On average, firms use about 28.8 million EUR in intermediate inputs, 229 workers, and 247,000 EUR in energy. On average, 37% perform no R&D at all, 32% choose to perform only internal R&D, 3% choose to perform only external R&D, and 28% choose to perform both internal and external R&D.

2.3 Motivating Evidence

In the following subsection, I provide several facts about the research and innovative activities in the Netherlands. First, I show the time-trend of R&D and innovations mode. Then, I show the persistence of R&D modes. Finally, I provide suggestive evidence that R&D modes are complementary.

Facts 1 (Time-trend of R&D: Internal v. External R&D) *The share of firms performing Internal R&D is larger than External R&D. The share of firms performing Internal R&D is increasing, especially after the expansion of the Dutch Innovation Box Policy. The share of firms performing External R&D remains constant throughout the sample period.*

Figure 1: Time trend of R&D Activities

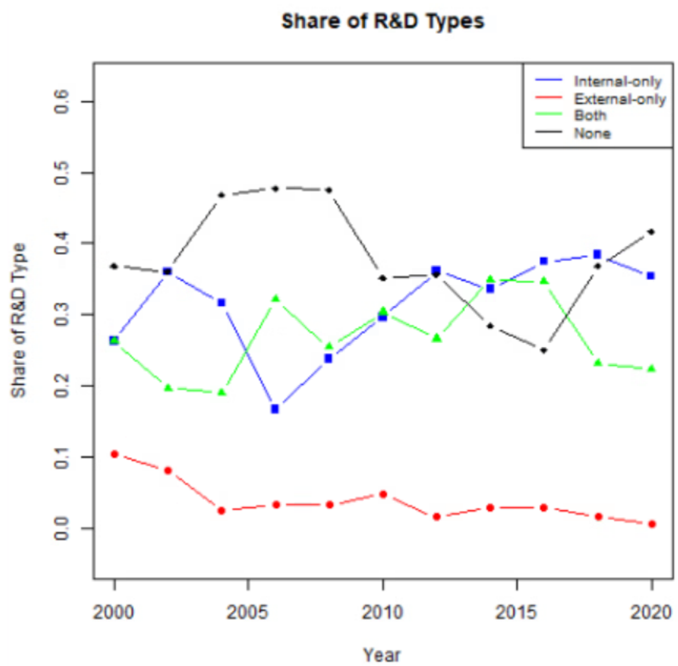


Notes.—The figure is constructed from an unbalanced panel of Dutch Production Statistics (PS) and Community Innovation Survey (CIS) datasets by taking the mean of R&D modes in each year. *Internal R&D* indicates that a firm performs an Internal R&D in a given year. *External R&D* indicates that a firm performs an External R&D in a given year.

Fact 1 is summarized by Figure 1. From the figure, we can see that the share of firms performing internal R&D is larger than External R&D. The trend of Internal R&D is also increasing, especially after the expansion of the Dutch Innovation Box Policy in 2010; that is, from around 50% to a peak of around 70% in 2016. The share of firms performing External R&D is also constant in the range of around 20% to 40% throughout the sample period.

Facts 2 (Time-trend of R&D: None, Internal-only, External-only, Both R&D) *A decrease in the share of firms performing no R&D at all, especially after the expansion of the Dutch Innovation Box Policy. An increase in the share of firms performing Internal-only R&D and Both R&D. A persistently small share of firms performing External-only R&D.*

Figure 2: Time trend of R&D Modes



Notes.—The figure is constructed from an unbalanced panel of Dutch Production Statistics (PS) and Community Innovation Survey (CIS) datasets by taking the mean of R&D modes in each year. *No R&D* indicates that a firm performs no R&D in a given year. *Internal-only R&D* denotes that a firm performs only internal R&D, while *External-only R&D* means that a firm only contracts out R&D to other strategic partners. *Both R&D* marks that a firm conducts both Internal and External R&D.

Fact 2 is summarized by Figure 2. From the figure, we first see that the share of firms performing Internal-only R&D (the blue line) has been increasing over the years, especially after the expansion of the Dutch Innovation Box Policy in 2010. We can also see a decrease in the share of firms performing no R&D at all, especially after the expansion, although it increases again in the later years (from 2018 to 2020). As for the share of firms performing both R&D, we see an increasing trend post 2010 but falling in 2018 and 2020. Finally, the share of firms performing only external R&D is persistently small over the sample period.

Facts 3 (R&D activities persistence) *Past R&D activities influence current R&D activities.*

Table 2: OLS: Persistence of R&D modes

OLS	***Dep. var***			
	No R&D (t)	**Internal-only (t)**	**External-only (t)**	**Both (t)**
No R&D (t-1)	0.4202^{***} (0.0296)			
Internal-only (t-1)		0.2788^{***} (0.0366)		
External-only (t-1)			0.1780^{**} (0.0561)	
Both (t-1)				0.3538^{***} (0.0351)
Year FE	Yes	Yes	Yes	Yes
Sub-Industry FE	Yes	Yes	Yes	Yes

Notes.—OLS of the current period of R&D modes on the previous period of R&D modes. Standard errors are in parentheses. I use heteroskedasticity and autocorrelation-consistent (HAC) standard errors. Significance level: $^{***} : \alpha = 0.001$, $^{**} : \alpha = 0.01$, $^{*} : \alpha = 0.05$, $^{\cdot} : \alpha = 0.1$.

Fact 3 is summarized by Table 2[11]. Table 2 provides an OLS regression of the current period of R&D modes on the previous period of R&D modes. We can see that they are all positive and statistically significant. Particularly, if a firm chooses no R&D at all in the current period, the probability of choosing no R&D at all in the next period is 42.02%. Similar interpretation also holds for other R&D modes; 27.88% for internal-only R&D, 17.80% for external-only R&D, and 35.38% for both R&D.

Facts 4 (Complementarity of Internal and External R&D) *Reduced-form evidence of com-*

[11] Similar result also holds if I perform probit instead of OLS. See Appendix A

plementarity between Internal and External R&D.

Table 3: Reduced-form of Complementarity of Internal and External R&D

	Dependent Variable		
	$log(VA)$	**Share New Product**	
	OLS	**OLS**	**Tobit (RE)**
No R&D	9.822***	15.92***	12.81***
	(0.2313)	(3.678)	(2.31)
Internal-only R&D	9.892***	15.36**	25.56***
	(0.2326)	(3.605)	(2.09)
External-only R&D	10.46***	13.82**	18.75***
	(0.3031)	(4.759)	(3.55)
Both R&D	10.33***	18.00***	30.93***
	(0.2360)	(3.612)	(2.14)
Year F.E	Yes	Yes	Yes
H0: Complementarity (p-value)	0.38	0.19	0.44

***Notes*.**—Significance level: $^{***}: \alpha = 0.001$, $^{**}: \alpha = 0.01$, $^{*}: \alpha = 0.05$, $^{\cdot}: \alpha = 0.1$. The dependent variable is the share of new product on revenue $\in [0, 100]$. Standard errors are in parentheses. I use heteroskedasticity and autocorrelation-consistent (HAC) standard errors. The null hypothesis, $H0$, of complementarity is that internal and external R&D are complements.

Fact 4 is summarized by Table 3. The table provides a simple, reduced-form results test for complementarity between Internal and External R&D. To do so, I follow similar approaches used by Arora (1996), Athey and Stern (1998), and Cassiman and Veugelers (2006) based on the theoretical work done by Milgrom and Roberts (1990, 1995)[12]. The

[12]Details on the theoretical and empirical implementation of Fact 4 can be found in Appendix B.

four parameters of interest are all positively significant. A quick calculation using the estimated parameters reveals that internal and external R&D are complementary. To empirically test the relationship, I construct a null hypothesis that complementarity holds. Then, I conduct a Wald test for the condition in Equation (14). Using the χ^2-statistic retrieved from the panel (random effect) Tobit and the sign from the Wald test, I can get the $p-$value of the test. The last row of Table 3 shows that the conclusion of complementarity between internal and external R&D holds. My result echoes the findings by Cassiman and Veugelers (2006), Hagedoorn and Wang (2012), and Love et al. (2014).

