High-Skill Immigration, Offshoring R&D, and Firm Dynamics*

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Abstract

Foreign inputs in the form of immigrant researchers and imported R&D services play an increasingly important role in firm's R&D activities. This paper studies firms' decision to use such inputs and its implications for firm performance and aggregate productivity. Using administrative data from Denmark, we document that firms with immigrant researchers are more likely to source R&D services from abroad, and that the use of both inputs increases R&D efficiency and boosts firm performance. We develop and estimate a firm dynamics model in which R&D can be done with a combination of domestic inputs, immigrant researchers, and imported R&D services. Two elements of the model—love for variety of ideas in R&D and an information channel of immigrants—imply complementarity between different R&D inputs, which is crucial to rationalize the empirical patterns on firm's R&D. Counterfactual experiments show that incorporating the use of foreign R&D inputs in the model is important for assessing the impacts of immigration, service offshoring, and R&D policies.

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1 Introduction

Reductions in trade barriers and advances in information technology over the past half century have made it easier for firms to source inputs globally. Recent studies suggest an important two-way relationship between the use of foreign intermediate inputs and firm productivity: on the one hand, productive firms self-select into adopting foreign inputs; on the other hand, access to foreign intermediate inputs improves firm performance, indirectly through its interaction with R&D as well as directly. In modeling and quantifying these channels, the literature has focused almost exclusively on the role of imported *production inputs*. Yet increasingly, firms across the globe also adopt foreign *R&D inputs*, either by sourcing R&D services from abroad or by recruiting immigrant researchers to the firm.[1]

Figure 1 shows the empirical relevance of these two options for global sourcing of R&D inputs for firms in Denmark, the country of focus in this paper. The left panel is immigrants' share of total research-related wage bill in Denmark.[2] The right panel is the share of foreign sourced R&D services in total R&D expenditures. Both panels show a clear upward trend during 2001–2014, indicating increasing dependence of Danish firms on foreign R&D inputs. By 2014, about 9% of the total R&D wage bill is spent on immigrant researchers; about 28% of the total R&D expenditures accrue to activities taking place abroad.

These two forms of foreign inputs can bring fresh ideas not seen in the domestic economy, boosting R&D efficiency and eventually firm performance. In this paper, we develop and estimate a dynamic firm heterogeneity model with endogenous R&D decisions to analyze the relationship between the use of foreign R&D inputs and firm productivity. The model conceptualizes firm's incentive to use foreign R&D inputs in addition to native researchers based on the notion of *love for variety of ideas*. We posit that three inputs—domestic researchers, immigrant researchers, and R&D services from abroad—are imperfect substitutes in the R&D process, so the marginal return from R&D investment is higher, when firms can flexibly combine different inputs. Recruiting immigrant researchers and sourcing R&D services globally are both costly, so only a small fraction of firms take advantage of the love for variety of ideas. The actual cost may depend on the inter-relation between different types of R&D inputs. More specifically, firms with immigrant researchers may face a lower cost of sourcing R&D services from abroad because immigrants can provide information and know-how about foreign R&D suppliers. This relationship leads to complementarity between the two options of foreign R&D inputs, which we call as the *information channel*.

The central implications of the model are that firms benefit from having access to foreign R&D inputs and that the decisions to use these two inputs are interdependent. Through counterfactual

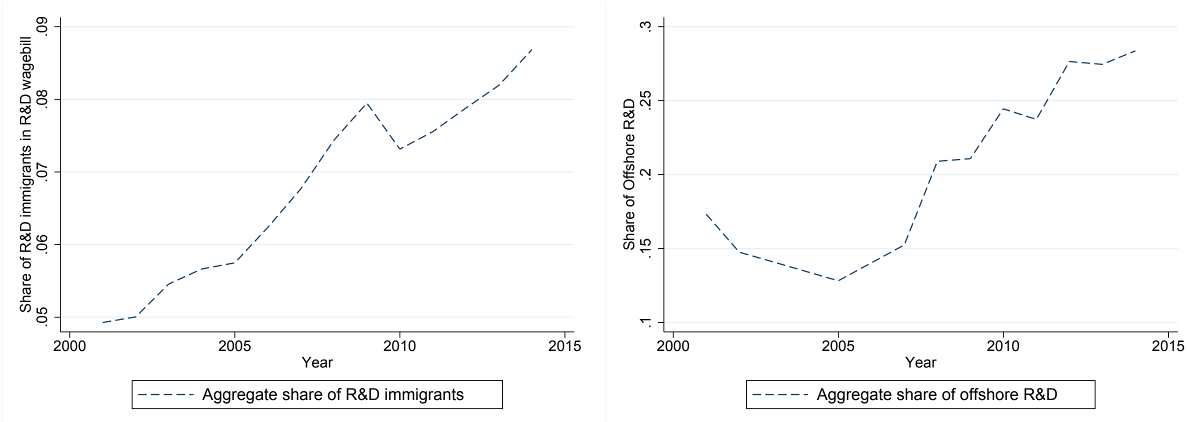
[1] According to the Patent Cooperation Treaty data, between 2000 and 2010, around 10-15% of inventors in developed countries are foreign nationals (Miguelez and Fink, 2013). Relatedly, many global firms source R&D services from abroad by establishing overseas R&D centers (Fan, 2020).

[2] We identify "research-related" workers based on their occupation. The precise definition is introduced when we describe the data.

Figure 1: Increasingly Globalized R&D Patterns of Danish Firms

(a) Immigrants among Researchers

(b) Offshore Share of R&D Expenditures



Notes: Immigrants' share in the total research wage bill is calculated using the sample of all employees in research-related occupations from the matched employer-employee data. The offshore R&D expenditures have two components: R&D services Danish firms purchase through arms' length contracts from abroad, and R&D carried out by foreign entities within the same business group of a Danish entity *for the use of that Danish entity*. The share on the right panel is the ratio between total offshore R&D expenditures and the sum of offshore R&D expenditures and R&D by Danish firms in Denmark. See Section 2 for details on data.

experiments, we show that the benefit from foreign R&D inputs accounts for a large share of firms' return to R&D. Due to the information channel, changes on the cost of hiring immigrant researchers have a significant impact on firms' decision to offshore R&D, and vice versa. Thus, in assessing the impacts of R&D policies, or liberalization in high-skill immigration and offshore R&D, it is crucial to take into account the existence of both types of foreign R&D inputs and the complementarity between them.

The model is grounded in the new facts we document using registry data from Statistics Denmark between 2001 and 2014. We link the matched employer-employee data, which allows us to identify the occupation and immigration status of individuals, to a number of surveys and administrative data sets at the firm level, covering firms' location, accounting information, R&D status, import and export, and participation in offshore R&D. With rich characteristics on both firms and workers, we are able to identify whether a firm hires immigrant researchers and assess how this decision correlates with the characteristics and other decisions of the firm.

We document three facts on firms' use of foreign R&D inputs. First, firms employing immigrant researchers are more likely to conduct offshore R&D. This correlation is robust after various firm characteristics, including their industry affiliation, are controlled for, and is present at the firm-destination region level—e.g., firms recruiting immigrants from Eastern Europe are more likely to source R&D services from Eastern Europe. We interpret this finding as capturing a possibility immigrant researchers bring the firm tacit knowledge about their home countries, which reduces the frictions firms face in sourcing R&D from these countries.

The second and third facts highlight a two-way relationship between the use of foreign R&D inputs and productivity. On the one hand, firms with immigrant researchers or conducting offshore R&D are more productive than firms doing R&D using domestic inputs only, hinting at self-selection based on productivity. On the other hand, controlling for their productivity and R&D expenditures, firms using foreign R&D inputs tend to have higher future productivity than the ones carrying out R&D excursively with domestic inputs. This correlation is robust when we control for industry-time fixed effects and firms' participation in international markets through import and export of physical goods. The effect is also present when we use production function estimation techniques to address simultaneity biases arising from firms' endogenous choice of production inputs.

Our model builds on the endogenous R&D model in Aw, Roberts and Xu (2011), Doraszelski and Jaumandreu (2013), and Bøler, Moxnes and Ulltveit-Moe (2015). In the model, heterogeneous firms choose whether to conduct R&D, and if so, how much to invest in R&D and whether to use immigrant researchers and/or foreign R&D services. Investment in R&D increases future productivity stochastically. Adopting multiple inputs at the same time is costly, but it enhances the efficiency of R&D investment and gives firms higher expected future productivity. The interpretation of this relationship is that by sourcing from a diverse source of imperfectly substitutable ideas, firms can achieve higher R&D efficiency, which is analogous to the idea of love for variety dating back to Ethier (1982). To account for the information value of immigrants, we allow for a possibility of reduced fixed and sunk costs when offshore R&D is done in the presence of immigrant researchers.

We structurally estimate the model through indirect inference. We uncover the importance of the love for the variety of ideas by matching the estimated impact of foreign R&D inputs on firm performance. In the data, conditioning on doing R&D, firms using foreign R&D inputs on average get an additional 2% productivity increase. Assuming a constant elasticity of substitution between the three types of inputs in R&D—native researchers, immigrant researchers, and imported R&D services—the 2% productivity premium translates into a constant elasticity of 1.36. We estimate the fixed and sunk R&D cost parameters governing the strength of the information channel using two sources of information. First, the patterns of transition between different R&D modes. Second, firms' response to a natural experiment, an R&D subsidy program introduced in Denmark in 2011 that reduced the effective user cost of R&D by 25% for eligible firms. Our estimation results suggest that the switch from doing R&D with only native researchers to using also foreign sourced R&D services incurs an average startup cost of about 6.2 million Danish Krone (DKK), or about 0.97 million USD, and a fixed cost of 4.2 million DKK. The presence of immigrant researchers in a firm reduces its start up cost by 16% and the fixed cost by 25%, which reaffirms the information channel.

With the estimated model, we first examine the quantitative importance of the key mechanisms that affect firms' R&D choice. Removing the information value of immigrants reduces the fraction of firms conducting R&D with immigrant researchers and that of firms offshoring R&D by 14.9 and 8.0 percentage points (p.p.), respectively. This suggests that, on the one hand, the information channel plays a vital role in firms' participation in offshore R&D; on the other hand, a sizable part of the firms' return from hiring immigrant researchers materializes through the reduced cost of offshore R&D. In total, the R&D participation rate decreases by 13.6 p.p. and the aggregate productivity decreases by 0.2% without the information channel in play. Eliminating the love for the varieties of ideas—by making different R&D inputs perfect substitutes—shuts down firms' incentive to either hire immigrant researchers or to offshore R&D.[3] This change decreases the R&D participation by 24.5 p.p. and the aggregate productivity by 0.4%. Together, these two experiments highlight the quantitative relevance of foreign R&D inputs in determining firms' R&D participation and the aggregate productivity.

Our second set of experiments focuses on policies that make it easier for firms to use foreign R&D inputs. We find that a 50% reduction in offshoring sunk costs leads to a 0.4% increase in the aggregate productivity and that a 50% reduction in the sunk cost of hiring immigrants increases the aggregate productivity by 0.2%. The information channel plays a crucial role in amplifying the impacts: without it, the impacts on aggregate productivity of these two policies would be almost halved. This experiment showcases that due to the complementarity between the two types of foreign inputs, evaluating policies on any of them will have to take into account the other.

Finally, we evaluate the impact of R&D subsidies in our model and compare it to that of a restricted model in which R&D is only carried out by native researchers. In response to a 50% decrease in the sunk costs associated with R&D, our model predicts a 0.81% increase in the aggregate productivity. The restricted model with only native researchers, i.e., with no love for variety of ideas in play, predicts only a 0.12% increase. The dramatic difference in the predictions of the two models arises because the return to R&D—hence the R&D participation—are both much lower in the restricted model. With foreign R&D inputs playing an increasingly prominent roles in firms' R&D, modeling these inputs and their interactions is crucial in understanding the return to R&D and the impact of R&D policies.

This paper contributes to four strands of the literature. First, we contribute to the literature estimating the impact of imported intermediate inputs on firm performance (e.g., Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Goldberg, Khandelwal, Pavcnik and Topalova, 2010; Halpern, Koren and Szeidl, 2015; Zhang, 2017 among others). While this literature also builds on the idea of Ethier (1982) and emphasizes a 'love-for-variety' in input use, their focus is on imported inputs for production. In contrast, our focus is on the impact of access to foreign inputs in R&D such as immigrant researchers and offshore R&D, both of which are ever more important as the global integration goes well beyond the exchange of goods, expanding to the exchange of ideas and movement of high-skill workers. We show that the use of foreign talent or imported R&D services has an independent effect on firm productivity above and beyond the effect stemming from the use of foreign production inputs. Because R&D investment contributes to firms' knowledge capital, which is carried forward to the future, improvement in R&D efficiency is accumulated and amplified over time. This dynamic effect of R&D inputs also differs

[3] More precisely, this assumption shuts down the *systematic* component in firms' incentive to use foreign R&D inputs. We allow for idiosyncratic components in their R&D decisions as well.

from the static impacts found in most papers from the literature on imported production inputs.

Second, our firm dynamics model with endogenous R&D and estimation methodology builds on the work of Doraszelski and Jaumandreu (2013), which has also been employed by Aw, Roberts and Xu (2011) and Bøler, Moxnes and Ulltveit-Moe (2015) to study the interaction between R&D and international trade. Most closely related, Bøler, Moxnes and Ulltveit-Moe (2015) argue that R&D and intermediate inputs are complements and jointly enhance firm performance. Compared to the existing works using this methodology, our main contribution is to look into the black box of R&D and examine the interaction between different inputs inside the box. To incorporate and quantify the use of these inputs, we use registry data from Denmark. We show that incorporating different R&D inputs not only matters when evaluating the policies on offshoring or immigration, but also matters for understanding the impacts of generic R&D subsidies which are commonly used in many countries.

By focusing on firms' decision to conduct offshore R&D, this paper is also related to a small set of recent works studying the impacts of R&D within multinational firms. For example, Bilir and Morales (2020) estimate how R&D in the headquarters and different affiliates of MNCs affects production in the same or nearby affiliates; Fan (2020) examines how MNCs optimally allocate R&D and production among their affiliates around the word. Different from the data sets used in these studies, our data capture the R&D services that a Danish firm sources from abroad for itself, excluding the R&D done in foreign headquarters/affiliates for a local use at those foreign locations. This leads us to develop a model of R&D sourcing that focuses on production in Denmark, instead of a model of multinational production.[4]

Finally, this paper is related to a broad literature on the consequences of high-skill immigration. Using industry-, regional-, and most recently, firm-level variations, the literature has documented two broad sets of results. First, high-skill immigrants increase firm performance (Markusen and Trofimenko, 2009; Peri, 2012; Ottaviano, Peri and Wright, 2018; Beerli, Ruffner, Siegenthaler and Peri, 2018). Second, the presence of immigrants encourages trade and offshoring activities between the origin and destination countries (Head and Ries, 1998; Rauch and Trindade, 2002; Burchardi, Chaney and Hassan, 2019; Olney and Pozzoli, 2018; Ramanarayanan et al., 2019). Our first contribution to the literature is to document empirical evidence of both channels in a unified setting for a specific yet important activity, R&D. Our finding suggests that one mechanism through which immigrants increase firm performance is exactly by helping the firm establish business connection at home. Second, we develop and estimate a dynamic heterogeneous firm model of R&D with immigrants. Compared to existing works that quantify the impacts of immigrants using structural models (see, e.g., Bound, Braga, Golden and Khanna, 2015; Burstein, Hanson, Tian and Vogel, 2020), our model incorporates two salient features of the data: that only the most productive firms recruit immigrants, and that immigrants and offshoring interact with each other. Both channels are important for evaluating impacts of

[4] To the extent that the R&D reported in our measure have spillover effects on the activities of the overseas headquarters or affiliates of the reporting entity in Denmark, our results underestimate the impact of offshore R&D.

immigration policies on firm and aggregate outcomes.[5]

The rest of the paper is organized as follows. In Section 2, we introduce the data and describe the salient features of the data. In Sections 3 and 4, we develop and estimate the model. Section 5 reports results from counterfactual experiments. Section 6 concludes.

