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

Jingting Fan† Eunhee Lee‡ Valerie Smeets§

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Abstract

We study firms' decision to use foreign R&D inputs—immigrant researchers and imported R&D services—and their impact on firm performance and aggregate productivity. Using Danish administrative data, we document that firms with immigrant researchers are more likely to source foreign R&D services, and that both immigrant researchers and imported R&D services enhance R&D efficiency and firm performance. We develop and estimate a model of firm dynamics that rationalizes these patterns. Counterfactual experiments highlight the crucial and complementary roles of immigrant researchers and imported R&D services in firm R&D. Without access to these inputs, both R&D participation and the aggregate return on R&D would decrease substantially.

Keywords: foreign sourcing, trade in intermediates, high-skill immigration, R&D

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†Department of Economics, The Pennsylvania State University, State College, PA 16802, USA. (e-mail: jxf524@psu.edu)

‡Department of Economics, Seoul National University, Seoul 08826, Republic of Korea. (e-mail: elee11@snu.ac.kr)

§Department of Economics and Business Economics, Aarhus University and CEPR, Aarhus 8210, Denmark. (e-mail: vas@econ.au.dk)

1 Introduction

Reductions in trade barriers and advances in communication technologies over the past half century have facilitated global sourcing of inputs for firms. 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 these inputs improves firm performance, both directly and indirectly through interactions with R&D.[1] In modeling and quantifying these channels, the existing literature has focused almost exclusively on the role of imported *production inputs*. Yet increasingly, firms across the globe also adopt foreign *R&D inputs* by sourcing R&D services from abroad or recruiting immigrant researchers, which give these firms access to fresh ideas that can serve as an engine for growth. Figure 1 shows the empirical significance 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 the 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 an increasing reliance of Danish firms on foreign R&D inputs.[2]

Why do firms source foreign ideas for R&D activities? How do these foreign R&D inputs affect firm performance and aggregate productivity? In this paper, we answer these questions by developing and estimating a dynamic model of firm R&D. We find that immigrant researchers and imported R&D services play pivotal and complementary roles in shaping firms' R&D activities. Alternative models that omit these inputs or their interaction may lead to different assessments of the effectiveness of innovation policies, such as R&D subsidies, as well as high-skill immigration and offshoring policies.

We build a model of firm dynamics and endogenous R&D (e.g., Aw, Roberts and Xu, 2011; Doraszelski and Jaumandreu, 2013; Bøler, Moxnes and Ulltveit-Moe, 2015) with two new mechanisms. First, when undertaking R&D, in addition to domestic researchers, firms can use imported R&D services and inputs provided by immigrant researchers. Using inputs from diverse sources enables firms to apply the best idea for each task, à la Antràs, Fort and Tintelnot (2017), thereby enhancing R&D efficiency. Second, recruiting immigrant researchers and globally sourcing R&D services require an upfront investment, so only a small fraction of firms can take advantage of these options. However, as immigrants may be able to provide information about foreign R&D suppliers, their presence at a firm could reduce the upfront cost of finding overseas suppliers, leading to dynamic interactions between the two foreign R&D inputs.

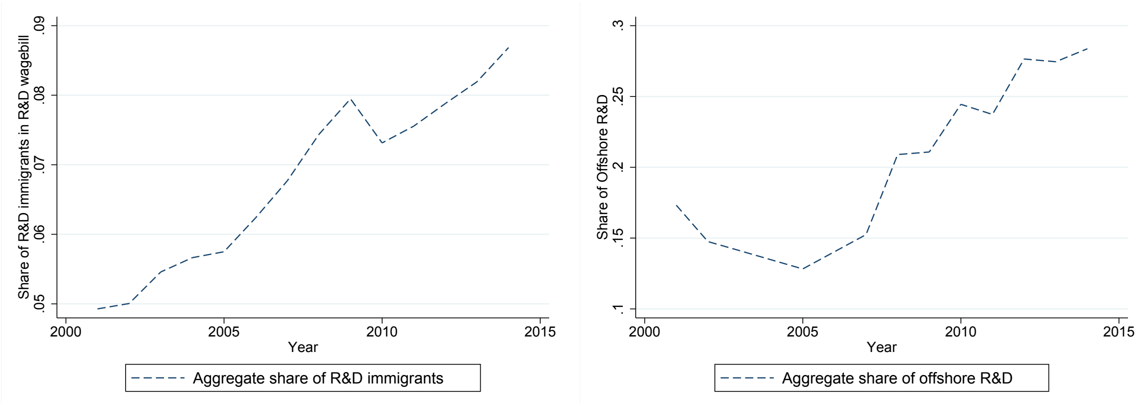
We document evidence for these mechanisms and quantify their importance in R&D. Counterfactual analyses suggest that the benefit from foreign R&D inputs is an important reason why firms undertake R&D in the first place. Without these inputs, the R&D participation rate would

[1]See, e.g., Amiti and Konings (2007), Goldberg, Khandelwal, Pavcnik and Topalova, 2010, Halpern, Koren and Szeidl (2015), Bøler, Moxnes and Ulltveit-Moe (2015), and Antràs, Fort and Tintelnot (2017).