Discussion on Identification.—However, the above reduced-form results are not without important caveats. First, while ignoring the censored part of the data, running a pooled-OLS gives biased and inconsistent estimates. The main reason is that the censored sample is not representative of the population[13]. I address the issue by running a Panel (Random Effect) Tobit model. Even though I have tried to reduce bias by using Tobit and exploiting the panel structure of the data, the endogeneity problem is not well resolved. Second, adding controls do not also improve the critical identification issue. Finally, as pointed out by Athey and Stern (1998), there is still a risk that these R&D activities are influenced by unobserved heterogeneity. As such, we have to be cautious while interpreting this result. The above result and its caveats are my primary motivation to develop the dynamic structural model discussed in the next section.

[13]There are more disturbances above the (true) regression line. In this case, we have a truncated distribution, while OLS places equal weights on positive and negative disturbances.

3 Model

In this section, I present my model. The model has two parts; a static and a dynamic part. In the static part, I discuss the supply and demand sides of the model. In particular, I highlight the discussion on the firm's revenue and profit under the assumption of monopolistic competition. I then move to the dynamic part of the model where I explain the relationship between R&D modes, the choice of innovation, productivity evolution, and -subsequently- the firm's revenue and profit. In this part, I outline the dynamic discrete choice employed in this model. This part contains insights on fixed costs of investment incurred whenever a firm decides to perform any R&D and the cost-complementarity of R&D.

3.1 Static Decisions: Supply and Demand

The general structure of the static part follows Aw et al. (2011), Boler et al. (2015), and Peters et al. (2017)[14]. In particular, I assume a monopolistic competition in the firm's static decisions. We can think of monopolistic competition as approximating a market in which strategic interactions among firms are weak (see Zhelobodko et al. (2012) and Thisse and Uschev (2018) for the discussion of the general case of monopolistic competition)

[14]***Alternative Demand System***.—One might argue that the demand side of my model is not very 'microfounded' as in the standard empirical IO literature since I am using a generic CES utility function. As shown by Anderson et al. (1992) and De Loecker (2011), the model (and subsequently its empirical implementation) of my approach can be thought as an equivalent of the standard discrete choice model often used in the empirical demand estimation literature. In particular, we can think of the demand elasticity in this model, η, as the same as in the Berry (1994)and Berry et al. (1995) models. The main difference is that this model does not distinguish between the cross- and ow-price elasticities. The approach employed in this paper can be generated from a standard logit model of consumer choice (see Appendix E). It is crucial to understand that the reason I use the CES-like approach stems from the lack of data on prices of output and its quantities at the firm level, which precludes the possibility to construct a random utility model of consumer choice a la Berry et al. (1995).

3.1.1 Demand

The representative consumer has a CES-like utility function. By implication, the demand curve faced by firm i is then assumed to follow the Dixit-Stiglitz form. That is,

$$Q_{it} = Q_t \left(\frac{P_{it}}{P_t} \right)^{\eta} \tag{1}$$

where Φ_t is the industry aggregate (i.e., the aggregate output of the industry over the aggregate price of the industry), P_{it} is the firm's output price, and η is the elasticity of demand which is assumed to be constant for all firms in the industry.

3.1.2 Supply

Now, suppose firm i's (log of) marginal cost is defined as follows

$$c_{it} = c(k_{it}, l_{it}, w_t) - \omega_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_w ln(w_t) - \omega_{it} \tag{2}$$

where k_{it} is the log of firm's capital stock, l_{it} is the log of the number of FTE workers, w_t is a vector of variable input prices common to all firms, and ω_{it} is the firm's productivity. The firm is assumed to produce a single output. There are several sources of cost heterogeneity in this model[15]. The first one is coming from the firm's capital stock which is directly observable in the data. The third source is from the number of workers the firms have, which is also directly observable in the data. The third source is the firm's productivity which is observed by the firm, but not observable by the econometrician. Notice here that the more productive the firm, the lower the marginal cost faced by the firm. The marginal cost does not vary with the firm's output level implying that demand shocks

[15]***Alternative Supply-Side*** .—The lack of information on prices, the number of products each firm produces, and the quality of each product precludes an analysis of the supply-side as in the standard empirical IO literature. For example, the absence of firm's output price makes it hard to model the supply-side as an oligopoly. In this model, I also assume a single-product firm throughout the economy since I do not observe the number of products.

in one market do not affect the static output decision in other markets. Therefore, I can compute revenue and profits in each market independently of the output levels in other markets.

3.1.3 Revenue

Using information from the demand-side and the marginal cost, I can get the log of firm's revenue as follows

Results 1 (Revenue equation) *The (log) revenue equation is derived from both the demand and supply sides, and follows the following expression*

$$r_{it} = (\eta+1)ln\left(\frac{\eta}{\eta+1}\right) + ln(\Phi_t) + (\eta+1)\left[\beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_w ln(w_t) - \omega_{it}\right] \quad (3)$$

Proof. See Appendix C for the full derivation. ■

From the above expression, the firm's revenue provides information on its marginal cost, in particular the productivity level ω_{it}. In the empirical implementation of the model, I will estimate the revenue functions and can interpret the source of the unobserved heterogeneity, ω_{it}. Note that while I describe ω_{it} as the firm's productivity, it could also include the quality of the product which would affect the demand for the firm's product, as well as the cost.

3.1.4 Static Profit

I can now recover the profit of the firm using the expression of the firm's revenue above as follows

Results 2 (Static profit equation) *The static profit equation is derived from both the revenue equation and the (log) marginal cost equation, and follows the following expression*

$$\pi_{it} = -\left(\frac{1}{\eta}\right) exp(r_{it}(k_{it}, l_{it}, \omega_{it}; \eta, \beta_0, \beta_k, \beta_l)) \tag{4}$$

Proof. We get the revenue expression by taking the exponent of the log revenue equation from Results 1. We get the cost expression by taking the exponent of the log marginal cost with the quantity from the demand side. To retrieve the static profit, subtract revenue and cost. See Appendix C for the full derivation. ■

The above expression allows me to recover the profit of the firm using estimates of the model and observables in the data. Note that, this profit will be an important ingredient of the firm's decision to choose modes of R&D in the dynamic discrete choice model developed in the next subsections.

3.2 Dynamic Decisions: Dynamic Discrete Choice of R&D modes

As mentioned in Section 2, I try to capture the WBSO through some form of subsidy from the government. In particular, if the firm receives this subsidy, it experiences a decrease in its costs of investing in certain modes of R&D. As such, the following single-agent dynamic discrete choice will incorporate investment costs as the main structural elements.

3.2.1 Setup

I assume that time is discrete with infinite horizon. A finite number of firms are indexed by i. The firm's state space is defined as $s_{it} = (\omega_{it}, k_{it}, l_{it})$, which is endogenously evolves as the firm decides which mode of R&D to choose. ω_{it} is the (discretized) productivity of firm i in a year t. In each year, firm i can choose to do no R&D at all, only internal R&D, only external R&D, or both internal and external R&D.

Each mode of R&D entails specific investment costs. For example, suppose firm i decides to perform an internal R&D. In that case, it needs to invest a certain cost of $\kappa^{internal}$ to procure the internal R&D. If the firm decides to do an external R&D, then, it needs to invest a certain cost of $\kappa^{external}$ in order to perform the external R&D. If the firm decides to do both R&D, it has to pay both type of investment costs. We can think of these costs as organization-specific investments that firms need to pay to perform a particular R&D. For firms that choose not to do no R&D at all, there is no specific investment cost.