2 Data and Facts

In this section, we first describe the data used in this paper. We then document new facts on the relationship between the employment of immigrant researchers, offshore R&D, and firm performance. These facts motivate the key ingredients of the structural model.

2.1 Data Sources

We merge several administrative datasets on firms and workers from Statistics Denmark over the period 2001 to 2014. We describe each dataset in detail below.

Workers. The information on workers comes from the Integrated Data for Labor Market Research (IDA, hereafter), an annual snapshot in each November covering all working-age individuals in the labor force in Denmark. The dataset has workers' country of origin and other demographic information, the firm and the establishment at which they work, and their occupation and wage. IDA allows us to construct an indicator for whether a firm hires immigrants in R&D-related roles. We define immigrants as workers whose country of origin is not Denmark.[6] We classify workers as in R&D-related roles based on their occupation.[7] An occupation is deemed as R&D-related if it involves creative and/or technical components such as design, test, and experimentation according to its job descriptions. This classification is broader than the definition of R&D as activities carried out by scientists or university researchers pushing the boundary of human knowledge, but it captures the fact that for many firms, some form of experimentation and innovation is needed to develop a new product.[8] Slightly abusing language, we will call workers in R&D-related occupations as R&D workers or researchers, and those with a foreign origin and R&D-related occupations as immigrant R&D workers or researchers throughout the paper.

[5] By putting the interaction between immigrants and offshoring activities, our work is also related to Morales (2020), who shows that foreign MNCs in the U.S. tend to hire high-skill workers from the headquarter countries. This finding suggests that immigrants who work at a U.S. affiliate may act as a bridge delivering information more easily from the foreign headquarter. Distinct from and complementary to the channel in Morales (2020), the information channel in our paper is best viewed as the one between the headquarters in Denmark and the home countries of these immigrants.

[6] Naturalized citizens count as immigrants.

[7] Over the sample period, occupation codes change with revisions of the International Standard Classification of Occupations Classification. We concord vintages of occupation codes following a procedure described in the appendix.

[8] Examples of R&D-related occupations are software developers, mechanical engineers, and technicians in chemical sciences. A drawback of this classification is that because it is based on occupation, it only captures those are directly involved in R&D-related activities. If a person is heading an R&D lab as a general manager, then s/he is not classified as R&D-related.

Firms. The information on firms' characteristics and activities comes primarily from the following two sources. The first source is the Regnskabsstatistik (FIRE, hereafter), an annual panel on firms' accounting information derived from the value-added tax administrative data. FIRE covers almost all private-sector firms above a certain size determined by the firm's ownership structure.[9] The information we extract from FIRE includes firm sales, value added, material use, wage bill, and capital stock which is constructed from the investment in fixed capital using the perpetual inventory method with a 8% discount rate. We adjust wage bills using the consumer price index and adjust other accounting variables using industry-level deflaters specific to each of these variables.

The second dataset for the firm-level information is the Danish equivalent of the European Community Innovation Survey (the R&D survey, hereafter), which provides information on firms' R&D activities. Aiming to gather as complete information on R&D-active firms as possible, the survey samples all firms satisfying one of the following criteria—1) have over 250 employees; 2) have more than 1 billion DKK in revenue; 3) spend at least 5 million DKK in R&D activities; or 4) operate in R&D-intensive industries—and include a stratified sample of all the remaining firms that do not satisfy any of these criteria. The final sample is an unbalanced panel of around 4,000 firms per year.

A unique and crucial feature of the R&D survey is that it contains information on not only firms' R&D expenditures within Denmark, but also their R&D expenditures overseas—*i.e.*, their offshore R&D. The questionnaire specifically requests that the offshore R&D expenditures reported should be for the use of the reporting entity in Denmark, so R&D done in a foreign affiliate/headquarters of a Danish firm for the affiliate/headquarters themselves, such as the development of a product for production in a foreign country, is not included.[10] The reported offshore R&D, in turn, is most appropriately viewed as the imported R&D services by the reporting entity. Correspondingly, the model we develop focuses on production of firms located in Denmark.[11]

For corroborative evidence on the offshore R&D measure, we also leverage the offshoring survey, which is a part of a larger European collaboration through the Eurostat. The main purpose of this survey is to gather information about global value chains and international sourcing. The survey samples all firms with 50 or more employees and a representative set of firms with

[9] Reporting to FIRE is mandatory for private corporations with an annual turnover above 500,000 DKK and for individually owned companies with an annual turnover above 300,000 DKK. When matched to the IDA, firms in FIRE account for about 86% of total private-sector employment in Denmark. Some firms in FIRE cannot be matched with the IDA as the latter covers only the labor market information of each November.

[10] Offshore R&D includes both the R&D expenditures incurred by a foreign related party and those outsourced through arm's length contracts. The exact wording of the questionnaire for R&D in a related party is "FoU udført af andre dele af koncernen i udlandet og anvendt internt i virksomheden," which means "R&D performed by other parts of the business group abroad and used internally in the company." Examples of offshore R&D include: the test of a new drug in an overseas lab; the design of new toy sets by designers in a foreign location for the parent firm.

[11] This feature differentiates the survey from other available datasets on affiliate R&D, such as the one from the U.S. Bureau of Economic Analysis, in which R&D reported in a foreign location could be carried out for the use of any entities within the organization. To understand such data, researchers would have to jointly consider the domestic and overseas production (see, e.g., Bilir and Morales, 2020).

10-49 employees. It reports whether a firm conducts R&D activities abroad in 2011, in house or through arms' length contracts, without requiring the reported R&D to be carried out solely for the benefit of the reporting entity in Denmark. While this notion of offshore R&D is broader than our baseline measure based on the R&D survey and is available only for 2011, it provides an alternative measure that we can use for validation.

Finally, both the R&D and the offshoring surveys include the information pertaining to which world regions a firm conducts offshore R&D in. In the appendix, we use this information to provide further evidence on the connection between offshore R&D and firms' employment of immigrant R&D workers.

2.2 Descriptive Statistics

Our baseline sample includes all firms that have more than 10 employees and are in both FIRE and the R&D survey. In order to validate the measure for offshore R&D, we also use the offshoring survey, in which case firms need to be in all three surveys. Table 1 presents the descriptive statistics of our sample. Since the offshoring survey is available only for 2011, we calculate all statistics based on that year.

Panel A of Table 1 reports the characteristics of the workers at the sample firms, summarized by workers' immigrant status and occupation. Approximately 16% of the workers are in occupations related to R&D, as defined previously. Among them, about 6% are immigrants. Not surprisingly, both immigrant and native R&D workers are more highly educated than non-R&D workers. They make on average 48 dollars per hour, significantly more than non-R&D workers.

Panel B of the table reports the characteristics of the firms in the sample by their size groups. The share of firms doing R&D is 23% in the total sample. This share is higher among larger firms than among small firms. Conditional on doing R&D, however, it is the smaller firms that devote a larger fraction of revenues to R&D, which is suggestive of large fixed costs associated with R&D activities.

The lower panel of Panel B reports firms' employment of immigrant R&D workers and participation in offshore R&D. About 13% of the firms in the sample conduct R&D with immigrant researchers, making up about half of all R&D-active firms. The share of firms engaging in offshore R&D is smaller, at around 4%. Both activities are more common among large firms. A significant fraction of firms doing offshore R&D—3% out of 4.1% overall, 9.9% out of 10.7% among larger firms with more than 250 employees—employ immigrant R&D workers, which suggests that the two activities are likely to be interconnected. On the other hand, only a small fraction of firms employing immigrant R&D workers are at the same time doing offshore R&D.

Panel C of Table 1 reports statistics on firms' mode of R&D, focusing on firms in the offshoring survey and using the measure of offshore R&D from this survey. Two patterns emerge from the reported statistics. First, across all firm size groups, a larger fraction of firms than reported in Panel B conduct offshore R&D, consistent with the R&D measure from the offshoring survey being broader than the one from the R&D survey. Second, like the one from the R&D survey,

Table 1: Descriptive Statistics

Panel A: Worker Characteristics				
	% of obs	% college+	% master +	Mean hourly wage (US$)
Immigrant R&D worker	1.20	73.33	33.90	46.5
Immigrant non-R&D	6.97	22.45	6.90	32.5
Native R&D	15.75	62.46	22.98	47.1
Native non R&D	76.09	17.10	5.35	35.4
Panel B: Firm Characteristics				
Number of employees	% of obs	Mean VA/L (US$)	% R&D firms	Mean R&D/Sales (%)
10-49	46.90	111,892	19.88	35.23
50-249	39.88	120,024	23.98	16.01
$\geq$ 250	13.22	126,534	37.69	5.72
All	100	117,072	23.87	21.37
		% R&D immi.	% Offshore R&D	% R&D immi. *and* Offshore R&D
10-49		7.74	2.60	1.08
50-249		14.29	4.08	3.15
$\geq$ 250		33.08	11.28	10.51
All		13.70	4.34	3.15
Panel C: Offshoring Survey				
Number of employees	% of obs	% R&D immi.	% Offshore R&D	% R&D immi. *and* Offshore R&D
10-49	23.17	12.84	5.05	2.52
50-249	56.54	14.85	5.45	3.85
$\geq$ 250	20.30	33.25	15.97	15.18
All	100	18.12	7.49	5.84

Notes: Panels A and B are based on the matched sample between IDA, FIRE, and the R&D survey, restricting to private sector firms with at least 10 employees. Panel C further restricts the aforementioned sample to firms included in the offshoring survey. Immigrants are identified based on their country of origin. In Panel B, offshore R&D is defined based on the acquisition of R&D services from abroad for the exclusive use of the firm located in Denmark in Panel B; in Panel C, a firm is classified as doing offshore R&D if it conducts R&D activities abroad in 2011 (offshoring survey definition). Monetary values are reported in US$. All statistics are based on 2011. The number of workers for Panel A is 542,841 while the number of firms underlying Panels B and C are 2,949 and 1,882 respectively.

this measure also shows a high conditional probability of employing immigrant R&D workers among firms doing offshore R&D and a low conditional probability of offshoring R&D among firms that have immigrant R&D workers.

2.3 Relationship between Immigrant Researchers, Offshore R&D, and Firm Performance

To understand the asymmetric patterns between the use of immigrant workers and offshore services in R&D in their conditional probabilities of both directions, we look into the frequency of transition of firms between the different R&D modes. In particular, we split firms into the following five modes: R&D inactive (denoted by 0), R&D with neither immigrant R&D worker nor offshore R&D services but with only native researchers (N), R&D with native and immigrant R&D workers (NI), R&D with native R&D workers and offshore services (NF), and R&D with both immigrant R&D workers and offshore services as well as native researchers (NIF).

Table 2: R&D Mode Choice and Firm Productivity

Panel A	Transition probability between R&D modes $t+1$				
t	0	N	NI	NF	NIF
0	0.933	0.034	0.024	0.004	0.006
N	0.330	0.527	0.092	0.041	0.010
NI	0.154	0.055	0.675	0.007	0.110
NF	0.219	0.342	0.041	0.338	0.059
NIF	0.062	0.010	0.277	0.026	0.625
Panel B	Frequency distribution and average productivity				
	0	N	NI	NF	NIF
mean VA/L (US$)	112,999	115,987	136,164	132,113	160,225
% of sample	77.80	7.95	9.14	1.48	3.63

Notes: This table reports the fraction of private firms (with at least 10 employees) in a mode in period t (indicated by the rows) moving into a different mode in period $t+1$ (indicated by columns), averaged over the 2001-2014. The modes are defined as follows: 0 for no R&D, N for native R&D, NI for native and immigrant R&D, NF for native and offshore R&D and NIF for native, immigrant and offshore R&D. The statistics for Panel B are for 2011, based on the same sample as Panel B of Table 1. Mean value added per labor is reported in US$.

Panel A of Table 2 reports the five-by-five transition matrix between R&D modes. Each row sums up to one. The entry in row m and column n of the matrix shows the fraction of the firms in mode m in period t moving to mode n in period $t+1$. The table shows that among the firms with immigrant R&D workers (the NI row), about 12% adopt offshore R&D (the NIF or NF column) in the next period. This is twice as the 5% probability that firms doing R&D without immigrant researchers in period t starting to use offshore R&D services in period $t+1$ (from N to either NIF or NF). On the other hand, among the firms doing offshore R&D, the fraction that starts employing immigrant R&D workers is around 10% (from NF to either NI or NIF), which is about the same as the share of the firms in N that switch to either NI or NIF modes.

These findings support the idea that the presence of immigrant researchers at a firm encourages offshore R&D, which can explain why the majority of firms doing offshore R&D also employ immigrants researchers. This effect could be due to either the enhanced benefit or the reduced cost of offshore R&D with a presence of immigrant researchers. More specifically, having immigrant researchers increases the marginal return from offshore R&D for a given level of R&D investment, as immigrants may bring diverse ideas. Alternatively, immigrant R&D workers may act as bridge between the headquarters and the foreign R&D affiliates, thereby reducing information friction in offshore R&D. Quantifying importance of these mechanisms will be one of the main focuses in our structural analysis.

In the appendix, we conduct regression analysis to show the following. First, this relationship is robust when productivity and other firm characteristics, including their size, industry affiliation, and importing/exporting status, are controlled for, so it is not driven by these factors.

Second, the relationship persists when we focus on the connection between immigrants from a specific world region and offshoring R&D to the same world region, which offers additional support for the role of immigrants in reducing the information friction. Third, only the presence of immigrant researchers, not other types of immigrants, increases the likelihood of offshore R&D. This suggests that the interaction is within R&D, rather than between R&D and other firm activities. Finally, we also show that the result is not due to a reverse causality by using a shift-share instrumental variable (IV) for firms' recruitment of immigrants, which exploits variations across Danish regions and industries in the employment of immigrants from different source regions in 2000 and the nation-wide inflow of immigrants between 2001 and 2014. We summarize these findings in Fact 1.

Fact 1: Firms with immigrant researchers are more likely to start offshore R&D. This pattern is robust to a number of firm-level controls and an IV strategy that addresses the reverse causality concern.

The literature has documented that R&D-active firms tend to be more productive than non-R&D firms and that firms' R&D activities are highly persistent. The statistics in Table 2 show that in our data, both the performance premium and the persistence of R&D apply to the *mode choice* of R&D. For example, 62% of the firms in mode NIF and 67% of the firms in mode NI will stay in the same mode in the following year. Panel B of the table reports the average labor productivity by mode. Firms doing R&D with foreign inputs tend to be more productive than firms in the 'N' mode.[12] This finding leads to the second fact.

Fact 2: Firms doing R&D with foreign inputs are more productive on average than non-R&D firms and those doing R&D without foreign inputs. Both firms' R&D status and the mode in which they carry out R&D are persistent.

The systematic variation in productivity between firms in different R&D modes suggests possible self-selection into adoption of foreign inputs, which motivates a heterogeneous firms model with *fixed costs* for using foreign inputs. The persistence in firms' R&D mode choices, in turn, can either be simply reflecting such self-selection in the presence of persistent productivity differences among firms, or be due to additional, *sunk costs*, for entry into an R&D mode. We will incorporate both forces in the model and let the data discipline their importance.