[2]These trends are also prominent in other countries. According to the Patent Cooperation Treaty data, between 2000 and 2010, 10-15% of inventors in developed countries were 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), Bircan, Javorcik and Pauly (2021), and Fan (2020) for details.

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

(a) Immigrants among Researchers (b) Offshore Share of R&D Expenditures



Notes: Plotted in the left panel is the 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.

decrease by about 60%, and the effect of R&D on aggregate productivity would shrink by 80%. Due to the crucial role of foreign inputs in R&D, their omission leads to a substantial underestimation of the effect of R&D subsidies on aggregate productivity. Moreover, as we estimate important complementarity between the two foreign inputs, policies that change the cost of hiring immigrant researchers have a large impact on firms' offshore R&D decisions, and vice versa. Not accounting for this interconnection underestimates the impacts of such policies on aggregate productivity by up to 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 observe the occupation and immigration status of individuals, to several surveys and administrative datasets at the firm level, covering firms' location, accounting information, R&D status, imports and exports, and participation in offshore R&D. Armed with the rich information on both firms and workers, we can measure whether a firm employs immigrant researchers or conducts offshore R&D and assess how these decisions correlate with various firm 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—for example, firms recruiting immigrants from Eastern Europe 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. This finding supports the notion that immigrant researchers bring knowledge about their home countries to the firm, reducing friction 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 only domestic inputs, which is consistent with self-selection into these activities based on productivity. On the other hand, controlling for firms' productivity and R&D expenditures, firms using foreign R&D inputs tend to have higher future productivity than those 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 importing and exporting 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 disentangle the mechanisms behind these facts and conduct policy experiments. In the model, heterogeneous firms choose whether to conduct productivity-enhancing R&D, and if so, how much to invest in R&D and whether to use immigrant researchers and/or imported R&D services. Adopting multiple R&D input types is costly, but it can increase R&D efficiency by exposing firms to different, potentially better, ideas for R&D tasks. In addition to giving firms an incentive to use foreign R&D inputs, this mechanism leads to an interaction between these inputs. For example, the availability of imported R&D services increases the overall return to R&D, encouraging more firms to participate in R&D and, in turn, increasing the use of domestic and immigrant researchers as well. To account for the selection into R&D based on productivity and the transition patterns between different modes of R&D that use different R&D input types, we incorporate flexible transition costs. For example, our specification allows firms with immigrant researchers to face potentially different upfront costs for importing R&D services compared to firms that do not have immigrant researchers.

We carry out the estimation in two tiers. In the first tier, we estimate the effects of foreign R&D inputs on firm performance using a Generalized Methods of Moments (GMM) approach. We find that doing R&D with only domestic input, on average, leads to a 1% productivity increase. On top of that, the use of any kind of foreign R&D input boosts productivity by 2.3%. Breaking down the use of foreign R&D inputs into immigrants, imported services, or both, we find that using immigrant researchers increases performance both directly and in conjunction with using imported R&D services. This finding indicates that the use of foreign R&D inputs increases firm performance and that these two input types play complementary roles.

To shed light on the nature of the interactions between R&D inputs and to conduct counterfactual experiments, in the second tier of the estimation, we exploit the restrictions of the model on firms' dynamic decisions to recover the structural parameters via indirect inference. In particular, we pin down the parameters governing the R&D process by matching the GMM estimates discussed above. We find that there is substantial heterogeneity in the quality of ideas from different sources, implying a large benefit from having access to foreign R&D inputs. The fixed and sunk costs of switching between R&D modes discipline selection by productivity into these modes. We pin down these costs using two sources of information: the patterns of firms' transition between R&D input sources and 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. We find that switching from doing R&D with only domestic researchers to using imported R&D services incurs an average startup cost of about 1.3 million USD and a fixed operation cost of 1.1 million USD. The presence of immigrant researchers in a firm reduces this cost by 30%. Thus, a part of firms' return from hiring immigrant researchers materializes through the reduced cost of adopting imported R&D services.