There are several possible reasons why a firm decides to do both internal and external R&D. First, both types of R&D may benefit the firm in terms of cost savings or better product quality. For example, a firm with expertise in online ticketing can decide to build a dynamic pricing algorithm from scratch (i.e., an internal R&D). At the same time, this firm can also consult with economists and computer scientists at several universities on the technical know-how on issues and state-of-the-art solutions related to the dynamic pricing algorithm (i.e., an external R&D). Doing both types of R&D allows the firm to gain an additional benefit from faster technological adoption of the dynamic pricing algorithm, even though it incurs an additional investment cost of doing both R&D types. I called this phenomenon as the cost-complementarity of internal and external R&D. On the other hand, it is also possible that doing both internal and external does not translate into any meaningful benefit for the firm. Following Miravete and Pernias (2006), I capture the cost-complementarity of internal and external R&D in a structural parameter $\kappa^{complement}$. In particular, I assume that this parameter $\kappa^{complement}$ can take on the following values.

$$\kappa^{complement} \begin{cases} > 0, & [Complement] \\ = 0, & [Independent] \\ < 0, & [Substitute] \end{cases}$$

In the above expression, three possible values exist for the cost-complementarity parameter, $\kappa^{complement}$. If it is positive, then both types of R&D complement each other. It is also possible that doing both types of R&D does not benefit the firm, i.e., both are independent. I also include in the parameter $\kappa^{complement}$ the possibility that both types of R&D are substitutes.

Each firm draws IID private cost shocks $\epsilon_{it}^{a_{it}}$ which follow a Type-1 Extreme Value. After observing the shocks, firm i take an action $a_{it} \in \{\text{none}, \text{internal-only}, \text{external-only}, \text{both}\}$. Private shocks reflect each firm's informational, managerial, and organizational conditions.

3.2.2 State Transitions

I assume that ω_{it} follows a controlled Markov process. In particular, the distribution of ω_{it} can be written as $G_\omega(\omega_{it} \mid \mathcal{I}_{it-1}) = G_\omega(\omega_{it} \mid \omega_{it-1}, \text{none}_{it-1}, \text{int}_{it-1}, \text{ext}_{it-1}, \text{both}_{it-1})$, where $\mathcal{I}_{it}$ is an information set which contains the information that the firm can use to solve its decision problem in period t. I can express the persistent productivity ω_{it} as $\omega_{it} = g_\omega(\omega_{it-1}, \text{none}_{it-1}, \text{int}_{it-1}, \text{ext}_{it-1}, \text{both}_{it-1}) + \xi_{it}$, where $E[\xi_{it} \mid \mathcal{I}_{it-1}] = 0$. Variables $\text{none}_{it-1}, \text{int}_{it-1}, \text{ext}_{it-1}, \text{both}_{it-1}$ are indicator variables (in period $t-1$) that refer to the decision of the firm to choose no R&D at all, only internal R&D, only external R&D, and both R&D, respectively. The random variable ξ_{it} captures the (unanticipated at period $t-1$) stochastic nature of improvement on the firm's persistent productivity ω_{it} in period t. By construction, ξ_{it} does not correlate with ω_{it-1}. Note that $\text{none}_{it-1}, \text{int}_{it-1}, \text{ext}_{it-1}, \text{both}_{it-1}$ are assumed to be predetermined variables; i.e., these variables are realized before ω_{it} is realized and functions of previous period information set; that is, $\{\text{none}_{it-1}, \text{int}_{it-1}, \text{ext}_{it-1}, \text{both}_{it-1}\} = \mathbb{X}(\mathcal{I}_{it-1}) \in \mathcal{I}_{it}$. Therefore, both variables also do not correlate with ξ_{it}.

3.2.3 Dynamic Programming Problem

Firms make their dynamic discrete choices to maximize their expected values. The future stream of profits is discounted by a factor $\beta \in (0, 1)$. The following Bellman equations characterize the dynamic programming problems of each firm

$$\begin{aligned} V(s_{it}) = \pi_{it}(s_{it}) \\ + \max \Big\{ & \underbrace{\beta EV^{\text{no R\&D}}(s_{it}) + \epsilon_{it}^{\text{no R\&D}}}_{\text{No R\&D}}; \\ & \underbrace{-\kappa^{\text{internal}} + \beta EV^{\text{internal}}(s_{it}) + \epsilon_{it}^{\text{internal}}}_{\text{Internal-only}}; \\ & \underbrace{-\kappa^{\text{external}} + \beta EV^{\text{external}}(s_{it}) + \epsilon_{it}^{\text{external}}}_{\text{External-only}}; \\ & \underbrace{-\kappa^{\text{internal}} - \kappa^{\text{external}} + \kappa^{\text{complement}} + \beta EV^{\text{both}}(s_{it}) + \epsilon_{it}^{\text{both}}}_{\text{Both}} \Big\} \end{aligned} \tag{5}$$

As I have explained above, key parameters on this dynamic discrete choice R&D model are the specific investment costs of internal R&D ($\kappa^{internal}$), the specific investment costs of external R&D ($\kappa^{external}$), and the cost-complementarity parameter ($\kappa^{complement}$). Here, I also assume that unobservables ϵ_{it}^{a} are additive.

I follow Rust (1987, 1994) in exploiting the property of the logit errors, $\epsilon_{it}^{a_{it}}$, and the assumption of the conditional independence over time. I get a closed-form expression for the expected value *before* observing private shocks $\epsilon_{it}^{a_{it}}$ as follows (the McFadden's social surplus)

$$\begin{aligned} EV(s_{it}) = \pi_{it}(s_{it}) + \gamma^{\text{Euler}} \\ + ln\Big[exp(\overline{V}_{it}^{no}) + exp(\overline{V}_{it}^{in}) + exp(\overline{V}_{it}^{out}) + exp(\overline{V}_{it}^{both})\Big] \end{aligned} \tag{6}$$

where γ^{Euler} is the Euler's constant. $\overline{V}_{it}^{no}, \overline{V}_{it}^{in}, \overline{V}_{it}^{out}, \overline{V}_{it}^{both}$ represent the deterministic part of the conditional (or "alternative-specific") values in Equation (5). As for the expected value (EV), I can define it as follows

$$
\begin{aligned}
EV^{\text{no R\&D}} &= \int_{\omega} V(s_{it+1})dG(\omega_{it+1} \mid \omega_{it}, a = \text{no R\&D}_{it}) \\
EV^{\text{internal}} &= \int_{\omega} V(s_{it+1})dG(\omega_{it+1} \mid \omega_{it}, a = \text{internal-only}_{it}) \\
EV^{\text{external}} &= \int_{\omega} V(s_{it+1})dG(\omega_{it+1} \mid \omega_{it}, a = \text{external-only}_{it}) \\
EV^{\text{both}} &= \int_{\omega} V(s_{it+1})dG(\omega_{it+1} \mid \omega_{it}, a = \text{both}_{it})
\end{aligned}
\tag{7}
$$

Note that the term $dG_{\omega}(\cdot)$ can be thought of as the transition probability or the previously discussed state transitions.

I can now define the conditional choice probabilities as follows

Results 3 (Conditional choice probabilities) *The conditional choice probabilities can be expressed as follows*

$$
\begin{aligned}
Pr(a_{it} = action) = \frac{exp(\overline{V}_{it}^{action})}{exp(\overline{V}_{it}^{no}) + exp(\overline{V}_{it}^{in}) + exp(\overline{V}_{it}^{out}) + exp(\overline{V}_{it}^{both})} \\
, \qquad \forall a_{it} \in \{no\ R\&D, internal, external, both\}
\end{aligned}
\tag{8}
$$

Proof. The full derivation of the probability can be found in the Appendix F. ■

I use these optimal choice probabilities to construct a likelihood function for the empirical implementation.

4 Empirical Implementation

In the previous section, I have several structural components of my model which need to be estimated. First, from the static decisions of the firm, I have to retrieve the elasticity of demand, η. I also need to estimate the static (myopic) profits of the firm, $\pi_{it}(s_{it})$. Before moving to the dynamic part, we need to retrieve information regarding the transition probability. Finally, I will recover the main parameters of interest from the dynamic part ($\kappa = (\kappa^{internal}, \kappa^{external}, \kappa^{complement})$).

4.1 Retrieving Elasticity of Demand

Let us discuss the first step outlined above. First, let us recover the elasticity of demand, η.