Having provided evidence for selection into adopting foreign R&D inputs by productivity, we now examine whether the use of foreign R&D inputs increases the return to R&D. We estimate the impact of conducting R&D with foreign inputs on productivity using the following specification:

$$\omega_{it} = \rho\omega_{it-1} + \gamma_{R\&D}\mathbb{I}(\text{R\&D}_{it-1}) + \gamma_{\text{off.}}\mathbb{I}(\text{off.}_{\ it-1}) + \gamma_{\text{immi.}}\mathbb{I}(\text{immi.}_{it-1}) + \vec{\beta}X_{it} + \phi_{j(i)t} + \zeta_{it}. \quad (1)$$

[12] The exception is firms in the NF mode, but they make up only 1% of the sample.

In equation (1), ω_{it} denotes the labor productivity—value added per worker—of firm i in industry $j(i)$ in year t. We specify ω_{it} to be a function of ω_{it-1} and firm i's R&D status at $t-1$. This specification follows the knowledge capital model of productivity dating back to Griliches (1979), according to which ω_{it}, the knowledge capital determining firm performance, is the sum of un-depreciated knowledge capital from the previous year, $\rho\omega_{it-1}$, and the new knowledge capital created through R&D. We postulate that the amount of knowledge capital created depends on not only whether a firm conducts R&D, but also how. Therefore, in addition to the indicator for firms' R&D status ($\mathbb{I}(\text{R\&D}_{it-1})$), we also include the indicators for the use of offshore R&D services ($\mathbb{I}(\text{off.}_{\ it-1})$) and immigrant researchers ($\mathbb{I}(\text{immi.}_{it-1})$) in the specification. We should expect $\gamma_{\text{off.}}$ and $\gamma_{\text{immi.}}$ to be positive, if drawing ideas from foreign inputs increases R&D efficiency. In some specifications, we will replace $\mathbb{I}(\text{R\&D}_{it-1})$ with intensive margin measures of R&D expenditures to allow for the variation in R&D intensity. Decisions on R&D likely depend on the characteristics of the industry and other decisions of the firm, both of which can impact firm productivity. We will control for these confounding factors by including the industry-time fixed effects, $\phi_{j(i)t}$, and time-varying firm-level controls, X_{it}, in the specification.

Table 3 presents the estimation results for equation (1). Column 1 shows that doing R&D is associated with 2.9% higher productivity and that conditional on doing R&D, offshoring R&D increases productivity by additional 3.7%. Column 2 shows a similar finding for the use of immigrant workers in R&D. In column 3, when both types of foreign R&D inputs are included in the regression at the same time, each of them has a large, positive, and statistically significant coefficient.

The international trade literature has documented a robust finding that a firm's importing and exporting of goods is significantly correlated with its productivity. To account for this finding, column 4 controls for firms' importing and exporting status in period t.[13] Consistent with the finding from the literature, the coefficients on the indicators of firms' importing and exporting status are both positive and statistically significant, but including these indicators does not significantly diminish the roles of immigrant researchers and offshore R&D on firm productivity. This result suggests that the correlation documented for firm productivity and the use of foreign R&D inputs is independent of the effects through trade in physical goods found in the literature.

A plausible explanation for the results reported in columns (1)-(4) is that the firms using foreign R&D inputs are significantly out-investing other firms and that a part of their extra R&D investment is attributed to immigration and offshore R&D dummies. To investigate this possibility, columns (5) through (8) measure R&D using the log of domestic R&D expenditures, instead of the R&D indicator. The coefficient of log domestic R&D expenditures is statistically significant but in general is not big enough for the estimated coefficients on the foreign R&D input dummies to be explained by the higher R&D expenditures of these firms.[14] Correspondingly, the

[13]Controlling for the lagged, instead of contemporaneous status gives essentially the same result.

[14]With a point estimate of 0.005 as in column (5), for example, for the foreign R&D input dummies to be entirely explained by the extra R&D investment by the firms using foreign inputs, their total log R&D investment needs to be 1,000 log points above that of the firms not using foreign inputs in R&D.

Table 3: Sourcing of R&D Inputs and Labor Productivity

Outcome var.	Labor Productivity$_{i,t}$								
Key control	Extensive margin of R&D Status				Intensive margin: domestic R&D				Total R&D
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor Productivity$_{i,t-1}$	0.657***	0.659***	0.658***	0.653***	0.656***	0.658***	0.657***	0.653***	0.653***
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
$\mathbb{I}(\text{R\&D}_{i,t-1})$	0.024***	0.025***	0.020***	0.014**					
	(0.005)	(0.005)	(0.005)	(0.005)					
Log domestic R&D $_{i,t-1}$					0.004***	0.004***	0.004***	0.003***	
					(0.001)	(0.001)	(0.001)	(0.001)	
Log total R&D $_{i,t-1}$									0.003***
									(0.001)
$\mathbb{I}(\text{off.}\ _{i,t-1})$	0.031***		0.029**	0.031***	0.023**		0.022*	0.025**	0.022*
	(0.012)		(0.012)	(0.012)	(0.011)		(0.011)	(0.011)	(0.012)
$\mathbb{I}(\text{immi.}_{i,t-1})$		0.026***	0.025***	0.021***		0.023***	0.023***	0.019***	0.019***
		(0.005)	(0.006)	(0.006)		(0.005)	(0.006)	(0.006)	(0.006)
Import dummy$_{i,t}$				0.043***				0.042***	0.042***
				(0.006)				(0.006)	(0.006)
Export dummy$_{i,t}$				0.016***				0.015***	0.015***
				(0.006)				(0.006)	(0.006)
Observations	33,064	37,859	32,914	32,914	33,064	37,859	32,914	32,914	32,914
Industry×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Labor productivity is defined as log real value-added per worker. Domestic R&D refers to domestic R&D expenditures. Total R&D refers to the sum of domestic R&D and offshoring R&D expenditures. All specifications include log firm size as well as industry*year fixed effects. Industries are defined following the NACE Rev.2 intermediate level aggregation (see Appendix A1). The sample is private sector firms with at least 10 employees, and the sample period covers 2001-2015 . Standard errors are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

coefficients associated with the offshore and immigrant R&D dummies remain very similar to the ones in columns (1)-(4). Finally, in the last column, we directly control for log of firms' *total*, instead of domestic, R&D expenditures. The estimates for the coefficients on the foreign R&D input indicators are virtually the same.[15]

It is also possible that the results reported in Table 3 are due to a simultaneity bias: since firms observe their productivity, at least partially, when making input choices, our productivity measure could be biased. The bias in the measurement of ω_{it-1} shows up in the error term and can be correlated with firms' R&D decisions in period $t-1$, if these decisions are made with the knowledge of ω_{it-1}. In Section 4, we address this concern in a theory-consistent way by taking advantage of a timing assumption on input decisions. Based on these empirical results, we have the third fact.

Fact 3: Conditioning on current productivity and total R&D expenditures, the firms that use foreign R&D inputs tend to have higher future productivity.

Fact 3 and the very fact that some firms conduct R&D with both domestic inputs and the two types of foreign inputs suggest that these inputs are imperfect substitutes. These facts motivate

[15] All results in Table 3 remain essentially the same, when we include additional time-varying firm controls, such as log employment.

us to model foreign inputs as providing different, potentially better, ideas to the R&D process.

Taking stock, we find that foreign R&D inputs in the form of immigrant researchers or imported R&D services account for a substantial fraction of total R&D spending made by Danish firms. On the one hand, there is robust evidence of selection into using foreign R&D inputs by productivity. On the other hand, the use of these foreign R&D inputs is associated with firms' improved future performance beyond the performance improvement implied by firms' total R&D expenditures. Moreover, these two types of foreign R&D inputs are tightly connected: the propensity of offshore R&D is higher among firms employing immigrant researchers. These facts imply that policies affecting the use of one of the R&D inputs would affect firms' use of the other R&D inputs, both of which would further interact with firms' overall R&D investment decisions. The main goal of our structural model in the next section is to disentangle these channels and quantify their impact on firm's performance.

3 Model

In this section, we introduce a new firm dynamics model where heterogeneous firms make productivity-enhancing R&D investment by combining inputs from domestic and foreign sources. Statically, given the current productivity and aggregate demand, each firm chooses the output quantity to maximize its profit. Dynamically, firms decide how to organize R&D using inputs from different sources: native researchers, immigrant researchers, and offshore R&D services.

3.1 Production, Demand, and Static Profit

We start by describing firms' static decisions. The production function for firm i at time t has the following form:

$$q_{i,t} = \exp\left(\omega_{i,t}\right) l_{i,t}, \tag{2}$$

where $l_{i,t}$ is the production labor of firm i at period t; $\omega_{i,t}$ denotes firm i's current (log) productivity which depends on firm's past productivity and R&D investment, as will be explained in the next subsection; $q_{i,t}$ is the output. Denoting the price for each unit of production labor as $W_{i,t}$, the marginal cost for an output unit is $\frac{W_{i,t}}{\exp(\omega_{i,t})}$.[16]

Firms sell their output in a monopolistic competitive output market, characterized by the following Dixit-Stiglitz demand:

$$q_{i,t} = \left(\frac{p_{i,t}}{P_t}\right)^{\eta} Q_t, \tag{3}$$

where $q_{i,t}$ and $p_{i,t}$ are the quantity and the price of the variety that firm i produces; $\eta < 0$ is the demand elasticity; Q_t is the aggregate demand faced by the firm; and P_t is the corresponding ideal aggregate price index. We interpret Q_t and P_t as capturing the conditions of the entire market faced by all Danish firms, including the condition in other European Union (EU) states and

[16]When taking the model to the data, we will extend the production function to include capital and materials, in addition to labor, as production inputs.

the rest of the world. In keeping with this interpretation, we make two simplifications. First, we abstract from firms' endogenous export decision, which could also affect their productivity (Aw et al., 2011). We motivate this assumption from the high degree of integration of Denmark in the world economy.[17] In empirical specifications, we will control directly for firm's exporting status to ensure that it does not confound the main channels. Second, we assume that Q_t and P_t are exogenous to individual firms and do not change in the counterfactual experiments considered later in this paper. This assumption is motivated by the fact that the counterfactual shocks we consider lead to only moderate changes in the aggregate productivity, so those shocks alone are unlikely to drive a substantial general equilibrium change in Q_t and P_t.

Firms choose l_{it} and p_{it} to maximize their static profit. Given the monopolistically competitive market structure, the optimal pricing rule implies $p_{i,t} = \frac{\eta}{\eta+1}\frac{W_t}{\exp(\omega_{i,t})}$, with $\frac{\eta}{\eta+1}$ being the markup over the marginal production cost. The total sales of firm i is then given by $[\frac{\eta}{\eta+1}\frac{W_t}{\exp(\omega_{i,t})}]^{\eta+1}\frac{Q_t}{P_t^{\eta}}$. Therefore, conditional on its productivity, firm i earns the following static profit in period t:

$$\pi_t(\omega_{i,t}) = -\frac{1}{\eta}\Phi_t \cdot \exp\left((\eta+1)\ln\left(\frac{\eta}{\eta+1}\right) - (\eta+1)\omega_{i,t}\right), \tag{4}$$

in which $\Phi_t \equiv \frac{W_t^{\eta+1}Q_t}{P_t^{\eta}}$ is a shifter common to all firms, capturing the overall profitability due to wages, demand, and the market competition.

3.2 The Evolution of Productivity and Love for the Variety of Ideas

Firm i's productivity evolves according to the following law of motion:

$$\omega_{i,t} = \rho\omega_{i,t-1} + \mathbf{I}_{rd_{i,t-1}>0} \cdot \gamma \cdot \log\left(rd_{i,t-1}\right) + \zeta_{i,t}, \tag{5}$$

where $\omega_{i,t-1}$ is the lagged (log) productivity of firm i; $rd_{i,t-1}$ is firm i's total *effective* investment in R&D in year $t-1$ with the coefficient γ being the R&D elasticity of productivity; $\mathbf{I}_{rd_{i,t-1}>0}$ is an indicator for firm i doing R&D in year $t-1$; $\zeta_{i,t}$ is an idiosyncratic error term representing unanticipated innovation in the productivity evolution process. It has a mean of zero and a standard deviation of σ_{ζ}.

As documented in the previous section, some firms use multiple R&D inputs at the same time, suggesting inputs from different sources are imperfect substitutes. Moreover, using diverse R&D inputs generates an added benefit on productivity. To rationalize these empirical regularities parsimoniously, we assume that firms can combine three types of R&D inputs—native researchers (N), immigrant R&D workers (I), and offshore R&D services (F)—via a constant elasticity of substitution function. The effective R&D investment of firm i in year $t-1$ is:

$$rd_{i,t-1} = \left[\left(A^N\right)^{\frac{1}{\theta}}\left(rd^N_{i,t-1}\right)^{\frac{\theta-1}{\theta}} + \left(A^I\right)^{\frac{1}{\theta}}\left(rd^I_{i,t-1}\right)^{\frac{\theta-1}{\theta}} + \left(A^F\right)^{\frac{1}{\theta}}\left(rd^F_{i,t-1}\right)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}. \tag{6}$$

[17] The openness of Denmark, measured in import plus export over GDP, is well over 100%.

In this function, $rd^{\tilde{x}}_{i,t-1}$ for each $\tilde{x} \in \{N, I, F\}$ denotes the amount of R&D input $\tilde{x}$ for effective R&D investment firm i makes, where the R&D input types are native researchers, immigrant researchers, and the foreign suppliers of R&D services (measured as offshore R&D in the data), respectively.[18] $A^{\tilde{x}}$ for each $\tilde{x} \in \{N, I, F\}$ denotes the efficiency of input $\tilde{x}$. $\theta > 1$ is the elasticity of substitution between these inputs. The imperfect substitution between R&D inputs can be rationalized as different inputs being embedded with ideas and techniques from different sources, thus bringing in gains from a diversity of ideas to the R&D process. We call this mechanism as the *love for variety of ideas*. This channel is the reason why firms have an incentive to adopt diverse inputs in the first place.

Firms can choose among different combinations of inputs in R&D. In principle, it is possible for firms to use only foreign inputs but no domestic inputs; in reality, this rarely happens. Thus, following the classification in Section 2, we assume that there are four *combinations* of R&D inputs for firms to choose from: using only inputs from native researchers (N); using inputs from both native and immigrant researchers (NI); using inputs from native researchers and foreign R&D services suppliers (NF); using all three types inputs simultaneously (NIF). We call these combinations of R&D activities as *R&D modes*. By denoting the mode for non-R&D firms as '0', the mode choice of firms is given by $x \in \{0, N, NI, NF, NIF\}$.

The cost for an effective unit of R&D investment for firms choosing R&D mode x, denoted by c^x, is given by

$$
\begin{aligned}
c^N &= \left(A^N\right)^{\frac{1}{1-\theta}} p^N \\
c^{NI} &= \left[A^N \left(p^N\right)^{1-\theta} + A^I \left(p^I\right)^{1-\theta}\right]^{\frac{1}{1-\theta}} \\
c^{NF} &= \left[A^N \left(p^N\right)^{1-\theta} + A^F \left(p^F\right)^{1-\theta}\right]^{\frac{1}{1-\theta}} \\
c^{NIF} &= \left[A^N \left(p^N\right)^{1-\theta} + A^I \left(p^I\right)^{1-\theta} + A^F \left(p^F\right)^{1-\theta}\right]^{\frac{1}{1-\theta}},
\end{aligned}
$$

where $p^{\tilde{x}}$ denotes the unit price for R&D of input $\tilde{x} \in \{N, I, F\}$. These costs apply to all firms in the economy and do not change over time, so we suppress the firm and time subscripts for simplicity. With imperfect substitution between R&D inputs and the elasticity of substitution between input types greather than 1 (i.e., $1 < \theta < \infty$), we have $c^x < c^N, \forall x \in \{NI, NF, NIF\}$. Therefore, conditional on the R&D expenditures, firms using multiple sources of ideas in R&D would have larger effective R&D investment. This in turn translates into a larger estimated increase in productivity for these firms than for the firms spending the same budget only on native researchers, which is exactly what Fact 3 in the previous section states. We will confirm this mechanism with the estimated value of θ in the next section.

