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

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Abstract

We study firms' decision to use foreign R&D inputs—immigrant researchers and imported R&D services—and the implications of this use for firm performance and aggregate productivity. Using Danish data, we document that firms with immigrant researchers are more likely to source foreign R&D services and that using either foreign input increases R&D efficiency and firm performance. We develop and estimate a model of firm dynamics that rationalizes these patterns. Counterfactual experiments show that the two foreign inputs play crucial yet complementary roles in R&D. Without access to these inputs, R&D participation and the aggregate return to R&D both would decrease substantially.

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1 Introduction

Reductions in trade barriers and advances in communication technologies 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 importing 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.[1] 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. Figure 1 shows the empirical relevance of these two global R&D sourcing strategies for firms in Denmark, the country of focus in this paper. The left panel is immigrants' share of total R&D-related wage bill. The right panel is the share of foreign sourced R&D services in total R&D expenditures. Both panels show a clear upward trend, indicating growing dependence of Danish firms on foreign R&D inputs.[2]

In this paper, we develop and estimate a dynamic model to analyze firms' decision to use foreign R&D inputs and the implications of this decision for firm-level and aggregate outcomes. We find that these two foreign inputs, immigrant researchers and offshore R&D, play crucial yet complementary roles in overall R&D. Alternative models that omit these inputs or the interaction between them would result in biased assessments of the effectiveness of innovation policies, e.g., R&D subsidies, as well as immigration and offshoring policies.

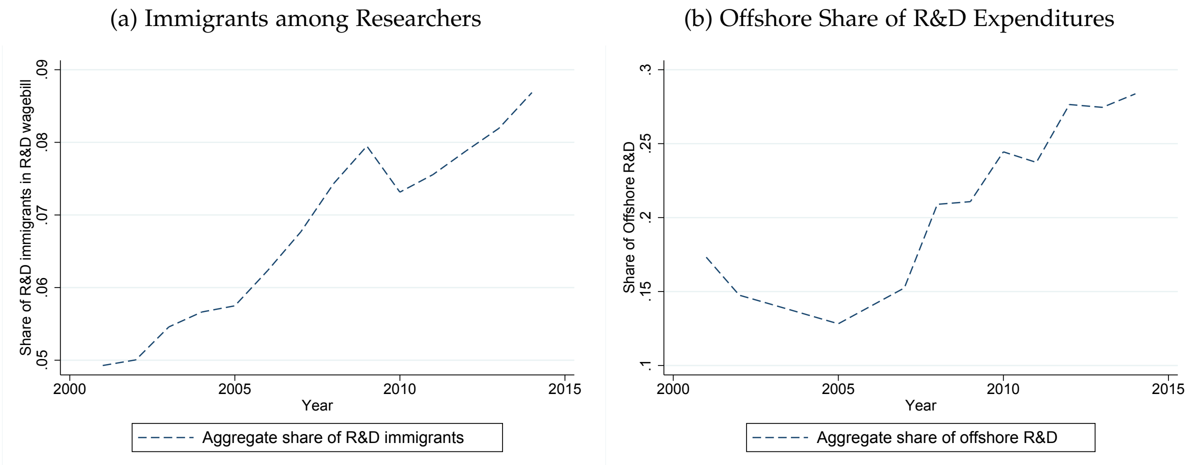
Our model is a model of firm dynamics with endogenous R&D as in Aw, Roberts and Xu (2011) and Doraszelski and Jaumandreu (2013), but features two important new mechanisms. First, we posit that three R&D inputs—domestic researchers, immigrant researchers, and imported R&D services—are imperfect substitutes, so the marginal return from R&D investment is higher when firms can flexibly combine these inputs. We label this mechanism as the *love for variety of ideas*. Second, recruiting immigrant researchers and sourcing R&D services globally both require upfront investments, so only a small fraction of firms take advantage of these options. However, as immigrants are able to provide information and knowhow about foreign R&D suppliers, firms with immigrant researchers might face a lower barrier in sourcing R&D services from abroad. We call this additional interaction between the two forms of foreign R&D inputs the *information channel*.

Using the estimated model, we show that the benefit from foreign R&D inputs is an important motive for firms to carry out R&D. Without access to these inputs, the R&D participation rate would decrease by 60% and the effect of R&D on aggregate productivity would shrink by 80%.

[1] Contributions to this literature include Amiti and Konings (2007), Goldberg, Khandelwal, Pavcnik and Topalova (2010), Halpern, Koren and Szeidl (2015), and Bøler, Moxnes and Ulltveit-Moe (2015), among others.

[2] These trends are equally prominent in other countries. According to the Patent Cooperation Treaty data, between 2000 and 2010, around 10-15% of inventors in developed countries are foreign nationals. Relatedly, many global firms source R&D services from abroad by establishing overseas R&D centers. Both phenomena have become more prevalent over the past decades. See, e.g., Miguelez and Fink (2013), and Fan (2020) for details.

Figure 1: Increasingly Globalized R&D Patterns of Firms Operating in Denmark



Notes: Plotted in the left panel is immigrants' share in the total research wage bill, calculated as the ratio of the wage bill of immigrants in R&D-related occupations over the wage bill of all workers in R&D-related occupations. Plotted in the right panel is the ratio between offshore R&D expenditures and total R&D expenditures, domestic and offshore combined, for firms operating in Denmark. In this definition, offshore R&D expenditures have two components: the R&D services purchased from abroad through arms' length contracts, and the R&D carried out by foreign entities within the same business group of a firm operating in Denmark *for the use of that firm*. See Section 2 for the definition of R&D-related occupations and additional details of the data.

Hence, omitting foreign inputs would lead researchers to substantially underestimate the effect of an R&D subsidy on aggregate productivity. Moreover, as we estimate important complementarity between the two foreign inputs, policies that change the cost of hiring immigrants have a large impact on firms' offshore R&D decision, and vice versa. Not accounting for such interconnection underestimates the impacts of these policies on aggregate productivity by 30-50%.

Our model is grounded in the new facts we document using administrative data from Statistics Denmark between 2001 and 2015. 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 datasets 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 engage in offshore R&D. This correlation is robust when various firm and industry characteristics are controlled for; when we focus on the firm-destination-region-level, i.e., firms recruiting immigrants from Eastern Europe, for example, are more likely to source R&D services from Eastern Europe; when we employ a shift-share design that exploits the increase in the supply of immigrants to rule out reverse causality. We interpret this finding as capturing the possibility that immigrant researchers bring knowledge about their home countries to the firm, which reduces the frictions 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 and firms engaging in offshore R&D are more productive than firms doing R&D using domestic inputs only, which is consistent with selection on productivity in these activities. 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 doing R&D exclusively 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. This effect is also present when we use production function estimation techniques to address the simultaneity bias in measuring productivity arising from firms' endogenous choice of inputs.

We develop and estimate a structural model to identify the mechanisms behind these facts and conduct policy experiments. In the model, heterogeneous firms choose whether to conduct R&D, and if so, how much to invest and whether to use immigrant researchers and/or imported R&D services. Investment in R&D increases future productivity stochastically. Adopting multiple R&D inputs at the same time is costly, but it enhances the efficiency of R&D investment. We interpret this mechanism analogously to the love for variety assumption dating back to Ethier (1982): by using R&D inputs from a diverse source, firms gain access to different, potentially better ideas, thus achieving higher R&D efficiency. In addition to giving firms an incentive to use foreign R&D inputs, this mechanism also leads to an interaction between these inputs. For example, the availability of imported R&D services increases the overall return to R&D, which encourages more firms to participate in R&D and, in turn, increases the use of immigrant researchers. To further 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. Both the existence and the size of the information value will be disciplined by the data.

We estimate the model through indirect inference. We uncover the importance of the love for 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 see on average an additional 2.3% productivity increase. Assuming a constant elasticity of substitution between the three types of inputs in R&D—domestic researchers, immigrant researchers, and imported R&D services—, this 2.3% productivity premium translates into a constant elasticity of 1.33. We estimate the fixed and sunk R&D cost parameters that govern the strength of the information channel using two sources of information: first, the patterns of firms' transition between different R&D modes; second, firms' response to a natural experiment, an R&D subsidy program introduced in Denmark in 2011, which reduced the user cost of R&D by 25% for eligible firms.

Our estimation finds that the switch from doing R&D with only domestic researchers to using also imported R&D services incurs an average startup cost of about 1.1 million USD and a fixed operation cost of 0.75 million USD. The presence of immigrant researchers in a firm reduces the startup cost by 16% and the fixed cost by 25%. This result suggests that the love for variety of ideas alone cannot account for the higher propensity of offshoring R&D among firms with immigrant researchers in the data. The information channel also plays an important role.

Our counterfactual experiments highlight the quantitative importance of foreign inputs in

R&D. We shut down the love for variety of ideas by making different R&D inputs perfect substitutes, which eliminates firms' incentive to either hire immigrant researchers or offshore R&D.[3] The R&D participation rate decreases from the baseline level of 40.3 percentage points (p.p.) to 15.7 p.p., and the economy retains only 20% of the effect of R&D on aggregate productivity computed in the benchmark equilibrium. This result has important implications for the effectiveness of innovation policies. For example, in the absence of the love for variety of ideas, the effect of a decrease in the sunk cost of R&D on aggregate productivity would be 85% smaller than the effect in the benchmark model. The omission of foreign inputs leads to a significant underestimation of the effect precisely because these inputs are an important reason why firms participate in R&D to begin with.

We also examine the interaction of the two foreign inputs via the information channel. As expected, the elimination of this channel from the benchmark reduces the fraction of firms carrying out R&D with imported R&D services. As a sizable part of firms' return from hiring immigrant researchers materializes through their complementarity with imported R&D services, the fraction of firms hiring immigrant researchers also decreases substantially. In total, the R&D participation rate decreases by 13.6 p.p., or a third of its baseline level. Accounting for the complementarity between offshore R&D and immigrant researchers is important for the evaluation of policies that target *either* of them. For example, in evaluating a policy that reduces the sunk cost of offshore R&D, an alternative model without the information channel would infer an aggregate productivity increase that is only half as large as the increase in the benchmark model.

This paper is related to four strands of the literature. First, it contributes to the literature that estimates 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; Antras, Fort and Tintelnot, 2017; Fieler, Eslava and Xu, 2018). While this literature also emphasizes the 'love for variety' in input use, their focus is on imported inputs for production. In contrast, we focus on foreign R&D inputs such as immigrant researchers and offshore R&D, which are ever more important as global integration expands beyond the exchange of goods 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 that of imported production inputs. Since R&D investment contributes to firms' knowledge capital, which is persistent, improvement in R&D efficiency is accumulated and amplified over time. This dynamic effect of R&D inputs sets this paper further apart from most papers from the literature on imported production inputs, which focuses on static effects.

Second, our model of firm dynamics with endogenous R&D and our estimation methodology build on the work of Doraszelski and Jaumandreu (2013), Aw, Roberts and Xu (2011), and Bøler, Moxnes and Ulltveit-Moe (2015). Most closely related, Bøler, Moxnes and Ulltveit-Moe (2015)

[3] More precisely, this change 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.

argue that R&D and intermediate inputs are complements and jointly enhance firm performance. Enabled by rich administrative data from Denmark, we contribute to this literature by looking inside the black box of R&D and by examining the interaction between different inputs inside this box. We show that incorporating different R&D inputs not only matters for evaluating various policies on offshoring or immigration, but also matters for understanding the impacts of generic R&D subsidies that are actively used in many countries.

By focusing on firms' decision to conduct offshore R&D, this paper is also related to a nascent literature studying the impacts of R&D within multinational corporations (MNCs). For example, Bilir and Morales (2020) estimate how R&D in the headquarters and foreign 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 world. Instead of developing a model of affiliate production within MNCs, we develop a model of R&D sourcing. This model speaks to a key feature of our data—that our measure of offshore R&D captures the R&D services that a firm operating in Denmark sources from abroad for itself and excludes the R&D done in foreign headquarters/affiliates exclusively for local use at those foreign locations.[4]

Finally, this paper is related to a broad literature on the consequences of high-skill immigration. The literature has documented two general patterns: that high-skill immigrants increase firm and regional economic performance, and that immigrants generate trade and other business linkages between the origin and destination countries.[5] Our first contribution to this literature is to document both patterns in a unified setting for a specific yet important activity, R&D. This finding suggests that one mechanism through which immigrants increase firm performance is exactly by helping the firm establish business connection at their home country. Our second contribution is to develop and estimate a dynamic heterogeneous firm model of R&D with immigrants, which allows us to quantify this mechanism. Compared to most existing works that estimate the impacts of immigrants using structural models (e.g., Burstein, Hanson, Tian and Vogel, 2020; Caliendo, Parro, Opromolla and Sforza, 2021), our model incorporates two salient features of the data, both of which are important for the evaluation of immigration policies: first, only the most productive firms recruit immigrants; second, immigrants and offshoring interact with each other. A few recent works have developed models with the second feature. In particular, Morales (2020) shows that *foreign MNCs in the U.S.* tend to recruit high-skill workers from the headquarter countries, which suggests that foreign employees working at a U.S. affiliate may act as a bridge facilitating the communication between the U.S. affiliate and foreign headquarters. Distinct from and complimentary to Morales (2020), the information channel in our paper

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

[5]Examples of research focusing on the first result include Peri (2012), Ottaviano, Peri and Wright (2018), Beerli, Ruffner, Siegenthaler and Peri (Forthcoming), Burchardi, Chaney, Hassan, Tarquinio and Terry (2020). Examples of research on the second result include Head and Ries (1998), Rauch and Trindade (2002), Burchardi, Chaney and Hassan (2019), Olney and Pozzoli (2018), Ramanarayanan and Cardoso (2019), among many others. While most studies find complementarity between immigration and economic linkages, some have documented a substitutable relationship (Glennon, 2020).

is best viewed as the one between the headquarters in Denmark and the home countries of these immigrants. This channel is similar in spirit as the one proposed in Yeaple (2018), but we are able to estimate the strength of the channel, which Yeaple (2018) was not able to do due to the data constraint.

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 offshore R&D, the employment of immigrant researchers, and firm performance. These facts motivate the key ingredients of the structural model.

2.1 Data Sources

We merge several datasets from Statistics Denmark on firms and workers over the period 2001 to 2015. Below we summarize the key pieces of information from these datasets; Appendix A.1 provides additional details.

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. Supplementing IDA with additional administrative datasets, we identify workers' birth country and other demographic information, the firm and the establishment at which they work, and their occupation and wage. This information allows us to construct an indicator of whether a firm hires immigrants in R&D-related roles, in which immigration status is defined by a worker's birth country and R&D-relatedness is determined by their occupation.

Following Bernard et al. (2020), we deem an occupation as R&D-related if, according to the job description, it involves creative and/or technical components such as design, testing, and experimentation. This classification of R&D related occupations is broader than the definition of R&D as activities carried out by scientists or university researchers that are 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.[6] Slightly abusing language, we will call workers in R&D-related occupations as R&D workers or researchers, and those in R&D-related occupations not born in Denmark as immigrant R&D workers or immigrant researchers.

Firms. The information on the characteristics and activities of firms comes primarily from two sources. The first source is the Regnskabsstatistik (FIRE, hereafter), an annual panel on

[6]Examples of R&D-related occupations include software developers, mechanical engineers, and technicians in chemical sciences. An advantage of our classification is that because it is based on occupation, it includes only the personnel directly involved in R&D-related activities. Supporting staffs in R&D units, e.g., accountants, do not count as researchers.

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.[7] The information we extract from FIRE includes firm sales, value added, material use, wage bill, and fixed capital investment. We use fixed capital investment to construct capital stock using the perpetual inventory method. We deflate the wage bill using the consumer price index and deflate all other accounting variables using their own industry-level deflators. We supplement this dataset with firm-level trade data to control for firms' import and export status in goods.

The second source 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 Danish krone (DKK) in revenue; 3) spend at least 5 million DKK in R&D activities; or 4) operate in R&D industries (NACE Rev.2 industry 72).[8] It also includes a stratified sample of all remaining firms, resulting in 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 by the foreign affiliates/headquarters of a Danish firm for the affiliates/headquarters themselves, such as the development of a product to be produced in a foreign country, is not included.[9] The reported offshore R&D, in turn, is most appropriately viewed as R&D services imported by the reporting entity.[10] Correspondingly, the model we develop focuses on the R&D sourcing and production decisions of the firms operating in Denmark.

For corroborative evidence on the offshore R&D measure, we also leverage the Offshoring Survey, which is part of a large European collaboration through 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 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

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

[8]Our analysis focuses on for-profit firms, so universities and research institutions will not be in our sample.

[9]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.

[10]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 model the decisions that generate such data, researchers would have to jointly consider the domestic and overseas production of firms (see, e.g., Bilir and Morales, 2020).

Table 1: Descriptive Statistics

Panel A: Worker Characteristics				
	% of obs	% College+	% Master +	Mean hourly wage (US$)
Immigrant R&D	1.20	73.33	33.90	46.5
Immigrant non-R&D	6.97	22.45	6.90	32.5
Native R&D	15.75	62.46	22.98	47.1
Native non R&D	76.09	17.10	5.35	35.4
Panel B: Firm Characteristics				
Number of employees	% of obs	Mean VA/L (US$)	% 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
		% Immi. R&D	% Offshore R&D	% Immi. R&D *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	% Immi. R&D	% Offshore R&D	% Immi. R&D *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, restricted 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 birth country. In Panel B, a reporting firm in Denmark is classified as doing offshore R&D if it uses R&D services sourced from abroad. In Panel C, a reporting firm is classified as doing offshore R&D if it conducts R&D activities abroad in 2011, i.e., according to the definition from the Offshoring Survey. Monetary values are in U.S. dollar. All statistics are based on 2011. The number of firms in Panels B and C are 2,949 and 1,882 respectively.

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 Survey and the Offshoring Survey include the information about the foreign region in which a firm conducts R&D. In Appendix A.2, 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 for-profit private-sector firms that have more than 10 employees and are in both FIRE and the R&D Survey. To validate the measure for offshore R&D, we will 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 17% of the workers are in occupations related to R&D, as defined previously. Among them, about 7% are immigrants. Not surprisingly, both immigrant and native R&D workers are more educated than non-R&D workers. They make on average $47 per hour, significantly above the average hourly wage of non-R&D workers.

Panel B of the table reports the characteristics of the firms in the sample by their size group. About 24% of firms in the sample participate in R&D. The R&D participation rate is higher among larger firms than 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 14% of the firms in the sample, or 57% of R&D active firms, conduct R&D with immigrant researchers. The share of firms engaging in offshore R&D is smaller, at around 4% of the sample. Both activities are more common among larger firms. An overwhelming majority of firms doing offshore R&D—3.15% out of 4.34% overall, 10.51% out of 11.28% among firms with more than 250 employees—employ immigrant R&D workers, which suggests that the two activities are likely interconnected. On the other hand, less than a quarter of the firms employing immigrant R&D workers conduct 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 conducts offshore R&D, consistent with the R&D measure in the Offshoring Survey being broader than the one in the R&D Survey. Second, like the one in the R&D Survey, this measure also shows a higher conditional probability of employing immigrant R&D workers among the firms doing offshore R&D than the conditional probability of offshoring R&D among the firms employing immigrant R&D workers.