Results 4 (Elasticity of demand) *The ratio of total variable cost (TVC) to the revenue is defined as follows*

$$\frac{TotalVariableCost}{Revenue} = 1 + \frac{1}{\eta}$$

Proof. From the static part I derived in the previous section, we can see that the ratio of total variable cost to firm's revenue equals $1 + 1/\eta$. Given that the revenue is $P_{it}Q_{it} = R_{it}$ and the cost is $\frac{1+\eta}{\eta}R_{it}$, we can simply take the ratio. ■

I can use the mean variable of the cost-revenue ratio for each industry as an estimate of one plus the inverse of industry demand elasticity. I define the total variable cost as the sum of the nominal intermediate inputs the firm uses and the nominal value of the energy input that the firm uses. As for the revenue, I use the nominal gross output. After retrieving this ratio, it is straightforward to get the demand elasticity η[16].

[16] I can also retrieve the demand elasticity as in Aw et al. (2011); Boler et al. (2015); Peters et al. (2017). Using the first-order condition for profit maximization, we know that the marginal cost equals the marginal revenue in each market. Therefore, the total variable cost is an elasticity-weighted combination of the total

Source of identification.—I can retrieve the parameter η as the implication of the static decisions part of the model, i.e., the monopolistic competition model. The demand elasticity parameter can be directly identified from the data at hand.

4.2 Productivity Estimation

To get the productivity estimates, ω_{it}, I use a similar approach as in Aw et al. (2011), Doraszelski and Jaumandreu (2013), and Peters et al. (2017). First, for an immediate result, we have the following estimating equation.

Results 5 (Estimating equation of productivity) *The estimating equation to retrieve the productivity ω_{it} follows the following expression*

$$\begin{aligned}
\hat{\phi}_{it} = {} & \beta_k^* k_{it} + \beta_l^* l_{it} + \alpha_1 \left(\hat{\phi}_{it-1} - \beta_k^* k_{it-1} - \beta_l^* l_{it-1}\right) \\
& - \alpha_2^* \left(\hat{\phi}_{it-1} - \beta_k^* k_{it-1} - \beta_l^* l_{it-1}\right)^2 \\
& + \alpha_3^* \left(\hat{\phi}_{it-1} - \beta_k^* k_{it-1} - \beta_l^* l_{it-1}\right)^3 \\
& - \alpha_4^* no_{it-1} - \alpha_5^* internal_{it-1} - \alpha_6^* external_{it-1} - \alpha_7^* both_{it-1} - \xi_{it}^*
\end{aligned} \tag{9}$$

the above estimating equation will be estimated using non-linear least squares.

Proof. See Appendix D. ■

Using Results 4 and 5, we can retrieve the productivity as follows

Results 6 (Estimated productivity) *The estimate of productivity can be expressed as the following*

$$\hat{\omega}_{it} = -(1/(\hat{\eta}+1))\hat{\phi}_{it} + \hat{\beta}_k k_{it} + \hat{\beta}_l l_{it} \tag{10}$$

value. We can regress the total variable cost on the revenue as follows

$$TVC_{it} = R_{it}\left(1 + \frac{1}{\eta}\right) + \gamma_c + \gamma_t + \varepsilon_{it}$$

where Q_{it} is the revenue output, γ_c is the sub-industry fixed effect, and γ_t is the time fixed effect.

Proof. See Appendix D. ■

Source of identification.—This approach is essentially a semiparametric one. As noted by Doraszelski and Jaumandreu (2013), the main ingredient for identification is that variables in the parametric part of the model are not perfectly predictable by the variables in the non-parametric part (in a simple regression sense).

4.3 Costs of R&D and Complementarity

In the previous section, we have arrived at the optimal choices probability that needs to be estimated. In order to retrieve the structural parameters, I employ the Maximum Likelihood Estimation approach. I can define the likelihood function for the firms' R&D mode as follows

$$L(a_{it}|s_{it};\kappa) = \prod_{i}^{N}\prod_{t}^{T_i} Pr(a_{it} = action)^{I_{\{a_{it}=action\}}} \tag{11}$$

where $\kappa = (\kappa^{internal}, \kappa^{external}, \kappa^{complement})$ is a vector that summarizes all the parameters of interest. There are two loops in estimating the dynamic discrete choice model. The Maximum Likelihood Estimation serves as the outer-loop in estimating Equation (11). Within each loop of the MLE, there is an inner loop involving the calculation of value functions. Essentially, it is a contraction mapping of the value function described in Equation (6). The algorithm to retain the structural parameters follows a successive approach of the nested-fixed point algorithm (NFXP-SA) as in Rust (1987)[17].

Source of identification.—Before discussing the identification of the model, it is important to note that the dynamic part of my model can be seen as a single-agent dynamic model rather than a fully-pledged dynamic games, since the (myopic) profits of the firm and the

[17]There are several ways to improve the speed of NFXP-SA; the first one is to perform the mathematical programming with equilibrium constraints (MPEC) developed by Su and Judd (2012). Another approach is to change the successive approach algorithm to the Newton-Kantorovich algorithm (NFXP-NK) developed by Iskhakov et al. (2016).

transition probability functions do not depend on other firms' actions, $\mathbf{a}_{-it}$. The single-agent dynamic model can also be viewed as an implication of a monopolistic competition in the static part of the model[18].

For the dynamic part of my model, there are some discussions on identification[19]. First, I do not intend to estimate the discount factor β since the identification of this discount factor is known to be impractical and problematic (see the discussion on the identification of the discount factor by Rust (1994), Magnac and Thesmar (2002), and Abbring and Daljord (2020)). Second, the identification of firms' profit only rely on the identification from the static part of the model. Third, I assume that the distribution of the unobservables, F_ϵ, follows the Type-1 Extreme Value distribution. Fourth, regarding the conditional independence assumption, the realization of one of the state variables, ω_{it}, is independent of the unobservable ϵ_{it}.

[18]A possible way to extend the standard empirical dynamic games á la Ericson and Pakes (1995) is to invoke a notion of oblivious equilibrium (see Weintraub et al. (2008) and its empirical implementation by Chen and Xu (2020)).

[19]As noted by Aguirregabiria et al. (2021), there is a set of sufficient assumptions for identification of single-agent dynamic model; (ID.1) No common knowledge unobservables, (ID.2) Additive unobservables, (ID.3) Known distribution of the unobservables, (ID.4) Conditional independence, (ID.5) Normalization of payoff of one choice alternative, (ID.6) Known time discount factors.

5 Results

5.1 Elasticity of Demand and Innovation Probability

As I have discussed in Sub-section 4.1, I can directly compute the ratio of the total variable cost to the total revenue as the model implies it. The result for the Dutch I(C)T industry is given in Table 4. As I have discussed in the previous section, in my case, the elasticity of demand is equal to both own- and cross-price elasticities in the standard Berry (1994) and Berry et al. (1995) logit and random coefficient models.

Table 4: Estimated Demand Elasticity

	Estimates
η	-1.794^{***} (0.164)

Notes.—The elasticity of demand, η, is derived from $TotalVariableCost/Revenue = 1 + 1/\eta$. The total variable cost consists of the sum of the firm's nominal intermediate inputs and energy. The revenue of the firm is the nominal firm's gross output. Standard errors of the demand elasticity are derived using Delta method.

The estimated demand elasticities for several industries are quite similar in magnitude as in Aw et al. (2011) and Peters et al. (2017), although they are not using the same set of industries. All the estimated parameters are statistically significant. The results on the demand elasticity will then be used for the productivity estimation and the construction of (myopic) firms' profits.

5.2 Productivity Parameters

To retrieve the productivity parameters, I estimate expressions detailed in Results 5 using nonlinear least squares. The result is given in Table 5.

Table 5: Estimated Productivity Parameters

Parameters	**Productivity Estimation** **Dependent var:** ϕ	**Parameters**	**Productivity Estimation** **Dependent var:** ϕ
$\beta_k(k)$	-0.193^{***} (0.012)	$\alpha_5(no\_rd)$	0.345^{***} (0.084)
$\beta_l(l)$	-0.650^{***} (0.025)	$\alpha_6(internal)$	0.384^{***} (0.084)
$\alpha_1(\omega)$	0.704^{***} (0.077)	$\alpha_7(external)$	0.390^{***} (0.102)
$\alpha_2(\omega^2)$	0.051^{*} (0.024)	$\alpha_8(both)$	0.387^{***} (0.085)
$\alpha_3(\omega^3)$	-0.002 (0.0.002)		
Subindustry FE	Yes		
Year FE	Yes		
$SD(\xi)$	0.347		
H0: Complementarity (p-value)	0.54		

Notes.—Significance level: $^{***}: \alpha = 0.001$, $^{**}: \alpha = 0.01$, $^{*}: \alpha = 0.05$, $^{\cdot}: \alpha = 0.1$. Standard errors are in parentheses. I use heteroskedasticity and autocorrelation-consistent (HAC) standard errors. $SD(\xi)$ indicates the standard deviation of the residuals from the estimating Equation (29).