Our counterfactual experiments highlight the quantitative relevance of foreign inputs in R&D. When we eliminate the heterogeneity in the quality of ideas for R&D from different sources—thereby eliminating the main source of the benefit from foreign inputs—the R&D participation rate decreases from the baseline level of 41.3 percentage points (p.p.) to 17.8 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 heterogeneous ideas across R&D input types, the effect of a decrease in the sunk cost of R&D on aggregate productivity would be 85% smaller than the effect computed in the benchmark model. The omission of foreign R&D 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 between foreign R&D inputs via the cost of switching R&D modes. If the presence of immigrant researchers at a firm does not affect the firm's upfront cost of using imported R&D services, not only does the share of firms that use imported R&D services decrease, but also the share of firms that recruit immigrant researchers decreases substantially. The R&D participation rate decreases by 14.8 p.p. or one-third of its baseline level. Accounting for this interaction between offshore R&D and immigrant researchers is relevant for evaluating the 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 this mechanism would result in 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 on 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; Antràs, Fort and Tintelnot, 2017; Fieler, Eslava and Xu, 2018). Different from this literature, which focuses on the productivity effect of imported production inputs, our paper focuses on foreign R&D inputs, namely, immigrant researchers and imported R&D services, which are becoming increasingly important as global integration expands beyond the exchange of goods to the exchange of ideas and the 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, improvements in R&D efficiency accumulate and amplify over time. This dynamic effect of R&D inputs further differentiates this paper from the bulk of 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 Aw, Roberts and Xu (2011), Doraszelski and Jaumandreu (2013), and Bøler, Moxnes and Ulltveit-Moe (2015). Most closely related, Bøler, Moxnes and Ulltveit-Moe (2015) 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 R&D inputs. We show that incorporating these R&D input types matters not only for evaluating various policies on offshoring or immigration but also for understanding the impacts of generic R&D subsidies that are actively used in many countries.

Our focus on firms' decision to conduct offshore R&D is also related to the 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 addresses 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.[3]

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 facilitate trade and other business linkages between the origin and destination countries.[4] Our first contribution to this literature is to document both patterns in the same setting for a specific yet important activity, R&D. We show that one important mechanism through which immigrants increase firm performance is by helping the firm establish business connections in 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 immigrant researchers; second, immigrant researchers and R&D 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-

[3]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.

[4]Examples of research focusing on the first result include Ottaviano, Peri and Wright (2018), Beerli, Ruffner, Siegenthaler and Peri (2021), 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.

skill workers from the headquarters 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 complementary to Morales (2020), the facilitating role of immigrant researchers for communication in our paper is best viewed as the one between the headquarters in Denmark and the home countries of these immigrants. This mechanism is similar in spirit to the one proposed in Yeaple (2018), but we are able to estimate it, which Yeaple (2018) did not pursue.

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 for 2001–2015. Below we summarize the key pieces of information from these datasets. Appendix A.1 provides additional details including the construction of the sample and the definition of key variables.

Workers. The information on workers comes from the Integrated Data for Labor Market Research (IDA, hereafter), an annual snapshot taken in each November covering all working-age individuals in the labor force. By supplementing IDA with additional administrative datasets, we identify workers' birth country and other demographic information, the firm and 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. We discuss the robustness results under alternative definitions of immigrants in Appendix A.3.

Following Bernard, Fort, Smeets and Warzynski (2020), we classify 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 pushing the boundary of human knowledge. However, it captures the fact that for many firms, some form of experimentation and innovation is needed to develop a new product.[5] Slightly

[5]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 and excludes supporting staff in R&D units (e.g. accountants).

abusing language, we refer to workers in R&D-related occupations as researchers and refer to researchers not born in Denmark as immigrant researchers.

Firms. The information on the characteristics and activities of firms primarily comes from two sources. The first source is Regnskabsstatistik (FIRE, hereafter), an annual panel on firms' accounting information derived from value-added tax administrative data. FIRE covers almost all private-sector firms above a certain size determined by the firm's ownership structure.[6] 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 other variables using the corresponding 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 collect as comprehensive information on R&D-active firms as possible, the survey samples all firms satisfying one of the following criteria: 1) having over 250 employees; 2) having more than 1 billion Danish krone (DKK) in revenue; 3) spending at least 5 million DKK in R&D activities; or 4) operating in R&D industries (NACE Rev.2 industry 72).[7] It also includes a stratified sample of all remaining firms, resulting in an unbalanced panel of approximately 4,000 firms per year.