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

To understand the asymmetric patterns in conditional probabilities between the use of immigrant workers and offshore services in R&D, we look into the frequency of firms' transition between different R&D modes. In particular, we split firms into the following five *R&D modes*: R&D inactive (denoted by 0), R&D with only domestic inputs but no imported services or immigrant researchers (N), R&D with domestic inputs and immigration researchers (NI), R&D with domestic inputs and imported R&D services (NF), and R&D with all three types of inputs (NIF).

Panel A of Table 2 reports the five-by-five transition matrix between these modes. Each row sums up to one. The entry in row m and column n of the matrix shows the fraction of firms in mode m in year t moving to mode n in year $t+1$. The table shows that among firms employing immigrant R&D workers (the NI row), about 12% adopt offshore R&D (the NIF or

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: Panel A of the 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). Each period is defined as a year and the reported values are the average of year-to-year transition over the sample period. 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$.

NF column) in the next year. This is twice as large as the 5% probability that firms doing R&D without immigrant researchers in year t start using offshore R&D services in year $t+1$ (from N to either NIF or NF). On the other hand, among 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 firms in mode N that switch to either NI or NIF modes.[11]

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 immigrant researchers. This effect could be due to either the enhanced benefit or the reduced cost of offshore R&D from the presence of immigrant researchers. More specifically, as immigrants may bring diverse ideas, having immigrant researchers can increase the marginal return from offshore R&D for a given level of R&D investment. Alternatively, immigrant researchers may act as a bridge between the headquarters and the foreign R&D suppliers, thereby reducing information frictions in offshore R&D. We will incorporate both mechanisms in the structural model developed in the next section and let the data discipline the existence and the strength of these mechanisms.

In Appendix A.2, we supplement the above findings with regression-based evidence on the relationship between offshore R&D and a firm's employment of immigrants. First, we show that this relationship is robust when productivity and other firm characteristics, including their size, industry affiliation, and importing/exporting status, are controlled for. This analysis rules out the possibility that the higher propensity among firms with immigrants to start offshore R&D is simply due to large and productive firms being more active in both decisions. Second, the

[11]The fraction of firms dropping out of R&D ranges between 6% for firms in the NIF mode to 33% for firms in the N mode, and the average probability of dropping out of R&D is around 21% in our sample. As a comparison, the odds of quitting R&D are between 20% and 50% in Bøler et al. (2015) and around 35% Aw et al. (2011).

relationship persists when we focus on the connection between immigrants from a specific foreign region and offshoring R&D to the same foreign region, which offers additional support for the role of immigrants in reducing information frictions. Third, only the presence of immigrant *researchers*, not other types of immigrants, increases the likelihood of offshore R&D. This result suggests that the interaction we document is within R&D, rather than between R&D and other activities. Finally, we also show that the result is not due to reverse causality by using a shift-share instrumental variable (IV) for firms' employment of immigrants, which exploits variations across Danish regions and industries in the stock of immigrants from different foreign regions in 2000 and the nation-wide inflow of immigrants between 2001 and 2015. 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' participation in R&D is persistent (see, e.g., Griliches, 2007 and the reference thereto). The statistics in Table 2 show that in our data, both the performance premium and the persistence of R&D apply to the *mode* of R&D as well. For example, 62.5% of firms in mode NIF and 67.5% of firms in mode NI will stay in the same mode in the following year. Panel B of the table reports the average of labor productivity—defined as value added per worker—by R&D mode. Firms doing R&D with foreign inputs tend to be more productive than firms in the N mode. These patterns lead to the second fact:

Fact 2: Firms doing R&D with foreign inputs are more productive on average than non-R&D firms and firms doing R&D without foreign inputs. Both firms' participation in R&D 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 the 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. Our model features both forces, and we will separate them in the structural estimation.

Having documented patterns consistent with selection into using foreign R&D inputs by productivity, we now examine whether this use increases the return to R&D. We estimate the impact of doing R&D with foreign inputs on productivity using the following specification:

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

In equation (1), ω_{it} denotes the log labor productivity of firm 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 that determines 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 not only on whether a firm conducts R&D, but also on how. Therefore, in addition to the indicator for firms' R&D status ($\mathbb{I}(\text{R\&D}_{it-1})$), we 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 variation in R&D intensity. Decisions on R&D likely depend on the characteristics of the industry and other firm-level decisions, both of which can impact firm performance. Denoting firm i's industry by $j(i)$, we will control for these confounding factors using industry-time fixed effects $\phi_{j(i)t}$ and time-varying firm characteristics X_{it}.

Table 3 presents the estimation results for equation (1). Column 1 shows that participation in R&D is associated with 2.4% higher productivity and that conditional on participation in R&D, the use of imported R&D services is associated with an additional 3.1% productivity gains. Column 2 shows a similar finding for the use of immigrant R&D workers. 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.

A robust finding from the trade literature is that participation in import and export (of goods) is strongly correlated with firm productivity (see Bernard et al., 2012 for a review). If the R&D decision also depends on trade participation (Aw et al., 2011; Bøler et al., 2015), then the correlation between R&D and future productivity could be driven by firms' participation in trade. To address this concern, column 4 controls for firms' importing and exporting status in period t.[12] Consistent with previous findings from the literature, the coefficients on the indicators of firms' importing and exporting status are both positive and statistically significant. However, the coefficients of immigrant researchers and offshore R&D remain similar. This result suggests that the correlation documented between firm productivity and the use of foreign R&D inputs is not picking up the effects of 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. The coefficients of log domestic R&D expenditures are statistically significant but generally not big enough for the estimated coefficients on the foreign R&D input indicators to be explained by the higher R&D expenditures of these firms.[13] Correspondingly, the coefficients associated with the offshore and

[12]Controlling for the lagged importing and exporting status gives essentially the same result.

[13]With a point estimate of 0.003 as in column 8, for example, for the 3% additional productivity gains enjoyed by firms doing offshore R&D to be entirely explained by the extra R&D investment made by these firms, the total log

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 Table A.3). The sample includes private sector firms with at least 10 employees, and the sample period covers 2001-2015. Standard errors are clustered at the firm-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

immigrant R&D indicators are 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.

It is still 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 using a control function approach in productivity estimation. Based on these empirical results, we have the third fact.

Fact 3: Conditioning on current productivity and total R&D expenditures, 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 not perfect substitutes. These facts motivate us to model foreign inputs as providing different, potentially better ideas to the R&D process.

Summary and Robustness. Taking stock, we find that foreign R&D inputs in the form of

R&D investment of these firms needs to be 1,000 log points above that of other firms.

immigrant researchers or imported R&D services account for a substantial fraction of total R&D spending made by firms in Denmark. On the one hand, there is 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 improved future performance beyond what can be explained by firms' total R&D expenditures. Moreover, these two types of foreign R&D inputs are tightly connected: the propensity to offshore R&D is higher among firms employing immigrant researchers.

We show in Appendix A.3 that these patterns are robust to alternative definitions of immigrants (e.g., based on whether a person moves to Denmark above a certain age or after completing all education) and other categorizations of R&D modes (e.g., by varying the minimum employment of immigrant researchers for a firm to be classified as hiring immigrant researchers; by examining 3- and 5-year transitions instead of year-to-year transitions). We also show that the results are not driven by the Danish affiliates of foreign multinational firms.

Together, these facts underscore the importance of foreign inputs in R&D. They also imply that policies affecting the adoption of one foreign R&D input would affect the adoption of the other input, which could reinforce the direct impact of such policies on R&D decisions. The main goal of our structural model in the next section is to disentangle these forces and quantify their impact on firm's performance.

3 Model

In this section, we introduce a dynamic model where heterogeneous firms make productivity-enhancing R&D investment by combining inputs from domestic and foreign sources. Statically, given current productivity and the aggregate demand, firms choose the output quantity to maximize their 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 the firm's past productivity and R&D investment, as will be explained in the next subsection; $q_{i,t}$ is the output. Denoting the wage for each unit of production labor as $W_{i,t}$, the marginal cost of production is $\frac{W_{i,t}}{\exp(\omega_{i,t})}$.[14]

Firms sell their output in a monopolistic competitive output market, characterized by the

[14]When taking the model to the data, we will extend the production function to incorporate capital and materials as additional production inputs.

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 the rest of the world. In keeping with this interpretation, we make two simplifications. First, we abstract from firms' endogenous export decision. We motivate this assumption from the high degree of integration of Denmark in the world economy.[15] 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 aggregate productivity, so these 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 $p_{i,t} = \frac{\eta}{\eta+1} \cdot \frac{W_t}{\exp(\omega_{i,t})}$, 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 the Love for Variety of Ideas

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

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

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; $\mathbb{I}(rd_{i,t-1} > 0)$ 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, which has a mean of zero and a standard deviation of σ_ζ.

As documented in Section 2, some firms use multiple R&D inputs at the same time, suggesting these inputs are not necessarily perfect substitutes. Moreover, these firms see larger produc-

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

tivity gains than firms relying on only domestic inputs. To rationalize these empirical regularities parsimoniously, we assume that firms can combine three types of R&D inputs—domestic researchers (N), immigrant researchers (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 is:

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

In this function, $rd^{\tilde{x}}_{i,t}$ for each $\tilde{x} \in \{N, I, F\}$ denotes the R&D input of type $\tilde{x}$ used by firm i. $A^{\tilde{x}}$ for each $\tilde{x} \in \{N, I, F\}$ denotes the efficiency of input $\tilde{x}$. Based on the values of $A^{\tilde{x}}$, our model can accommodate a case where foreign inputs are more technically advanced than domestic researchers, as well as a case of their being inferior, possibly due to frictions in communication.

Under the restriction of $1 < \theta < \infty$, different R&D inputs are not perfectly substitutable. This imperfect substitution can be rationalized as different inputs being embedded with ideas and techniques from different sources, thus bringing in the gains from a diversity of ideas to the R&D process. We call this mechanism the *love for variety of ideas*. Similar setups have been widely employed in the literature to explain firms' use of foreign intermediate production inputs (e.g., Halpern et al., 2015) and to analyze the impacts of immigrants on domestic workers and the local economy (e.g., Yeaple, 2018; Ottaviano et al., 2018). In our model, this channel is the reason why firms have an incentive to adopt diverse inputs for R&D activities in the first place. The strength of this channel depends critically on the value of θ, which we will estimate structurally.

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 our data, however, 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 suppliers of R&D services (NF); using all three types of inputs simultaneously (NIF). As previously, we call these combinations of R&D activities *R&D modes*. By denoting the mode for non-R&D firms as *0*, the mode choice of firms is given by $x \in X \equiv \{0, N, NI, NF, NIF\}$.

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 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. Our setup implies $c^x < c^N, \forall x \in \{NI, NF, NIF\}$. Therefore, conditional on their 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 domestic inputs, which is exactly what Fact 3 in Section 2 states. As previously mentioned, how much larger the increase in productivity is for firms using foreign R&D inputs will depend on our estimate of θ.

In addition to giving firms a reason to use either offshore R&D or immigration researchers, equation (6) also introduces the first source of interaction between these two inputs—via the return to R&D. For example, with $c^{NIF} < c^{NF}$, firms in the NIF mode can reap a higher return from the same R&D expenditures than firms in the NF mode. Thus, the presence of immigrants gives firms a stronger incentive to participate in not only R&D but also offshore R&D.

Despite the benefits from the employment of immigrant researchers and from the adoption of imported R&D services, not all firms engage in these activities, hinting at significant upfront costs for these options. Moreover, the persistence of R&D mode decisions observed in the data (Fact 2 in Section 2) naturally motivates a dynamic model. We now introduce the fixed and sunk costs of R&D and describe firms' dynamic decisions.

3.3 Dynamic Decisions

Firms' dynamic decisions unfold as follows. At the beginning of period t, firms discover 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 maximize the static profit, as described in Section 3.1, and then decides the current period's R&D mode and total R&D expenditures.

For the firms having chosen R&D mode x in the previous period, switching to mode x' requires an irreversible investment of $\tilde{F}^{x,x'} + \iota^{x'}_{i,t}$. In this total cost, $\tilde{F}^{x,x'}$ is the systematic component that is common to all firms switching from mode x to mode x'. The dependence of this component on firms' previous R&D status reflects the upfront costs associated with entering a new mode, e.g., the cost of setting up a new R&D team or finding a reliable overseas R&D supplier. $\iota^{x'}_{i,t}$ is the idiosyncratic component of the cost for the new mode choice. We assume that $\iota^{x'}_{i,t}$ is drawn randomly and independently (across i, t, and x') from a mean-zero 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 they are located in a region where many immigrants live; firms might also encounter a talented researcher or a reliable foreign supplier by sheer luck. Such 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 $\iota^{x'}_{i,t}$ and then decide whether to carry out R&D and how. 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 before the realization of $\iota^x_{i,t}$ of a firm with state $\mathbf{s}_{i,t}$, denoted by $V_t(\mathbf{s}_{i,t})$, is given by:

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

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

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

In equation (7), the $V^x_t(\mathbf{s}_{i,t})$ 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 $\iota^{x'}_{i,t}$, the probability of a firm switching from R&D mode x to R&D mode x' is given by:

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

We parameterize the average 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. Putting this structure in a matrix form, we have

$$\tilde{\mathbf{F}}_{5\times5} = \mathbf{1}_{5\times1} \cdot \mathbf{f}_{1\times5} + \mathbf{F}_{5\times5},$$

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 a vector of fixed operation costs; $\mathbf{F}$ is a 5 by 5 matrix of sunk cost components. The element in the m-th row and the n-th column of matrix $\tilde{\mathbf{F}}$, for example, corresponds to the sunk cost of switching from the m-th mode in X to the n-th mode in X.

We assume that a decision to do no R&D ($x' = 0$) incurs neither cost, i.e., $f^0 = 0$ and $F^{x,0} = 0$ for every x. We also assume that there is no sunk cost if firms do not switch R&D modes, i.e., $F^{x,x'} = 0$ if $x = x'$. We parameterize the remaining 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 each column correspond to each of the five R&D modes in the order of

$\{0, N, NI, NF, NIF\}$, with rows indicating firms' current mode x and columns indicating their mode x' in the next period.

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 domestic workers, immigrant workers, and offshore sources, respectively. These costs 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 services 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.[16] 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 the presence of immigrants to reduce the cost of offshore R&D through two components: in the sunk cost via $F^{IF} > 0$ and in the fixed cost via $f^{NIF} < f^{NI}$. We will let the data tell whether these inequalities are satisfied and which component is more important.

A plausible explanation for why we *might* estimate $f^{NIF} < f^{NI}$ and/or $F^{IF} > 0$ is that immigrants in the R&D team, knowing the language and affiliate logistics better, can facilitate communication between the headquarters and offshore R&D affiliates. This explanation is consistent with the empirical results reported in Appendix A.2, which show a strong connection between the origin country of immigrant researchers and the destination for offshore R&D. Following the extensive literature that documents the importance of immigrants in facilitating international business (e.g., Rauch and Trindade, 2002; Burchardi et al., 2019), we label the cost advantage in offshoring from the presence of immigrants as the *information channel*. This is the second source of interaction between the two foreign R&D inputs.

In summary, the model rationalizes firms' use of diverse R&D inputs through the notion of the love for variety of ideas. It further accommodates the higher propensity of offshoring among firms with immigrant researchers via two channels: through the increased return to R&D when both foreign R&D inputs are used simultaneously, and through the information channel. We will estimate the model in the next section to uncover the quantitative importance of these mechanisms for R&D decisions.

3.4 Discussion on Model Assumptions

Before turning to the estimation, we discuss the rationale for four modeling choices. First, at the center stage of our model are the decisions of firms in Denmark looking to optimally source inputs for their R&D. This setup fits the measure of offshore R&D in the survey but overlooks the possibility that some firms in the sample are the Danish affiliates of foreign MNCs. A natural concern, then, is that because MNCs already have an international network, having immigrant

[16] Since 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.

researchers in their Danish affiliate might have a smaller impact on the cost of sourcing R&D inputs from abroad. Thus, to the extent that MNCs indeed do not benefit much from the information channel, our structural estimation will underestimate the importance of this channel for the firms originating in Denmark. For robustness, we show in Appendix A.3 that the empirical patterns are similar when affiliates of foreign MNCs operating in Denmark are excluded from our sample.

Second, in the model, the benefit from the information channel accrues only to firms with immigrant *R&D workers*, but not to firms with other types of immigrant workers. This choice is motivated by the data: as shown in Appendix A.2, when indicators for both R&D and non-R&D immigrants are included in the regression specification for the information channel, only the indicator for R&D immigrants has a robust correlation with offshore R&D.

Third, we incorporate an interaction between immigrant researchers and offshore R&D via higher returns embedded in the CES function, but we do not allow for richer interactions via $A^{\tilde{x}}$. For example, one might think that firms are able to increase A^F in equation (6) by hiring more immigrant researchers. An implication of this mechanism is that the shares of R&D expenditures on inputs I and F should be positively correlated among the firms using both. Since the support for this implication is relatively weak in our data, we choose not to incorporate this mechanism in the model.[17]

Finally, we assume that each firm makes binary decisions of whether to hire immigrants and to offshore R&D, rather than a decision of which foreign regions to hire immigrant researchers from and to offshore R&D to. This assumption greatly simplifies the structural estimation but may seem too restrictive for the information channel of immigrants. Note, however, that most firms in our data source R&D only from one foreign region.[18] Even among firms with more than 250 employees, the average number of offshore R&D destination regions is only 1.6. Our model can be viewed as a special case of a more general 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* foreign region to do so.

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.

[17]Specifically, when we regress the immigrants' share of firms' total R&D wage bill on the offshore share of R&D expenditures, we find a positive but statistically insignificant coefficient. This finding also guides us to adopt a generic CES specification, as opposed to a nested-CES specification, for R&D.

[18]Examples of foreign regions in the data are Eastern Europe, North America, China, India, etc.

4.1 The Distribution of Idiosyncratic Cost Shocks

A key set of parameters in our model is the matrix $\tilde{\mathbf{F}}$ that governs the cost of switching R&D modes. An intuitive approach to identify $\tilde{\mathbf{F}}$ is to use the patterns of transition between R&D modes 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, as shown in equation (8), transition patterns alone do not separately identify $\tilde{\mathbf{F}}$ and ν.

We overcome this challenge by taking advantage of a natural experiment in Denmark, the introduction of an R&D subsidy policy in 2011, to identify ν. This policy rebates 25% of total R&D expenses for firms incurring 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 subsidy changes the probability of switching R&D modes among the eligible firms.

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

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

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.[19] The expression shows that the log odds ratio is the sum of two components: static R&D expenses, and dynamic gains due to the improvement in expected future productivity.

With the aforementioned R&D subsidy in place, equation (10) becomes:

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

in which τ is the subsidy as a share of R&D expenses. Equation (11) differs from equation (10) 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 by $V'_{t+1}(\cdot)$ and $rd^{*'}_{i,t}(\cdot)$, respectively.