[18]Compared to the production function specified in equation (2), we effectively assume that the high-skill R&D labor is not part of the production labor.

Despite having immigrant researchers or imported R&D services makes R&D investment more effective due to the love for variety of ideas, not all firms adopt them. This suggests the existence of fixed and sunk costs for such choices. In addition, the persistence of the R&D mode decision observed in the data naturally motivates a dynamic model. In the next subsection, we introduce the fixed and sunk costs of R&D and describe firms' dynamic decisions.

3.3 Dynamic Decisions

The timeline for firms' dynamic problem is as follows. At the beginning of period t, firms learn the realization of $\zeta_{i,t}$, hence their current productivity, $\omega_{i,t}$, given by equation (5). Knowing $\omega_{i,t}$, firm i chooses output $q_{i,t}$ to maximizes the static profit, as described in Section 3.1, and then determines the current period's R&D mode and total R&D expenditures.

Conducting R&D via mode x' requires an irreversible investment of $\tilde{F}^{x,x'} + \epsilon_{i,t}^{x'}$. In this total cost, $\tilde{F}^{x,x'}$, for $x, x' \in \{0, N, NI, NF, NIF\}$, is the systematic component that is common to all firms switching from mode x to mode x'. This component depends on firms previous R&D status because there can be sunk costs associated with entry into a different mode, e.g., the cost of setting up a new R&D team or nestling a reliable overseas R&D supplier. $\epsilon_{i,t}^{x'}$ is the idiosyncratic component. We assume that $\epsilon_{i,t}^{x'}$ is drawn randomly and independently (across i, t, and x') from a Type-I extreme value distribution with a scale parameter $\nu > 0$. This idiosyncratic cost can be associated with a number of factors: for example, some firms might be in a better position to recruit immigrant researchers because it is located in a region where many immigrants live; firms that are already relying heavily on international suppliers might also find sourcing foreign R&D services relatively easier than other firms. All of these factors lead firms to make different decisions on R&D modes but are unobserved to the econometrician, so we capture them in the idiosyncratic term.

Firms observe the current draw of their idiosyncratic cost for each R&D mode, $\epsilon_{i,t}^{x'}$, and make decisions on R&D modes. We denote firm i's state in period t as $\mathbf{s}_{i,t} = (\omega_{i,t}, x_{i,t-1})$, where $x_{i,t-1}$ is firm i's R&D mode choice in period $t-1$. Then, the expected value of a firm with current state $\mathbf{s}_{i,t}$ before the realization of $\epsilon_{i,t}^{x}$, denoted by $V_t(\mathbf{s}_{i,t})$, is given by:

$$V_t(\mathbf{s}_{i,t}) = \pi(\omega_{i,t}) + \int \max_{x \in X} \left[V_t^x(\mathbf{s}_{i,t}) - \widetilde{F}^{x_{i,t-1},x} - \epsilon_{i,t}^{x} \right] d\epsilon, \tag{7}$$

$$\text{where } X \equiv \{0, N, NI, NF, NIF\}$$

$$\text{and } V_t^x(\mathbf{s}_{i,t}) \equiv \begin{cases} \delta \cdot E_t V_t(\mathbf{s}_{i,t+1} \mid \mathbf{s}_{i,t}), \text{ for } x = 0 \\ \max\limits_{rd_{i,t}} \left\{ -rd_{i,t} \cdot c^x + \delta E_t V_t(\mathbf{s}_{i,t+1} \mid \mathbf{s}_{i,t}, x, rd_{i,t}) \right\}, \text{ for } x \in X \setminus \{0\} \end{cases}$$

In equation (7), the $V_t^x(\mathbf{s}_{i,t})$ term inside the integral is the present discounted value of R&D mode x for firm i at time t; $\delta \in (0,1)$ is the discount rate; $rd_{i,t}$ is the effective investment in R&D, aside from the fixed and sunk cost payments. Under the distributional assumption for $\epsilon_{i,t}^{x'}$, the probability of a firm switching from an R&D mode x to an R&D mode x' is given by:

$$m_t^{x,x'}(\mathbf{s}_{i,t}) = \frac{\exp\left(\frac{1}{\nu}V_t^{x'}(\mathbf{s}_{i,t}) - \frac{1}{\nu}\widetilde{F}^{x,x'}\right)}{\sum_{x''\in X}\exp\left(\frac{1}{\nu}V_t^{x''}(\mathbf{s}_{i,t}) - \frac{1}{\nu}\widetilde{F}^{x,x''}\right)}. \tag{8}$$

We parameterize the cost of changing R&D modes, $\widetilde{F}^{x,x'}$, with various interpretable components. Specifically, we assume that the cost $\widetilde{F}^{x,x'}$ consists of a fixed operation cost component independent of firms' previous R&D status, denoted by $f^{x'}$, and a status-dependent component that governs the cost associated with *switching between modes*, denoted by $F^{x,x'}$. The total cost $\widetilde{F}^{x,x'}$ is the sum of the two components. If we put this structure in a matrix form, we have

$$\tilde{\mathbf{F}}_{5\times 5} = \mathbf{1}_{5\times 1}\cdot \mathbf{f}_{1\times 5} + \mathbf{F}_{5\times 5},$$

where the subscript of each variable denotes the dimension of the variable. $\mathbf{1}$ is a 5 by 1 vector of ones; $\mathbf{f} = (f^0, f^N, f^{NI}, f^{NF}, f^{NIF})$ is the vector of fixed operation costs; $\mathbf{F}$ is a 5 by 5 matrix of sunk cost components. The mn-th element of $\tilde{\mathbf{F}}$, for example, corresponds to the cost of switching from the m-th mode in X to the n-th mode in X.

We assume that doing no R&D activity ($x = 0$) incurs neither cost, i.e., $f^0 = 0$ and $F^{x,0} = 0$ for every x, and that there is no sunk cost if firms do not switch R&D mode, i.e., $F^{x,x'} = 0$ if $x = x'$. We parameterize the remaining sunk cost components of $\mathbf{F}$ as

$$\mathbf{F} = \begin{bmatrix} 0 & F^N & F^N + F^I & F^N + F^F & F^N + F^I + F^F - F^{IF} \\ 0 & 0 & F^I & F^F & F^I + F^F - F^{IF} \\ 0 & F^{I0} & 0 & F^F + F^{I0} & F^F - F^{IF} \\ 0 & F^{F0} & F^I + F^{F0} & 0 & F^I \\ 0 & F^{I0} + F^{F0} & F^{F0} & F^{I0} & 0 \end{bmatrix}, \tag{9}$$

where each row and column corresponds to the five R&D modes $\{0, N, NI, NF, NIF\}$ in the same order, with rows indicating firms' current mode x and columns indicating their next mode x'.

Components in $\mathbf{F}$ have intuitive explanations. First, F^N, F^I, and F^F capture the cost of setting up new R&D operations to be carried out by native workers, immigrant workers, and overseas suppliers, respectively. These are only to be paid by firms that did not use the R&D inputs of the corresponding type in the previous period. Second, F^{I0} and F^{F0} represent the cost associated with *dropping* immigrant workers and offshore R&D suppliers from the R&D process, respectively. Dropping an input from R&D could be costly because the rest of the R&D team may need to be reorganized to accommodate the change.[19]

Last but not least, the reduced-form facts suggest that adding offshore R&D into the R&D bundle can be easier for firms with immigrant R&D workers. Our parameterization of $\tilde{\mathbf{F}}$ allows

[19] Because in the data, virtually all R&D active firms hire native researchers, we assume that when firms drop input from native researchers they shut down R&D all together. In this case, they do not need to pay the reorganization cost required to continue R&D, so we assume the cost of dropping the N mode to be zero.

for presence of immigrants to reduce the cost of offshore R&D through two components: in the sunk cost via $F^{IF} > 0$ or in the fixed cost via $f^{NIF} < f^{NI}$. We will let the data tell whether these inequalities are satisfied and which component is relatively more important.

A plausible explanation for the interaction between immigrant researchers and offshore R&D is that immigrants in the R&D team, knowing the language and affiliate logistics better, can facilitate communications between the headquarters and offshore R&D affiliates and make information flows between two locations easier. This explanation is consistent with the empirical results reported in the Appendix, which shows a strong connection between the origin country of immigrant researchers and the destination for offshore R&D. Following the extensive literature that has documented the importance of immigrants in facilitating international business (Rauch and Trindade, 2002; Burchardi et al., 2019), we label the cost advantage in the presence of immigrants for offshoring as the *information channel of immigrants*.

In summary, the model rationalizes firms' use of diverse R&D inputs through the notion of love for the variety of ideas; it further allows for the higher propensity of offshoring among firms with immigrant researchers by specifying flexible costs of switching between R&D modes. We will estimate the model in the next section to uncover the importance of these mechanisms for R&D decisions.

3.4 Discussion on the Model Assumptions

Before turning to the estimation, we discuss the rationale for three simplifying assumptions in the model. First, at the center stage of the model are the decisions of Danish firms looking to optimally source their R&D for the use within their domestic branch. This setup fits the measure of offshore R&D in the survey, but it overlooks the possibility that some of the firms could be the Danish affiliates of foreign multinational firms. A natural concern, then, is that because these multinational firms already have an international network, having immigrant R&D workers in their Danish affiliate should have a smaller impact on the cost of sourcing R&D inputs from abroad. Thus, it is possible that the pattern we document on the connection between immigrant R&D workers and offshore R&D would be weaker for these firms. In this regard, our structural analysis throughout the paper captures the lower bound of the importance of this cost-reducing information channel. As a robustness, we show in the Appendix that the empirical patterns are similar when affiliates of foreign multinationals are excluded from our sample.

Second, our setting allows only firms with immigrant *R&D workers*, rather than firms with any types of immigrant workers, to benefit from the information channel. This choice is motivated by the data: as shown in the appendix, when indicators for both R&D and non-R&D immigrants are included in regressions, only R&D immigrants are positively correlated with offshore R&D.

Third, we assume each firm makes only a binary decision of whether to hire immigrants or offshore R&D, instead of deciding from which world regions to hire immigrant researchers or where to offshore R&D. This assumption greatly simplifies the structural analysis but may seem too restrictive for the information channel of immigrants. Note that most firms in our data source

R&D only from one world region.[20] Even among the firms with more than 250 employees, the average number of offshore R&D destination regions is only 1.6. We can view the model here as a special case of a model with the following two-step R&D decision: firms first choose whether to hire immigrant and/or whether to offshore R&D, and then pick *one* world region to do this.

4 Model Estimation

This section explains how we estimate the model. Some parameters can be estimated without fully solving for firms' dynamic optimization problem, so we estimate these parameters independently. Other parameters will be estimated jointly via an indirect inference procedure.

4.1 The Distribution of Idiosyncratic Cost Shocks

A key set of parameters of the model is the elements that consist of the fixed and sunk costs $\tilde{\mathbf{F}}$. Since $\tilde{\mathbf{F}}$ governs the cost of switching R&D modes, an intuitive approach for estimation of these parameters is to estimate them using the pattern of transition between different modes observed in the data. A challenge for this approach, however, is that because $\tilde{\mathbf{F}}$ enters firms' mode choice only jointly with the reciprocal of ν, the scale parameter of the distribution of idiosyncratic costs shocks, as shown in equation (8), transition patterns alone do not separately identify $\tilde{\mathbf{F}}$ and ν.[21]

In the first step of the estimation, we take advantage of a natural experiment in Denmark, the introduction of an R&D subsidy regime in 2011, to estimate ν. The subsidy policy rebates 25% of total R&D expenses for R&D-active firms that incur a loss, thereby reducing their effective cost of R&D. This, in turn, could encourage more firms to conduct R&D. We can identify ν by examining how the probability of switching R&D modes changed among the eligible firms after the policy was introduced.

To see this, consider first the choice of the firms entering period t with R&D mode N and productivity $\omega_{i,t}$. Combining equations (7) and (8) gives us the log of the ratio between the share of these firms staying in mode N in the current period and the share quitting R&D all together:

$$\log\left(\frac{m^{N,0}(\omega_{i,t})}{m^{N,N}(\omega_{i,t})}\right) = \underbrace{\frac{1}{\nu}[c^N \cdot rd^*_{i,t}(N,\omega_{i,t}) + f^N]}_{\text{R\&D expenses}} \tag{10}$$
$$+ \frac{\delta}{\nu}\underbrace{[E_t V_{t+1}(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=0) - E_t V_{t+1}(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=rd^*_{i,t}(N,\omega_{i,t}))]}_{\text{Improvement in continuation value from optimally chosen R\&D}}.$$

In the above expression, $rd^*_{i,t}(\cdot)$ is the optimal effective R&D given firm i's current productivity and its choice to be in mode N. The expression shows that the log odds ratio is the sum of

[20] Examples of world regions in the data are Emerging Europe, East Europe, North America, China, etc.

[21] This observation is analogous to the result in the trade literature that gravity regressions alone cannot separately identify trade elasticity and trade costs.

two components: static R&D expenses, and dynamic gains due to the improvement in expected future productivity.

With the subsidy in place, equation (10) becomes:

$$\begin{aligned}\log(\frac{m'^{N,0}(\omega_{i,t})}{m'^{N,N}(\omega_{i,t})}) =&(1-\tau)\times\frac{1}{\nu}[c^N\cdot rd^{*'}_{i,t}(N,\omega_{i,t})+f^N] \\ &+\frac{\delta}{\nu}[E_tV'_{t+1}(\omega_{i,t+1}|\omega_{i,t},rd_{i,t}=0)-E_tV'_{t+1}(\omega_{i,t+1}|\omega_{i,t},rd_{i,t}=rd^{*'}_{i,t}(N,\omega_{i,t}))],\end{aligned} \tag{11}$$

in which τ is the subsidy as a share of R&D expenses. Compared to equation (10), equation (11) differs in two aspects. First, the user cost of R&D is now $(1-\tau)$ fraction of the pre-policy level. Second, in principle the value and policy functions could change in response to the subsidy, so they are denoted $V'_{t+1}(\cdot)$ and $rd^{*'}_{i,t}(\cdot)$, respectively.