A unique and crucial feature of the R&D Survey is that it contains information not only on firms' R&D expenditures within Denmark but also on their R&D expenditures overseas, i.e., their offshore R&D. The questionnaire specifically requires that the reported offshore R&D expenditures pertain only to the activities of the reporting entity within Denmark. Therefore, any R&D conducted by a Danish firm's foreign affiliates for these affiliates themselves, such as the development of a product intended for production outside Denmark, should not be included.[8] The reported offshore R&D, in turn, is best viewed as R&D services imported by the reporting entity in Denmark.[9] Correspondingly, the model we develop focuses on the R&D sourcing and production decisions of the firms operating in Denmark. In addition to foreign suppliers, firms can also outsource R&D activities to other firms within Denmark. According to the R&D survey, the fraction of R&D expenditures via domestic outsourcing remained largely flat at merely 5%

[6]Reporting to FIRE is mandatory for private corporations with an annual turnover above 500,000 Danish Krone (DKK), or about 80,000 USD, 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 is a snapshot for only each November.

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

[8]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.

[9]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, in principle, be carried out for the use of any entities within the organization. A suitable model for such data should incorporate the domestic and overseas production of firms (see, e.g., Bilir and Morales, 2020).

over the sample period. This evidence leads us to focus on *foreign* R&D sourcing.

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 conducted R&D activities abroad in 2011, either in-house or through arms' length contracts, without requiring the reported R&D to be carried out solely for the benefit of the reporting entity in Denmark. While this notion of offshore R&D is broader than our baseline measure from the R&D Survey and is available only for 2011, it provides an alternative measure that we use for validation.

Finally, both the R&D Survey and the Offshoring Survey ask firms about the foreign region in which they conduct 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 by workers' immigrant status and occupation. Approximately 17% of workers are in occupations related to R&D defined previously. Among them, about 7% are immigrants. Not surprisingly, both immigrant and native researchers are more educated than non-R&D workers. They make on average $47 per hour, well above the hourly wage of non-R&D workers.

Panel B of the table reports the characteristics of the firms in the sample by their size. About 24% of firms in the sample participate in R&D. R&D participation is more common among large firms than small firms. Conditional on doing R&D, however, it is small firms that devote a larger fraction of revenues to R&D, which is suggestive of large fixed costs associated with R&D.

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, employ 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 researchers, which suggests that the two activities are likely interconnected. On the other hand, less than a quarter of the firms employing immigrant researchers conduct offshore R&D, indicating potential asymmetry.

Panel C of Table 1 reports statistics on the mode of R&D of the firms in the Offshoring Survey, using the measure of offshore R&D from this survey. Two patterns emerge from the reported

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 conducted R&D activities abroad in 2011, following the definition from the Offshoring Survey. Monetary values are in U.S. dollars. All statistics are based on 2011. The number of firms in Panels B and C are 2,949 and 1,882, respectively.

statistics. First, across all firm size groups, a larger fraction of firms than reported in Panel B conducts offshore R&D, consistent with the offshore R&D measure in this survey being broader than the one in the R&D Survey. Second, like the one in the R&D Survey, this measure also indicates that the vast majority of firms offshoring R&D employ immigrant researchers, while less than half of the firms employing immigrant researchers offshore R&D.

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 imported services in R&D, we look into the frequency of firms' transition between different *modes of R&D*, defined as: R&D inactive (denoted by 0), R&D with only domestic inputs (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). We leverage the information on individual workers' occupations and countries of origin in IDA, along with data on offshore R&D expenditures from the R&D survey, to classify firms into these R&D modes; see

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. Mean value added per labor is reported in US$.

Appendix Table A.5 for a detailed explanation.

Panel A of Table 2 reports the frequency of transition 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 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 fraction of firms in mode N that switch to either NI or NIF mode.

These patterns 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. In Appendix A.2, we supplement these findings with regression-based evidence on the relationship between offshore R&D and a firm's employment of immigrant researchers. First, we show that this relationship is robust when controlling for productivity and other firm characteristics, including size, industry affiliation, and past R&D investment. This analysis rules out the possibility that the higher propensity among firms with immigrant R&D workers to start offshore R&D is simply due to large, productive, or more R&D-intensive firms being more active in both decisions. Second, the relationship remains consistent when we focus on the connection between immigrant researchers from a particular foreign region and offshoring R&D to that same foreign region. This finding provides support for the role of immigrant researchers in mitigating the information friction on their origin country. 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. Lastly, we also show that the result is not due to reverse causality by using a shift-share instrumental variable (IV) for firms' employment of immigrant researchers. This approach leverages variations across Danish regions and industries in the stock of immigrants from different foreign regions in 2000, alongside the nationwide influx of immigrants between 2001 and 2015. Fact 1 summarizes these findings.