[19] As firms' choice between modes 0 and N can be inferred from their choice of $rd_{i,t}$, (i.e., $rd_{i,t} = 0$ means the firm chooses to quit R&D; $rd_{i,t} = rd^*_{i,t}(\omega_{i,t}, N)$ means the firm continues with mode N), we suppress firms' mode from their value functions. In the rest of this section, we use $E_t V_{t+1}(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t} = 0)$ as shorthand for $E_t V_{t+1}((\omega_{i,t+1}, 0)|(\omega_{i,t}, N), rd_{i,t} = 0)$ and $E_t V_{t+1}(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t} = rd^*_{i,t}(\omega_{i,t}, N))$ as shorthand for $E_t V_{t+1}((\omega_{i,t+1}, N)|(\omega_{i,t}, N), rd_{i,t} = rd^*_{i,t}(\omega_{i,t}, N))$.

Given the uncertain and temporary nature of this policy and the restriction on eligibility for only loss-making firms, we assume that firms perceive the value function in the post-policy world as similar to the one before policy, i.e., $V_{i,t}(\cdot) \approx V'_{i,t}(\cdot)$.[20] Under this assumption, we can express firms' continuation value net of R&D investment as the following:

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

The two equalities in (12) follow from the definition of $rd_{i,t}$ as the solution to the Bellman equation (7). The two approximations stem from our assumption of $V_{i,t}(\cdot) \approx V'_{i,t}(\cdot)$ and the Envelope Theorem, respectively. Condition (12) shows that up to the first order, the net (of R&D expenses) continuation value 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. By combining this condition with equations (10) and (11), and the approximation of $V_{i,t}(\cdot) \approx V'_{i,t}(\cdot)$, we get:

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

According to (13), the change in the propensity of a loss-making firm continuing R&D due to the R&D subsidy depends on the amount of the subsidies $\tau(c^N \times rd^{*}_{i,t}(\omega_{i,t}, N) + f^N)$, and the parameter ν, which governs firms' responsiveness to the subsidy. In the model, firms' charac-

[20] From the perspective of firms qualifying for this subsidy in year t, they would qualify again 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; 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	
Panel A: all industries							
		2011				2012	
		N	0			N	0
2010	N	113	39	2011	N	144	24
	0	27	427		0	37	373
Panel B: manufacturing							
		2011				2012	
		N	0			N	0
2010	N	52	17	2011	N	67	11
	0	15	135		0	19	116

Notes: The sample consists of loss-making firms in 2011 and 2012 with at least 10 employees for all industries (Panel A) and manufacturing only (Panel B). N refers to firms reporting positive domestic R&D expenditures while 0 refers to firms reporting zero domestic R&D expenditures.

teristics are uniquely determined by their current productivity and their 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 incurring larger R&D expenditures.

Table 4 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 in total around 600 loss-making firms making transitions between these modes in each period. Before the subsidy was enacted, 26% of the firms in mode N stopped doing R&D; this share decreases to 14% in 2012, after the policy took effect. As Panel B shows, similar patterns hold among the sample of approximately 220 loss-making manufacturing firms. These patterns are consistent with the goal of the subsidy policy to encourage R&D participation.

To control for differences in firm productivity, we split the observations in 2011 and 2012 into B bins by their lagged 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 firms in 2011 with similar productivity as a comparison group for firms in 2012. Formally, we estimate the following linear probability model:

$$\mathbb{I}(i \text{ quits R\&D in } t) = \beta_0 \mathbb{I}(t = 2012) + \sum_{b=1}^{B} \beta_b \mathbb{I}(\omega_{i,t-1} \in \Omega_b) + \beta_{emp} \ln(\text{emp}_{i,t-1}) + \epsilon_{i,t},$$

where $\mathbb{I}(i \text{ quits R\&D in } t)$ is an indicator variable that takes a value of 1 if a firm-year observation stops doing R&D; β_b is a fixed effect for all observations belonging to the b-th productivity bin Ω_b; β_0 is the key coefficient of interest, capturing the effect of the policy. To rule out a possibility

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

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 on loss-making firms. All specifications control for lagged log firm size, lagged firm productivity (defined as log valued added per worker), and industry fixed effects. Columns 1-3 and 5-7 report specifications using productivity bin fixed effects with a varying number of bins, while columns 4 and 8 use a quadratic function of lagged productivity. The sample consists of firms in the entire private sector or manufacturing in 2011 and 2012 that have at least 10 employees. Robust standard errors are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of systematic differences in firms' behavior based on their size and industry, we always control for industry fixed effects and lagged log firm employment.

Columns 1 through 3 in Panel A of Table 5 report the results from this specification, with the number of productivity bins, B, 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 was introduced, the probability that firms quit doing R&D decreased by around 12%. Columns 5 through 8 provide a placebo test by focusing on firms making a profit, which were ineligible for the subsidy. This placebo test shows 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.

Estimates reported in Panel A do not easily translate 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:

$$\mathbb{I}(i \text{ quits R\&D in } t) = \begin{cases} 1, & \text{if } \beta_0 \cdot \mathbb{I}(t = 2012) \cdot \log(r\&d_{i,t-1}) + \sum_{b=1}^{B} \beta_b \mathbb{I}(\omega_{i,t-1} \in \Omega_b) + \beta_{emp} \log(\text{emp}_{i,t-1}) + \epsilon_{i,t} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

Assuming that $\epsilon_{i,t}$ is drawn from the standard logistic distribution, this specification is the reduced-form counterpart of the structural 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.[21] Because of this difference, we estimate an elasticity from equation (14), before converting it to a semi-elasticity.[22]

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 report results for manufacturing firms. The estimated coefficients for manufacturing firms are qualitatively similar but larger in magnitudes.

Our preferred specification, reported in column 7 of the table, gives an estimate of -0.330. To convert this number into the value for the semi-elasticity given in equation (13), $-\frac{\tau}{\nu}$, we assume that the elasticity estimate holds for the firm with the median R&D expenditures. With the median R&D expenditures in the regression sample being 0.44 million USD, we have $-\frac{\tau}{\nu} = \frac{-0.330}{0.44} = -0.75$. Plugging in $\tau = 0.25$ gives us $\nu = 0.33$.

4.2 R&D and the Evolution of Productivity

In the second step of the estimation, we estimate 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 $x \in \{N, NI, NF, NIF\}$). These cost parameters, in turn, depend 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 expenditures that firm i spends at time $t-1$ within Denmark, i.e., on native researchers and/or immigrant researchers, the period-t productivity of firm

[21] To see this, note that the logistic assumption in equation (14) implies that the pre- and after-policy log odds ratios are, respectively, $\log(\frac{m_t^{N,0}(\mathbf{s}_{i,t})}{m_t^{N,N}(\mathbf{s}_{i,t})}) = \sum_{b=1}^{B} \beta_b \mathbb{I}(\omega_{i,t-1} \in \Omega_b) + \beta_{emp} \log(\text{emp}_{i,t-1})$ and $\log(\frac{m'^{N,0}(\mathbf{s}_{i,t})}{m'^{N,N}(\mathbf{s}_{i,t})}) = \beta_0 \log(r\&d_{i,t-1}) + \sum_{b=1}^{B} \beta_b \mathbb{I}(\omega_{i,t-1} \in \Omega_b) + \beta_{emp} \log(\text{emp}_{i,t-1})$. Taking the difference between the two gives an elasticity-specification of equation (13).

[22] 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 with the distribution of R&D expenditures highly skewed, 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.

i is given by:

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

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

The third line inside the curly bracket of equation (15) completes the specification for the productivity of firms in R&D mode NF. Conditional on the total R&D spending *within* Denmark, these firms would see an additional boost of $\gamma\theta \cdot \log \frac{c^N}{c^{NF}}$ in productivity. The coefficient before $\log \frac{c^N}{c^{NF}}$ is $\gamma\theta$ instead of γ as in the 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 inside the curly bracket of equation (15) is for the firms using all three types of R&D inputs. Because $c^{NI} > c^{NIF}$ and $c^N > c^{NI}$, the systematic boost on productivity in the NIF mode is also positive and greater than in the NI mode.

Based on the interpretation of 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. $\tilde{\rho}$ and $\tilde{\gamma}_m$ for $m = 0, 1, 2, 3$ are the structural parameters corresponding to the parameters in equation (15).[23] We stack $\tilde{\gamma}_m$ in a vector denoted by $\tilde{\boldsymbol{\gamma}} = (\tilde{\gamma}_0, \tilde{\gamma}_1, \tilde{\gamma}_2, \tilde{\gamma}_3)$.

Comparison between equations (15) and (16) clarifies how $\tilde{\boldsymbol{\gamma}}$ summarizes the benefit of having access to additional sources of ideas. These parameters contain all information about θ, and $A^{\tilde{x}}$ 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 $\tilde{\boldsymbol{\gamma}}$ has been estimated, we can plug it back in equation (15) and treat it as the law of motion of productivity that firms perceive when making R&D decisions.

There are, however, two challenges in estimating equation (16). First, $\omega_{i,t}$ is unobserved to the econometrician. Second, firm-level R&D expenditures are notoriously difficult to measure,

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

so e_{it-1} is likely subject to severe measurement errors. Moreover, only a few firms in the sample are in the NF mode. These factors limit our ability to estimate all reduced-form parameters in equation (16) precisely, even if $\omega_{i,t}$ is known.

To address the first challenge, we apply a two-step control function approach, which recovers $\omega_{i,t}$ jointly with the parameters governing firms' productivity evolution.[24] To meet the second challenge, instead of taking the estimates for equation (16) as the structural parameters, 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 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. The log output *quantity* of firm i in year t, denoted by $\tilde{q}_{i,t}$, 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. The log of the optimally chosen price for the output of firm i, $\tilde{p}_{i,t}$, is:

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

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

By combining equations (17) and (18), we obtain the following expression for the measured revenue (the data):

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

In this specification, $\tilde{\epsilon}_{i,t}$ is the log of a multiplicative measurement error in revenue.[25] $\tilde{\beta}_a$, $a \in \{m, k, l\}$ is the revenue elasticity of input a that takes into account the demand elasticity of consumers.

Firms' productivity evolves according to equation (16). We allow capital and labor to be dynamic inputs that are subject to adjustment costs, which implies that $\tilde{k}_{i,t}$ and $\tilde{l}_{i,t}$ do not necessarily capture all information contained in $\omega_{i,t}$. On the other hand, materials are assumed to be a static

[24] Our estimation of $\omega_{i,t}$ takes into account that firms' R&D mode choice both depends on their current productivity and affects their future productivity. This approach addresses the concern raised by De Loecker (2013) that if productivity is estimated without taking into account firms' endogenous decisions (such as R&D or export), one might fail to detect the impact of these endogenous decisions on productivity.

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

input, chosen after firms observe $\omega_{i,t}$ and have decided $\tilde{k}_{i,t}$ and $\tilde{l}_{i,t}$, so it can be inverted to recover productivity. Following the insight of Levinsohn and Petrin (2003) and Ackerberg et al. (2015), we use materials as a control for productivity in a two-step estimation procedure detailed below.

Step 1. The first step is to come up with a control function for $\omega_{i,t}$. 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 $\tilde{m}_{i,t} = m_t(\omega_{i,t}, \tilde{k}_{i,t}, \tilde{l}_{i,t}, z_{i,t})$. We include in $z_{i,t}$ 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 international trade. Participation in importing might affect material use because the access to foreign suppliers can reduce the effective price of intermediate goods. Participation in exporting might also affect material use because exporters face a larger demand than non-exporters and might choose to produce more for any given level of capital and labor. Therefore, we include lagged firms' importing and exporting status in $z_{i,t}$. Second, since the quality of workers differs across firms (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 firms' average wage in $z_{i,t}$. Finally, firms' capital stock, calculated based on the perpetual inventory method, 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 the investment rate in $z_{i,t}$ to control for the potentially 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 general function of $\tilde{k}_{i,t}$, $\tilde{l}_{i,t}$, $\tilde{m}_{i,t}$, and $z_{i,t}$, i.e., $\omega_{i,t} = \tilde{\omega}_t(\tilde{k}_{i,t}, \tilde{l}_{i,t}, \tilde{m}_{i,t}, z_{i,t})$. Plugging this expression into equation (19) gives:

$$\begin{aligned} \tilde{y}_{i,t} &= \tilde{\beta}_k \tilde{k}_{i,t} + \tilde{\beta}_l \tilde{l}_{i,t} + \tilde{\beta}_m \tilde{m}_{i,t} + \tilde{\omega}_t(\tilde{k}_{i,t}, \tilde{l}_{i,t}, \tilde{m}_{i,t}, z_{i,t}) + \tilde{P} - \frac{1}{\eta}\tilde{Q} + \tilde{\epsilon}_{i,t} \\ &\equiv h_t(\tilde{k}_{i,t}, \tilde{l}_{i,t}, \tilde{m}_{i,t}, z_{i,t}) + \tilde{\epsilon}_{i,t}. \end{aligned}$$

We specify $h_t(\cdot)$ as the sum of the following components: a cubic function of capital, investment, employment, wage, and the interaction between these variables; the indicators for firms' importing and exporting status; and the yearly and industry dummies. The first step comes down to estimating $h_{i,t}(\cdot)$ using the OLS, which separates $h_{i,t}(\cdot)$ from measurement errors in revenue, $\tilde{\epsilon}_{i,t}$. We denote the estimated value for firm i in period t as $\tilde{h}_{i,t}$.

Step 2. With $\tilde{h}_{i,t}$ in hand, we express $\omega_{i,t} = \frac{\eta}{\eta+1}[\tilde{h}_{i,t} - \tilde{\beta}_k \tilde{k}_{i,t} - \tilde{\beta}_l \tilde{l}_{i,t} - \tilde{\beta}_m \tilde{m}_{i,t} - \tilde{P} + \frac{1}{\eta}\tilde{Q}]$. By substituting this expression into equation (16), we obtain:

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

The left hand side in the equation is either the data or the parameters to be estimated. The right hand side is the innovation in firms' productivity. We estimate equation (20) using the generalized method of moments (GMM).

GMM Sample, Identification, and Results. Since the production function specified in (19) is most appropriate for the manufacturing industry, in this GMM estimation and all subsequent structural estimations, we restrict the sample to manufacturing firms. To form the moment conditions, recall that $\tilde{k}_{i,t}$, $e_{i,t-1}$, and $x_{i,t-1}$ are determined before the innovation term in productivity $\zeta_{i,t}$ realizes, so 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 for $\tilde{l}_{i,t}$. The term $[\frac{\eta+1}{\eta}\overline{\omega} + (1-\rho)(\tilde{P} - \frac{1}{\eta}\tilde{Q})]$ captures the R&D cost and the aggregate market demand shifters that are common to all firms. We allow this term to vary across industries by including industry dummies in the specification and use these dummies as their own instruments. Finally, under our timing assumption, $\tilde{m}_{i,t}$ is chosen after the realization of $\zeta_{i,t}$, so it is endogenous. As discussed in Ackerberg et al. (2015), we cannot use $\tilde{m}_{i,t-1}$ to instrument for $\tilde{m}_{i,t}$ because once capital, labor, and productivity are controlled for, $\tilde{m}_{i,t-1}$ should in principle not contain additional information about $\tilde{m}_{i,t}$. Instead, we estimate $\tilde{\beta}_m$ by exploiting firms' first-order condition for materials (see e.g., Griliches, 1979; Gandhi et al., 2020).

Specifically, we show in Appendix B.2 that the first-order condition for material use implies:

$$
\underbrace{\frac{P_{m,t} \cdot \exp(\tilde{m}_{i,t})}{\exp(\tilde{y}_{i,t})}}_{\text{measured material revenue share}} \cdot \exp(\tilde{\epsilon}_{i,t}) = \underbrace{\tilde{\beta}_m}_{\text{revenue elasticity of materials}}, \tag{21}
$$

in which $P_{m,t}$ is the price for materials. The first term on the left-hand side is the measured revenue share of materials. Assuming that multiplicative revenue measurement errors $\exp(\tilde{\epsilon}_{i,t})$ have a mean of 1, we can use the method of moments to estimate $\tilde{\beta}_m$ from equation (21).[26] In the baseline analysis, we assume that $\tilde{\beta}_m$ is common across industries and estimate it by pooling all firms in the sample. In a robustness exercise reported in the appendix, we allow for industry-specific $\tilde{\beta}_m$. In both cases, we plug in the estimated value for $\tilde{\beta}_m$ to equation (20) and estimate all

[26] Alternatively, we can assume that $\tilde{\epsilon}_{i,t}$ has a zero mean, in which case a log-linearized version of equation (21) can be estimated via the OLS to obtain $\tilde{\beta}_m$. It turns out that these two approaches give very similar estimates.

remaining parameters jointly. To account for the uncertainty in the generated regressors $\tilde{h}_{i,t}$ and $\tilde{\beta}_m$, we calculate standard errors by bootstrapping the entire estimation procedure.

Columns 1-3 in Table 6 report the GMM estimates for 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 we find in Section 2. This result could be due to a downward bias from the measurement errors in R&D expenditures or potential heterogeneous effects by firm size.[27]

More important to our purpose, we find statistically significant and economically sizable effects from the adoption of NI and NIF modes. The estimated coefficient for the NF indicator is marginally negative but statistically insignificant, which could be the result of there being only a small number of firms in the NF mode. The lower panel of Table 6 reports the estimates for revenue elasticities of capital, labor, and materials. All estimates are of reasonable values and stable across specifications.

The second column includes a dummy variable for firms' importing status both in the control function $h(\cdot)$ and in the law of motion for productivity. This specification allows importing to play two roles: directly improving firms' productivity, and altering firms' use of intermediate materials conditional on their productivity. The result from this specification shows that our main finding is not due to a possible correlation between the use of foreign R&D inputs and importing. Column 3 further includes exporting status in both the control function and the law of motion for productivity. The estimated coefficients remain largely the same.

Auxiliary Regression. As discussed earlier, due to possible measurement errors in R&D expenditures and the small number of observations in the NF mode, we may not be able to estimate all 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.