Given the uncertain and temporary nature of this policy and the qualification requirement which specifies that only loss-making firms are eligible, we assume that firms perceive the value function in the post-policy world as similar to the one before policy, i.e., $V_{i,t}(\cdot)\approx V'_{i,t}(\cdot)$.[22] Under this assumption, we can express firms' continuation value net of R&D investment as the following:

$$\begin{aligned}&E_tV'_{t+1}(\omega_{i,t+1}|\omega_{i,t},rd_{i,t}=rd^{*'}_{i,t}(N,\omega_{i,t}))-(1-\tau)\times\frac{1}{\nu}[c^N\cdot rd^{*'}_{i,t}(N,\omega_{i,t})+f^N] \\ &=\max_{rd_{i,t}}\{E_tV'_{t+1}(\omega_{i,t+1}|\omega_{i,t},rd_{i,t})-(1-\tau)\times\frac{1}{\nu}(c^N\cdot rd_{i,t}+f^N)\} \\ &\approx\max_{rd_{i,t}}\underbrace{\{E_tV_{t+1}(\omega_{i,t+1}|\omega_{i,t},rd_{i,t})-(1-\tau)\times\frac{1}{\nu}(c^N\cdot rd_{i,t}+f^N)\}}_{\equiv f(rd_{i,t},\tau)} \\ &\approx\max_{rd_{i,t}}\{f(rd_{i,t},0)\}+\tau\cdot\frac{\partial f(rd_{i,t},\tau)}{\partial\tau}|_{rd_{i,t}=\arg\max_{rd_{i,t}}\{f(rd_{i,t},0)\}} \\ &=E_tV_{t+1}(\omega_{i,t+1}|\omega_{i,t},rd_{i,t}=rd^{*}_{i,t}(N,\omega_{i,t}))-\frac{1}{\nu}[c^N\cdot rd^{*}_{i,t}(N,\omega_{i,t})+f^N]+\tau\times\frac{1}{\nu}[c^N\cdot rd^{*}_{i,t}(N,\omega_{i,t})+f^N].\end{aligned} \tag{12}$$

The first equality in (12) follows the definition of $rd_{i,t}$ as the solution to the Bellman equation (7); the approximation in the second line stems from our assumption of $V_{i,t}(\cdot)\approx V'_{i,t}(\cdot)$; the third and fourth lines are derived from the Envelope Theorem. Condition (12) shows that up to the first order, the net (of R&D expenses) continuation of the firm in the presence of R&D subsidy τ is simply the pre-policy net continuation value plus the subsidy that the firm can now receive.

[22] From the perspective of firms qualifying for this subsidy in year t, they would qualify in the next year only if all of the following conditions hold: i) the subsidy policy is still active; ii) they continue to be in a loss position; and iii) they are actively doing R&D. Given the uncertainty in policy and the potential upside risk of R&D-active firms, it is likely that firms do not anticipate all three conditions to hold in the future. We also note that assuming $V_{i,t}(\cdot)\approx V'_{i,t}(\cdot)$ does not mean that firms perceive their continuation values to be the same as before. Rather, the assumption is that, the perceived continuation value, *given* the mode of R&D chosen by the firm and the realization of productivity in the next period, is the same as before.

Table 4: R&D Decisions of Loss-Making Firms

		Loss-making firms in 2011				Loss-making firms in 2012	
		2011				2012	
		N	0			N	0
2010	N	52	17	2011	N	67	11
	0	15	135		0	19	116

Notes: The sample is loss-making firms in manufacturing in 2011 and 2012 with at least 10 employees. N refers to firms doing domestic R&D (i.e. reporting positive domestic R&D expenditures) while 0 refers to firms not doing R&D (i.e. reporting zero domestic R&D expenditures).

Combining this condition with equations (10) and (11) gives us

$$\begin{aligned}
&\log\left(\frac{m'^{N,0}(\omega_{i,t})}{m'^{N,N}(\omega_{i,t})}\right) - \log\left(\frac{m^{N,0}(\omega_{i,t})}{m^{N,N}(\omega_{i,t})}\right) \qquad (13)\\
=&\frac{\delta}{\nu}E_t V'_{t+1}(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=0) - \frac{\delta}{\nu}E_t V_{t+1}(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=0)\\
&+\frac{\delta}{\nu}E_t V_{t+1}(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=rd^*_{i,t}(N,\omega_{i,t})) - \frac{1}{\nu}[c^N \cdot rd^*_{i,t}(N,\omega_{i,t}) + f^N]\\
&-\frac{\delta}{\nu}E_t V'_{t+1}(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=rd^{*'}_{i,t}(N,\omega_{i,t})) - (1-\tau)\times\frac{1}{\nu}[c^N \cdot rd^{*'}_{i,t}(N,\omega_{i,t}) + f^N]\\
\approx&\frac{1}{\nu}\times\tau\times[c^N \cdot rd^*_{i,t}(N,\omega_{i,t}) + f^N].
\end{aligned}$$

According to this condition, the change in the propensity of a loss-making firm continuing R&D, in response to the R&D subsidy program, is modulated by the firm's current R&D expenditures ($rd^*_{i,t} \cdot c^N + f^N$) which determine the amount of subsidies the firm will receive, and the parameter ν which governs firms' responsiveness to the subsidy. In the model, firm characteristics are uniquely determined by their current productivity and its participation in R&D in the previous period. Equation (13) suggests that we can determine ν by checking if, conditional on their productivity, loss making firms are less likely to quit doing R&D after the policy is introduced and if the decrease in their propensity to quit is higher for firms investing more in R&D.

Table **??** reports the transition of loss-making firms in 2011 (before the policy) and 2012 (after the policy) between R&D mode N and R&D mode 0. There are around 240 loss-making firms making transitions between these modes in both periods. Before the subsidy was enacted, 26% of the firms in mode N stopped doing R&D; in 2012, when the subsidies took effect, only 14% quit doing R&D, which is consistent with the goal of the subsidy policy to encourage firms to keep doing R&D.

To control for differences in firm productivity, we split the observations in 2011 and 2012 into K bins by their labor productivity. We then examine, within each bin, whether the observations from 2012 show a higher or lower likelihood of quitting R&D than those from 2011. In effect, we are using the 2011 firms with similar productivity as a comparison group for firms in 2012.

Formally, we estimate the following linear probability model:

$$\mathbb{I}(i \text{ quits R\&D in } t) = \beta_0 \cdot \mathbb{I}(t = 2012) + \sum_{k}^{K-1} \beta_k \mathbb{I}(\omega_{i,t} \in k) + \beta_l \ln(\text{emp}_{i,t-1}) + \epsilon_{i,t},$$

where $\mathbb{I}(i$ quits R&D in $t)$ is an indicator variable that takes a value of 1 if a firm-year observation quits R&D; β_k is a fixed effect for all observations belonging to the k-th productivity bin; β_0 is the key coefficient of interest, capturing the effect of the policy. To rule out a possibility of systematic differences in firms' behavior based on their size, we always control for firm size which is measured as lagged log employment.

Columns (1) through (3) in Panel A of Table 5 report the results from this specification, with the number of productivity bins, K, ranging from 5 to 15. Column (4) controls for a flexible function of productivity instead of the bin dummies. All columns give similar estimates: after the policy is introduced, the probability that firms quit doing R&D decreased by about 12%. Columns 5 through 8 provide a placebo test by focusing on the profit-making firms, which were ineligible for the subsidy. This placebo test assures that the results in columns (1)-(4) are not due to a change in the macroeconomic conditions between 2011 and 2012 that affected all firms simultaneously.

The estimates reported in Panel A, however, do not translate easily into the structural parameter of interest, $\frac{1}{\nu}$. We thus estimate a logistic specification with the independent variable being the *log of R&D expenditures*, as below:

$$\mathbb{I}(i \text{ quits R\&D in } t) = \begin{cases} 1, & \text{if } \beta_0 \cdot \mathbb{I}(t = 2012) \cdot \log(r\&d_{i,t-1}) + \sum_{k}^{K-1} \beta_k \mathbb{I}(\omega_{i,t} \in k) + \beta_l \ln(\text{emp}_{i,t-1}) + \epsilon_{i,t} > 0 \\ 0, & \text{otherwise.} \end{cases} \quad (14)$$

When $\epsilon_{i,t}$ is drawn from the standard logistic distribution, this specification implies log odds ratios corresponding to equation (13), with the only difference being that $\log(r\&d_{i,t-1})$, instead of $r\&d_{i,t-1}$, is included in the specification.[23] Therefore, what we estimate is an elasticity, instead of a semi-elasticity.[24]

Columns (1) through (4) of Panel B report the results from the logistic regression. The estimated coefficients are all around -0.16. Since our subsequent productivity estimation and counterfactual simulations will focus on the manufacturing sector, columns (5) through (8) also report results for only manufacturing firms. The sample shrinks by two thirds, but the estimated

[23] To see this, note that the logistic assumption in equation (14) implies that, the pre- and after-policy log odds ratios are, $\log(\frac{m^{N,0}(\omega_{i,t})}{m^{N,N}(\omega_{i,t})}) = \sum_k^{K-1} \beta_k \mathbb{I}(\omega_{i,t} \in k) + \beta_l \ln(\text{emp}_{i,t-1})$ and $\log(\frac{m'^{N,0}(\omega_{i,t})}{m'^{N,N}(\omega_{i,t})}) = \beta_0 \cdot \log(r\&d_{i,t-1}) + \sum_k^{K-1} \beta_k \mathbb{I}(\omega_{i,t} \in k) + \beta_l \ln(\text{emp}_{i,t-1})$, respectively. Combining the two gives an elasticity-specification of equation (13).

[24] Alternatively, we could have used the level of R&D expenditure as the explanatory variable to directly estimate $-\frac{\tau}{\nu}$. We do not adopt this alternative because the distribution of R&D expenditure is highly skewed. As a result, specifications with the level of expenditure as the explanatory variable are heavily influenced by a small number of big firms. Nevertheless, using a level specification gives qualitatively similar results.

Table 5: R&D Subsidy and Firm R&D

Panel A	Linear Probability Model							
	Loss-making firms				Placebo: profitable firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_0	-0.124***	-0.116**	-0.122***	-0.132***	-0.026	-0.026	-0.027	-0.022
	(0.047)	(0.046)	(0.046)	(0.045)	(0.024)	(0.025)	(0.024)	(0.024)
Observations	299	299	299	299	952	952	952	952
Firm size$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Productivity$_{i,t-1}$	-	-	-	Yes	-	-	-	Yes
Number of bins	5	10	15	-	5	10	15	-
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	Logistic Model							
	All industries				Manufacturing only			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_0	-0.165***	-0.156***	-0.165***	-0.166***	-0.239**	-0.240**	-0.330**	-0.197**
	(0.043)	(0.043)	(0.043)	(0.041)	(0.102)	(0.110)	(0.140)	(0.085)
Observations	253	253	253	253	103	103	89	103
Firm size$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Productivity$_{i,t-1}$	-	-	-	Yes	-	-	-	Yes
Number of bins	5	10	15	-	5	10	15	-
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel A reports the results from a linear probability model; Panel B reports the results from a logistic model. All specifications control for lag log firm size and lag firm productivity (defined as log valued added), and include industry fixed effects. Industries are defined following the NACE Rev.2 intermediate level aggregation. Columns (1)-(3) and (5)-(7) report specifications using various productivity bins fixed effects, while columns (4) and (8) use a quadratic function of lag productivity. Panel A reports results for loss-making and profitable private sector firms while Panel B breaks down results for loss-making firms in the private sector and manufacturing. The sample is firms in the private sector or manufacturing in 2011 and 2012 that have at least 10 employees. Robust standard errors in parenthesis * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

coefficients are relatively similar to the ones from all industries.

Our preferred specification reported in column (7) of the Table gives an estimate of -0.330. To convert this number into a value for the semi-elasticity given in equation (13), $-\frac{\tau}{\nu}$, we assume that the elasticity estimate holds for the median firm. With the median R&D expenditure being 2.5 million DKK in the regression sample, and the subsidy rate being $\tau = 0.25$, we have $-\frac{0.25}{\nu} = \frac{-0.330}{2.5}$, which implies $\nu = 1.89$.

4.2 R&D and the Evolution of Productivity

In the second step of the estimation, we estimate the moments that will pin down the parameters governing the evolution of firm productivity. These parameters include ρ, γ, the standard deviation σ_ζ of the error term in equation (5), and the cost for each effective unit of R&D investment, c^x for each R&D mode $x \in \{N, NI, NF, NIF\}$, which in turn depends on the efficiency $A^{\tilde{x}}$ and the price $p^{\tilde{x}}$ of each type of R&D input $\tilde{x} \in \{N, I, F\}$.

Letting $e_{i,t-1} > 0$ denote the R&D expenditure that firm i spends within Denmark, i.e., on native researchers and/or immigrant researchers, the period-t productivity of firm i is given by:

$$\omega_{it} = \rho\omega_{it-1} + \gamma\log(e_{it-1}) - \log(c^N) \tag{15}$$
$$+ \begin{cases} \zeta_{i,t}, & \text{if } x_{i,t-1} = N \\ \gamma(\log(c^N) - \log(c^{NI})) + \zeta_{i,t}, & \text{if } x_{i,t-1} = NI \\ \gamma\theta[\log(c^N) - \log(c^{NF})] + \zeta_{i,t}, & \text{if } x_{i,t-1} = NF \\ \gamma[\theta(\log(c^{NI}) - \log(c^{NIF})) + (\log(c^N) - \log(c^{NI}))] + \zeta_{i,t}, & \text{if } x_{i,t-1} = NIF \end{cases}$$

where $x_{i,t-1}$ denotes firm i's R&D mode choice at time $t-1$ as previously defined. Each line of this equation indicates one mode of doing R&D. For example, the first line of the equation states that for the firms in R&D mode N, the effective R&D bundle is $\log(rd_{i,t-1}) = \log(e_{it-1}) - \log(c^N)$. The second line inside the curly bracket indicates that compared to firms in mode N with the same domestic R&D expenditures, the NI firm will see a larger productivity increase, captured in $\gamma(\log(c^N) - \log(c^{NI})) > 0$, due to the gains from a variety of ideas.[25]

The third line inside the curly bracket of equation (15) completes the specification for the productivity for firms in R&D mode NF. Conditional on the total R&D spending *within* Denmark, these firms would see an additional boost of $\gamma\theta\big(\log(c^N) - \log(c^{NF})\big)$ in productivity. The coefficient before the $\big(\log(c^N) - \log(c^{NF})\big)$ is $\gamma\theta$ instead of γ as in the case of NI mode. It captures that, first, conditional on R&D investment in Denmark, firms in mode NF also make additional spending on imported R&D services; second, given the total spending on R&D, the effective R&D will be larger. Finally, the last line of equation (15) is for the firms using all three types of R&D inputs. Because $c^{NI} > c^{NIF}$ and $c^N > c^{NI}$ when $\theta > 1$, the systematic boost on productivity in the case of the NIF mode is also positive and greater than that in the case of the NI mode.

Based on the interpretation of the equation (15), we specify the following regression:

$$\omega_{it} = \overline{\omega} + \tilde{\rho}\omega_{it-1} + \tilde{\gamma}_0\log(e_{i,t-1}) + \tilde{\gamma}_1\mathbb{I}(x_{i,t-1} = NI) + \tilde{\gamma}_2\mathbb{I}(x_{i,t-1} = NF) + \tilde{\gamma}_3\mathbb{I}(x_{i,t-1} = NIF) + \zeta_{i,t}, \tag{16}$$

in which $\overline{\omega}$ is a productivity shifter that captures the cost of domestic R&D common to all firms. $\tilde{\gamma}_m$ for each $m = 0, 1, 2, 3$ and $\tilde{\rho}$ are the structural parameters corresponding to the parameters in equation (15).[26]

Comparison between equations (15) and (16) clarifies how $\tilde{\gamma}_m$ for each $m = 1, 2, 3$, summarizes the benefit of having access to additional sources of ideas. These parameters contain all information about $A^{\tilde{x}}$ and $p^{\tilde{x}}$ for $\tilde{x} = N, I, F$ that firms need to know when deciding whether to adopt an additional input in R&D. Once $\tilde{\gamma}_m$ for each $m = 1, 2, 3$ have been estimated, as an

[25] We base our interpretation of the additional terms in the law of motion for the firms doing R&D with foreign inputs on the case where $\theta > 1$ throughout this section, but we do not make this specific restriction in estimation. We confirm $\theta > 1$ after we estimate the model, as the implied value of θ is directly derived from the estimates.