From the result, we can see the following. First, the current period's productivity is influenced by the previous period's productivity. Both α_1 and α_2 are statistically significant. Second, the estimated parameters governing the relationship between the marginal costs and capital and labor are negative and statistically significant. In terms of magnitude, the estimated parameters are quite similar to the estimates of the elasticity of output to capital and labor in recent literature[20]. We can also observe that the coefficients governing firms' mode of R&D (α_5, α_6, α_7, and α_8) are positive and significant. Furthermore, the last row of Table 29 also provides evidence that internal and external R&D complement each other in the realm of productivity via a Wald test[21].

The estimated parameters shown in Table 5 will be used to construct the (discretized) productivity of the dynamic structural model. The standard errors from the (predicted) residuals, shown in the second to the last row of Table 5, will also be used to construct the transition probability.

5.3 Costs of Innovation and Complementarity

First, I consider $30 \times 30 \times 30$ grids of k, ω and l. I set the discount factor to $\beta = 0.95$. I then run the MLE algorithm similar to Rust (1987). The resulting parameters of costs of innovation can be found in Table 6. This table provides information on the dynamic structural parameters; the internal R&D cost, the external R&D cost, and the complementarity parameter.

[20] See for example De Loecker and Warzynski (2012), De Loecker et al. (2020), and Dobbelaere and Mairesse (2013).

[21] The full description of the test can be found in Appendix B and is similar to my reduced-form motivating evidence described in Section 2.

Table 6: Costs of Innovation and Cost-Compelementarity

Parameters	**Costs of R&D and Complementarity**		
	Full Period: 2000 - 2020	**Before Innovation Box: 2000 - 2008**	**After Innovation Box: 2012 - 2020**
$\kappa^{internal}$	0.127^{***}	0.569^{***}	-0.063
	(0.049)	(0.096)	(0.062)
$\kappa^{external}$	2.453^{***}	2.239^{***}	2.695^{***}
	(0.120)	(0.186)	(0.177)
$\kappa^{complement}$	2.295^{***}	2.153^{***}	2.502^{***}
	(0.132)	(0.217)	(0.188)
log-likelihood	-2836.652	-786.940	-1784.994

Notes.—The unit of the estimated parameters are in million of EUR (real). The gradients and Hessian are obtained by finite-difference approximation evaluated at the estimated parameters. Gradients are below $1e-4$. Tilt and radius of curvature for these parameters are below $1e-3$, computed by axial search at each parameter. Standard errors are obtained by computing the square root of the diagonal of the inverse Hessian.

As we can see from Table 6, in the Dutch I(C)T industry, the external R&D costs exceed costs of internal R&D. The estimates suggest that the high cost of doing external R&D is among the main reasons we do not observe many firms performing strategic alliances with other firms or universities, knowledge acquisition from outside of their firms, or outsourcing their research activities to other firms. If we take a look at both the second and third columns of Table 6, the average external R&D costs are ≈ 4 times higher than the average costs of internal R&D faced by the firm, before and after the expansion of the Dutch Innovation Box Policy; that is, 0-0.57 million EUR v. 2.2-2.7 million EUR.

After the expansion of the Dutch Innovation Policy (the third column of Table 6), we observe a significant decrease in the cost of performing internal R&D; that is, from the initial 0.57 million EUR to zero[22]. Another interesting observation is that the cost of external R&D is increasing after the expansion of the Dutch Innovation Box policy. We think that this increase is a direct by-product of the Dutch Innovation Box policy whereby firms are very limited to outsourcing or acquiring knowledge outside the boundary of the firm as explained in Section 2.

In general, we can also think of the estimated costs here as the estimated transaction costs of certain mode of R&D, in the spirit of Coase's theory of the firm. For instance, there might be a hold-up problem associated with conducting external R&D. A potential firm might refrain from contracting out or joint R&D ventures with third parties because by doing so might reduce or give the other parties advantages over their privately-held state of technology. Thus, potentially reducing their own future profits (see the discussion of hold-up problem and property rights by Grossman and Hart (1986)). Another possibility is that the high cost of external R&D reflects haggling and friction due to the complexity and incompleteness of an R&D contract between the firm and third parties (see Bajari and Tadelis (2001) and Tadelis (2002) on this type of procurement contract). We can also think of the high cost faced to perform external R&D as the financial constraints faced by the firm, as argued by Brunner et al. (2023).

Through the lens of transaction costs, we can also explain the estimated costs of internal R&D in the Dutch I(C)T industry, particularly from the implementation of WBSO (from the cost side). After the implementation of the policy, for average firms in the sector, the cost of performing internal R&D is close to zero. The government may have indirectly footed the bill for firms to conduct this R&D mode. For example, by providing a tax reduction for participating firms, firms can now setup their internal R&D shop and hire scientists or technicians to run the unit. Recall from Section 2, the WBSO program entails

[22] Another strong possible reasoning of how we arrived at zero cost of internal R&D is that we see fewer firms performing no R&D at all, i.e., fewer variations in the decisions to do no R&D at all impacting our ability to nail the estimates of internal R&D cost.

firms to pay a lower wage rate and national insurance contributions.

Table 6 also gives us a picture of the cost-complementarity parameter (in the last row of each panel). We can see that both internal and external R&D might complement each other from the cost side, i.e., the estimated parameter is positive ($\kappa^{complement} > 0$). If we consider the full period sample, the average total cost of performing both types of R&D is $\kappa^{internal} + \kappa^{external} - \kappa^{complement} = 0.285$ million EUR. Similarly we can also compute the average total cost before and after the expansion of the Dutch Innovation Box Policy. Before the expansion, the average total cost of performing both types of R&D was 0.655 million EUR, and after the implementation, is 0.193 million EUR. From these estimates, we can infer that it is cheaper to perform only internal R&D compared to performing both R&D. However, these two options are cheaper compared to performing only external R&D.

6 Simulation Analysis

The simulation analysis tries to mimic some elements of the Dutch Tax Incentives for Innovation scheme. In this version of the paper, I tried to approach the WBSO R&D remittance program (the cost side) as a reduction in the cost of innovation activities. In particular, I investigate two things: 1. what would happen to the share of R&D activities in the economy following this program, and 2. what would happen to the welfare following this program. I also explore what would happen if we mute the cost-complementarity between internal and external R&D.

I consider three cases of an R&D 'subsidy.' The first case is a uniform five percent reduction in the cost of R&D activities (i.e., both internal and external R&D). This case reflects the 'first-best' scenario that the government could implement without any jurisdiction consideration in implementing the program. The second case is a 20% reduction in the cost of internal R&D, while keeping the cost of external R&D the same. This case tries to mimic what the Dutch government has implemented regarding the overall program outlined in the Dutch Tax Incentives for Innovation scheme. Finally, the third case is a five percent reduction in the cost of external R&D.

6.1 Change in the share of R&D activities

First, let us discuss the change in the share of R&D activities in the economy. Table 7 summarizes the results of the simulation exercise. The first column ('Actual Share') denotes the initial share of each R&D activity in the economy; throughout the sample period, 36.8% of firms perform no R&D at all, 32% of firms perform only internal R&D, 3.2% of firms perform only external R&D, and 27.7% of firms perform both internal and external R&D.

Table 7: Change in the share of R&D activities

Change in the Share of R&D Activities	**Actual Share**	$\Delta^c = share^c - share$					
		5% uniform		**20% internal**		**5% external**	
		Base	***No Comp.***	***Base***	***No Comp.***	***Base***	***No Comp.***
No R&D	0.368	-0.016	0.115	-0.006	0.116	-0.015	0.116
Internal-only	0.324	-0.012	0.104	0.003	0.113	-0.012	0.103
External-only	0.032	0.002	0.015	-0.001	0.01	0.002	0.015
Both	0.277	0.024	-0.235	0.003	-0.239	0.024	-0.235

Notes.—Base: changes only to the costs. No Comp: Set the cost-complementarity to zero. Negative sign indicates ”decreasing”.