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

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

[27] Our estimate is in line with the literature. Focusing on a neighbouring country, Norway, Bøler et al. (2015) estimate heterogenous R&D returns by size. They find a larger coefficient for large firms and a negative coefficient for small firms, implying an average return that is similar to 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***
	(0.146)	(0.130)	(0.123)	(0.129)	(0.110)	(0.155)	(0.146)	(0.149)	(0.149)
$\log(e_{i,t-1})$	0.002***	0.002***	0.002***						
	(0.001)	(0.001)	(0.001)						
$\mathbb{I}(x_{i,t-1} = N)$				0.010***	0.009***	0.009**	0.010***	0.010***	0.010***
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{I}(x_{i,t-1} = NI)$	0.022***	0.022***	0.022***	0.024***	0.023***	0.023***			
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)			
$\mathbb{I}(x_{i,t-1} = NF)$	-0.006	-0.006	-0.006	-0.003	-0.003	-0.003			
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)			
$\mathbb{I}(x_{i,t-1} = NIF)$	0.042***	0.043***	0.043***	0.048***	0.049***	0.049***			
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)			
$\mathbb{I}(x_{i,t-1} \in \{NI, NF, NIF\})$							0.023***	0.023***	0.023***
							(0.007)	(0.007)	(0.007)
Revenue elasticities									
$\tilde{\beta}_l$	0.457***	0.457***	0.457***	0.459***	0.458****	0.458***	0.461***	0.460***	0.460***
	(0.010)	(0.009)	(0.011)	(0.009)	(0.009)	(0.015)	(0.014)	(0.015)	(0.015)
$\tilde{\beta}_k$	0.107***	0.106***	0.106***	0.108***	0.107***	0.107***	0.109***	0.108***	0.108***
	(0.014)	(0.012)	(0.011)	(0.012)	(0.010)	(0.014)	(0.014)	(0.014)	(0.014)
$\tilde{\beta}_m$	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	9,320	9,320	9,320	9,320	9,320	9,320	9,320	9,320	9,320

Notes: $\mathbb{I}(x_{i,t-1} = N)$ is an indicator for doing domestic R&D, identified from the R&D Survey if firms report positive domestic R&D expenditures. $\mathbb{I}(x_{i,t-1} = NI)$ is an indicator for having R&D immigrants; $\mathbb{I}(x_{i,t-1} = NF)$ is an indicator for offshore R&D; $\mathbb{I}(x_{i,t-1} = NIF)$ is an indicator for firms having both R&D immigrants and offshore R&D. $\mathbb{I}(x_{i,t-1} \in \{NI, NF, NIF\})$ is an indicator for diversified R&D, i.e. whether the firm either has immigrant R&D, offshore R&D, or both. β^m is estimated via equation (21). All specifications include industry fixed effects, with industries defined at the NACE Rev.2 intermediate level aggregation. The sample is manufacturing firms with at least 10 employees. Bootstrapped standard errors are clustered by firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We take three estimates from Column 9 of Table 6: the estimated autocorrelation, and the estimated coefficients of the R&D indicator and the diverse R&D mode indicator. We supplement these estimates with three additional empirical moments: the average R&D expenditure share on domestic inputs among NI firms (0.903, denoted by s^N_{NI}), the average R&D expenditure share on domestic inputs among NIF firms (0.558, denoted by s^N_{NIF}), and the standard deviation of log firm sales (1.27). The R&D expenditure shares contain information on the cost difference between different R&D modes (e.g., $\log \frac{c^N}{c^{NI}}$ and $\log \frac{c^N}{c^{NF}}$), and are therefore informative about $\tilde{\boldsymbol{\gamma}}$. The standard deviation of log firm sales will pin down σ_ζ.

We arrange these moments in a vector as below

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

$\hat{\boldsymbol{\alpha}}$ will serve as the target in the indirect inference procedure that pins down the structural parameters $\tilde{\rho}$, $\tilde{\boldsymbol{\gamma}}$, and σ_ζ. We stack the structural parameters to be estimated as $\boldsymbol{\lambda} = (\tilde{\rho}, \tilde{\boldsymbol{\gamma}}, \sigma_\zeta)$.

Formally, for any given value of $\boldsymbol{\lambda}$, we simulate the model and use the simulated data to generate the regression coefficients in $\hat{\boldsymbol{\alpha}}$ that are from column 9 of Table 6.[28] We also calculate the standard deviation of log sales as well as firms' R&D shares s^N_{NI} and s^N_{NIF} from the simulated data.[29] We can then choose $\boldsymbol{\lambda}$ so that the moments from the simulated data match their empirical counterparts. Since the model moments hinge 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.

Robustness. We report three sets of robustness exercises for Table 6 in Appendix B.3. First, in the baseline analysis, we estimate a revenue function derived from firms' optimal quantity choice under a CES demand. As an alternative, we estimate a value added production function, which does not take a stand on firms' optimal output choice. Second, in the baseline analysis, we classify firms as engaging in R&D with domestic researchers if they report incurring R&D expenditures. While this definition is conventional and consistent with existing estimates of the return to R&D (e.g., Aw et al., 2011; Doraszelski and Jaumandreu, 2013; Bøler et al., 2015), one might be concerned about possible inconsistencies between this measure and our definition of immigration researcher that is based on occupations. We show that the results are robust if we define participation in domestic R&D based on the occupations of a firm's employees. Third, in the baseline analysis, we assume that material shares are common across industries. The results are similar if we estimate material shares for each industry separately.

4.3 Joint Estimation of the Remaining Parameters

Aside from the parameters governing the law of motion of firm productivity, collected in $\boldsymbol{\lambda}$, the remaining parameters to be internally pinned down include the aggregate demand shifter Φ_t and the fixed and sunk costs of R&D modes $\widetilde{\mathbf{F}}$. We estimate $(\boldsymbol{\lambda}, \Phi_t, \widetilde{\mathbf{F}})$ jointly. For given parameters, we solve firms' optimization problem and simulate the steady state of the model. We then search over the parameter space to minimize the distance between the model's steady state moments and their empirical counterparts. As in the productivity estimation, this process focuses on manufacturing firms. We describe the moments that identify each parameter and our estimation procedures below.

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 are 144 million DKK, or about

[28] 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 $\hat{\boldsymbol{\alpha}}$, we also scale the regression coefficients from the simulated data by $\frac{\eta+1}{\eta}$.

[29] Appendix B.4 shows that for a given guess of $\tilde{\boldsymbol{\gamma}}$ and without the knowledge of $A^{\tilde{x}}$ or $p^{\tilde{x}}$, for $\tilde{x} \in \{N, I, F\}$, we can verify whether the expenditure shares in the model, s^N_{NI} and s^N_{NIF}, are equal to their empirical counterparts, which means that we can estimate all parameters relevant for firm's R&D decisions without having to first estimate $A^{\tilde{x}}$ or $p^{\tilde{x}}$ for all $\tilde{x} \in \{N, I, F\}$.

25.6 million USD. Focusing on the steady state of the model, we assume that $\Phi_t = \Phi$ is a constant and choose Φ so that the median sales among the model firms would be 25.6 million USD.

Fixed and Sunk Costs of R&D Modes. $\widetilde{\mathbf{F}}$ directly determines the probability that a given firm switches from one R&D mode to another. We can thus pin down $\widetilde{\mathbf{F}}$ using the observed transition matrix between R&D modes. Since each row of the transition matrix sums up to 1, it leaves us with 20 independent moments to pin down a total of 10 parameters in $\widetilde{\mathbf{F}}$, 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 $(\boldsymbol{\lambda}, \Phi, \widetilde{\mathbf{F}}) \in \Lambda$, where Λ denotes the parameter space. These parameters fall into two categories. The parameters in the first category, $\boldsymbol{\lambda}$ and Φ, are just-identified, with the same number of moments as there are parameters. The second category of the parameters, $\widetilde{\mathbf{F}}$, are over-identified. To maintain a tight connection between the parameters and the moments identifying them, our estimation solves the following constrained optimization problem:

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

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

The first three elements of $\hat{\boldsymbol{\alpha}}$ in the constraint, as defined in equation (22), are the first three estimated coefficients reported in Column 9 of Table 6. The remaining three elements of $\hat{\boldsymbol{\alpha}}$ are the two R&D expenditure shares (s^N_{NI} and s^N_{NIF}) and the standard deviation of the log of firm sales. $\boldsymbol{\alpha}(\boldsymbol{\lambda}, \Phi, \widetilde{\mathbf{F}})$ are the model-generated values for those six moments conditional on the parameter choice $(\boldsymbol{\lambda}, \Phi, \widetilde{\mathbf{F}})$. This constraint ensures that all moments in $\hat{\boldsymbol{\alpha}}$ are matched exactly.

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 $\nu = 0.33$ 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 constant 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. The estimate for $\tilde{\rho}$ is 0.463, which is very close to the moment that pins it down (0.465). $\tilde{\gamma}_0$ from the joint estimation is larger than the estimated coefficient in column 3 of Table 6, which is consistent with an attenuation bias due to errors in the continuous measure of R&D expenditures. Likely because intensive margin returns pick up a larger fraction of the total returns to R&D, the estimates for

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	0.33	(-)
η	demand elasticity	Aw et al. (2011)	-6.56	(-)
δ	discount rate	-	0.95	(-)
B. Jointly Estimated				
Φ	aggregate demand	median sales: 25.6 million USD	-	
$\tilde{\rho}$	autocorrelation in productivity	Table 6 Column 9	0.463	(0.0095)
$\tilde{\boldsymbol{\gamma}}$	return to R&D	Table 6 Column 9 + shares	$\tilde{\gamma}_0 = 0.0032$	(3.7e-4)
			$\tilde{\gamma}_1 = 0.0010$	(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($sales$))=1.27	0.20	(1.1e-3)
$\widetilde{\mathbf{F}}$	fixed and sunk costs in R&D	Table 8	Table 8	

Notes: Panel A reports parameters that are estimated externally or calibrated. Panel B reports the outcome from the structural estimation. The numbers in parentheses in the last column of Panel B are the standard errors, generated through 200 bootstraps of the entire estimation procedure, including the GMM estimation and the indirect inference described in equation (23).

$\tilde{\gamma}_1$ and $\tilde{\gamma}_3$ are smaller than their counterparts in the specification in column 3 of Table 6. Finally, we estimate a positive value for $\tilde{\gamma}_2$. The contrast between this estimate and the negative estimate in Table 6 stems from the difference in the source of identification: in this joint estimation, $\tilde{\gamma}_2$ is identified from the diversified R&D dummies in combination with the R&D expenditure shares s^N_{NI} and s^N_{NIF}, whereas in Table 6, it is primarily identified from a small number of observations in the NF mode.

We show in Appendix B.4 that our estimate of $\tilde{\boldsymbol{\gamma}}$ implies $\theta = 1.33$ as the elasticity of substitution between R&D inputs, i.e., different sources of R&D inputs are not easily substitutable. This estimate is tightly connected to the large estimated gains from using diverse R&D modes in the auxiliary regression. The low elasticity estimate also means the love for variety of ideas plays an important role in accounting for the return from R&D.

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 a mean difference between the model and the data in the order of 0.02. The fit of the NF row is worse than that of other rows, which is likely due to the relatively lower weight on these moments given the small number of firms in the NF mode. The last row of Panel A reports the mode distribution of firms. The model fits the data closely despite the mode distribution not being directly targeted.

Panel B of Table 8 reports the estimates for fixed and sunk cost parameters. The upper part of the panel is the total cost of transition between R&D modes, combining fixed and sunk cost components. Two observations are noteworthy. First, the diagonal elements are substantially smaller than the other values in the same column, suggesting that sunk costs play an important role. In terms of quantitative magnitude, we find that the startup cost of doing R&D with mode N is around 1.17 million USD. Compared with the average R&D expenditures of 1.78 million USD in the data, this estimate suggests that an important part of R&D expenditures are on the

Table 8: Transition Matrix and Cost Estimates

Panel A: Transition probability and steady 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	-	1.167	(0.039)	2.073	(0.080)	3.005	(0.305)	3.545	(0.203)
N	0	-	0.019	(0.017)	0.926	(0.073)	1.857	(0.301)	2.398	(0.200)
NI	0	-	0.493	(0.062)	0.014	(0.021)	2.331	(0.292)	1.486	(0.168)
NF	0	-	0.019	(0.017)	0.926	(0.073)	0.748	(0.250)	1.472	(0.174)
NIF	0	-	0.493	(0.062)	0.014	(0.021)	1.222	(0.242)	0.560	(0.138)
Breakdown	f^N	f^{NI}	f^{NF}	f^{NIF}	F^N	F^I	F^F	F^{IF}	F^{I0}	F^{F0}
	0.019	0.014	0.748	0.560	1.147	0.912	1.110	0.183	0.474	0.000
	(0.017)	(0.021)	(0.255)	(0.145)	(0.043)	(0.067)	(0.105)	(0.102)	(0.069)	(1e-7)

Notes: Panel A of the table reports the transition probability between modes in the steady state of the estimated model and in the data, averaged among manufacturing firms with more than 10 employees over the sample period. The steady state distribution for the data are firms' frequency distribution across modes over the same period. Panel B reports the estimates for the cost parameter matrix $\widetilde{\mathbf{F}}^{x,x'}$ and the breakdown of the matrix into individual components as described in Section 3. Numbers in parentheses are bootstrapped standard errors. Numbers in the lower panel are in million US dollar.

fixed and sunk cost components. Second, we find that $\tilde{F}^{N,NF} > \tilde{F}^{NI,NIF}$ holds. 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 offshore R&D. This finding also suggests that the interaction between offshore R&D and high-skill immigration via the increased benefit of R&D, embedded in equation (6), is not enough to generate the higher propensity of starting offshore R&D among firms with immigrant researchers observed in the data. The information channel is also needed.[30]

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 the information value of immigrants is captured in $\tilde{F}^{N,NF} - \tilde{F}^{NI,NIF}$ and can be decomposed into the sunk cost component F^{IF} and the fixed cost component $f^{NF} - f^{NIF}$. According to this decomposition, each of the sunk and fixed cost components accounts for approximately half of the information value of immigrants.

[30]One might be concerned that the key elements in the transition matrix that identify $\tilde{F}^{N,NF} > \tilde{F}^{NI,NIF}$, e.g., a higher frequency of the $NI \rightarrow NIF$ switch than the $NI \rightarrow NF$ switch, are entirely driven by large and productive firms doing more of all activities. If so, our estimation could be forcing a size-driven effect on the information channel. We note that first, as shown in Appendix A.2, the transition pattern is robust after controlling for firm size and productivity. Second and more importantly, to the extent that size plays a role in firms' joint use of imported R&D services and immigrant researchers, our heterogeneous firm model incorporates such channels. In this sense, our estimate of the information channel picks up what cannot be explained by firm size alone.

5 Counterfactuals

We use the estimated model to conduct counterfactual analysis. Our goals are two-fold. First, we examine the role of the love for variety of ideas and the information channel in shaping firm-level R&D decisions and aggregate productivity. Second, we quantify the impacts of policies that affect firms' access to foreign inputs or the overall R&D costs, including 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 imported R&D services as well as immigrant researchers. However, because offshore R&D involves significant costs, most firms are not able to reap the full benefit of diversified R&D. This observation leads to the second reason why firms hire immigrant researchers: they reduce the cost of offshore R&D by facilitating communication between headquarters and offshore R&D sites. 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' R&D decisions.

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 enjoyed by firms with immigrants, 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 infinity, making native researchers, immigrant researchers, and imported R&D services perfect substitutes for one another.[31] In this case, 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 benchmark and the two counterfactual economies. When the information channel is eliminated, the number of firms in mode NIF decreases by more than 80%. Interestingly, the fraction of firms in the NI mode also decreases by about two fifths, even though firms in this mode are not *directly* affected by the elimination of the information value. This decrease reveals that many of the firms choosing the NI mode in the benchmark economy are motivated by opportunities to transit into the NIF mode in the future. In total, the fraction of firms doing R&D decreases by 13 p.p., from 40% to 27%, underscoring the importance of the information channel for participation in R&D. When the love for variety of ideas is eliminated, as shown in the third column of panel (a), less than 16% of firms conduct R&D, predominately in mode N. The few firms in the modes NI, NF, and NIF choose them entirely out of idiosyncratic reasons captured in $\iota^{x}_{i,t}$.

[31] We implement this counterfactual by setting $\tilde{\gamma}_m = 0$ for $m = 1, 2, 3$ 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 for 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 of firms from each mode, respectively. Panel (c) reports the (sales-weighted) average log productivity among all firms and among firms in 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 smaller than the decrease in the share of firms in these modes. This difference reflects a compositional change of firms within a mode. For example, in the absence of the information channel, the overall cost of the NIF mode is higher than in the benchmark model. Therefore, firms choosing the NIF mode tend to be larger and more productive than before, and they would outspend firms in other modes of R&D.

We now examine the impact of these model mechanisms on aggregate productivity. Reported in panel (c) is the sales weighted average log productivity among all firms and among firms in each R&D mode. Shutting down the information channel reduces aggregate productivity by 0.2%, whereas imposing perfect substitution between different R&D inputs reduces aggregate productivity by 0.4%.[32] 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 aggregate productivity, the average productivity of some modes increases. In fact, the average productivity increases in all modes upon the elimination of the information channel. This result 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, while 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.

To assess the importance of foreign inputs for the gains in aggregate productivity from R&D, we conduct an additional experiment that eliminates the incentive to conduct R&D by assuming doing R&D has no effect on firms' future productivity. Aggregate productivity falls to 0.279, which is only slightly lower than 0.280, the aggregate productivity when the love for variety of ideas is eliminated. The modest difference between these two numbers shows that in a small open economy like Denmark, the majority of the productivity gain from R&D realizes only because

[32]These moderate impacts on aggregate productivity reflect the small estimates for the returns to R&D in Table 6. As our main points are on the importance of foreign inputs and the interaction between them, we focus on the *relative* magnitudes of aggregate productivity gains across experiments.

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 among all firms and among firms in each R&D mode.

of the access to foreign inputs. When forced to carry out R&D with only domestic inputs, the economy can reap only 20% ($= \frac{0.280-0.279}{0.284-0.279} \times 100$) of the full return from R&D.

In summary, the counterfactual results show that access to foreign inputs account for 60% of firms' participation in R&D and 80% of the gains in aggregate productivity from R&D. Moreover, firms' R&D choices depend crucially on the cost of doing R&D in different modes and the extent to which such costs could be mitigated by immigrant researchers. Accounting for these mechanisms is important for explaining the observed R&D choices and, as we will show in the next subsections, for policy evaluations.

5.2 High-Skill Immigration and Offshore R&D Policies

Firms' access to immigrant researchers and offshore R&D services are both heavily influenced by national policies, which are often a subject of heated debates. 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 costs of hiring immigrant researchers and of starting offshore R&D, F^I and F^F, respectively. The reduction in F^I can be thought of as a reform that eases the frictions in hiring foreigners; the decrease in F^F could capture either an improvement in the information technology (IT) that facilitates international collaboration or an investment treaty that makes it easier for firms to set up an R&D operation in 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 immigration in recent decades, leading to rapid increases in migration in the region (Caliendo et al., 2021), while the advancement of IT over the past two decades has made communication easier than ever.

Table 10 reports the results from these experiments. The liberalization in high-skill immigration increases the share of firms with immigrant researchers by a total of 10.5 p.p. About a third of this increase 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 baseline model. The overwhelming majority of the increase, again, occurs in the NIF mode. With offshore R&D becoming less costly, we also see more firms choosing the NI mode, which reflects the option value of immigrants: firms hire immigrants first, anticipating that in the future, when

Table 11: Counterfactual Changes with and without the Information Channel

	(a) Immigration policy					(b) 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 (p.p.)										
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 aggregate productivity (overall, %)										
with the information channel	0.14					0.37				
without the information channel	0.10					0.18				

Notes: Panel I reports changes (in percentage points) in the share of firms by R&D mode between the benchmark equilibrium and the new equilibrium under either the immigration policy (panel (a)) or the offshoring policy (panel (b)), with or without the information channel in play. Panel II reports changes (in %) the overall aggregate productivity between the benchmark equilibrium and the new equilibrium under either the immigration policy (panel (a)) or the offshoring policy (panel (b)), with or without the information channel in play.

they either become productive enough to overcome the switching cost or are hit with a favorable idiosyncratic shock, they can take advantage of the information channel and switch to the NIF mode more easily.