[26] Concretely, $\tilde{\rho} = \rho$; $\tilde{\gamma}_0 = \gamma$; $\tilde{\gamma}_1 = \gamma(\log(c^N) - \log(c^{NI}))$; $\tilde{\gamma}_2 = \gamma\theta[\log(c^N) - \log(c^{NF})]$; $\tilde{\gamma}_3 = \gamma[\theta(\log(c^{NI}) - \log(c^{NIF})) + (\log(c^N) - \log(c^{NI}))]$.

econometrician, we can plug them back in equation (15) and treat it as the model-consistent law of motion of productivity that firms perceive when making R&D decisions.

There are two challenges in estimating equation (16), however. First, $\omega_{i,t}$ is unobserved to the econometrician. Second, empirically, firm-level R&D are notoriously difficult to measure, so e_{it-1} is likely subject to severe measurement errors. Moreover, only very few firms in the sample are in the NF mode. Both factors limit our ability to estimate all reduced-form parameters in equation (16) precisely, even if $\omega_{i,t}$ are known.

To overcome the first challenge, we follow a two-step control function approach, which recovers $\omega_{i,t}$ jointly with the parameters governing firms' productivity evolution.[27] To overcome the second challenge, in estimating the parameters governing the productivity evolution, we specify an auxiliary regression that is less susceptible to biases from measurement errors and the small number of firms in the NF mode. We then discipline the structural parameters of the model by matching the estimates from the auxiliary regression. We now explain each step of the estimation procedures in detail.

In productivity estimation, we introduce capital, labor, and materials as inputs in production to be consistent with the data. The log output *quantity*, denoted by $\tilde{q}_{i,t}$, for firm i at time t is:

$$\tilde{q}_{i,t} = \omega_{i,t} + \beta_k \tilde{k}_{i,t} + \beta_l \tilde{l}_{i,t} + \beta_m \tilde{m}_{i,t}, \tag{17}$$

where $\tilde{k}_{i,t}$, $\tilde{l}_{i,t}$, and $\tilde{m}_{i,t}$ denote the log of capital, labor, and materials, respectively, for firm i in period t.[28] The log of the optimally chosen price for the output of firm i, $\tilde{p}_{i,t}$, is:

$$\tilde{p}_{i,t} = \frac{1}{\eta}\tilde{q}_{i,t} + \tilde{P}_t - \frac{1}{\eta}\tilde{Q}_t, \tag{18}$$

where $\tilde{P}_t$ and $\tilde{Q}_t$ are the log of aggregate price and demand, respectively.

By combining equations (17) and (18), we obtain the measured revenue (data) as follows:

$$\begin{aligned} \tilde{y}_{i,t} &\equiv \tilde{q}_{i,t} + \tilde{p}_{i,t} + \epsilon_{i,t} \\ &= \frac{\eta+1}{\eta}\omega_{i,t} + \tilde{\beta}_k \tilde{k}_{i,t} + \tilde{\beta}_l \tilde{l}_{i,t} + \tilde{\beta}_m \tilde{m}_{i,t} + \tilde{P}_t - \frac{1}{\eta}\tilde{Q}_t + \epsilon_{i,t}, \\ &\text{where } \tilde{\beta}_k \equiv \frac{\eta+1}{\eta}\beta_k,\ \tilde{\beta}_m \equiv \frac{\eta+1}{\eta}\beta_m,\ \tilde{\beta}_k \equiv \frac{\eta+1}{\eta}\beta_m. \end{aligned} \tag{19}$$

[27]Our estimation of $\omega_{i,t}$ takes into account the fact that firms' R&D mode choices depend on their productivity, addressing the concern raised by De Loecker (2013) that if productivity is estimated without taking firms' endogenous decisions (such as R&D or export) into account, one might fail to detect the impact of these endogenous decisions on productivity.

[28]For baseline analysis, we postulate an output quantity production function and estimate its parameters in a theory-consistent way. In the Appendix, we present the results for the case when we estimate a value-added production function, with value-added calculated as the difference between revenue and material use. Both cases give qualitatively similar results. The advantage of the baseline approach is that it is consistent with the monopolistic competitive model, in which firms choose the output quantity and the optimal markup over the production cost, instead of choosing the value added.

In this specification, $\epsilon_{i,t}$ is the log of a multiplicative measurement error in revenue.[29] $\tilde{\beta}_x$, $x \in \{m, k, l\}$ is the revenue elasticity of input x.

Firms' productivity evolves according to equation (16). We allow capital and labor to be dynamic inputs that are subject to adjustment costs. This implies that $\tilde{k}_{i,t}$ and $\tilde{l}_{i,t}$ are not necessarily optimal given the realization of $\omega_{i,t}$. On the other hand, materials are assumed to be a static input, chosen after firms observe $\omega_{i,t}$ and have decided $\tilde{k}_{i,t}$ and $\tilde{l}_{i,t}$. This implies that $\tilde{m}_{i,t}$ and $\frac{\eta+1}{\eta}\omega_{i,t}$ in equation (19) are correlated, hence the OLS estimate of input elasticities biased. Following the insight of Levinsohn and Petrin (2003) and Ackerberg et al. (2015), we use materials as a control to isolate the impact of productivity using a two-step estimation procedure as detailed below.

Step 1. The first step is to come up with a control of $\omega_{i,t}$ from observables. By noting that $\tilde{m}_{i,t}$ is chosen given $\tilde{k}_{i,t}$, $\tilde{l}_{i,t}$, and $\omega_{i,t}$, we write the material use as a general function $\tilde{m}_{i,t} = m_t(\omega_{i,t}, \tilde{k}_{i,t}, \tilde{l}_{i,t}, z_{i,t})$, where $z_{i,t}$ includes a number of firm-level controls that might affect material use but are absent from our structural model. The first set of controls are on firms' participation in the international market. A robust finding from the trade literature is that access to imported intermediates has a positive impact on firm performance (e.g., Amiti and Konings, 2007; Halpern et al., 2015). In our context, access to imported materials can have an impact on material use by reducing the effective price of intermediate goods. Relatedly, with the access to the international market, exporters might choose to produce more than non-exporters for any given level of capital and labor, thus using more materials. We include firms' importing and exporting status in $z_{i,t}$. Second, since the quality of workers differs across firms as documented by Fox and Smeets (2011), $\tilde{l}_{i,t}$ might be a noisy proxy for the effective labor at a firm. Following Doraszelski and Jaumandreu (2013), we include the firm-level average wage in $m_t(\omega_{i,t}, \tilde{k}_{i,t}, \tilde{l}_{i,t}, z_{i,t})$. Finally, firms' capital stock, calculated based on the perpetual inventory method and deflated by industry capital prices, might not accurately reflect the efficiency-adjusted capital stock. In particular, newer vintages of machines might be more efficient than the old ones. We include investment rate in $z_{i,t}$ to control for the potential higher efficiency of more recent capital installations.

Conditional on capital, labor, and all these other factors, firms' material use increases monotonically in their productivity. We can thus invert $m(\cdot, \tilde{k}_{i,t}, \tilde{l}_{i,t}, z_{i,t})$ to express $\omega_{i,t}$ as a generic function of capital, labor, material use, and $z_{i,t}$: $\omega_{i,t} = \tilde{\omega}_t(\tilde{k}_{i,t}, \tilde{l}_{i,t}, \tilde{m}_{i,t}, z_{i,t})$. Plugging this expression into equation (19) gives:

$$\begin{aligned}\tilde{y}_{i,t} &= \tilde{\beta}_k \tilde{k}_{i,t} + \tilde{\beta}_l \tilde{l}_{i,t} + \tilde{\beta}_m \tilde{m}_{i,t} + \tilde{\omega}_t(\tilde{k}_{i,t}, \tilde{l}_{i,t}, \tilde{m}_{i,t}, z_{i,t}) + \epsilon_{i,t} \\ &\equiv h_t(\tilde{k}_{i,t}, \tilde{l}_{i,t}, \tilde{m}_{i,t}, z_{i,t}) + \epsilon_{i,t}.\end{aligned}$$

We specify $h_t(\cdot)$ as the sum of a cubic function of capital, investment, employment, and wage, and yearly dummies and indicators for firms' importing and exporting status. The first step comes down to estimating $h_{i,t}(\cdot)$ using the ordinary least squares (OLS) method, which separates $\hat{h}_{i,t}(\cdot)$ from the measurement errors in revenue, $\epsilon_{i,t}$

[29] Alternatively, $\epsilon_{i,t}$ can be interpreted as an additional productivity shock that realizes after all production decisions, including the decision on material use, have been made.

Step 2. With $\hat{h}_t(\cdot)$ in hand from the first step, we express $\omega_{i,t} = \hat{h}_t(\cdot) - \beta_k \tilde{k}_{i,t} - \beta_l \tilde{l}_{i,t} - \beta_m \tilde{m}_{i,t}$. By substituting this expression into equation (16), we obtain:

$$\begin{aligned} \hat{h}_{i,t} - \tilde{\beta}_k \tilde{k}_{i,t} - \tilde{\beta}_l \tilde{l}_{i,t} - \tilde{\beta}_m \tilde{m}_{i,t} = \frac{\eta+1}{\eta}\overline{\omega} + \rho \cdot (\hat{h}_{i,t-1} - \tilde{\beta}_k \tilde{k}_{i,t-1} - \tilde{\beta}_l \tilde{l}_{i,t-1} - \tilde{\beta}_m \tilde{m}_{i,t-1}) \\ + \frac{\eta+1}{\eta}[\tilde{\gamma}_0 \log(e_{i,t-1}) + \tilde{\gamma}_1 \mathbb{I}(x_{i,t-1} = NI) + \tilde{\gamma}_2 \mathbb{I}(x_{i,t-1} = NF) + \tilde{\gamma}_3 \mathbb{I}(x_{i,t-1} = NIF) + \zeta_{i,t}]. \end{aligned} \tag{20}$$

As discussed in Ackerberg et al. (2015), in a setting like ours, once capital, labor, and productivity are all controlled for, material usage does not have independent variation. We adopt the first-order approach (see, e.g., Gandhi et al., 2020) to estimate β_m using the average revenue shares of materials.

Specifically, we show in the Appendix that the first-order condition for material use implies:

$$\frac{P_{m,t} \exp(\tilde{m}_{i,t})}{\exp\left(\tilde{y}_{i,t}(\tilde{m}_{i,t} | \omega_{i,t}, \tilde{k}_{i,t}, \tilde{l}_{i,t})\right)} \cdot \exp(\epsilon_{i,t}) = \tilde{\beta}_m \tag{21}$$

in which $P_{m,t}$ is the price for materials. The first term on the left-hand side of the equation is the measured revenue share of materials, which has a direct empirical counterpart. Assuming that multiplicative revenue measurement errors, $\exp(\epsilon_{i,t})$, have a mean of 1, we can use the method of moments to estimate $\tilde{\beta}_m$ from equation (21).[30]

GMM Identification, Sample, and Results. We plug the estimated $\hat{\tilde{\beta}}_m$ into equation (20) and estimate the remaining parameters using the Generalized Method of Moments (GMM). To form the moment conditions, we rely on the fact that $k_{i,t}$ and $e_{i,t-1}$ are determined before the innovation term in productivity, $\zeta_{i,t}$, realizes, which means that they are independent of $\zeta_{i,t}$. Labor use, on the other hand, may react to $\zeta_{i,t}$. Since $\tilde{l}_{i,t-1}$ and $\tilde{k}_{i,t-1}$ are chosen before $\zeta_{i,t}$ is known, they can serve as instrumental variables (IV) for $\tilde{l}_{i,t}$. We further allow $\overline{\omega}$ to vary by industry. In this regard, we add industry dummies to the specification and use these dummies as their own IVs. Finally, because the production function specified in (19) is most appropriate for the manufacturing industry, we restrict the sample for estimation to manufacturing firms from now on. We calculate standard errors by bootstrapping the entire estimation procedure to account for the uncertainty in the generated regressors.

Columns (1)-(3) report Table 6 reports the GMM estimation of equation (20). In the baseline specification reported in the first column, the estimated coefficient for the intensive margin of R&D is statistically significant, but fairly small, as in the reduced-form section. This could be due to a downward bias from the measurement errors in R&D expenditures, or due to potential heterogeneous effects by firm size.[31] More important to our purpose, we find statistically signifi-

[30] Alternatively, we can assume that $\epsilon_{i,t}$ have a mean of zero, in which case a log linearized version of equation (21) can be estimated via the OLS to obtain $\hat{\tilde{\beta}}_m$. These two approaches give very similar estimates. In the baseline estimation, we assume all firms have the same material share and obtain $\tilde{\beta}_m$. In the Appendix, we estimate industry-specific material elasticities and show that they lead to similar conclusions from the GMM.

[31] Our estimate is in line with the literature. Focusing on Norway, Bøler et al. (2015) find a larger R&D coefficient for big firms and a negative coefficient for small firms, so the average return is of around a similar magnitude as ours.

Table 6: R&D and Productivity Evolution

	GMM estimation of (20)			GMM estimation of the auxiliary regressions					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\omega_{i,t-1}$	0.465***	0.473***	0.474***	0.465***	0.472***	0.473***	0.460***	0.465***	0.465***
	(0.153)	(0.151)	(0.142)	(0.144)	(0.147)	(0.151)	(0.159)	(0.139)	(0.130)
$\log(e_{i,t-1})$	0.002***	0.002***	0.002***						
	(0.001)	(0.001)	(0.001)						
$\mathbb{I}_{i,t-1}(i \in N)$				0.010***	0.009***	0.009***	0.010***	0.010***	0.010***
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{I}_{i,t-1}(i \in NI)$	0.022**	0.022**	0.022**	0.024**	0.023**	0.023**			
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)			
$\mathbb{I}_{i,t-1}(i \in NF)$	-0.006	-0.006	-0.006	-0.003	-0.003	-0.003			
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)			
$\mathbb{I}_{i,t-1}(i \in NIF)$	0.042**	0.043**	0.043**	0.048**	0.049**	0.049**			
	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)			
$\mathbb{I}_{i,t-1}(i \in NI \bigcup NF \bigcup NIF)$							0.023*	0.023**	0.023**
							(0.008)	(0.007)	(0.007)
Input elasticities									
$\tilde{\beta}_l$	0.457	0.457	0.457	0.459	0.458	0.458	0.461	0.460	0.460
	(0.016)	(0.018)	(0.017)	(0.017)	(0.016)	(0.017)	(0.015)	(0.015)	(0.014)
$\tilde{\beta}_k$	0.107	0.106	0.106	0.108	0.107	0.107	0.109	0.108	0.108
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)	(0.016)	(0.014)	(0.013)
$\tilde{\beta}_m$	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Lag import dummy		yes	yes		yes	yes		yes	yes
Lag export dummy			yes			yes			yes
Number of observations	9320	9320	9320	9320	9320	9320	9320	9320	9320

Notes: Sample includes manufacturing firms with 10+ employees. β^m is estimated via equation (21). Standard errors (in parenthesis) are calculated from 200 bootstrap (by firms) samples. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

cant and economically sizable impacts of adopting NI and NIF modes. The estimated coefficient for the NF dummy is slightly negative but rather imprecisely estimated, which is likely the result of there being only a small number of firms in the NF mode.

The second column includes a dummy variable for firms' import status in both the control function $h(\cdot)$ and in the productivity law of motion, equation (20). This specification allows importing to play two roles, both of which are well documented in the literature: directly improving firm productivity; changing firms' use of intermediate materials. By controlling for these two channels, column (2) of Table 6 shows that our main finding is not due to possible correlation between the use of foreign R&D inputs and importing. Column (3) allows exporting to enter both $\hat{h}(\cdot)$ and equation (20). Most coefficients do not change. The lower panel of Table 6 reports the estimates for the input elasticities. All estimates are reasonable and stable across specifications.