Fact 1: Firms employing immigrant researchers are more likely to start offshore R&D. This pattern is robust to the inclusion 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 (e.g., Griliches, 2007 and the reference therein). The statistics in Table 2 show that 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 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 observed differences in average productivity among firms across R&D modes suggest the possibility of self-selection based on productivity into the use of foreign R&D inputs, which motivates a heterogeneous firms model that incorporates *fixed costs* for adopting foreign R&D inputs. The persistence in firms' R&D mode choices, in turn, can either simply reflect such self-selection in the presence of persistent productivity differences among firms or be attributed to additional *sunk costs* for entry into a different R&D mode. We will incorporate both mechanisms into the model. By disciplining these costs in structural estimation, we will be able to disentangle self-selection based on productivity from other forces influencing firms' R&D decisions.

Having shown that the use of foreign R&D input is associated with higher current productivity, we examine whether, controlling for current productivity, it is also associated with higher future productivity. We estimate the following specification:

$$\omega_{it} = \rho\omega_{it-1} + \gamma_{R\&D}\mathbb{I}(\text{R\&D}_{i,t-1}) + \gamma_{\text{off.}}\mathbb{I}(\text{off}_{it-1}) + \gamma_{\text{immi}}\mathbb{I}(\text{immi.}_{it-1}) + X'_{it}\vec{\beta} + \phi_{j(i)t} + \zeta_{it}. \quad (1)$$

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 whether a firm incurs R&D expenditures in period $t-1$ ($\mathbb{I}(\text{R\&D}_{i,t-1})$), 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.[10] If drawing ideas from foreign sources improves R&D efficiency, $\gamma_{\text{off.}}$ and $\gamma_{\text{immi.}}$ should be positive. In some specifications, we replace $\mathbb{I}(\text{R\&D}_{i,t-1})$ with intensive margin measures of R&D expenditures to allow variations in R&D intensity to play a role. Decisions on R&D likely depend on the characteristics of the industry and other firm-level decisions such as exporting and importing, all of which can impact firm performance. Denoting firm i's industry by $j(i)$, we 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 a 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 gain. 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.

It is well-known that participation in importing and exporting of goods is strongly correlated with productivity (see Bernard, Jensen, Redding and Schott, 2012 for a review). If firms' R&D decisions also depend on trade participation (Aw, Roberts and Xu, 2011; Bøler, Moxnes and Ulltveit-Moe, 2015), then the correlation between R&D and future productivity could be driven by trade in goods. More importantly, if, due to their business connections abroad, importers and exporters of goods face lower costs when sourcing foreign R&D inputs and consequently use these inputs more frequently, our estimates might be susceptible to a selection bias. To address these concerns, column 4 controls for firms' importing and exporting status in period t.[11] The indicators for importing and exporting both have large and positive coefficients, and their inclusion in the regression diminishes the coefficient for R&D participation. Importantly, however, the coefficients on the indicators for immigrant researchers and offshore R&D remain largely the same. This result suggests that our findings are not driven by selection into using foreign R&D inputs based on participation in trade.

Another plausible explanation for the results presented in columns 1-4 is that firms using foreign R&D inputs are simply out-investing other firms in R&D and the effect of the additional investment is attributed to immigration and offshore R&D indicators. To investigate this potential explanation, 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 the coefficients associated with the offshore and immigrant R&D indicators do not change significantly from those in columns 1-4. In column 9, we control for the log of firms' *total*, instead of domestic, R&D expenditures. The estimates for the coefficients on the foreign R&D input indicators remain virtually the same.

[10] $\mathbb{I}(\text{off}_{it-1})$ takes a value of 1 if firm i has positive offshore R&D expenses according to the R&D survey. $\mathbb{I}(\text{immi}_{it-1})$ takes a value of 1 if firm i employs an immigrant researcher in $t-1$.

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

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

	Dependent variable: 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 the log of 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 the log of firm size, as well as industry×year fixed effects. Industries are defined following the NACE Rev.2 intermediate-level aggregation (see Appendix Table A.4). 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

It is still possible that the results reported in Table 3 are subject to a simultaneity bias: since firms observe their productivity—at least partially—when making input choices, our productivity measure could be biased. In Section 4, we address this concern by employing a control function approach in productivity estimation. We summarize our findings in Fact 3.

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

Summary and Robustness. Taking stock, we find that foreign R&D inputs in the form of immigrant researchers or imported R&D services account for a substantial fraction of total R&D spending made by firms in Denmark. On the one hand, there is evidence of selection into using foreign R&D inputs based on 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 the age at which a person moves to Denmark or upon completion of all education) and different 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 demonstrate that the results are not driven by the Danish affiliates of foreign multinational firms.

Together, these facts underscore the contribution of foreign inputs in improving R&D efficiency and highlight the interdependence between the two types of foreign R&D inputs. They also imply that policies affecting the adoption of one input would affect the adoption of the other, which in turn could reinforce the direct impact of such policies on R&D. The main goal of our structural model in the following section is to disentangle these forces and to quantify their impact on firm performance and aggregate productivity.