We examine the impact of these two policies on aggregate productivity. As shown in the last row in panel (c) of Table 10, immigration liberalization increases aggregate productivity by 0.2% and the offshore R&D policy increases aggregate productivity by 0.4%. The average productivity in individual modes, on the other hand, declines from the baseline levels. Again, the difference between the responses in aggregate and mode-specific productivity is due to a compositional change: the new participants of 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 demonstrate the importance of the information channel for firms' R&D decisions. To understand how this 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 the alternative model. Table 11 reports the main findings. For both policies, the information channel clearly amplifies the changes in firms' mode choices. The difference between the two models is especially pronounced in the share of firms in the NIF mode, who benefit most directly from the information channel. The lower panel in the table reports the impact on aggregate productivity of these two policies in the benchmark and the alternative model. It shows that 29% of the productivity impact of the immigration policy and 51% of the productivity impact of the offshoring policy are due to the information value of immigrant researchers.

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	100	100	100	100	0.284	0.292

Notes: Columns marked as 'R&D subsidy' report the results from the counterfactual scenario on the R&D subsidy 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 among all firms and among firms in each R&D mode.

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

In the last set of exercises, we study the importance of foreign inputs in the evaluation of R&D policies. Many countries, Denmark included, adopt policies in the form of direct subsidies or tax rebates to promote R&D investment. Such policies often amount to substantial costs. For example, the R&D subsidies for loss-incurring firms, which we exploit in Section 4 to estimate ν, cover 25% of firms' R&D expenses up to 5.5 million DKK (0.83 million USD) per year. This number is more than half of the startup R&D cost estimated in Table 8. Our last exercise captures the essential features of this policy, which does not make a distinction between the type of R&D expenditures that firms claim, by decreasing fixed and sunk R&D costs for each mode by half from their baseline levels.

Table 12 summarizes the effects of this experiment. 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 was the case for the immigration policy and the offshoring policy in Section 5.2, although aggregate productivity increases by 0.8%, the shift in composition toward more diversified R&D leads to decreases in the average productivity among firms in each R&D mode.

Compared to the existing studies that estimate firms' return to R&D, 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 subsidies on firm's R&D choices and aggregate productivity? To answer this question, Table 13 compares the effect of the same R&D subsidy 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 in this alternative model, the R&D subsidy leads to a much smaller increase in firms' participation in R&D. Moreover, this small increase in participation is concentrated among the N and NI modes, as opposed to among the NIF mode, where the return to R&D is the highest. The different responses in R&D mode choices lead to a significantly different prediction on aggregate productivity: without the love for variety of ideas, the same R&D subsidy policy generates only 0.12% aggregate productivity gains, less than one-sixth 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 returns to R&D. Our experiment suggests that omission of

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: Panel I reports changes (in percentage points) in the share of firms by R&D mode between the benchmark equilibrium and the new equilibrium under the R&D subsidy policy, with or without the love for variety of ideas channel in play. Panel II reports changes (in %) the overall aggregate productivity between the benchmark equilibrium and the new equilibrium under the R&D subsidy policy, with or without the love for variety of ideas channel in play.

these inputs could lead to a substantial bias in the evaluation of R&D policies.[33]

6 Conclusion

While a large literature has examined the sourcing of foreign inputs in production, less is known about the sourcing of R&D inputs. Using unique data from Denmark, this paper examines firms' decision to use two foreign R&D inputs—immigrants researchers and imported R&D services—and the impacts of this decision on firm performance and aggregate productivity.

We find that investment in R&D generates a higher return when firms are able to use either of the two foreign inputs, which we interpret as the love for variety of ideas in R&D. We also document evidence consistent with the information value of immigrants: firms can reduce the barriers they face in sourcing R&D services from abroad by employing immigrant researchers. We conceptualize these mechanisms in a model of firm dynamics with endogenous R&D choices. Through counterfactual experiments, we highlight that access to foreign inputs is essential for firms' participation in R&D and that these inputs play a complementary role in overall R&D. We further show that omitting these inputs or the interaction between them would result in biased assessments of the effectiveness of innovation policies, and immigration and offshoring policies.

The reliance of firms on foreign R&D inputs has been steadily increasing in many developed countries. This paper is a step towards a better understanding of firms' global organization of R&D. We consider the R&D sourcing decision of Danish firms, for which there is unique information in our data. Some large global firms carry out R&D in foreign locations to be used for local production, which neither our measure nor our model captures. Understanding firms' decision to carry out R&D in different locations, for both local and global uses, and how these decisions interact with immigration policies is an important avenue for future research.

[33] It is possible that if we estimate a model with only domestic R&D to fit the same return to overall R&D observed in the data, such bias could be smaller. This alternative, however, is subject to the Lucas critique. For example, if the model is estimated in an open economy with foreign R&D inputs, its predictions for an R&D subsidy in a closed economy would still be wrong.

References

Ackerberg, Daniel A, Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Amiti, Mary and Jozef Konings, "Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia," *American Economic Review*, 2007, *97* (5), 1611–1638.

Antras, Pol, Teresa C Fort, and Felix Tintelnot, "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms," *American Economic Review*, 2017, *107* (9), 2514–64.

Aw, Bee Yan, Mark J Roberts, and Daniel Yi Xu, "R&D Investment, Exporting, and Productivity Dynamics," *American Economic Review*, 2011, *101* (4), 1312–44.

Beerli, Andreas, Jan Ruffner, Michael Siegenthaler, and Giovanni Peri, "The Abolition of Immigration Restrictions and the Performance of Firms and Workers: Evidence from Switzerland," *American Economic Review*, Forthcoming.

Bernard, Andrew B, J Bradford Jensen, Stephen J Redding, and Peter K Schott, "The Empirics of Firm Heterogeneity and International trade," *Annu. Rev. Econ.*, 2012, *4* (1), 283–313.

_ , Teresa C Fort, Valerie Smeets, and Frederic Warzynski, "Heterogenous Globalization: Offshoring and Reorganization," *NBER Working Paper 26864*, 2020.

Bilir, L Kamran and Eduardo Morales, "Innovation in the Global Firm," *Journal of Political Economy*, 2020, *128* (4), 1566–1625.

Bøler, Esther Ann, Andreas Moxnes, and Karen Helene Ulltveit-Moe, "R&D, International Sourcing, and the Joint Impact on Firm Performance," *American Economic Review*, 2015, *105* (12), 3704–39.

Burchardi, Konrad B, Thomas Chaney, and Tarek A Hassan, "Migrants, Ancestors, and Foreign Investments," *The Review of Economic Studies*, 2019, *86* (4), 1448–1486.

_ , _ , Tarek Alexander Hassan, Lisa Tarquinio, and Stephen J Terry, "Immigration, Innovation, and Growth," *NBER Working Paper 27075*, 2020.

Burstein, Ariel, Gordon Hanson, Lin Tian, and Jonathan Vogel, "Tradability and the Labor-Market Impact of Immigration: Theory and Evidence From the United States," *Econometrica*, 2020, *88* (3), 1071–1112.

Caliendo, Lorenzo, Fernando Parro, Luca David Opromolla, and Alessandro Sforza, "Goods and Factor Market Integration: a Quantitative Assessment of the EU Enlargement," *Journal of Political Economy*, 2021, *129* (12), 3491–3545.

Doraszelski, Ulrich and Jordi Jaumandreu, "R&D and Productivity: Estimating Endogenous Productivity," *Review of Economic Studies*, 2013, *80* (4), 1338–1383.

Ethier, Wilfred J, "National and International Returns to Scale in the Modern Theory of International Trade," *The American Economic Review*, 1982, *72* (3), 389–405.

Fan, Jingting, "Talent, Geography, and Offshore R&D," *Unpublished Manuscript*, 2020.

Fieler, Ana Cecília, Marcela Eslava, and Daniel Yi Xu, "Trade, Quality Upgrading, and Input Linkages: Theory and Evidence from Colombia," *American Economic Review*, 2018, *108* (1), 109–46.

Fox, Jeremy T. and Valerie Smeets, "Does Input Quality Drive Measured Differences in Firm Productivity?*," *International Economic Review*, 2011, *52* (4), 961–989.

Gandhi, Amit, Salvador Navarro, and David A Rivers, "On the Identification of Gross Output Production Functions," *Journal of Political Economy*, 2020, *128* (8), 2973–3016.

Glennon, Britta, "How Do Restrictions on High-Skilled Immigration Affect Offshoring? Evidence from the H-1B Program," *NBER Working Paper 27538*, 2020.

Goldberg, Pinelopi Koujianou, Amit Kumar Khandelwal, Nina Pavcnik, and Petia Topalova, "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India," *The Quarterly Journal of Economics*, 2010, *125* (4), 1727–1767.

Griliches, Zvi, "Issues in Assessing the Contribution of Research and Development to Productivity Growth," *The Bell Journal of Economics*, 1979, pp. 92–116.

_ , *R&D, Patents and Productivity*, University of Chicago Press, 2007.

Halpern, László, Miklós Koren, and Adam Szeidl, "Imported Inputs and Productivity," *American Economic Review*, 2015, *105* (12), 3660–3703.

Head, Keith and John Ries, "Immigration and Trade Creation: Econometric Evidence from Canada," *Canadian Journal of Economics*, 1998, pp. 47–62.

Kasahara, Hiroyuki and Joel Rodrigue, "Does the Use of Imported Intermediates Increase Productivity? Plant-Level Evidence," *Journal of Development Economics*, 2008, *87* (1), 106–118.

Levinsohn, James and Amil Petrin, "Estimating Production Functions Using Inputs to Control for Unobservables," *The Review of Economic Studies*, 2003, *70* (2), 317–341.

Loecker, Jan De, "Detecting Learning by Exporting," *American Economic Journal: Microeconomics*, 2013, *5* (3), 1–21.

Miguelez, Ernest and Carsten Fink, "Measuring the International Mobility of Inventors: A New Database," *WIPO Economics & Statistics Series No.8*, 2013.

Morales, Nicolas, "High-Skill Migration, Multinational Companies and the Location of Economic Activity," *Available at SSRN 3336003*, 2020.

Olley, G Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–1297.

Olney, William W and Dario Pozzoli, "The Impact of Immigration on Firm-level Offshoring," *Review of Economics and Statistics*, 2018, pp. 1–19.

Ottaviano, Gianmarco IP, Giovanni Peri, and Greg C Wright, "Immigration, Trade and Productivity in Services: Evidence from U.K. Firms," *Journal of International Economics*, 2018, *112*, 88–108.

Peri, Giovanni, "The Effect of Immigration on Productivity: Evidence from US States," *Review of Economics and Statistics*, 2012, *94* (1), 348–358.

Ramanarayanan, Ananth and Miguel Cardoso, "Immigrants and Exports: Firm-level Evidence from Canada," *Unpublished Manuscript*, 2019.

Rauch, James E and Vitor Trindade, "Ethnic Chinese Networks in International Trade," *Review of Economics and Statistics*, 2002, *84* (1), 116–130.

Yeaple, Stephen Ross, "2. The Innovation Activities of Multinational Enterprises and the Demand for Skilled-Worker, Nonimmigrant Visas," in "High-Skilled Migration to the United States and its Economic Consequences," University of Chicago Press, 2018, pp. 41–70.

Appendix For Online Publication

High-Skill Immigration, Offshore R&D, and Firm Dynamics

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Appendix A Data and Empirics

A.1 Data Source and Variable Construction

Summary. Our analysis uses multiple datasets on both workers and firms, linked together through unique worker and firm identifiers. Table A.1 summarizes where each piece of information is from. The rest of this subsection introduces individual datasets and explains the construction of the key variables.

Table A.1: Summary of Data Sources

Information on firms		Information on workers	
Dataset	**Variable**	**Dataset**	**Variable**
IDA	worker Id	IDA	employment status, hourly wage, occupation, city
FIRE	main industry, and balance sheet and income statement items	BEF	immigration status and country of origin
FUI (The R&D Survey)	domestic R&D and offshore R&D status/expenditures, foreign region of R&D affiliates	UDDA	education
The Offshoring Survey	whether a firm has offshore activities in 2011, and in which foreign regions		
UHDI	firm import and export flows		
FATI	whether a firm is an affiliate of a foreign firm		

Note: This table summarizes the sources of information on workers and firms.

IDA. The Integrated Database for Labor Market Research (IDA) is a linked employer-employee database provided by Statistics Denmark (DST, hereafter) that contains the universe of workers and firms in Denmark. The IDA database is organized into four datasets containing information on persons, employment, workplaces and firms, which we link together through common identifiers. The employment data are a snapshot in November for each year, so workers out of the labor force in November are not included. For workers reporting multiple employment spells in November, we keep their primary job.

We identify workers in R&D-related tasks based on their reported occupation in IDA, coded according to the Danish equivalent of the International Standard Classification of Occupations (DISCO codes, hereafter). For each occupation, we inspect its task contents and classify it as being R&D related or not based on whether the job likely involves testing, creation, or designing, or requires technical knowledge of a STEM subject. This strategy follows Bernard et al. (2020), who classify occupations into four groups: R&D, management, production and manual work, and services and support activities.

Table A.2: R&D occupations in DISCO88 and DISCO08 Classifications

DISCO 88 Classification (3-digit)	
Professionals	
211	Working on topics in physics, chemistry, astronomy, meteorology, geology and geophysics
212	Working with mathematical and statistical concepts, theories and methods
213	Computer planning and system development
214	Architectural and engineering work, etc.
221	Working on topics within the biological branches of science
222	Work on topics in medicine, dentistry, veterinary science and pharmacy
Technicians and Associate Professionals	
311	Technician work in physics, chemistry, mechanics and so on
312	Computer technical work
313	Work with sound, light and images at film and theater performances, etc. and operation of medical equipment
321	Technician work in biology, medicine, agriculture and so on
DISCO 08 Classification (3-digit)	
Professionals	
211	Work in Physics and Geology
212	Working with mathematical, actuarial and statistical methods and theories
213	Working in life sciences
214	Engineering (except in electrical engineering)
215	Engineering work in electrical technology
216	Working with architecture, infrastructure and design
221	Medical work
222	Nursing and midwifery work
223	Work in natural medicine and alternative medicine
224	Paramedical work
225	Veterinary work
226	Other health work
251	Development and analysis of software and applications
252	Working with databases and networks
Technicians and Associate Professionals	
311	Engineering work in the physical sciences and engineering
314	Technician work in life sciences
321	Technician work in the medical and pharmaceutical field
351	Operations technician work and user support work in the field of information and communication technology
352	Technician work in audiovisual media and telecommunications

Our empirical analysis focuses on year 2001 to year 2015. A change in DISCO took place in 2008. We classify occupations in DISCO codes both before and after the change (DISCO88 and DISCO08, respectively). We check and make sure that the change in occupation classifications in 2008 does not in itself lead to abrupt changes in the share of R&D workers.

Table A.2 reports the occupations classified as R&D-related in DISCO88 and in DISCO08. In general, the occupations related to R&D activities are a subset of DISCO Groups 2 (Professionals) and 3 (Technicians and Associate Professionals). Note also that R&D-related occupations under our classification do not include managers (often associated with DISCO Group 1). This way we are not selecting occupations based on the skill level or the wage level *ex ante* but selecting them based on the nature of required tasks.

The dataset includes around 2.4 million individuals aged between 15 and 70, and 140,000 firms per year. Many firms in Denmark are small. Restricting the sample to firms with at least 10 employees leaves us with around 2.1 millions workers and 28,000 firms per year. Focusing on this sample, we construct workers' hourly wage and the municipality of their workplace, which we use to compute the main (or modal) geographic location of each firm in Denmark.

BEF. We supplement IDA with information from the national registers (BEF, provided by DST, which covers the universe of individuals in Denmark) to identify immigrants. In the baseline analysis, we define immigrants as those who are born outside Denmark. In various robustness exercises reported in Appendix Section A.3, we also consider alternative definitions of immigrants, taking advantage of the rich set of demographic information we have in the data.

UDDA. We use the education register (UDDA, provided by DST) to supplement IDA with education information. We consider two levels of higher education: at least some college education and at least a master's degree. In the data, the first group corresponds to the following codes: 'short higher education', 'medium-term higher education', 'bachelor', 'master's and PhD programs', while the second group includes only 'master's and PhD programs'.

FIRE. We match IDA with the Accounting Statistics (FIRE) over the period 2000 to 2015. FIRE provides accounting information such as revenues, value-added, investments, materials, wage bill, and employment. This dataset also provides information about the firm's main industry, based on the NACE industry classification, concorded to NACE Rev.2.

The information in FIRE originates from the Tax Authorities, which require the accounting information to be reported by companies with an annual turnover above 0.5 million Danish krone (DKK), and by individually owned companies with an annual turnover above 0.3 million DKK as part of their individual tax return. Due to this sampling strategy, we exclude firms with an annual turnover of less than 0.3 million DKK. We exclude government activities and public services firms, not-for-profit firms (based on a firm's legal status such as not-for-profit funds, associations, non-profit associations, government owned, church owned, and not specified), or firms in agriculture or extraction. After matching this FIRE sample with the IDA sample, we end up with around 95,000 firms per year. Restricting to firms with at least 10 employees leaves us with around 17,000 firms per year.[1]

We deflate the wage bill by the consumer price index and deflate revenues, value-added, capital, investment, and materials by their respective industry-specific deflators, all provided by DST. Since these industry-specific deflators are at the NACE Rev.2 Intermediate Aggregation level (A*38 Codes, see Table A.3), we define the industry firms accordingly. This leaves us with a total of 25 industry groups for the entire private sector and 11 industry groups for the manufacturing sector.

We calculate firms' capital stock by applying the perpetual inventory method to their fixed capital investments, assuming a depreciation rate of 8%: $K_{i,t} = 0.92 * K_{i,t-1} + I^r_{i,t}$. In the first year when a firm appears in the sample, we use its total assets as the initial capital stock.

FUI (the R&D Survey). We match the IDA$\times$FIRE matched data with FUI, which is an R&D Survey released by DST since 1991. The survey is the Danish equivalent of the European Community Innovation Survey. It covers all firms that either have over 250 employees, have more

[1]To avoid biases from reporting errors in our structural estimation, we exclude observations showing abnormal accounting statistics. More specifically, we exclude observations with either revenue labor ratio, material labor ratio, or capital labor ratio falling outside of the 1 to 99 percentile of their broad industry groups.