Auxiliary Regression. As discussed earlier, due to measurement errors and the small number of observations in the NF mode, we may not be able to estimate the coefficients in equation (20) precisely. Thus, we estimate an auxiliary regression, in which the intensive margin measure of R&D is replaced with a dummy, and the three diverse modes of R&D—NI, NF, and NIF—are grouped together. We introduce this auxiliary regression in two steps for transparency.

If we split firms in our sample by size and estimate heterogeneous returns, we obtain similar findings.

As the first step, in the results reported in columns (4) through (6) of Table 6, we include an indicator for conducting R&D, instead of $\log(e_{i,t-1})$, in the regression. This R&D dummy captures the impact of $\log(e_{i,t-1})$ for the firm with the average log R&D expenditure. We find that the estimated coefficient for R&D dummy is around 1% and statistically significant, while the coefficients for other variables do not change significantly.

In the second step, reported in columns (7) through (9), we further replace the mode-specific dummies for NI, NF, NIF with a joint dummy, which takes a value of one if any of these modes are on. This dummy can be loosely viewed as the frequency-weighted average value of the estimates for $\mathbb{I}_{i,t-1}(i \in NI)$, $\mathbb{I}_{i,t-1}(i \in NF)$, and $\mathbb{I}_{i,t-1}(i \in NIF)$. Our preferred estimate in column (9) of Table 6 suggests that on average, doing R&D increases productivity by 1%. Adopting foreign R&D modes adds a 2.3% on top of that.

We take three estimates from Column (9) of Table 6: the estimated autocorrelation, the R&D dummy, and the diverse R&D mode dummy. For indirect inference, these estimates are supplemented by three additional empirical moments: 1) the average R&D expenditure share on domestic inputs among NI firms (0.903, denoted by s^N_{NI}); 2) the average R&D expenditure share on domestic inputs among NIF firms (0.558, denoted by s^N_{NIF}); 3) the standard deviation of log firm sales (1.2 denoted by $sd(\tilde{y})$). The R&D expenditure shares contain information on the cost difference between different R&D modes ($\log(c^N) - \log(c^{NI})$ and $\log(c^N) - \log(c^{NIF})$, respectively), and are informative about $\tilde{\gamma}_i, i = 1, 2, 3$. The standard deviation of log firm sales will pin down σ_ξ.

We stack these moments in a vector as below

$$\hat{\alpha} = (0.465, 0.010, 0.023, 0.903, 0.558, 1.27), \tag{22}$$

which will serve as the target in the indirect inference procedure that pins down the structural parameters $\tilde{\rho}$, $\tilde{\gamma}_i, i = 0, 1, 2, 3$, and σ_ξ. Formally, for any given values of $\tilde{\rho}$, $\tilde{\gamma}_i, i = 0, 1, 2, 3$, and σ_ζ, we simulate the model and use the simulated data to generate targeted regression coefficients in $\hat{\alpha}$ corresponding to column (9) of Table 6.[32] We also calculate the standard deviation of log sales as well as firms' R&D shares s^F_{NIF} and s^I_{NI} from the simulated data.[33] We then search over the space of $\tilde{\rho}$, $\tilde{\gamma}_i, i = 0, 1, 2, 3$ and σ_ζ so that these model-generated moments are exactly the same as the target. Because the model counterparts of $\hat{\alpha}$ hinges on the distribution of firms over different R&D modes, which depends also on the fixed and sunk costs $\tilde{\mathbf{F}}$, we combine this indirect inference approach with the estimation of the other remaining parameters of the model, as will be described in the next subsection.

[32] Note from equation (20) that the R&D coefficient estimated from the GMM is the product of the true R&D coefficients governing firms' evolution of productivity, defined in equation (16), and the elasticity of substitution in the product market, $\frac{\eta+1}{\eta}$. For consistency, in generating the model counterpart of $\hat{\alpha}$, we also scale the regression coefficients from the simulated data by $\frac{\eta+1}{\eta}$.

[33] The Appendix shows that we can verify whether the expenditure shares in the model, s^I_{NI} and s^F_{NIF}, are equal to their empirical counter parts, for a given guess of $\tilde{\gamma}_i, i = 0, 1, 2, 3$, without the knowledge of $A^{\tilde{x}}$ or $p^{\tilde{x}}$, for $\tilde{x} \in \{N, I, F\}$. This means that in matching these moments, we do not need to estimate $A^{\tilde{x}}$ or $p^{\tilde{x}}$.

4.3 Joint Estimation of the Remaining Parameters

Aside from the parameters governing the law of motion of firm productivities, the remaining parameters are the aggregate demand shifter Φ_t and the fixed and sunk costs of various R&D modes, $\widetilde{\mathbf{F}}$. We estimate these parameters jointly. For given parameters, we solve firms' optimization problem and simulate the steady state of the model. We then compare the moments of the steady state distribution to their empirical counterparts. We search for the parameters, so the distance between the model moments and their empirical counterparts are minimized. We describe the moments that identify each parameter and our estimation procedure below. As in the productivity estimation, we focus on manufacturing firms.

Aggregate Demand Shifter. Φ_t (from equation (4)) is the aggregate demand shifter that affects the scale of all firms. The median sales of the firms in our sample is 144 million DKK, or about 23 million USD. With a focus on the steady state of the model, we assume that Φ_t is a constant and choose Φ_t so that the model firms have a median sales of 144 million DKK.

Fixed and Sunk Costs of R&D Modes. $\widetilde{\mathbf{F}}$ directly determines the probability that a given firm switches from one mode of R&D to another. We can thus pin down $\widetilde{\mathbf{F}}$ using the observed transition matrix between R&D modes. Because each row sums up to 1, the transition matrix leaves us with 20 independent moments to pin down a total of 10 parameters for the mode-switching cost matrix $\widetilde{\mathbf{F}}$ as specified in equation (9). We weight the transition probabilities by the number of firms in each origin mode.

Estimation Procedures. We collect all parameters to be estimated in $\lambda \in \Lambda$, with $\lambda \equiv (\rho, \tilde{\gamma}_0, \tilde{\gamma}_1, \tilde{\gamma}_2, \tilde{\gamma}_3, \sigma_{\xi}, \Phi, \widetilde{\mathbf{F}})$. These parameters fall into two categories. The parameters in the first category, parameters for productivity and firm size, are just-identified, with the same number of moments as the parameters. The second category of the parameters, $\widetilde{\mathbf{F}}$, are over-identified. To maintain a tight connection between the parameters and the moments that identify them, our estimation solves the following constrained optimization problem:

$$\min_{\lambda \in \Lambda} \sum_{x,x'} n(x) \cdot \left(m^{x,x'}(\lambda) - \hat{m}^{x,x'} \right)^2 \tag{23}$$
$$s.t.\ \alpha(\lambda) = \hat{\alpha},$$

where the variables with a hat denote empirical moments and the variables without a hat are model-implied values under a particular choice of the parameter $\lambda \in \Lambda$.

In the constraint, as defined in equation (22), the first three elements of $\hat{\alpha}$, are the three estimated coefficients reported in Column 9 of Table 6—the estimated autocorrelation, the R&D dummy, and the diverse R&D mode dummy. The last three elements of $\hat{\alpha}$ are the two R&D expenditure shares (s^I_{NI} and s^F_{NIF}) and the standard deviation of the log of firm sales. $\alpha(\lambda)$ are the model-generated values for those six moments conditional on the parameter choice λ. Placing this in the constraint of the optimization problem ensures that all just-identified moments in $\hat{\alpha}$ are matched exactly.

Table 7: Summary of Structural Parameters

Parameters	Descriptions	Source/Target	Value	(s.e.)
A. Estimated Independently/calibrated				
ν	scale parameter for the idiosyncratic cost in R&D	Table 5	1.89	(-)
η	demand elasticity	Aw et al. (2011)	-6.56	(-)
δ	discount rate	-	0.95	(-)
B. Jointly Estimated				
Φ	aggregate demand	median sales: 144 million DKK	-	
ρ	autocorrelation in productivity	Table 6 Column 9	0.463	(0.0095)
$\tilde{\gamma}_i$	return to R&D	Table 6 Column 9 + shares	$\tilde{\gamma}_0 = 0.0032$	(3.7e-4)
$(i = 0, 1, 2, 3)$			$\tilde{\gamma}_1 = 0.0010$	(2.4e-5)
			$\tilde{\gamma}_2 = 0.0067$	(2.5e-3)
			$\tilde{\gamma}_3 = 0.0072$	(1.5e-3)
σ_ξ	sd. of the innovation term in productivity	sd(log($sales$))	0.2017	(1.1e-3)
$\mathbb{F}^{x,x'}$	fixed and sunk costs in R&D	Table 8	Table 8	

Notes: Panel A of the table reports parameters that are estimated externally or calibrated. Panel B of the table reports the outcome from the structural estimation. The numbers in parenthesis in the last column of Panel B are the standard errors, generated through bootstrapping of the estimation procedure, including the GMM estimation and the indirect inference described in equation (23).

In the objective function, $m^{x,x'}$ is the fraction of mode x firms in a period that chooses mode x' in the next period; $n(x)$ is the fraction of firms in mode x in the steady state. Therefore, $\sum_{x,x'} n(x) \cdot \left(m^{x,x'}(\lambda) - \hat{m}^{x,x'}\right)^2$ simply adds up the discrepancies in the transition patterns between the model and the data, weighted by the share of firms in each mode.

Estimation Results and Fit of the Model. Panel A of Table 7 reports the parameters that we take as given in the indirect inference. We pick $\nu = 1.89$ based on the estimates in Table 5. We set the demand elasticity η to be -6.56. This choice follows the estimate of Aw et al. (2011) and implies a markup of around 18%. Finally, we set the discount rate $\delta = 0.95$.

Panel B of Table 7 summarizes the results from the indirect inference procedure. Among others, $\rho = 0.463$ is very similar to the empirical counterpart. $\tilde{\gamma}_0$ from the joint estimation is larger than the estimated coefficient in column (3) of Table 6, which is consistent with a possible attenuation bias for intensive-margin R&D expenditures. The estimate for $\tilde{\gamma}_1$ is smaller than its counterpart of the empirical specification from Table 6, and that for $\tilde{\gamma}_3$ is larger than its counterpart in Table 6. Once we address the issue with the small number of observations for the NF mode, our structural estimates feature a stronger benefit of doing more diversified R&D mode for firm's productivity.

Our estimates of $\tilde{\gamma}_i, i = 0, 1, 2, 3$ imply $\theta = 1.33$ as the elasticity of substitution between different types of R&D inputs, which highlights that different sources of R&D inputs are not strongly substitutable. This finding is a direct result of the large gains from using diverse R&D modes in the auxiliary regression.

Panel A of Table 8 reports the empirical transition matrix for manufacturing firms and the model counterpart. Our model is able to fit the transition patterns reasonably well, with mean difference between the model and the data in the order of 0.02. The fit of the row 'NF' is worse than that of other rows, which is likely due to the fact that there are very few firms in 'NF' mode,

Table 8: Transition Matrix and Cost Estimates

Panel A: Transition probability and stead state distribution: model versus data										
	0		N		NI		NF		NIF	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
0	0.890	0.902	0.061	0.069	0.033	0.015	0.005	0.007	0.011	0.007
N	0.276	0.260	0.592	0.560	0.082	0.114	0.042	0.035	0.008	0.031
NI	0.115	0.116	0.059	0.059	0.684	0.691	0.011	0.003	0.131	0.132
NF	0.140	0.119	0.380	0.256	0.033	0.052	0.407	0.387	0.040	0.186
NIF	0.049	0.042	0.011	0.021	0.252	0.248	0.021	0.025	0.667	0.664
SS dist.	0.582	0.597	0.134	0.130	0.171	0.157	0.021	0.019	0.092	0.096
Panel B: The estimated cost matrix and breakdowns										
$\widetilde{\mathbf{F}}^{x,x'}$	0		N		NI		NF		NIF	
0	0	-	6.556	(0.218)	11.648	(0.450)	16.884	(1.712)	19.921	(1.139)
N	0	-	0.109	(0.097)	5.201	(0.408)	10.437	(1.690)	13.474	(1.123)
NI	0	-	2.771	(0.346)	0.078	(0.120)	13.099	(1.640)	8.351	(0.942)
NF	0	-	0.109	(0.097)	5.201	(0.408)	4.201	(1.405)	8.270	(0.977)
NIF	0	-	2.771	(0.346)	0.078	(0.120)	6.864	(1.358)	3.147	(0.773)
Breakdowns	f^N	f^{NI}	f^{NF}	f^{NIF}	F^N	F^I	F^F	F^{IF}	F^{I0}	F^{F0}
	0.109	0.078	4.202	3.147	6.447	5.123	6.235	1.031	2.662	0.000
	(0.097)	(0.119)	(1.431)	(0.814)	(0.240)	(0.377)	(0.591)	(0.574)	(0.388)	(1e-6)

Notes: Panel A of the table reports the transition probability between modes in the data and in the estimated model. Panel B reports the estimates for the cost parameters $\widetilde{\mathbf{F}}^{x,x'}$. Numbers in parenthesis are bootstrapped standard errors.

so these moments are weighted less. The last row of Panel A reports the mode distribution of firms. The model fits the data closely despite the mode distribution is not directly targeted.

Panel B of Table 8 reports the estimates for the sunk and fixed cost parameters. The upper part of the panel is the total cost of transition between R&D modes, combining both fixed and sunk cost components. Two observations are noteworthy. First, the diagonal elements are generally smaller than the other values in the same row, suggesting that sunk costs play an important role. In terms of quantitative magnitude, we find that the start-up cost of doing R&D in mode N is around 6.6 million DKK. Compared with the average R&D expenditures of 10 million DKK in the data, this estimate suggests that an important part of R&D expenditures are on the fixed and sunk cost components. Second, we find that $\tilde{F}^{N,NF} > \tilde{F}^{NI,NIF}$. Compared to the firms that do not have any immigrant R&D workers, firms with immigrant R&D workers face 20% lower cost in starting to use offshore R&D services.

The last row of Panel B are the breakdowns of the composite cost matrix by mode-specific fixed costs and the sunk costs associated with mode switching. Note that $\tilde{F}^{N,NF} - \tilde{F}^{NI,NIF}$ is the sum of a sunk cost component, F^{IF}, and a variable cost component, $f^{NF} - f^{NIF}$. The breakdowns show that the sunk and fixed cost components each accounts for approximately half of the information value of immigrants.

5 Counterfactuals

We use the estimated model to conduct counterfactual analysis. Our goals are two-fold. First, we use our model to understand the role of the love for variety of ideas and the information channel of immigrants in shaping firm-level R&D decisions and the aggregate productivity. Second, we quantify the impacts of policies that affect firms' access to foreign inputs or the overall R&D costs, such as liberalization in high-skill immigration and offshore R&D, and an R&D subsidy.

5.1 The Role of the Love for Variety of Ideas and the Information Channel

In the model, firms hire immigrant researchers for two main reasons. First, immigrants bring different, potentially better, ideas, into the R&D process, which increases the return to R&D. This love for variety of ideas effect comes from offshore R&D as well as immigrant researchers. However, because offshore R&D involves significant costs in general, most firms are not able to reap the full benefit of the diversified R&D. This fact leads to the second reason why firms hire immigrant researchers: by facilitating communications between the headquarter and the offshore R&D affiliates, they reduce the cost of offshore R&D. In this subsection, we conduct two experiments to quantify the gains from the love for variety of ideas and the importance of the information channel in firms' decision to hire immigrants.