3 Model

In this section, we introduce a dynamic model in which heterogeneous firms make productivity-enhancing R&D investments by combining inputs from both domestic and foreign sources. Statically, given current productivity and aggregate demand, firms choose the output quantity to maximize their profit. Dynamically, firms decide how to structure R&D using inputs from domestic researchers, immigrant researchers, and imported 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 is:

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

where $o_{i,t}$ is a composite production input made of capital, labor, and materials; $\omega_{i,t}$ 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 cost for each unit of the composite production input as $W_{i,t}$, the marginal cost of production is $\frac{W_{i,t}}{\exp(\omega_{i,t})}$.[12]

Firms face the following Dixit-Stiglitz demand:

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

where $q_{i,t}$ and $p_{i,t}$ are the quantity and the price of the variety that firm i produces; $\eta < 0$ is the demand elasticity; Q_t is the aggregate demand faced by the firm; and P_t is the corresponding ideal price index. We interpret Q_t and P_t as capturing the conditions of the entire world market faced by Danish firms. In keeping with this interpretation, we make two simplifications. First, we abstract from firms' endogenous export decisions. We motivate this assumption from the

[12] In the structural model, we assume o_{it} is static and can be flexibly adjusted; when we estimate production function in the next section, we will be able to relax this assumption, allowing some of the inputs to face adjustment costs. There, we will parameterize this composite production input along with specifying which inputs are flexible and which are subject to adjustment costs.

high degree of integration of Denmark within the world economy.[13] To ensure that this assumption does not confound the main channels, we control for firms' exporting status in subsequent empirical specifications. Second, we assume that Q_t and P_t are exogenous to individual firms and do not change in the counterfactual exercises. This assumption is motivated by the fact that the counterfactual shocks we consider lead to only moderate changes in aggregate productivity and are unlikely to drive a substantial general equilibrium change in Q_t and P_t.

Firms choose o_{it} and p_{it} to maximize their static profit. The optimal pricing rule under monopolistic competition 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 production input costs, demand, and market competition.

3.2 Productivity Evolution and the Sourcing of R&D

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 $t-1$, with $\mathbb{I}(rd_{i,t-1} > 0)$ being an indicator for whether firm i engaged in R&D in $t-1$; $\zeta_{i,t}$ represents unanticipated innovation in the productivity evolution process with a mean of zero and a standard deviation of σ_ζ; the coefficient γ is the elasticity of productivity with respect to effective R&D investment.

Firms create effective R&D investment by completing different tasks for R&D. Specifically, in each year, to carry out R&D, firms need to execute a continuum of firm-specific tasks indexed by $\mu \in (0,1)$. These tasks are combined via a constant elasticity of substitution function to produce the effective R&D investment, that is,

$$rd_{i,t-1} = \left(\int_0^1 k_{i,t-1}(\mu)^{\frac{\sigma-1}{\sigma}} d\mu\right)^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

where $\sigma > 0$ is the elasticity of substitution between these tasks, and $k_{i,t-1}(\mu)$ is the efficiency unit of task μ completed by firm i.

Each task $\mu \in (0,1)$ can be completed using one of the three types of R&D inputs—domestic researchers (N), immigrant researchers (I), or offshore R&D services (F). We denote these in-

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

put types by $\tilde{x} \in \{N, I, F\}$. Since undertaking R&D by using more than one R&D input type can amount to substantial fixed and sunk costs, as we elaborate in the next section, not all R&D-active firms use all three types. Following the classification in Section 2, we assume that firms choose from four *combinations* of R&D inputs: 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).[14] As before, we call these combinations of inputs as *R&D modes*. Denoting the R&D-inactive mode by *0*, a firm's R&D mode in any period is $x \in X \equiv \{0, N, NI, NF, NIF\}$.

For each task $\mu \in (0,1)$, firms in a mode $x \in X \setminus \{0\}$ choose the least costly way of completing it among the R&D input sources available to them. For example, firms in mode NIF have access to three sources, domestic researchers, immigrant researchers, and offshore suppliers of R&D, and they would choose the best source to complete each task μ. Then, the unit cost of task μ for firm i in mode $x = NIF$ is

$$c_i^{NIF}(\mu) = \min\{\frac{p^N}{a_i^N(\mu)}, \frac{p^I}{a_i^I(\mu)}, \frac{p^F}{a_i^F(\mu)}\}, \tag{7}$$