Following the first case, we can see that a uniform reduction of five percent in cost changes the share of R&D activities in several directions. We see a decrease in the share of no R&D activity by 1.6% and also a fall in the share of firms performing only internal R&D by 1.2%. At the same time, we see an increase in the share of firms performing only external R&D by 0.2% and a 2.4% increase in the share of firms performing both types of R&D. Overall, the result suggests that firms that initially choose not to do R&D will choose to perform one or two types of R&D due to the reduction of the cost. Similarly, a decrease in the share of firms performing only internal R&D might suggest they are now performing both types of R&D due to the reduction in the financial constraints.

A similar interpretation holds for both the second and third cases, i.e., 20% reduction in costs for internal-only R&D and a five percent reduction for external-only R&D, respectively. The main difference between the first, the second, and the third cases is that the reduction in the share of firms performing no R&D at all is bigger for the first case, followed by the third case, and the second case is the last.

Another interesting phenomenon is how cost-complementarity is an important element to consider. Without this cost-complementarity, we see a completely different picture in the share of firms performing R&D activity in the economy. Let's take a look at the first case (i.e., 5% uniform); instead of reducing the share of firms with no R&D activity at all, we see an 11.5% increase in the share. We also see that the share of firms performing only internal R&D increased by 10.4%. Furthermore, the share of firms performing both types of R&D drops by 23.5%. A similar phenomenon holds across the other two cases. Overall, this exercise suggests that without cost-complementarity, firms would not perform both types of R&D, and perhaps resort to performing no R&D at all.

6.2 Change in Welfare

Now, let us discuss the change in welfare following the three exercises. Table 8 summarizes the results of the simulation exercise. I define the change in welfare as $\Delta V^c = (V^c - V)/V$, where V^c and V are the deterministic part of the value function in the simulation and actual scenario, respectively.

Table 8: Change in Value

	$\Delta V^c = (V^c - V)/V$					
	5% uniform		**20% internal**		**5% external**	
Change in	***Base***	***No Comp.***	***Base***	***No Comp.***	***Base***	***No Comp.***
Value	2.735%	1.022%	0.968%	0.923%	2.49%	0.792%

Notes.—Base: changes only to the costs. No Comp: Set the cost-complementarity to zero. Negative sign indicates "decreasing".

In the first case scenario, we can see that a uniform reduction of five percent in the cost of R&D increases the welfare by 2.74%. The second-best scenario is a reduction only for the external R&D; that is, the welfare increases to 2.49%. The worst scenario is the 20% reduction only for the cost of performing internal R&D.

An interesting phenomenon is how cost-complementarity plays a crucial role in welfare. Without cost-complementarity, the first case will only lead to a change in welfare by 1.022%. Meanwhile, 20% reduction only for the internal R&D cost will lead to 0.923%, a similar result to the case where we consider cost-complementarity (i.e., 0.97% change in welfare). The contrasting result is for the third case; without considering cost-complementarity, providing a five percent reduction only for the external R&D cost will only translate to an increase in the welfare by 0.79%, instead of the initial 2.49% increase in welfare where we considered complementarity between both internal and external R&D.

7 Conclusion

This paper analyzes the costs and benefits of internal and external R&D. I employ reduced-form specifications to understand whether such activities are complements. To rationalize the reduced-form result and understand the origin of R&D complementarities, I build and estimate a structural model.

My empirical model is tailored to exploit the microdata collected in the Dutch Production Statistics and the Community Innovation Surveys. The model has three key structural parameters: the internal R&D-specific cost, the external R&D-specific cost, and the cost-complementarity parameter. I find that the cost of performing external R&D is ≈ 4 times higher than the associated costs of conducting internal R&D. This high cost faced by firms is why we do not find many firms contract out their research to any strategic partners. My estimated costs also reflect the associated transaction costs of performing such contract.

The estimated structural parameters allow me to perform counterfactual exercises that try to mimic an element of the Dutch Tax Incentives for Innovation scheme. I find that a uniform subsidy, i.e., a subsidy on both internal and external R&D costs, leads the most change in the share and in the welfare of R&D active firms, followed by subsidizing only external R&D costs. I also find that cost-complementarity plays an important role in these exercises, without considering complementarity between internal and external R&D, both will reduce the total changes in the share of R&D active firms and the overall welfare in the economy.

Many interesting research avenues can be explored further. For instance, I would like to understand the *ex-post* policy evaluation of the Dutch Tax Incentives for Innovation scheme overall on the firms' innovation portfolio. I would also like to understand whether this program creates an adverse incentives for firms to mislabel their other expenditures as innovation-related expenses.

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A Probit: Persistence of R&D modes

Probit	*Dep. var*			
	No R&D (t)	**Internal-only (t)**	**External-only (t)**	**Both (t)**
No R&D (t-1)	1.171*** (0.0895)			
Internal-only (t-1)		0.7635*** (0.0950)		
External-only (t-1)			1.198*** (0.2105)	
Both (t-1)				1.017*** (0.0821)
Year FE	Yes	Yes	Yes	Yes
Sub-Industry FE	Yes	Yes	Yes	Yes

B Details on the Reduced-form Testing of Complementarity between Internal and External R&D

I now provide a simple, reduced-form test for complementarity between $InternalR\&D$ and $ExternalR\&D$. To do so, I follow similar approaches used by Arora (1996), Athey and Stern (1998), and Cassiman and Veugelers (2006). First, let us define Π as a firm's profit function that is assumed to be supermodular. The arguments of this profit function are $InternalR\&D$ and $ExternalR\&D$. Then, as shown by Milgrom and Roberts (1990, 1995), $InternalR\&D$ and $ExternalR\&D$ are complementary only if

$$\Pi(1,1) - \Pi(0,1) \geq \Pi(1,0) - \Pi(0,0) \tag{12}$$

The main intuition of Equation (12) is that adding an activity while the other activity is already being performed has a higher incremental effect on profits than adding the activity in isolation. In our case, performing External R&D on top of the Internal R&D can only be deemed more profitable (compared to profits from performing *only* Internal R&D) if the above condition holds.

In the empirical implementation, I run the following specification

$$\begin{aligned} y_{ijt} = &\ \theta_{11} BothR\&D_{ijt} + \theta_{10} InternalR\&D_{ijt} \\ &+ \theta_{01} ExternalR\&D_{ijt} + \theta_{00} NoR\&D_{ijt} + \zeta_t + \varepsilon_{ijt} \end{aligned} \tag{13}$$

where the dependent variable y_{ijt} is either value-added or the share of the new products produced by each firm in a given year. ζ_t indicate year-fixed effect. Since the dependent variable, of the share of the new products ranges from 0 to 100, a standard OLS will yield biased estimates. Given this concern, and the ability to exploit the panel structure of the model, I estimate Equation (13) using a Panel (Random Effect) Tobit model.

Testing for the complementarity boils down to checking if

$$\theta_{11} - \theta_{10} \geq \theta_{01} - \theta_{00} \tag{14}$$

The testing condition itself is straightforward to implement since it is essentially an inequality test for four coefficients.