In the first experiment, we shut down the information channel by increasing f^{NIF} to the level of f^{NF} and reducing F^{IF} to zero. These two changes remove the cost advantage in doing offshore R&D that firms with immigrants enjoy in the baseline model, so the main motivation for any firm to hire immigrants stems from the diversity they bring to R&D. In the second experiment, we shut down the love for variety of ideas by setting θ to infinite, making native researchers, immigrant researchers, and imported R&D services perfect substitutes for each other.[34] As a result, the only reason firms ever consider paying the cost and adopting foreign R&D inputs is because they have a favorable mode-specific idiosyncratic draw.

The first panel in Table 9 reports the distribution of firms by R&D mode in the baseline and the steady states of the two counterfactual economies. When the information channel is eliminated, the fraction of firms doing R&D decreases by 13 p.p., from 40% to 27%. The number of firms in mode NIF decreases by about 86%, which highlights the importance of the information channel in enabling firms to benefit fully from diversified R&D. Interestingly, the fraction of firms in the NI mode decreases by almost half, despite that firms in this mode are not *directly* affected by the elimination of the information value. This decrease reveals that about half of the firms in the NI mode in the baseline economy are motivated by opportunities to transit into the NIF mode in the future, which is made easier due to the information channel. When the love for variety of ideas is eliminated, as shown in the third column of panel (a), only 16% of firms conduct R&D, mostly in mode N. The remaining few firms in mode NI, NF, and NIF choose these out of idiosyncratic reasons captured in $\epsilon^x_{i,t}$.

[34] We implement this counterfactual by setting $\tilde{\gamma}_i = 0$ for $i = 1, 2, 3$ in the productivity law of motion.

Table 9: Firms' R&D Choice and Aggregate Productivity: Benchmark vs. Alternative Models

	(a) Share of firms (%)			(b) Share of R&D expenditure (%)			(c) Aggregate (log) productivity		
R&D modes	Benchmark	No info	No variety	Benchmark	No info	No variety	Benchmark	No info	No variety
No R&D	59.74	73.38	84.25	-	-	-	0.257	0.263	0.271
N	13.03	14.09	12.87	30.41	50.68	81.83	0.280	0.291	0.318
NI	15.72	9.05	2.76	36.60	32.88	17.46	0.271	0.293	0.310
NF	1.90	2.10	0.07	5.62	9.96	0.42	0.393	0.422	0.317
NIF	9.61	1.39	0.05	27.37	6.47	0.29	0.369	0.410	0.309
All	100	100	100	100	100	100	0.284	0.282	0.280

Notes: Columns marked as "No info" report the results from the alternative model specification where there is no information channel of immigrant researchers, and columns marked as "No variety" report the results from the alternative specification where different types of R&D inputs are perfect substitutes. Panels (a) and (b) report the share (%) of firms by R&D mode and the share (%) of R&D expenditure from each mode, respectively. Panel (c) reports the (sales weighted) average log productivity for the entire economy and among firms each R&D mode.

The shift in firms' R&D mode choices translates into a qualitatively similar shift in the distribution of R&D expenditures by mode, reported in panel (b) of the table. Quantitatively, the decrease in the share of R&D spending by firms in modes NI and NIF is less pronounced than the decrease in the share of firms in these modes. This reflects a compositional change of firms in a mode. For example, in the absence of the information channel, the firms choosing the NIF mode tend to be the largest and most productive, and therefore outspend firms in other modes in R&D.

We now examine the impact of these model mechanisms on the aggregate productivity. Reported in panel (c) is the (sales-weighted) average log productivity for the entire economy and among firms in each R&D mode. Shutting down the information channel reduces the aggregate productivity by 0.2%, whereas imposing perfect substitution between different R&D inputs reduces the aggregate productivity by 0.4%. Intuitively, both experiments make R&D more costly, so firms participate less in, and benefit less from, R&D. Somewhat counter-intuitively, despite the decrease in the aggregate productivity, the average productivity in some modes increases. In fact, the average productivity increases in all modes upon the elimination of the information channel. This is entirely driven by the change in the composition of firms between modes: when entering the NIF mode is more costly, the most productive firms remain and the less productive firms switch to other modes. Because the switchers are still more productive than existing firms in other less costly modes, the average productivity in all mode increases.

In summary, the counterfactual results show that firms' decisions on R&D activities crucially depend on the benefits of new ideas brought in by foreign R&D inputs, the costs associated with different R&D modes, and the extent to which immigrant researchers mitigates such costs. These mechanisms are important in matching the observed R&D patterns in the data. Since firms' R&D mode choice depends on their productivity and in turn affects the path of future productivity evolution, correctly accounting for these mechanisms is also important for studying the aggregate productivity.

Table 10: Changes in R&D and Productivity– Benchmark versus Counterfactual Policy Changes

	(a) Share of firms by mode (%)			(b) Share of total R&D expenditure (%)			(c) Aggregate (log) productivity		
R&D modes	Benchmark	Immigration	Offshoring	Benchmark	Immigration	Offshoring	Benchmark	Immigration	Offshoring
No R&D	59.74	47.43	34.12	-	-	-	0.257	0.251	0.245
N	13.03	14.44	11.51	30.41	25.64	16.09	0.280	0.270	0.261
NI	15.72	23.00	28.38	36.60	41.22	39.98	0.271	0.270	0.256
NF	1.90	2.25	3.19	5.62	4.97	5.49	0.393	0.374	0.361
NIF	9.61	12.88	22.81	27.37	28.17	38.44	0.369	0.366	0.348
All	100	100	100	100	100	100	0.284	0.286	0.288

Notes: Columns marked as "Immigration" report the results from the counterfactual scenario on the immigration policy, and the columns markets as "Offshoring" report the results from the counterfactual change on the offshoring policy, as described in the text. Panels (a) and (b) report the share (%) of firms by R&D mode and the share (%) of R&D expenditure from each mode, respectively. Panel (c) reports the (sales weighted) average log productivity for the entire economy and among firms each R&D mode.

5.2 High-Skill Immigration and Offshore R&D Policies

Firms' access to immigrant researchers and foreign suppliers of R&D services are both heavily influenced by various changes in national policies, which often trigger heated debates on their economic and social impacts. We use the model to study the effects of two policies: liberalization in high-skill immigration and promotion of offshore R&D. We model these policies as a 50% reduction in the sunk cost of hiring immigrant researchers, F^I, and of starting offshore R&D, F^F, respectively. The reduction in F^I can be thought of as a reform that eases the frictions in hiring foreigners, while the decrease in F^F could capture an improvement in the IT that facilitates international collaboration, or an investment treaty that makes it easier for Danish firms to set up an R&D operation in a foreign countries. These 50% changes might seem unrealistically large, but note that the integration of the new member states into the EU represents one of the most drastic liberalization in both immigration and international investment in recent decades, leading to rapid increases in the importance of foreign researchers and R&D suppliers in the Danish economy, as documented in Figure 1a.

Table 10 reports the results from these experiments. The liberalization in high-skill immigration increases the share of firms with immigration researchers by a total of 10.5 p.p. About 31% of this increases occurs in mode NIF. The liberalization in offshore R&D increases the share of firms in NF or NIF mode by around 14.5 p.p., more than doubling the share in the benchmark model. The overwhelming majority of the increase occurs in the NIF mode—firms hiring immigrants face a lower cost of offshoring, and are thus in a better position to take advantage of the reduced cost of offshore R&D. With offshore R&D becoming less costly, more firms also choose the NI mode, which reflects the option value of immigrants: firms hire immigrants first, anticipating that when they either become productive enough to overcome the switching cost or get a favorable idiosyncratic draw in the future, they can take advantage of the information channel and switch to the NIF mode.

We examine the impact of these two policies on the aggregate productivity. As shown in panel (c), immigration liberalization increases the aggregate productivity by 0.2% and the offshore R&D

Table 11: Counterfactual Changes with and without the Information Channel

	Immigration policy					Offshoring R&D policy				
	No R&D	N	NI	NF	NIF	No R&D	N	NI	NF	NIF
I. Changes in the share of firms by mode (pp)										
with the information channel	-12.31	1.41	7.28	0.36	3.26	-25.62	-1.52	12.65	1.29	13.20
without the information channel	-11.69	1.69	8.80	0.08	1.13	-10.30	1.83	3.35	2.83	2.29
II. Changes in the aggregate productivity (overall, %)										
with the information channel	0.14					0.37				
without the information channel	0.10					0.18				

Notes: The results reported in Panel II. are for the entire economy.

policy increases the aggregate productivity by 0.4%. The average productivity in individual modes, on the other hand, all decline from their baseline levels. Again, the difference between the responses in the aggregate and mode-specific productivity is due to a compositional change: the new participants of R&D and diversified R&D are less productive than existing participants but more productive than firms staying in the no R&D mode, so their switch brings down the average productivity in all modes.

The results in Section 5.1 show that the information channel is important in driving firms' R&D decisions. To understand how the information channel moderates the two policies, we simulate both policies in the alternative model without the information channel as defined in Section 5.1, and compare the impacts of each policy between the benchmark and alternative models.[35] Table 11 reports the main findings. For both policies, the information channel clearly amplifies firms' adjustment in mode choices. The difference is especially pronounced in the share of the firms in the NIF mode, who benefit most directly from the information channel. The lower panel in the table reports the aggregate productivity impact of these two policies in the benchmark and restricted models. It shows that a 29% of the productivity impact of the immigration policy and a 51% of the productivity impact of the offshore policy are due to the information value of immigrant researchers.

5.3 R&D Subsidies in the Age of Globalized R&D

In the last set of exercises, we use the model to study the impacts of R&D policies. Many countries adopt various policies to promote R&D investment in the form of direct subsidies or tax rebates which often amount to substantial amounts. Denmark is no exception. For example, the subsidies for loss-incurring firms which we exploit in Section 4 to estimate ν cover 25% of the R&D expenses up to DKK 5.5 million per year, a number that is more than half of the start-up R&D cost estimated in Table 8. Since this particular policy does not make a distinction between

[35]We do not compare the effects of these policies between the benchmark model and the alternative model where different R&D inputs are perfect substitutes because firms in that alternative model only adopt foreign R&D inputs for idisocynratic reasons and hence do not respond to the change in sunk costs systematically.

Table 12: Changes in R&D and Productivity: Benchmark versus R&D Subsidy

	(a) Share of firms by mode (%)		**(b) Share of total R&D expenditure (%)**		**(c) Aggregate (log) productivity**	
R&D modes	Benchmark	R&D subsidy	Benchmark	R&D subsidy	Benchmark	R&D subsidy
No R&D	59.74	14.05	-	–	0.257	0.217
N	13.03	11.12	30.41	11.34	0.280	0.232
NI	15.72	19.04	36.60	19.85	0.271	0.239
NF	1.90	13.34	5.62	16.19	0.393	0.317
NIF	9.61	42.44	27.37	52.61	0.369	0.324
All	-	-	-	-	0.284	0.292

Notes: Panels (a) and (b) report the share (%) of firms by R&D mode and the share (%) of R&D expenditure from each mode, respectively. Panel (c) reports the average of log productivity for all firms that belong to each R&D mode, weighted by each firm's sales. The last row for Panel (c) reports the aggregate log productivity for all firms regardless of the R&D decision, weighted by each firm's sales.

the type of R&D expenditures that firms claim, we implement a policy experiment that decreases all types of fixed and sunk R&D costs by 50% from their baseline level.

Table 12 summarizes the results from the counterfactual simulation on the R&D subsidy policy. With the subsidies, substantially more firms are engaged in R&D especially via modes NF and NIF, resulting in a shift in R&D expenditures towards these modes as well. As was the case for the immigration policy and the offshoring policy in Section 5.2, the shift in composition toward more diversified R&D leads to a much higher overall aggregate productivity for the economy, while the average productivity among firms in each mode goes down. Overall, the subsidy increases the aggregate productivity by 0.8%.

Compared to existing studies that estimate firms' return to R&D (Aw et al., 2011; Bøler et al., 2015; Bilir and Morales, 2020), the main novelty of this paper is to allow for the use of foreign R&D inputs. Does this feature matter in evaluating the effect of R&D subsidies on firms' R&D decisions and the aggregate productivity? To answer this question, Table 13 compares the effect of the same policy between the benchmark model and an alternative model with $\theta \to \infty$, in which case firms reap no benefit from the diversity of ideas. We find that much fewer firms respond to the R&D subsidy by participating in R&D in this alternative model. Also, those that respond are concentrated among the N and NI modes, as opposed to be among the NIF mode where the return to R&D is the highest. The different responses at the level of R&D modes lead to a significantly different prediction on the aggregate productivity: with no love for variety of ideas, the R&D subsidy generates only 0.12% aggregate productivity gains, less than one-fifth the prediction of the benchmark model.

In the age of globalized R&D, foreign R&D inputs are playing an increasingly important role and have become a major source of the return to R&D. Our experiment suggests that the omission of these inputs in the evaluation of R&D policies could lead to a substantial bias.

Table 13: Counterfactual Changes from an R&D Subsidy

	No R&D	N	NI	NF	NIF
I. Changes in the share of firms by mode (pp)					
Benchmark	-45.69	-1.91	3.32	11.45	32.83
Without the love for variety of ideas channel	-25.48	12.78	10.09	1.27	1.34
II. Changes in the aggregate productivity (overall, %)					
Benchmark	0.81				
Without the love for variety of ideas channel	0.12				

Notes: The results reported in Panel II. are for the entire economy.

6 Conclusion

In the integrated world economy, firms source their input from suppliers around the world. While the impact of access to intermediate inputs has been well-documented in the international trade literature, we have a limited understanding of firm's use of foreign inputs in R&D. Using unique data from Denmark that links workers to firms and covers firms' domestic use of foreign R&D, we study empirically and quantitatively firms' decision to hire immigrant researchers and to use import R&D services, and the joint impacts of these decisions on firm performance. We find that firms' R&D investment generates a higher return when they are able to use either of the two foreign inputs, which we interpret as the "love for variety of ideas" effect in R&D. We document empirical evidence which supports the existence of substantial costs of using foreign R&D inputs. Such costs can be potentially mitigated if one type of R&D input helps firms use another type of R&D input. In this regard, we find that hiring immigrant researchers reduces the barriers firms face in sourcing R&D services from abroad, which we call as the "information channel".

To conceptualize these mechanisms, we develop and estimate a model of firm dynamics with endogenous R&D choices. Counterfactual experiments using the model suggest an important role of the information channel of immigrant researchers in firm's productivity. Due to the interdependence of the three types of R&D inputs, policies affecting one R&D input have an amplified effect on firm- and aggregate outcomes by affecting the other types of R&D inputs at the same time. We show these mechanisms through experiments about various policies including an immigration liberalization policy, an offshore R&D policy, and an R&D subsidy policy.

This paper is a step towards a better understanding of firms' global organization of R&D. One of the strength of our data is that it includes firms' use of R&D services produced abroad, which allows us to interpret foreign sourced R&D as an input into the R&D of firms located in Denmark. Many large global firms carry out R&D in foreign locations to be used for local production, which our measure do not capture. To be consistent with our data, we control for these forces using firms' import and export in the empirical analysis but abstract from modeling affiliate R&D in the quantitative section. Modeling and measuring the distribution of R&D expenditures among affiliates and their uses is an important venue for future research. In developing this model, we have also abstracted from the spillovers between firms, which can be an important channel for the gains to propagate through the economy. Another direction for future research is to model and estimate these spillovers.

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