where $p^{\tilde{x}}$ denotes the unit cost for input from source $\tilde{x} \in \{N, I, F\}$; $a_i^{\tilde{x}}(\mu)$ is the idiosyncratic efficiency draw of firm i for task μ from source $\tilde{x}$. We assume that these efficiency draws are independent across firms and R&D sources, and distributed according to a Fréchet distribution with the scale parameter $A^{\tilde{x}} > 0$ and the shape parameter $\theta > 0$.[15] Depending on the values of $A^{\tilde{x}}$ and $p^{\tilde{x}}$, foreign inputs can be, on average, either more cost-effective or less so than the domestic input. We assume that $p^{\tilde{x}}$ and $A^{\tilde{x}}$ are common across firms; later on, we discuss the implications of heterogeneous $p^{\tilde{x}}$ and $A^{\tilde{x}}$—and the resulting self-selection of firms into different R&D modes—on identification and on the interpretation of our estimates.

We define $c_{i,t-1}^x(\mu)$ for $x = N, NI, NF$ similarly to equation (7). Integrating $c_{i,t-1}^x(\mu)$ over $\mu \in (0,1)$, we obtain the unit cost of *effective R&D investment* for firms in mode $x \in X \setminus \{0\}$

$$\begin{aligned} c_{i,t-1}^x &= \left(\int_0^1 \left(c_{i,t-1}^x(\mu) \right)^{1-\sigma} d\mu \right)^{\frac{1}{1-\sigma}} \\ &= \Gamma(\theta,\sigma) \left[A^N \left(p^N \right)^{-\theta} + A^I \left(p^I \right)^{-\theta} \cdot \mathbb{I}(x_{it-1} \in \{NI, NIF\}) + A^F \left(p^F \right)^{-\theta} \cdot \mathbb{I}(x_{it-1} \in \{NF, NIF\}) \right]^{-\frac{1}{\theta}}, \end{aligned} \tag{8}$$

where the second line applies the property of the Fréchet distribution (Eaton and Kortum, 2002). $\Gamma(\theta, \sigma)$ is a constant that depends only on θ and σ.[16] Under common and time-invariant $p^{\tilde{x}}$ and $A^{\tilde{x}}$, $c_{i,t-1}^x$ does not vary by firm or over time. We suppress the firm and time subscripts hereafter.

With $\theta > 0$, equation (8) implies $c^N > c^{NI}, c^{NF} > c^{NIF}$, i.e., firms sourcing more diverse R&D

[14] Other modes, such as those with only immigrant researchers or offshore suppliers without any native researcher, rarely occur in our data, so we exclude these options for simplicity.

[15] Within a firm, draws for a given task can be either independent or correlated across periods.

[16] $\theta > 0$ is a requirement for the Fréchet distribution. As in Eaton and Kortum (2002), we assume $\sigma < \theta + 1$ to ensure that $\Gamma(\theta, \sigma)$ is well-defined.

inputs have a lower marginal cost of R&D. This is true even if immigrant researchers and offshore suppliers are *on average* less competent and/or more expensive than domestic researchers. Intuitively, firms sourcing from diverse sources are exposed to more ideas for each task, captured in the Fréchet draws. By choosing the idea that is most suitable for each task, they can achieve higher R&D efficiency. This is the primary advantage of having access to foreign R&D inputs.

Firm i chooses the quantity for each task $k_{i,t-1}(\mu)$ for $\mu \in (0,1)$. Given the CES structure, this problem can be cast as choosing the effective R&D investment $rd_{i,t-1}$ given the unit cost c^x, resulting in a total cost of $e_{i,t-1} \equiv rd_{i,t-1}c^x$. The above discussion suggests that controlling for R&D expenditures $e_{i,t-1}$, firms sourcing R&D inputs more diversely on average make a larger effective R&D investment and thus see larger productivity improvement than firms accruing all such expenses on domestic researchers. This is in line with Fact 3 presented in Section 2.

Discussion. Two aspects about firms' R&D sourcing decisions are worth discussing. First, as noted in Antràs, Fort and Tintelnot (2017), the sourcing decision described in (6) can be alternatively formulated using the Armington model of trade in intermediate services, in which firms make effective R&D investment using inputs from different sources that are distinguished from each other with an elasticity of substitution $\theta + 1$. Such isomorphism, together with the restriction $\theta > 0$, might give an impression that we impose *ex-ante* that different R&D input sources are substitutes—in the sense that an increase in the availability or a decrease in the cost of one R&D input type will reduce firms' use of other R&D input types. This is *not* the case. As firms adopt more input types, the cost of effective R&D investment decreases, which creates two sources of complementarity between inputs: more firms will participate in R&D; conditional on participation, lower marginal cost of R&D incentivizes firms to increase R&D investment. Both margins increase firms' R&D expenditures on all inputs.[17]