Table A.3: NACE Rev.2 Intermediate Level Aggregation - Private Sector Classification

A*38 Code	ISIC Rev. 4/ NACE Rev. 2	Divisions (NACE-2)
CA	Manu. of food products, beverages and tobacco products	10 to 12
CB	Manu. of textiles, apparel, leather and related products	13 to 15
CC	Manu. of wood and paper products, and printing	16 to 18
CD	Manu. of coke, and refined petroleum products	19
CE-CF	Manu. of chemicals, chemical products and pharmaceuticals	20 to 21
CG	Manu. of rubber and plastics products, and other non-metallic mineral products	22 to 23
CH	Manu. of basic metals and fabricated metal products, except machinery and equipment	24 to 25
CI-CJ	Manu. of computer, electronic, optical products, electrical equipment	26 to 27
CK	Manu. of machinery and equipment n.e.c.	28
CL	Manu. of transport equipment	29 to 30
CM	Other manu., and repair and installation of machinery and equipment	31 to 33
D-E	Utilities	35 to 39
F	Construction	41 to 43
G	Wholesale and retail trade and repair of motor vehicles and motorcycles	45
G	Wholesale trade, except of motor vehicles and motorcycles	46
G	Retail trade, except of motor vehicles and motorcycles	47
H	Transportation and storage	49 to 52
H	Postal and courier activities	53
I	Accommodation and food service activities	55 to 56
JA	Publishing, audiovisual and broadcasting activities	58 to 60
JB	Telecommunications, IT and other information services	61
JC	IT and other information services	62 to 63
K	Financial and insurance activities	64 to 66
L	Real estate activities	68
M-N	Professional services	69 to 82

than 1 billion DKK in revenue, spend at least 5 million DKK in R&D activities, or operate in R&D industries (defined as NACE 2-digit Rev.2 industry 72). In addition, it includes a stratified sample of all the remaining firms that do not satisfy any of these criteria. The R&D sample is an unbalanced panel of around 4,000 firms per year.

The survey reports firms' R&D expenditures in Denmark, which we label as domestic R&D expenditures, for all years from 2001. We classify firms as doing domestic R&D in year t if they report positive domestic R&D expenditures that year. The survey also asks about R&D expenditures bought overseas, either via a foreign subsidiary, foreign consultants, foreign unrelated firms, or foreign research institutes. This variable is available for the following years: 2001-2003, 2005 and 2007-2014. The survey question is specific in that only R&D expenditures *for the exclusive use of the reporting firm in Denmark* should be included.[2] We classify a firm as doing offshore R&D in year t if it reports positive R&D expenditures bought overseas for the use of the entity being surveyed in Denmark that year.

Finally, the survey also asks whether firms have R&D workers present in their foreign affiliates, broken down by broad geographic locations. This information is available from 2009 to 2012 for 4 geographic areas (Europe, United States and Canada, China, Rest of the World) and from 2013 to 2016 for 8 geographic areas (EU15, New European Member States, Other European Countries, United States and Canada, China, India, Central or South America, Rest of the World). We

[2]The exact wording of the questionnaire is 'FoU udført i udlandet og anvendt internt i virksomheden,' which means 'R&D performed abroad and used internally in the company.'

group the 2013-2016 geographic information into the 4 geographic areas of 2009-2012 and define firms as having R&D workers in a foreign region n in year t if they report having R&D personnel in that region in year t.

Our final IDA$\times$FIRE$\times$FUI sample, restricted to firms with at least 10 workers, contains approximately 47,000 firm-year observations over 2001-2015, which amounts to around 3,000 firms per year. This is the sample on which we calculate descriptive statistics in Section 2 of the paper.

The Offshoring Survey. For corroborative measures of offshore R&D, we also use a survey on offshoring conducted in 2012 by DST (in partnership with Eurostat). The survey samples all firms with 50 or more employees and a representative set of firms with 10-49 employees, resulting in a sample of around 4,500 firms. The survey asks whether a firm conducts R&D activities abroad in 2011, in house or through arms' length contracts.[3] This information is further broken down by 8 broad geographical areas (EU15, New European Member States, Other European Countries, United States and Canada, China, India, Other Asian Countries, Rest of the World). As the data can be quite sparse in the last two regions (Other Asian Countries and Rest of the World), when using the geographical dimension of the Offshoring Survey, we only consider the first six regions. Matching the Offshoring Survey with our IDA$\times$FIRE$\times$FUI sample, we end up with around 1,900 firms for 2011.

UHDI. We supplement our data with the information on firms' participation in international trade over 2001-2015 (UHDI, provided by DST). UHDI is based on two main sources: Intrastat and Extrastat. Intrastat is based on reports to DST from around 7,000 companies per year about their trade in goods with companies in other EU countries. The reporting thresholds under Intrastat have been set so that the reporting companies' trade volume amounts to at least 93% of all Danish EU imports and 97% of all Danish EU exports. Extrastat covers the universe of import and export transactions between Denmark and non-EU countries.

We aggregate the UHDI data, which are at the firm$\times$year$\times$product$\times$country level, to either the firm$\times$year or the firm$\times$year$\times$country level. From this, we identify whether firms are exporting or importing goods in a given year, and to/from which foreign regions.

FATI. In a robustness exercise in Section A.3, we show that the information channel exists among firms that are not an affiliate of a foreign multinational. To this end, we supplement the main data with FATI (provided by DST), which identifies foreign multinational firms in Denmark.

A.2 Regression Evidence on the Information Channel

Table 2 in the text shows that a higher fraction of firms with immigrants than firms without immigrants start doing offshore R&D in the next period, a pattern consistent with immigrants researchers reducing the frictions firms face in sourcing R&D services from abroad. One concern with this interpretation is that this pattern could be confounded by other firm characteristics,

[3] Note that the offshore R&D measure from this survey differs from the one from the R&D Survey. While the Offshoring Survey reports offshore R&D performed by suppliers and affiliates, it does not specify whether it is to be exclusively used by the firm in Denmark, so that it could also include R&D conducted for the sole use of the firm's affiliates.

such as their industry or size. In this section, we provide regression evidence to address this and additional concerns.

Specifically, in Section A.2.1, we estimate firm-level regressions to directly control for industry and firm characteristics that might be correlated with R&D offshoring decisions. In Sections A.2.2 and A.2.3, we exploit variation at the *firm-foreign region* level, which increases the credibility of the information channel. We will also use a shift-share design that exploits the increase in the supply of immigrant researchers from different foreign regions in Denmark to further address the reverse causality concern—i.e., firms may hire immigrants because establishing a foreign source of imported R&D services decreases the cost of hiring immigrants.

A.2.1 Firm-Level Evidence

Our firm-level specification of the information channel is as below:

$$\mathbb{I}(\text{off. R\&D}_{it}) = \beta \, \mathbb{I}(\text{immi}_{it-1}) + \tilde{v}_{d(i)j(i)t} + \vec{\tilde{\alpha}}\vec{X}_{it} + \tilde{e}_{it}. \tag{A.1}$$

In this specification, the outcome variable is an indicator for whether firm i in industry $j(i)$ located in a Danish location $d(i)$ reports in the R&D Survey that it does offshore R&D in period t. We split Denmark into 5 geographic regions and call each geographic region as a 'city' to avoid confusion when we explore variations across foreign regions later. The key explanatory variable is $\mathbb{I}(\text{immi}^{n}_{it-1})$, an indicator for whether firm i has an immigrant employee in R&D related occupations in period $t-1$. $\tilde{v}_{d(i)j(i)t}$ are city-industry-year fixed effects, which ensures that our estimate of β does not pick up a higher propensity of hiring immigrants or offshoring R&D among firms in specific cities or industries. $\vec{X}_{it}$ is a vector of time-varying firm characteristics, including firm size, labor productivity, and lagged importing and exporting status.

Table A.4 reports the estimation results. The first column controls for the fixed effects only. In the second and third columns, we further control for log employment and labor productivity of the firm, which rules out the possibility that the correlation is simply due to large and productive firms being more likely to engage in both activities. The coefficient of interest, β, is positive and statistically significant in all of the first three columns.

The literature has documented a strong impact of the presence of immigrants on regional and industry-level imports and exports (e.g. Ottaviano et al., 2018). To show that our estimate is not picking up the relationship documented in these studies, columns 4 and 5 control for firm-level import and export status, which barely changes the point estimate of β. Column 5 is our preferred specification. It suggests that, compared to similar firms in the same city and industry, firms with immigrant researchers have a 4 percentage point higher likelihood of conducting offshore R&D.

The role of immigrants working outside R&D. On the basis of the specification in column 5, we include an indicator for whether a firm employs immigrants outside R&D-related occupations. We find a small negative coefficient for this indicator, so the presence of non-research immigrants is not positively correlated with offshore R&D.[4] More importantly, the coefficient for the immigrant researcher indicator does not change, which lends support to the focus of our model on the information value of immigrant *researchers*.

Table A.4: The Information Channel: Firm-Level Regressions

	OLS (2001-2014)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\text{R\&D immi}_{i,t-1})$	0.081***	0.041***	0.038***	0.038***	0.038***	0.038***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\mathbb{I}(\text{Non-R\&D immi}_{i,t-1})$						-0.011**
						(0.004)
Observations	30,930	30,930	30,589	30,589	30,589	30,589
Firm size$_{i,t}$		yes	yes	yes	yes	yes
Productivity$_{i,t}$			yes	yes	yes	yes
Import status$_{i,t-1}$				yes	yes	yes
Export status$_{i,t-1}$					yes	yes
City$\times$industry$\times$year FE	yes	yes	yes	yes	yes	yes

Notes: The sample is private sector firms with at least 10 employees over 2001-2014. The outcome variable is an indicator taking a value 1 if firm i offshores R&D to any destination in year t, and 0 otherwise. Offshoring is defined based on the R&D Survey. Firm size is log employment and productivity is log value added per worker. Cities are defined as the five main geographic regions within Denmark. Industries are defined at the NACE Rev.2 two-digit level. Standard errors (in parentheses) are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2.2 Firm-Destination-Level Evidence and Results from a Shift-Share Design

Table A.4 shows that conditional on other characteristics, firms with immigrant researchers are more likely to engage in offshore R&D. A mechanism that could be driving this correlation is that, by hiring immigrants, firms gain tacit knowledge about the home countries of these immigrants, thereby reducing the frictions they face in sourcing R&D services from these countries. This mechanism is in line with the reduced-form research on the network effect of immigrants on international business (Rauch and Trindade, 2002). To the extent that this channel is indeed the driving force, we should expect the effect to be specific to the origin country of immigrants. For example, immigrant researchers from China might use their knowledge of the language and local business to help the firm source R&D services from China, but their knowledge would be less useful for firms looking to source R&D services from Latin America.

In this subsection, we use firm-destination-level variation to test whether having immigrant researchers from a foreign region n is correlated with offshoring R&D to the same foreign region n. An added benefit of using a firm-destination-level specification is that we will be able to exploit the variation in the supply of immigrant researchers from different foreign regions to establish a causal effect of the presence of immigrant researchers.

[4] While the coefficient for non-research immigrants is statistically significant in this particular specification, in other specifications (OLS or IV, firm-level or firm-destination level; see Table A.5), both the sign and the statistical significance of the coefficient differ. Thus, there is no robust evidence for the correlation between the presence of non-research immigrants and offshore R&D in either direction.

OLS specification. Our firm-destination-level specification is as follows:

$$\mathbb{I}(\text{off. R\&D}_{it}^{n}) = \beta\, \mathbb{I}(\text{immi}_{it-1}^{n}) + \tilde{\phi}_{it} + \tilde{v}_{d(i)t}^{n} + \tilde{\eta}_{j(i)t}^{n} + \vec{\tilde{\alpha}} \vec{X}_{it}^{n} + \tilde{e}_{it}^{n}. \tag{A.2}$$

Compared to Equation (A.1), the main difference in this specification is that the outcome variable and the main explanatory variable are specific to each foreign region n.

We use the R&D Survey to construct $\mathbb{I}(\text{off. R\&D}_{it}^{n})$. Between 2009 and 2015, the R&D Survey asks in which foreign regions a firm has affiliate R&D employment, which gives us an extensive margin measure of offshore R&D by firm i in foreign region n.[5] Between 2009 and 2012, the survey groups foreign countries into 4 regions: EU, USA and Canada, China, and the RoW. Between 2013 and 2015, the survey groups foreign countries into 8 regions: EU15, EU New Member States (former Eastern European countries), Other European countries, USA and Canada, Central and South America, China, India, and RoW. For brevity, in what follows, we group the latter 8 regions into the 4 regions in 2009-2012, which ensures that our sample has consistently defined foreign regions for 2009-2015.[6]

The key explanatory variable is $\mathbb{I}(\text{immi}_{it-1}^{n})$, an indicator for whether firm i has immigrants from region n in R&D related occupations, constructed from the IDA database. $\tilde{\phi}_{it}$ are firm-year fixed effects, which will absorb time-varying firm characteristics that might drive the correlation between $\mathbb{I}(\text{off. R\&D}_{it}^{n})$ and $\mathbb{I}(\text{immi}_{it-1}^{n})$. Some firms might be located in a Danish region (city) with a strong connection to a foreign region or operate in an industry in which foreign region n is a common offshore destination. These factors could influence both $\mathbb{I}(\text{off. R\&D}_{it}^{n})$ and $\mathbb{I}(\text{immi}_{it-1}^{n})$. Our inclusion of industry-destination-time and city-destination-time fixed effects, denoted by $\tilde{v}_{d(i)t}^{n}$ and $\tilde{\eta}_{j(i)t}^{n}$, addresses this concern. In fact, we will include the more demanding $\tilde{v}_{d(i)t}^{n} \times \tilde{\eta}_{j(i)t}^{n}$ fixed effects as a control. Finally, $\tilde{X}_{it}^{n}$ are control variables which capture other potential connections between firm i and region n.

Columns 1 to 3 of Table A.5 report the OLS estimation results. We find that firms with immigrant researchers from foreign region n are more likely to engage in offshore R&D with region n. This effect is present when city-industry-destination-year fixed effects are controlled for. It is also not due to the correlation between either of the two decisions and firms' importing/exporting relationship with region n. The point estimate suggests that firms hiring immigrant researchers from a foreign region n will have a 1% increase in the probability of conducting offshore R&D in location n. This coefficient is smaller than the coefficient from the firm-level regressions (which was around 4%), which could be due to the battery of fixed effects magnifying the attenuation bias.

A shift-share design. A remaining concern is that firms might choose to hire immigrant and conduct offshore R&D due to firm-destination-specific factors unobserved to the econometrician.

[5] This measure contains geographic variation, but does not capture offshore R&D conducted through arms' length transactions. In Section A.2.3 of this appendix, we use a measure from the Offshoring Survey, which includes both in-house and arms' length offshore R&D by geographic region.

[6] As an alternative, we also focus on 2013-2015 and use the 8-region grouping, which enables us to separate India and different parts of the EU from bigger groups. The result is similar and available upon request.

Table A.5: The Information Channel: Firm-Destination-Level Regressions

	OLS (2009-2015)			IV (2009-2015)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\text{R\&D immi}^n_{i,t-1})$	0.011***	0.011***	0.010***	0.124***	0.125***	0.123***
	(0.004)	(0.004)	(0.004)	(0.039)	(0.039)	(0.038)
$\mathbb{I}(\text{Non-R\&D immi}^n_{i,t-1})$			0.005***			-0.002
			(0.002)			(0.002)
Observations	89,320	89,320	89,320	79,624	79,624	79,624
Import status$^n_{i,t-1}$		yes	yes		yes	yes
Export status$^n_{i,t-1}$		yes	yes		yes	yes
Firm×year FE	yes	yes	yes	yes	yes	yes
City×industry×destination×year FE	yes	yes	yes			
City×destination×year FE				yes	yes	yes
Industry×destination×year FE				yes	yes	yes
Exclude 2000 firms				yes	yes	yes
First stage						
$s^n_{j(i),d(i),2000} \cdot (L^n_t - L^n_{2000})$				6.052***	6.024***	6.309***
				(1.235)	(1.225)	(1.295)
Robust first-stage F				24.00	24.18	23.72

Notes: This table reports the results from the estimation of Equation (A.2). In this table a firm is classified as offshoring if it reports having R&D workers at its foreign affiliates in destination n (this information is available for 2009-2015). Destinations comprise of 4 groups: European Union, United States and Canada, China and the rest of the world. The indicators for immigrant R&D workers and immigrant non-R&D workers reflect immigrants from destination n. Cities and industries are defined as in Table A.4. Columns 1 to 3 report the OLS specifications, while columns 4 to 6 report the IV specifications. For the IV specifications, we exclude firms reporting having immigrant R&D workers in 2000. The sample consists of private-sector firms over 2009-2015, with at least 10 employees. Standard errors are reported in parentheses and clustered by firm*year in 1-3 and by industry*city*destination in 4-6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

It is also possible that our finding is driven by reverse causality—by sourcing R&D services from a foreign region, firms can more easily tap into the local talent pool and bring immigrant researchers to work in Denmark.[7]

To address this concern, we employ an alternative approach, which is based on a shift-share instrumental variable that exploits the variation in firms' exposure to immigrant researchers in their Danish location and industry. Specifically, we use the following as an instrument for $\mathbb{I}(\text{immi}^n_{it-1})$:

$$s^n_{j(i),d(i),2000} \cdot (L^n_{t-1} - L^n_{2000}).$$

where $j(i)$ and $d(i)$ denote the industry and the (Danish) city of firm i, respectively; $s^n_{j(i),d(i),2000}$ is the share of immigrant researchers from a foreign region n in year 2000 working in city $d(i)$ and industry $j(i)$; $(L^n_{t-1} - L^n_{2000})$ is the increase in the total number of immigrant researchers from country n between 2000 and year $t-1$.

The relevance of this instrument comes from the fact that immigrants tend to be attracted to

[7]Our OLS specification partly addresses this concern by using the lagged immigrant researcher indicator as the explanatory variable. We also note that the reverse causality concern in itself does not invalidate our model—it also implies that the two activities are complements and that policies affecting one will have an indirect effect on the other, which is exactly what our model seeks to capture.

locations and industries with a high density of existing immigrants from the same origin. The exclusion restriction that we impose for identification is that, conditioning on firm fixed effects and a number of industry, city, and foreign region controls, the initial distribution of immigrant researchers affects offshoring decisions through firms' employment of immigrant researchers. Since the instrument is constructed using the 2000 distribution of high-skill immigrants, this assumption would be violated if firms employing immigrant researchers in 2000 show up in our regression panel, leading to a mechanical first stage. To rule out this concern, in the IV specifications, we exclude firms that hire immigrant researchers in 2000.[8]

Columns 4 to 6 of Table A.5 report the IV estimation results. Our design has a reasonably strong first stage, with the expected sign and the K-P F statistics of above 20. The point estimate of the coefficient of interest is positive and statistically significant. Interestingly, the coefficient is an order of magnitude larger than the OLS estimate. A part of this difference might be due to measurement errors being addressed by the instrumental variable approach. Perhaps more importantly, this difference could also arise from heterogeneous effects. Recall that the instrument exploits variation in the supply of immigrants from a particular origin in the local labor market. Firms in a local labor market with more immigrants from a particular origin might reap more returns from the information channel, if the hired immigrant is able to provide valuable information exactly from their connection to the home country through the local immigrant community. This finding also echoes the results from the literature that uses regional and industry-level data and argue for the external values of immigrants.

The difference in magnitude notwithstanding, the OLS and the IV results provide the evidence of complementarity—based on entirely orthogonal variations—showing that the presence of immigrant researchers in a firm encourages offshore R&D. On the other hand, the presence of other non-R&D immigrants does not have a robust correlation with offshore R&D.