C Details on the Derivation of the Static Part

Proof of Result 1: Revenue Equation.. First, recall the demand function is the following:

$$
\begin{aligned}
Q_{it} &= Q_t \left(\frac{P_{it}}{P_t}\right)^{\eta} \\
&= \frac{Q_t}{P_t^{\eta}} P_{it}^{\eta} \\
&= \Phi_t P_{it}^{\eta}
\end{aligned}
\tag{15}
$$

Each firm maximizes its profit,

$$
\pi_{it} = P_{it} Q_{it} - C_{it} Q_{it} \tag{16}
$$

We can substitute Q_{it} using the expression we have in the demand function, we have the following.

$$
\pi_{it} = \Phi_t P_{it}^{1+\eta} - C_{it} \Phi_t P_{it}^{\eta} \tag{17}
$$

Take the first-order condition with respect to P_{it}, we have the following.

$$
\frac{\partial \pi_{it}}{\partial P_{it}} = (1+\eta) \Phi_t P_{it}^{\eta} - \eta C_{it} \Phi_t P_{it}^{\eta-1} = 0 \tag{18}
$$

Simple algebra of the above first-order condition provides us with the following relation between price P_{it} and marginal cost C_{it}.

$$
P_{it} = \frac{\eta}{\eta+1} C_{it} \tag{19}
$$

Now, revenue can be expressed as $R_{it} = P_{it} Q_{it}$. We can further re-write the revenue equation, using both the simplified expression of demand function and the relationship between price and marginal cost, as follows.

$$
\begin{aligned}
R_{it} &= P_{it} Q_{it} \\
&= \Phi_t P_{it}^{1+\eta} \\
&= \Phi_t \left(\frac{\eta}{\eta+1} C_{it}\right)^{1+\eta}
\end{aligned}
\tag{20}
$$

Take the log of the above expression and recall the functional form of log of marginal cost,

$ln(C_{it}) = c_{it}$, we have the following.

$$
\begin{aligned}
r_{it} &= ln(R_{it}) \\
&= (1+\eta)ln\left(\frac{\eta}{\eta+1}\right) + ln(\Phi_t) \\
&+ (1+\eta)ln\Big[\beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_w ln(w_t) - \omega_{it}\Big]
\end{aligned}
\tag{21}
$$

We now have the final expression of Results 1. ■

Proof of Result 2: Static Profit Equation.. First, we define profit as follows.

$$
\pi_{it} = P_{it}Q_{it} - C_{it}Q_{it} \tag{22}
$$

using the relation between price and marginal cost, we can rewrite the above expression as follows.

$$
\begin{aligned}
\pi_{it} &= P_{it}Q_{it} - \frac{\eta+1}{\eta}P_{it}Q_{it} \\
&= R_{it} - \frac{\eta+1}{\eta}R_{it} \\
&= -\frac{1}{\eta}R_{it}
\end{aligned}
\tag{23}
$$

Then, using the expression derived in Results 1, we have the following.

$$
\pi_{it} = -\frac{1}{\eta}exp(r_{it}(k_{it}, l_{it}, \omega_{it}, w_t, \Phi_t; \eta, \beta_0, \beta_k, \beta_l, \beta_w)) \tag{24}
$$

As we will see later, r_{it} can be reduced further to only depend only on k_{it}, l_{it}, ω_{it}, and parameters $\eta, \beta_0, \beta_k, \beta_l$. In other words, w_t and Φ_t will be absorbed as time-specific effects. Therefore, we can now have the final expression of π_{it} as follows.

$$
\pi_{it} = -\frac{1}{\eta}exp(r_{it}(k_{it}, l_{it}, \omega_{it}; \eta, \beta_0, \beta_k, \beta_l)) \tag{25}
$$

We now have the final expression of Results 2.

■

D Details on the Productivity Estimation

First, the expression in Equation (3) is appended with an IID error term u_{it}. That is,

$$
\begin{aligned}
r_{it} &= (\eta+1)ln\left(\frac{\eta}{\eta+1}\right) + ln(\Phi_t) \\
&+ (\eta+1)\Big[\beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_w ln(w_t)\Big] \underbrace{-(\eta+1)\omega_{it} + u_{it}}_{\text{Composite Error Term}}
\end{aligned} \tag{26}
$$

I borrow insights from Olley and Pakes (1996) to re-write the unobserved productivity, ω_{it}, in terms of some observables which are correlated with it. In particular, as in Levinsohn and Petrin (2003); Ackerberg et al. (2015), and Gandhi et al. (2021), I use the firm's intermediate input, m_{it}, and the firm's energy input, n_{it}, as firm i's choice of this variable input depends on the level of productivity. The essence of Olley and Pakes (1996) is that this observable, i.e., intermediate input expenditures of the firm, contains information on its productivity level[23]. Then, I can write the level of productivity, conditional on the capital stock, as a function of the variable input levels, $\omega_{it}(k_{it}, l_{it}, m_{it}, n_{it})$. This method allows me to use the intermediate inputs of the firm to control for the productivity in Equation (26). I then combine the demand elasticity terms into an intercept γ_0, and the time-varying aggregate demand shock and market-level factor prices into a set of time and industry dummies ($D_t^{(1)}$ and $D_j^{(2)}$), I can re-write Equation (26) as follows

$$
\begin{aligned}
r_{it} &= \gamma_0 + \sum_{t=1}^{T}\gamma_t^{(1)}D_t^{(1)} + \sum_{j=1}^{J}\gamma_j^{(2)}D_j^{(2)} + (\eta+1)\Big[\beta_k k_{it} + \beta_l l_{it} - \omega_{it}\Big] + u_{it} \\
&= \gamma_0 + \sum_{t=1}^{T}\gamma_t^{(1)}D_t^{(1)} + \sum_{j=1}^{J}\gamma_j^{(2)}D_j^{(2)} + h(k_{it}, l_{it}, m_{it}, n_{it}) + \nu_{it}
\end{aligned} \tag{27}
$$

The function $h(\cdot)$ represents the combined effect of capital and productivity. In particular, I approximate this function with third-order polynomials. I estimate Equation (27) with a simple OLS. From here, I can get a fitted value of the $h(\cdot)$ where I denote it as $\hat{\phi}_{it}$. This $\hat{\phi}_{it}$ is an estimate of $(\eta+1)\Big[\beta_k k_{it} + \beta_l l_{it} - \omega_{it}\Big]$.

As discussed in the previous section, I assume that ω_{it} follows a controlled Markov process. I assume the distribution of ω_{it} can be written as $G_\omega(\cdot)$. For the empirical imple-

[23]There are two crucial assumptions for this insight to work. The first one is the scalar unobservability assumption. The intuition behind this assumption is that in choosing the input, firms only require one unobservable (in our case ω_{it}). The second assumption is the strictly monotone assumption. This assumption dictates that the intermediate input must be strictly monotone in ω. Levinsohn and Petrin (2003) show that the assumption is not too restrictive in the case of manufacturing plants in Chile. These assumptions allow us to invert the intermediate input, $m_{it} = \mathbb{M}_t(k_{it}, l_{it}, \omega_{it})$.

mentation of my model, I model the evolution of ω_{it} as follows

$$\begin{aligned}
\omega_{it} &= g_\omega(\omega_{it-1}, \mathrm{no}_{it-1}, \mathrm{int}_{it-1}, \mathrm{ext}_{it-1}, \mathrm{both}_{it-1}) + \xi_{it} \\
&= \alpha_0 + \alpha_1\omega_{it-1} + \alpha_2(\omega_{it-1})^2 + \alpha_3(\omega_{it-1})^3 \\
&\quad + \alpha_4\mathrm{no}_{it-1} + \alpha_5\mathrm{int}_{it-1} + \alpha_6\mathrm{ext}_{it-1} + \alpha_7\mathrm{both}_{it-1} + \xi_{it}
\end{aligned} \tag{28}$$

Here, I assume that ξ_{it} is IID across time and firms and is drawn from a normal distribution with zero mean and variance σ_ξ^2.