A.2.3 Corroborative Evidence from the Offshoring Survey

As discussed earlier, the foreign-region-specific measure of offshore R&D from the R&D Survey is for in-house employment only, but firms can also source R&D services from independent foreign suppliers. One concern is that if in-house employment crowds out outside suppliers, then the results in Table A.5 might capture simply this substitution effect and does not imply that firms use imported R&D services more frequently.[9] To address this concern, we use an alternative measure of offshore R&D from the Offshoring Survey, which captures in-house as well as outsourced offshore R&D. Because this survey is only available for the year 2011, we use a cross-sectional specification.

Table A.6 reports the estimation results. Columns 1 and 2 are at the firm-level as in Equation

[8]For robustness, we use 1995 as the base year for constructing the instrument while excluding firms hiring immigrant researchers in 1995. This specification gives us similar results. Because firms' industry classification prior to 2000 is different from that between 2000 and 2015, we choose to focus on the instrument using 2000 as the base year for consistency with the rest of the paper.

[9]This concern does not apply to the results in Table A.4.

Table A.6: The Information Channel: Corroborative Evidence from the Offshoring Survey

	OLS (2011)			
	Firm-Level		Firm-Destination-Level	
	(1)	(2)	(3)	(4)
$\mathbb{I}$(R&D immi$_{i,t-1}$)	0.048***	0.048***	0.013*	0.012*
	(0.015)	(0.015)	(0.007)	(0.007)
$\mathbb{I}$(Non-R&D immi$_{i,t-1}$)		-0.005		0.008**
		(0.011)		(0.003)
Observations	4,042	4,042	24,336	24,336
Firm size$_{i,t}$	Yes	Yes		
Productivity$_{i,t}$	Yes	Yes		
Firm FE			Yes	Yes
Import$_{i,t-1}$	Yes	Yes	Yes	Yes
Export$_{i,t-1}$	Yes	Yes	Yes	Yes
City$\times$industry FE	yes	yes		
City$\times$industry$\times$destination FE			yes	yes

Notes: In this table a firm is classified as offshoring if it reports in the Offshoring Survey to have R&D activities abroad in 2011. The sample consists of private-sector firms with at least 10 employees. Specifications are at the firm level (columns 1 and 2) and the firm-foreign region-level (columns 3 and 4). Foreign regions in columns 3 and 4 comprise of 6 groups: EU15, New European Member States (former Eastern European countries), other European countries, United States and Canada, China, and India. Control variables are defined as in Table A.4 and Table A.5. Standard errors (in parentheses) are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(A.1); and columns 3 and 4 are at the firm-foreign region-level, with 6 foreign regions: EU15, New European Member States (former Eastern European countries), other European countries, United States and Canada, China, and India. The results show that this alternative measure of offshore R&D leads to quantitatively similar estimates for both firm- and firm-foreign region-level specifications, even though it is from a different source and covers only one year. Moreover, we continue to find that the coefficient of non-R&D immigrants has different signs, with or without statistical significance, across specifications, suggesting that the information value for offshore R&D is primarily through immigrants working in R&D-related occupations.

A.3 Robustness Exercise for Reduced-Form Facts

In this section, we report additional robustness exercises for the reduced-form facts. Together, they address three broad categories of concerns: on the definition of immigrants, on possible measurement errors associated with the categorization of firms' R&D modes, and on the role of foreign multinational firms in driving our findings.

A.3.1 Alternative Definitions of Immigrants

The first broad concern is on the definition of immigrants. In the baseline analysis, we define immigrants as those born outside Denmark. Our model highlights two roles of immigrants: that they possess specific knowledge about their home country—thus bringing information value to the firm—and that their different backgrounds and expertises add extra value to the R&D process. Not all researchers born outside Denmark can play these two roles. For example, an immigrant brought into Denmark as an infant might not be able to speak the language of her home country; educated in Denmark, she might not provide the diversity of ideas to the R&D process. Related to this concern, immigrant researchers from other Scandinavian countries might be relatively more similar to Danish researchers. Our reduced-form facts might simply capture the close economic ties between Scandinavian countries, rather than the broader role that immigrants possibly play in their local economy.

We note that to the extent that such concerns are empirically relevant, by including all immigrants—rather than only the ones that are likely to play the two roles a priori—our empirical analysis would *underestimate* the role of immigrants. In this subsection, we provide direct evidence that excluding the immigrants who might not be very different from native workers does not weaken our reduced-form results. Specifically, we consider the following alternative definitions of immigrants: those who enter Denmark at age 18 or above; those who enter Denmark at age 22 or above; those who enter Denmark after receiving their highest level of education. We also exclude immigrants from Sweden and Norway.

Table A.7 reports the evidence for the information channel under these narrower definitions of immigrant researchers. For brevity, we focus on the firm-level OLS specifications. Column 1 replicates our preferred specification, reported in column 5 of Table A.4. The remaining columns of the table report the results using the various alternative definitions of immigrant researchers. If any, we find that the information channel is stronger when we focus on immigrant researchers likely to be more different from Danish researchers by using these alternative definitions.

Table A.8 reports the robustness exercises for Table 3 in the paper on the sourcing of R&D inputs and firm performance. The first two columns reproduce our preferred specification, columns 4 and 8 of Table 3, respectively. The remaining columns estimate the same specifications with alternative definitions of immigrant researchers. Across specifications, we find that estimates for the immigrant researcher indicator with alternative definitions are similar to or slightly larger than the ones in the baseline specification.

Table A.7: The Information Channel: Alternative Definitions of Immigrants

	baseline	**> 18 yr**	**> 22 yr**	**completed education**	**non-Scandinavians**
	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}(\text{R\&D immi}_{i,t-1})$	0.038***	0.044***	0.048***	0.058***	0.041***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)
Observations	32,858	32,858	32,858	32,858	32858
Firm size$_{i,t}$	yes	yes	yes	yes	yes
Productivity$_{i,t}$	yes	yes	yes	yes	yes
Import status$_{i,t-1}$	yes	yes	yes	yes	yes
Export status$_{i,t-1}$	yes	yes	yes	yes	yes
City×industry×year FE	yes	yes	yes	yes	yes

Notes: This table reports the robustness for the information channel based on different definitions of immigrants. Specifications follow column 5 of Table A.4. Column 1 replicates the baseline result; columns 2 and 3 focus on immigrants arriving in Denmark after age 18 and 22, respectively; column 4 focuses on immigrants arriving in Denmark after having completed all education; column 5 exclude immigrants from Norway and Sweden. Standard errors (in parentheses) are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Sourcing of R&D Inputs and Labor Productivity: Alternative Definitions of Immigrants

	baseline		>18 yr		>22 yr		completed education		non-Scandinavians	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{I}(\text{R\&D}_{i,t-1})$	0.014**		0.014**		0.014**		0.014***		0.014**	
	(0.005)		(0.005)		(0.005)		(0.005)		(0.005)	
Log domestic R&D $_{i,t-1}$		0.003***		0.003***		0.003***		0.003***		0.003***
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$\mathbb{I}(\text{off.}_{i,t-1})$	0.031***	0.025**	0.031***	0.024**	0.031***	0.024**	0.030**	0.024**	0.031***	0.024**
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
$\mathbb{I}(\text{immi.}_{i,t-1})$	0.021***	0.019***	0.021***	0.019***	0.022***	0.020***	0.023***	0.021***	0.023***	0.021***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	32,914	32,914	32,914	32,914	32,914	32,914	32,914	32,914	32,914	32,914
Industry×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the robustness for the relationship between firms' labor productivity and sourcing of R&D inputs. The first two columns reproduce columns 4 and 8 of Table 3. The remaining columns estimate the exact same specifications as the first two columns, but using different definitions for immigrant researchers. See the notes of Table A.7 for these alternative definitions. All specifications control for firms size, lagged productivity, and import and export status. Standard errors (in parentheses) are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.3.2 Measurement Errors in Firms' R&D Modes

In the baseline specifications, we classify a firm as employing immigrant researchers if at least one immigrant researcher is on its payroll. One might be concerned that this classification is too liberal—perhaps, more than one employee is needed for a firm to reap the full benefit from immigrant researchers. If so, our classification introduces measurement errors in firms' R&D modes. Such measurement errors could have implications for both reduced-form and structural analyses. For the reduced-form facts, they tend to bias the coefficient of interest towards zero; for the structural estimation, in the presence of measurement errors, the year-to-year transition matrix we use to recover the fixed and sunk costs of R&D might differ from the actual transition patterns, which could lead to biases on the strength of the inferred information channel.

We address the concern on reduced-form and structural estimation separately. Tables A.9 and A.10 report the evidence on the information channel and on the relationship between international sourcing of R&D and firm performance, with different cutoffs of the number of immigrant researchers to classify firms as hiring immigrants for R&D. The results are consistent across specifications. In particular, in line with the biases due to measurement errors, when we increase the threshold for a firm to be considered as having immigrant researchers, the estimated effect for the information channel increases.

Table A.9: The Information Channel: Alternative Mode Classifications

	baseline	**# of immi ≥ 2**	**# of immi ≥ 5**
	(1)	(2)	(3)
$\mathbb{I}(\text{R\&D immi}_{i,t-1})$	0.038***		
	(0.005)		
$\mathbb{I}(\text{R\&D immi}_{i,t-1} \geq 2)$		0.079***	
		(0.006)	
$\mathbb{I}(\text{R\&D immi}_{i,t-1} \geq 5)$			0.133***
			(0.006)
Observations	32,858	32,858	32,858
Firm size$_{i,t}$	yes	yes	yes
Productivity$_{i,t}$	yes	yes	yes
Import status$_{i,t-1}$	yes	yes	yes
Export status$_{i,t-1}$	yes	yes	yes
City$\times$industry$\times$year FE	yes	yes	yes

Notes: This table reports robustness results for different thresholds when classifying firms as employing immigrant researchers. Specifications follow column 5 of Table A.4. Column 1 replicates the baseline result; columns 2 and 3 define a firm as employing immigrant researchers if at least two and five immigrant researchers, respectively, are on the payroll. Standard errors (in parentheses) are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To demonstrate that the baseline classification does not introduce significant biases into the structural estimation, we report two additional sets of results. First, in Table A.11 we report the firms' transition patterns between different R&D modes under three different classifications of hiring immigrant researchers. Since the structural estimation focuses on manufacturing firms, we do so for manufacturing firms only. The left panel of Table A.11 replicates the transition matrix in Table 8 of the text. The middle and right panels correspond to the cases where at least two

Table A.10: Sourcing of R&D Inputs and Labor Productivity: Alternative Mode Classifications

	baseline		# of immi. ≥ 2		# of immi. ≥ 5	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\text{R\&D\_}i, t-1)$	0.014**		0.012**		0.015***	
	(0.005)		(0.005)		(0.005)	
Log domestic R&D $_{i,t-1}$		0.003***		0.002***		0.003***
		(0.001)		(0.001)		(0.001)
$\mathbb{I}(\text{off.}_{i,t-1})$	0.031***	0.025**	0.028**	0.022*	0.029**	0.022*
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)
$\mathbb{I}(\text{immi.}_{i,t-1})$	0.021***	0.019***				
	(0.006)	(0.006)				
$\mathbb{I}(\text{immi.}_{i,t-1} \geq 2)$			0.041***	0.039***		
			(0.007)	(0.007)		
$\mathbb{I}(\text{immi.}_{i,t-1}) \geq 5$					0.036***	0.032***
					(0.010)	(0.010)
Observations	32,914	32,914	32,914	32,914	32,914	32,914
Industry$\times$year FE	Yes	Yes	Yes	Yes	Yes	Yes
Other firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first two columns reproduce columns 4 and 8 of Table 3. The remaining columns estimate the exact same specifications as the first two columns, but require a firm to have at least two and five immigrant researchers respectively to be considered as having immigrant researchers. Standard errors (in parentheses) are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and five immigrant researchers respectively need to be on the payroll for a firm to be considered as hiring immigrant researchers. Not surprisingly, fewer firms move to either NI or NIF mode under these classifications. Nevertheless, the key patterns that identify the importance of sunk costs, and the presence and the direction of the information channel, are consistent across the three panels. First, the diagonal elements tend to be larger than off-diagonal ones, indicating substantial sunk costs. Second and third, highlighted in bold: the frequency of the NI to NIF transition is much higher than the frequency of the N to NF transition, but the frequency of the NF to NIF transition is not much higher than the frequency of the N to NI transition. These patterns are consistent with the information value of immigrant researchers for offshore R&D, but not the other way around. Thus, even though different classifications of firms' R&D modes generate different transition matrices, these transition matrices will lead to qualitatively similar estimates for the fixed and sunk costs.

A distinct, though related, concern is that by focusing on the year-to-year mode changes, we might introduce excess mobility in the transition matrix. In particular, if a firm lost its only immigrant researcher in November but was not able to fill the position until a month later, we would count this firm as transitioning out of the NI mode in the current year, only to transition back in the next year. To address this concern, we report in Table A.12 both three- and five-year transition matrices. The qualitative patterns that identify the information channel and its direction are robust.

Table A.11: Transition between R&D Modes: Alternative Classifications

Baseline definition

t \ $t+1$	0	N	NI	NF	NIF
0	0.89	0.06	0.03	0.01	0.01
N	0.28	0.59	**0.08**	**0.04**	0.01
NI	0.11	0.06	0.68	0.01	**0.13**
NF	0.14	0.38	0.03	0.41	**0.04**
NIF	0.05	0.01	0.25	0.02	0.67

# of Immi. ≥ 2

t \ $t+1$	0	N	NI	NF	NIF
0	0.89	0.08	0.02	0.01	0.01
N	0.24	0.64	**0.06**	**0.05**	0.01
NI	0.09	0.08	0.65	0.02	**0.16**
NF	0.13	0.36	0.05	0.40	**0.06**
NIF	0.04	0.02	0.21	0.03	0.70

# of Immi. ≥ 5

t \ $t+1$	0	N	NI	NF	NIF
0	0.89	0.09	0.01	0.01	0.00
N	0.21	0.69	**0.02**	**0.08**	0.00
NI	>0.05	0.10	0.61	<0.02	**0.22**
NF	>0.08	0.37	<0.03	0.49	**0.04**
NIF	0.03	0.02	0.16	0.02	0.76

Notes: The left panel reproduces the transition matrix used to discipline the model (Table 8 of the text). The middle and right panels require firms to employ at least 2 and 5 immigrant researchers, respectively, to be in the NI or NIF modes. In some cells in the right panel, only the range is reported because tabulating the status of firms for groups below a certain size is prohibited per the confidentiality requirement of Statistics Denmark.

Table A.12: Transition between R&D Modes: Longer Durations

Baseline (1 year transition)

t \ $t+1$	0	N	NI	NF	NIF
0	0.89	0.06	0.03	0.01	0.01
N	0.28	0.59	**0.08**	**0.04**	0.01
NI	0.11	0.06	0.68	0.01	**0.13**
NF	0.14	0.38	0.03	0.41	**0.04**
NIF	0.05	0.01	0.25	0.02	0.67

3 year transition

t \ $t+3$	0	N	NI	NF	NIF
0	0.81	0.09	0.08	0.01	0.01
N	0.37	0.42	**0.16**	**0.04**	0.02
NI	0.18	0.07	0.54	0.01	**0.19**
NF	0.26	0.32	0.15	0.16	**0.11**
NIF	0.08	0.02	0.31	0.03	0.56

5 year transition

t \ $t+5$	0	N	NI	NF	NIF
0	0.72	0.12	0.12	0.01	0.03
N	0.35	0.33	**0.22**	**0.06**	0.04
NI	0.18	0.11	0.50	0.01	**0.20**
NF	0.24	0.35	0.20	0.12	**0.10**
NIF	0.07	0.05	0.31	0.02	0.55

Notes: The left panel reproduces the year-to-year transition matrix used to discipline the model (Table 8 of the text). The middle and right panels are 3- and 5- year transition matrices, respectively.

A.3.3 The Role of Foreign Multinationals

Finally, we discuss the possibility that the evidence on the information channel is entirely driven by Danish affiliates of foreign multinational firms. Suppose, for example, that the Danish subsidiary of General Electric hires American engineers while using R&D services produced at the U.S. headquarters at the same time. This might not be necessarily due to these American engineers bringing knowledge about the U.S. headquarters that could help the affiliate use the imported R&D services. Instead, the use of American engineers and American R&D services could be independent decisions within the conglomerate.

To address this concern, we show that excluding the affiliates of multinational firms from the sample does not affect our findings. Table A.13 reports the results from firm- and firm-destination level regressions focusing on domestic firms only. The first two columns of the table replicate columns 5 and 6 of Table A.4. Columns 3 and 4 replicate columns 2 and 3 of Table A.5. The sample shrinks by around 25%, but the estimates are essentially the same.

Table A.13: The Information Channel: Excluding Affiliates of Foreign Multinationals

	Firm-Level (2001-2014)		Firm-Destination (2009-2015)	
	(1)	(2)	(3)	(4)
$\mathbb{I}(\text{immi}_{i,t-1})$	0.036***	0.036***	0.014**	0.013**
	(0.007)	(0.007)	(0.006)	(0.006)
$\mathbb{I}(\text{Non-R\&D immi}_{i,t-1})$		-0.009**		0.006***
		(0.004)		(0.002)
Observations	23,371	23,371	67,636	67,636
Firm size$_{i,t}$	Yes	Yes	-	-
Productivity$_{i,t}$	Yes	Yes	-	-
Import$_{i,t-1}$	Yes	Yes	-	-
Export$_{i,t-1}$	Yes	Yes	-	-
City×industry× year FE	Yes	Yes	-	-
Firm-year FE			Yes	Yes
Import status$^n_{i,t-1}$			Yes	Yes
Export status$^n_{i,t-1}$			Yes	Yes
City×industry×destination× year FE			Yes	yes

Notes: This table provides evidence for the information channel, excluding affiliates of foreign multinationals from the sample. Columns 1 and 2 follow the specifications in columns 5 and 6 of Table A.4; columns 3 and 4 follow the specifications in columns 2 and 3 of Table A.5. Standard errors (in parentheses) are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.4 Descriptive Statistics on the Source of Immigrants

Table A.14 reports the shares of the top 10 source countries for immigrants working in R&D or non-R&D for the year 2011. Immigrant researchers are mostly from other advanced countries (Germany, the UK, etc.) and countries with an abundant supply of engineer talents, such as Iran, Poland, China, and India. On the other hand, a higher share of immigrants in non-R&D related fields are from South Asia. Germany and Poland are among the top senders of both types of immigrants, likely because of their large size, their geographic proximity to Denmark, and their EU membership.

Table A.14: The Origin Countries of Immigrants

Immigrants in R&D		Immigrant not in R&D	
Country	Share	Country	Share
Germany	8.55%	Poland	11.35%
UK	6.92%	Turkey	8.27%
Iran	5.18%	Germany	5.58%
Poland	4.90%	Bosnia	5.18%
Sweden	4.24%	Sri Lanka	3.31%
China	4.04%	Thailand	3.28%
Bosnia	3.81%	Vietnam	3.13%
India	3.78%	Iraq	3.00%
Norway	3.66%	Philippines	2.98%
USA	3.55%	Romania	2.91%
All others	51.37%	All others	51.00%

Note: All statistics are based on the same sample underlying Table 1. The left panel reports the top 10 sending countries of immigrant researchers; the right panel reports the top 10 sending countries of immigrant non-researchers.

Appendix B Theory and Structural Estimation

B.1 Derivation of Equation (4)

Under the monopolistic competition setting,

$$\begin{aligned}
\pi(\omega_{i,t}) = & \overbrace{-\frac{1}{\eta}}^{\text{profit margin}} \cdot \overbrace{[\frac{\eta}{\eta+1}\frac{W_t}{\exp(\omega_{i,t})}]^{\eta+1}\frac{Q_t}{P_t^{\eta}}}^{\text{sales}} \\
&= -\frac{1}{\eta}\cdot\frac{W_t^{\eta+1}Q_t}{P_t^{\eta}}\cdot\exp\left((\eta+1)\ln\left(\frac{\eta}{\eta+1}\right)-(\eta+1)\omega_{i,t}\right), \\
&\equiv -\frac{1}{\eta}\cdot\Phi_t\cdot\exp\left((\eta+1)\ln\left(\frac{\eta}{\eta+1}\right)-(\eta+1)\omega_{i,t}\right),
\end{aligned}$$

where $\Phi_t \equiv \frac{W_t^{\eta+1}Q_t}{P_t^{\eta}}$ is an aggregate demand shifter that is common to all firms.

B.2 Estimation of the Share of Materials

Under our assumption on the timing of firms' actions, firms choose materials to maximize their profit, given $\tilde{k}_{i,t}$, $\tilde{l}_{i,t}$, and $\omega_{i,t}$. The profit of firm i as a function of its material use is:

$$\exp\left(\tilde{y}_{i,t}(\tilde{m}_{i,t}|\omega_{i,t},\tilde{k}_{i,t},\tilde{l}_{i,t})\right) - P_{m,t}\cdot\exp(\tilde{m}_{i,t}),$$

in which $P_{m,t}\cdot\exp(\tilde{m}_{i,t})$ is the cost of material with $P_{m,t}$ being the material price, and $\tilde{y}_{i,t}(\tilde{m}_{i,t}|\omega_{i,t},\tilde{k}_{i,t},\tilde{l}_{i,t})$ is the firm's *actual* revenue:

$$\tilde{y}_{i,t}(\tilde{m}_{i,t}|\omega_{i,t},\tilde{k}_{i,t},\tilde{l}_{i,t}) = \frac{\eta+1}{\eta}\omega_{i,t} + \tilde{\beta}_k\tilde{k}_{i,t} + \tilde{\beta}_l\tilde{l}_{i,t} + \tilde{\beta}_m\tilde{m}_{i,t} + \tilde{P}_t - \frac{1}{\eta}\tilde{Q}_t.$$

Taking the first order condition of profit with respect to $\tilde{m}_{i,t}$ gives us:

$$\exp\left(\tilde{y}_{i,t}(\tilde{m}_{i,t}|\omega_{i,t},\tilde{k}_{i,t},\tilde{l}_{i,t})\right)\cdot\tilde{\beta}_m = P_{m,t}\cdot\exp(\tilde{m}_{i,t}). \tag{B.1}$$

We measure the revenue of firm i with a (log-additive) error $\tilde{\epsilon}_{i,t}$, i.e., the actual log revenue of firm i is the measured log revenue minus $\tilde{\epsilon}_{i,t}$:

$$\tilde{y}_{i,t}(\tilde{m}_{i,t}|\omega_{i,t},\tilde{k}_{i,t},\tilde{l}_{i,t}) = \tilde{y}_{i,t} - \tilde{\epsilon}_{i,t}.$$

From equation (B.1) we thus have:

$$\frac{P_{m,t} \cdot \exp(\tilde{m}_{i,t})}{\exp\left(\tilde{y}_{i,t}\right)} = \tilde{\beta}_m \exp(-\tilde{\epsilon}_{i,t}) \tag{B.2}$$

$$\Longleftrightarrow \log\left(\frac{P_{m,t} \cdot \exp(\tilde{m}_{i,t})}{\exp(\tilde{y}_{i,t})}\right) = \log(\tilde{\beta}_m) - \tilde{\epsilon}_{i,t}.$$

In this specification, the left hand side is the measured log revenue share of materials. The right hand side is the log revenue elasticity with respect to materials (scaled by a function of the demand elasticity) and a measurement error. Since material use is independent of measurement error, we can use the method of moments to estimate $\tilde{\beta}_m$ by computing the sample average of $\log(\frac{P_{m,t} \cdot \exp(\tilde{m}_{i,t})}{\exp(\tilde{y}_{i,t})})$.

In the baseline estimation (Table 6), we pool all firms to estimate the average material share. For robustness, we also estimate equation (B.2) by industry to obtain industry-specific material shares, which we then plug into the GMM estimation of equation (20). The main findings from this exercise, reported in Section B.3 of this appendix, are essentially the same as the baseline results.

B.3 Robustness Exercise for Production Function Estimation

In this section, we conduct three sets of robustness exercises on the GMM estimation of the production function. In the first exercise, we consider an alternative definition of firms' R&D status; in the second and third sets, we treat materials in the production function in two different ways: by estimating a value-added production function, implicitly assuming materials enter total revenue additively, and by extending the baseline specification to incorporate industry-specific material shares. The key findings—the positive impact of R&D on productivity and the value of using diverse R&D inputs—remain robust to these alternative choices.

B.3.1 Alternative Definition of R&D Modes

Recall that in estimating the law of motion of productivity, we include the indicators for whether a firm conducts R&D and in which mode. We use the employment of immigrant researchers and the sourcing of R&D from abroad, reported in the R&D Survey, to define the modes with I and F options, respectively. In defining the modes with N, i.e., R&D with native researchers, there are two options. In the baseline, we define mode N based on whether a firm reports positive domestic R&D expenditures. This treatment has the advantage of being consistent with how R&D has been measured in existing studies, but can lead to some discrepancies. For example, some firms might report incurring R&D expenditures, but do not have employees in R&D-related occupations; and vice versa. Such discrepancies arise because the expenses firms can include as 'R&D expenditures' according to the accounting principles do not always align with the occupational contents of their employees. An alternative option is to define modes with N based on the employment of Danish workers in R&D-related occupations. We show that our main finding is robust to this alternative.

In this exercise, a firm is considered to be in the N mode only if it employs native researchers; correspondingly, a firm is considered to be in NI, NF, or NIF modes, if in addition to I and/or F, it also employs native researchers. Table B.1 reports the results, which follow the specifications in Table 6. The coefficients on R&D and different modes of R&D are similar to those in Table 6.

Table B.1: R&D and Productivity Evolution: Alternative Classification of R&D Modes

	GMM estimation of (20)			GMM estimation of the auxiliary regressions					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\omega_{i,t-1}$	0.460***	0.468***	0.469***	0.468***	0.474***	0.474***	0.466***	0.470***	0.470***
	(0.149)	(0.114)	(0.113)	(0.114)	(0.112)	(0.119)	(0.140)	(0.110)	(0.117)
$\log(e_{i,t-1})$	0.002***	0.002***	0.002***						
	(0.001)	(0.001)	(0.001)						
$\mathbb{I}(x_{i,t-1} = N)$				0.013**	0.012**	0.012**	0.011*	0.010**	0.010**
				(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
$\mathbb{I}(x_{i,t-1} = NI)$	0.023***	0.023***	0.023***	0.038***	0.036***	0.036***			
	(0.007)	(0.006)	(0.006)	(0.011)	(0.010)	(0.011)			
$\mathbb{I}(x_{i,t-1} = NF)$	-0.003	-0.004	-0.004	0.016**	0.014*	0.014*			
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)			
$\mathbb{I}(x_{i,t-1} = NIF)$	0.043***	0.044***	0.044***	0.067***	0.066***	0.066***			
	(0.015)	(0.013)	(0.013)	(0.018)	(0.017)	(0.018)			
$\mathbb{I}(x_{i,t-1} \in NI \bigcup NF \bigcup NIF)$							0.036***	0.035***	0.035***
							(0.012)	(0.010)	(0.010)
Import dummy$_{i,t-1}$		yes	yes		yes	yes		yes	yes
Export dummy$_{i,t-1}$			yes			yes			yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	9,237	9,237	9,237	9,238	9,238	9,238	9,238	9,238	9,238

Notes: This table replicates Table 6 in the text under different classifications of R&D indicators. In particular, a firm is considered to be in mode N if it employs native researchers; a firm is considered to be in NI, NF, or NIF modes, if in addition to I and/or F, it also employs native researchers. Bootstrapped standard errors are clustered by firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3.2 Estimation of the Value Added Production Function

In the baseline specifications, we estimate the law of motion parameters by specifying a production function for total revenue. This specification has the advantage of being compatible with the monopolistic competition environment. An alternative approach is to focus on value added as in the seminal work by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015), which implicitly treat materials as additive in the total revenue function.

Formally, we assume that firms' log value added is:

$$\tilde{y}_{i,t} = \omega_{i,t} + \tilde{\beta}_k \tilde{k}_{i,t} + \tilde{\beta}_l \tilde{l}_{i,t} + \tilde{\epsilon}_{i,t},$$

in which $\tilde{\epsilon}_{i,t}$ is a measurement error; $\tilde{l}_{i,t}$ and $\tilde{k}_{i,t}$ are log labor and capital; $\omega_{i,t}$ is total factor productivity for the value added equivalent of equation (16). As in Olley and Pakes (1996), firms make their investment decision in period $t-1$, after the realization of $\zeta_{i,t-1}$ but before the realization of $\tilde{\epsilon}_{i,t}$.

We write the investment policy function as $i_{i,t} = i_t(\omega_{i,t}, \tilde{k}_{i,t}, \tilde{l}_{i,t}, z_{i,t})$, where $z_{i,t}$ is the set of controls that might affect the investment decision of a firm, such as the firm's import/export status and average wage. Given our assumption on the evolution of productivity, strict monotonicity of investment in $\omega_{i,t}$ holds, so we can invert the investment function for a proxy for productivity, i.e.,

$$\omega_{i,t} = i^{-1}(i_{i,t}, \tilde{k}_{i,t}, \tilde{l}_{i,t}, z_{i,t}).$$

We adopt the two-step procedure as in Olley and Pakes (1996). In the first step, we include a flexible function of $i_{i,t}$, $\tilde{k}_{i,t}$, $\tilde{l}_{i,t}$ and $z_{i,t}$ to purge out the measurement errors in the value added. In the second stage, we estimate $\tilde{\beta}_k$, $\tilde{\beta}_l$, along with the other parameters in the productivity law of motion using GMM, as in the baseline analysis. We bootstrap (by firm) the entire procedure for statistical inference.

Table B.2 reports the results. Focusing on value added, this approach estimates a higher persistence in productivity than in the baseline specifications. The key coefficients of interest—those associated with R&D status—are similar to Table 6.

Table B.2: R&D and Productivity Evolution: Value-Added Production Function

	GMM estimation			GMM estimation of the auxiliary regressions					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\omega_{i,t-1}$	0.739***	0.745***	0.749***	0.733***	0.738***	0.742***	0.721***	0.725***	0.729***
	(0.100)	(0.100)	(0.097)	(0.100)	(0.094)	(0.097)	(0.097)	(0.096)	(0.094)
$\log(e_{i,t-1})$	0.002***	0.002***	0.002***						
	(0.001)	(0.001)	(0.001)						
$\mathbb{I}(x_{i,t-1} = N)$				0.011***	0.010***	0.010***	0.010***	0.009**	0.009**
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{I}(x_{i,t-1} = NI)$	0.017**	0.017**	0.017**	0.016**	0.016**	0.016**			
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)			
$\mathbb{I}(x_{i,t-1} = NF)$	-0.021***	-0.021***	-0.021***	-0.018**	-0.018**	-0.018**			
	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)			
$\mathbb{I}(x_{i,t-1} = NIF)$	0.023**	0.023*	0.023*	0.029**	0.029**	0.029**			
	(0.013)	(0.014)	(0.014)	(0.015)	(0.016)	(0.016)			
$\mathbb{I}(x_{i,t-1} \in NI \bigcup NF \bigcup NIF)$							0.016**	0.015**	0.015**
							(0.008)	(0.008)	(0.008)
Import dummy$_{i,t-1}$		yes	yes		yes	yes		yes	yes
Export dummy$_{i,t-1}$			yes			yes			yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	9260	9260	9260	9260	9260	9260	9260	9260	9260

Notes: This table follows the same sample and specifications as in Table 6. Different from in Table 6, in which we estimate a revenue production function, in this table we estimate a value-added production function. Bootstrapped standard errors are clustered by firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3.3 Industry-specific Material Shares

By focusing on the value added production function, the robustness exercise reported in Table B.2 allows individual firms to differ in their material use. In this subsection, we conduct an alternative robustness exercise, in which we estimate a revenue production function, allowing for material shares to differ by industry.

To this end, we first estimate equation (B.2) by industry, obtaining industry-specific material shares. We plug in these shares into equation (20), which we then estimate via GMM using the same set of instruments as in the baseline analysis. Table B.3 reports the results. The estimates are essentially the same as when a common material share is applied to all firms.

Table B.3: R&D and Productivity Evolution: Industry Specific Material Shares

	GMM estimation of (20)			GMM estimation of the auxiliary regressions					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\omega_{i,t-1}$	0.452***	0.468***	0.468***	0.452***	0.468***	0.468***	0.445***	0.459***	0.458***
	(0.165)	(0.174)	(0.170)	(0.169)	(0.165)	(0.162)	(0.190)	(0.168)	(0.181)
$\log(e_{i,t-1})$	0.002***	0.002***	0.002***						
	(0.001)	(0.001)	(0.001)						
$\mathbb{I}(x_{i,t-1} = N)$				0.010***	0.009***	0.0109***	0.010****	0.009***	0.009***
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{I}(x_{i,t-1} = NI)$	0.026***	0.025***	0.025***	0.027***	0.026***	0.026***			
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)			
$\mathbb{I}(x_{i,t-1} = NF)$	-0.005	-0.006	-0.006	-0.003	-0.003	-0.003			
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)			
$\mathbb{I}(x_{i,t-1} = NIF)$	0.041***	0.042***	0.042***	0.046***	0.047***	0.047***			
	(0.016)	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)			
$\mathbb{I}(x_{i,t-1} \in NI \bigcup NF \bigcup NIF)$							0.025***	0.025***	0.025***
							(0.010)	(0.009)	(0.009)
Import dummy$_{i,t-1}$		yes	yes		yes	yes		yes	yes
Export dummy$_{i,t-1}$			yes			yes			yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	9,320	9,320	9,320	9,320	9,320	9,320	9,320	9,320	9,320

Notes: This table replicates Table 6 in the text allowing industry-specific material shares. Bootstrapped standard errors are clustered by firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.4 More on the Constraint Optimization Problem (23)

In the constraint optimization problem (23), we search for $(\boldsymbol{\lambda}, \Phi, \widetilde{\mathbf{F}})$ in the parameter space denoted by Λ to solve the following problem:

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

where the variables with a hat denote empirical moments and those without a hat are model-implied values under a particular choice of the parameter $(\boldsymbol{\lambda}, \Phi, \widetilde{\mathbf{F}}) \in \Lambda$.[10]

Note that among the constraints is the share of R&D spending by NI and NIF firms on native R&D inputs, $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$, which depend on the R&D production function parameters, $A^{\tilde{x}}$ and $p^{\tilde{x}}$ for $\tilde{x} \in \{N, I, F\}$. Because these parameters are not included in λ, a natural question is how we are able to verify that the chosen parameter can indeed match $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$. Below we show that the values of $\tilde{\gamma}_i, i = 0,1,2,3$ are sufficient statistics for us to verify that the model implied R&D spending shares, i.e., s^N_{NI} and s^N_{NIF}, match their data counterparts.

Concretely, from equations (15) and (16) of the text, we have

$$\begin{cases} \tilde{\gamma}_0 = \gamma, \quad (1) \\ \tilde{\gamma}_1 = \gamma(\log(c^N) - \log(c^{NI})), \quad (2) \\ \tilde{\gamma}_2 = \gamma\theta[\log(c^N) - \log(c^{NF})], \quad (3) \\ \tilde{\gamma}_3 = \gamma[\theta(\log(c^{NI}) - \log(c^{NIF})) + (\log(c^N) - \log(c^{NI}))], \quad (4) \end{cases} \tag{B.3}$$

In the structural estimation, for any given value of $\tilde{\gamma}_i, i = 0,1,2,3$, we know the left hand side of the above equations. We will then be able to use these equations to check whether the model implied s^N_{NI} and s^N_{NIF} equal their empirical counterparts, $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$.

First, note that from line 1 and 2 of equation (B.3), we have

$$\gamma = \tilde{\gamma}_0, \qquad \log(\frac{c^N}{c^{NI}}) = \frac{\tilde{\gamma}_1}{\tilde{\gamma}_0}.$$

Plug these two equations into line 4 of equation (B.3) and re-arrange to obtain

$$\log(\frac{c^N}{c^{NIF}}) = \frac{1}{\theta\tilde{\gamma}_0}[\tilde{\gamma}_3 - \tilde{\gamma}_1(1-\theta)].$$

[10] Note that $\boldsymbol{\lambda} = (\tilde{\rho}, \tilde{\gamma}_0, \tilde{\gamma}_1, \tilde{\gamma}_2, \tilde{\gamma}_3, \sigma_{\xi})$.

For the intensive margin shares to match s^N_{NI} and s^N_{NIF}, we must have

$$\log(\frac{c^N}{c^{NI}}) \cdot (1-\theta) = \log(\hat{s}^N_{NI})$$
$$\log(\frac{c^N}{c^{NIF}}) \cdot (1-\theta) = \log(\hat{s}^N_{NIF}),$$

in which the right hand side is the data and the left hand side can be backed out from $\tilde{\gamma}$.

Combing the above equations, we have:

$$\frac{\tilde{\gamma}_1}{\tilde{\gamma}_0}(1-\theta) = \log(\hat{s}^N_{NI}) \tag{B.4}$$
$$\frac{1-\theta}{\tilde{\gamma}_0\theta}[\tilde{\gamma}_3 - \tilde{\gamma}_1(1-\theta)] = \log(\hat{s}^N_{NIF}).$$

Thus, to verify whether a given guess of $\boldsymbol{\lambda}$ can match both R&D spending shares, we can use the first line of equation (B.4) to back out θ. We can then plug this θ into the second line of (B.4) and verify whether the equation holds. If the equality holds, then it means that $\tilde{\gamma}_i, i = 0, 1, 2, 3$ can satisfy both constraints. This result allows us to choose the parameters that can minimize the deviation of the model from the data on the transition patterns within the set of parameters that matches both $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$, without estimating $A^{\tilde{x}}$ and $p^{\tilde{x}}$ for $\tilde{x} \in \{N, I, F\}$.

Backing out θ. Once the estimation routine is complete, we can use the first line in equation (B.4) to find the implied value for θ. Plugging the values for $\tilde{\gamma}_0$, $\tilde{\gamma}_1$, and $\hat{s}^N_{NI}$ gives us $\theta = 1.33$.