I can now substitute the productivity ω_{it} using $\hat{\phi}_{it}$. That is, substituting $\omega_{it} = -(1/(\eta + 1))\hat{\phi}_{it} + \beta_k k_{it} + \beta_l l_{it}$ to the Equation (28). After some algebra, I obtain the following estimating equation

$$\begin{aligned}
\hat{\phi}_{it} &= \beta_k^* k_{it} + \beta_l^* l_{it} + \alpha_1\left(\hat{\phi}_{it-1} - \beta_k^* k_{it-1} - \beta_l^* l_{it-1}\right) \\
&- \alpha_2^*\left(\hat{\phi}_{it-1} - \beta_k^* k_{it-1} - \beta_l^* l_{it-1}\right)^2 \\
&+ \alpha_3^*\left(\hat{\phi}_{it-1} - \beta_k^* k_{it-1} - \beta_l^* l_{it-1}\right)^3 \\
&- \alpha_4^*\mathrm{no}_{it-1} - \alpha_5^*\mathrm{internal}_{it-1} - \alpha_6^*\mathrm{external}_{it-1} - \alpha_7^*\mathrm{both}_{it-1} - \xi_{it}^*
\end{aligned} \tag{29}$$

where the star, $(*)$, represents that the coefficients α and β are multiplied by $(\eta + 1)$[24]. The above expression will be estimated with nonlinear least squares. From the estimated parameters, I can recover an estimate of productivity for each observation as follows

$$\hat{\omega}_{it} = -(1/(\hat{\eta} + 1))\hat{\phi}_{it} + \hat{\beta}_k k_{it} \tag{30}$$

Source of identification.—This approach is essentially a semiparametric one. As noted by Doraszelski and Jaumandreu (2013), the main ingredient for identification is that variables in the parametric part of the model are not perfectly predictable by the variables in the non-parametric part (in a simple regression sense). Apart from a similar identification as in Olley and Pakes (1996) and Doraszelski and Jaumandreu (2013), the estimating equation in Equation (29) makes use of information on the demand elasticity. This demand elasticity is identified, and the source of its identification has been discussed in the previous subsection.

[24] With some exceptions for $\alpha_2^* = \alpha_2(\eta + 1)^{-1}$ and $\alpha_3^* = \alpha_3(\eta + 1)^{-2}$

E Alternative Demand System

I follow a standard discrete choice model of consumer choice a la Berry (1994) and Berry et al. (1995). The indirect utility function can be described as follows

$$V_{ijt} = \eta p_{jt} + \xi_{ijt} + \varepsilon_{jt} \tag{31}$$

where p_{jt} is the logarithmic price, ξ_{ijt} is the idiosyncratic preference shock which follows a Type-1 Extreme Value distribution, and ε_{jt} is an unobserved demand shock.

Using the Berry's inversion as in Berry (1994) for the above expression, I can get a well-known expression for the market share of good j relative to the outside option as follows

$$ln(ms_{jt}) - ln(ms_{ot}) = \eta p_{jt} + \xi_{ijt} + \varepsilon_{jt} \tag{32}$$

Consider only the case of single-product firm ($i = j$). From the log of market share, I can re-arrange the above expression using that $ln(ms_{it}) = ln(q_{it}) - ln(Q_t)$, as in the demand expressed in Equation (**??**). Then, I obtain the expression for log price $ln(p_{jt})$. Note that $ln(r_{it}) = ln(p_{it}q_{it})$. Rearranging this expression with information on the expression of $ln(p_{it})$ and Equation (**??**), we get the following expression for log revenue

$$ln(r_{it}) = \kappa_0 + \kappa_k ln(k_{it}) + \omega^*_{it} + u_{it} \tag{33}$$

where $\kappa_0 = \frac{1}{|\eta|} ln(ms_{ot})$, $\kappa_k = (\eta + 1)\beta_k$, and $\omega^*_{it} = -(\eta + 1)\omega_{it}$. The above expression is similar to the estimating equation denoted in Equation (27) absence of the year fixed effects. As noted by De Loecker (2011), the total output enters in exactly the same way, leading to identification of η in the production function framework. Anderson et al. (1992) give remark that in the usual logit demand structure, the estimated parameter η is used to compute own and cross-price elasticities. However, in this setup with log prices in the indirect utility function, they are identical.

F Derivation of the Probability

As I have outlined in the main text, suppose $\varepsilon_{it}(a_{it})$ is IID that follows a Type 1 Extreme Value distribution. The density of each private shock is $f(\varepsilon_{it}) = e^{-\varepsilon_{it}}e^{-e^{-\varepsilon_{it}}}$. The cumulative distribution is $F(\varepsilon_{it}) = e^{-e^{-\varepsilon_{it}}}$.

Suppose firm i chooses action *both*. In choosing this particular alternative, it must be that the value of doing *both* is higher than other alternatives than itself. We can express it as follows

$$
\begin{aligned}
Pr(a_{it} = both) &= Prob\left(\overline{V}_{it}^{both} + \varepsilon_{it}^{both} > \overline{V}_{it}^{j} + \varepsilon_{it}^{j}, \forall j \neq both\right) \\
&= Prob\left(\varepsilon_{it}^{j} < \varepsilon_{it}^{both} + \overline{V}_{it}^{both} - \overline{V}_{it}^{j}, \forall j \neq both\right)
\end{aligned}
$$

where $\overline{V}_{it}^{both}$ and $\overline{V}_{it}^{j}, \forall j \neq both$ are the deterministic part of the conditional (or "alternative-specific") values.

Since ε's are independent, we can express the conditional probability as follows

$$
Pr(a_{it} = both|\varepsilon_{it}^{both}) = \prod_{j\neq both} e^{-e^{-\left(\varepsilon_{it}^{both}+\overline{V}_{it}^{both}-\overline{V}_{it}^{j}\right)}}
$$

Then,

$$
\begin{aligned}
Pr(a_{it} = both) &= \int \left(Pr(a_{it} = both|\varepsilon_{it}^{both})\right) f(\varepsilon_{it}^{both})d\varepsilon_{it}^{both} \\
&= \int \left(\prod_{j\neq both} e^{-e^{-\left(\varepsilon_{it}^{both}+\overline{V}_{it}^{both}-\overline{V}_{it}^{j}\right)}}\right) e^{-\varepsilon_{it}^{both}} e^{-e^{-\varepsilon_{it}^{both}}} d\varepsilon_{it}^{both} \\
&= \int \left(\prod_{j} e^{-e^{-\left(\varepsilon_{it}^{both}+\overline{V}_{it}^{both}-\overline{V}_{it}^{j}\right)}}\right) e^{-\varepsilon_{it}^{both}} d\varepsilon_{it}^{both} \\
&= \int exp\left(-\sum_{j} e^{-\left(\varepsilon_{it}^{both}+\overline{V}_{it}^{both}-\overline{V}_{it}^{j}\right)}\right) e^{-\varepsilon_{it}^{both}} d\varepsilon_{it}^{both} \\
&= \int exp\left(-e^{-\varepsilon_{it}^{both}} \sum_{j} e^{-\left(\overline{V}_{it}^{both}-\overline{V}_{it}^{j}\right)}\right) e^{-\varepsilon_{it}^{both}} d\varepsilon_{it}^{both}
\end{aligned}
$$

Now suppose $x = exp(-\varepsilon_{it}^{both})$. We also know that $-exp(-\varepsilon_{it}^{both})d\varepsilon_{it}^{both} = dx$. As ε_{it}^{both} approaches infinity, x approaches zero. Similarly, as ε_{it}^{both} approaches negative infinity, x becomes infinitely large. Replacing the above expression with the new term, we have the following

$$
\begin{aligned}
Pr(a_{it} = both) &= \int_{\infty}^{0} exp\left(-x\sum_{j} e^{-\left(\overline{V}_{it}^{both} - \overline{V}_{it}^{j}\right)}\right)(-dx) \\
&= \int_{0}^{\infty} exp\left(-x\sum_{j} e^{-\left(\overline{V}_{it}^{both} - \overline{V}_{it}^{j}\right)}\right)dx
\end{aligned}
$$

Evaluating the integral in the last line, we arrive at the following expression

$$
\begin{aligned}
Pr(a_{it} = both) &= \left.\frac{exp\left(-x\sum_{j} e^{-\left(\overline{V}_{it}^{both} - \overline{V}_{it}^{j}\right)}\right)}{-\sum_{j} e^{-\left(\overline{V}_{it}^{both} - \overline{V}_{it}^{j}\right)}}\right|_{0}^{\infty} \\
&= \frac{1}{\sum_{j} e^{-\left(\overline{V}_{it}^{both} - \overline{V}_{it}^{j}\right)}} \\
&= \frac{e^{\overline{V}_{it}^{both}}}{\sum_{j} e^{\overline{V}_{it}^{j}}}
\end{aligned}
$$

Similarly, we can derive the optimal choice probability for other actions as well. As such, we will arrive at the expression denoted in Equation (**??**).