Second, we assume that firms' efficiency draws for each task are independent across R&D input types. It is possible that draws across input types are correlated *asymmetrically*.[18] For example, immigrant researchers may share more similar ideas with offshore suppliers than native researchers. An equally plausible case is that, since both domestic and immigrant researchers work in Denmark, their ideas are more similar. Asymmetric correlation of this sort implies that the expenditure share on offshore R&D by firms in the NIF mode should be correlated with their expenditures share on immigrant researchers. In our data, we do not find a statistically significant pattern of such implications. Thus, although richer correlation structures between draws can be flexibly incorporated by generalizing the extreme-value distribution for task-specific draws (e.g., Lind and Ramondo, 2022), we adopt a symmetric case as the benchmark due to its theoretical

[17] The potency of these forces depends on the return to R&D investment γ, the demand elasticity η, and the Fréchet shape parameter θ. With more elastic demand for goods or higher return to R&D investment, firms will increase their total R&D spending by more as they adopt additional R&D input types. As a result, the spending on each R&D input type would increase when new input types are added, effectively making different R&D inputs complements. On the other hand, if the efficiency draws between R&D sources are more similar (i.e., a larger θ), then the addition of input sources will divert spending from existing inputs. In this case, different inputs are more likely to be substitutes.

[18] Our independent-draw setup is isomorphic to a setup in which draws from different input types are correlated *symmetrically*; see footnote 14 of Eaton and Kortum (2002).

simplicity and the lack of empirical support for the alternatives.[19]

3.3 Dynamic Decisions

Despite the benefits of having access to different sources of ideas, not all firms employ immigrant researchers or adopt imported R&D services, which hints at significant upfront costs for these options. Moreover, the persistence of R&D mode decisions observed in the data (Fact 2) naturally motivates a model with dynamic interactions in choosing an R&D mode. We now introduce the fixed and sunk costs of R&D and describe firms' dynamic decisions.

At the beginning of period t, firms discover the realization of $\zeta_{i,t}$, hence their current productivity $\omega_{i,t}$. 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 R&D mode $x_{i,t}$ and the total effective R&D expenditure $rd_{i,t}$.

For firms that have chosen mode x in period $t-1$, switching to mode x' in period t requires an irreversible investment of $\tilde{F}^{x,x'} + \iota_{i,t}^{x'}$, where $\tilde{F}^{x,x'}$ is the systematic component that is common to all firms switching from mode x to mode x'. The dependence of the cost 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. $\iota_{i,t}^{x'}$ represents an idiosyncratic cost for firm i in mode x', and it is drawn independently (across i, t, and x') from a mean-zero Type-I extreme value distribution with a scale parameter $\nu > 0$.[20] This idiosyncratic cost can stem from various factors: for example, some firms may recruit immigrant researchers more easily because they operate in a region with many immigrants; firms may encounter a talented immigrant researcher or a reliable foreign supplier by sheer luck. This component accounts for the possibility that firms with similar observable characteristics choose different R&D modes.

Firms observe the current draw of their idiosyncratic cost for each R&D mode and 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 $\iota_{i,t}^{x}$ of a firm with state $\mathbf{s}_{i,t}$, denoted by $V_t(\mathbf{s}_{i,t})$, is given by:

$$
\begin{aligned}
V_t(\mathbf{s}_{i,t}) = \pi(\omega_{i,t}) + \int \max_{x \in X} \left[V_t^x(\mathbf{s}_{i,t}) - \widetilde{F}^{x_{i,t-1},x} - \iota_{i,t}^{x} \right] d\iota, \qquad (9) \\
\text{where } X \equiv \{0, N, NI, NF, NIF\} \\
\text{and } V_t^x(\mathbf{s}_{i,t}) \equiv \begin{cases} \delta \cdot E_t V_{t+1}(\mathbf{s}_{i,t+1} \mid \mathbf{s}_{i,t}), \text{ for } x = 0 \\ \max\limits_{rd_{i,t}} \left\{ -rd_{i,t} \cdot c^x + \delta E_t V_{t+1}(\mathbf{s}_{i,t+1} \mid \mathbf{s}_{i,t}, x, rd_{i,t}) \right\}, \text{ for } x \in X \setminus \{0\}. \end{cases}
\end{aligned}
$$

In equation (9), the $V_t^x(\mathbf{s}_{i,t})$ term inside the integral is the present discounted value of R&D mode

[19] This same finding also leads us to the assumption that the Fréchet scale parameters $A^{\tilde{x}}$ are exogenous. If, for example, firms could increase A^F in equation (8) by hiring more immigrant researchers, then NIF firms would exhibit correlated spending shares on immigrant researchers and offshore R&D, which is not observed in the data.

[20] The assumption of *iid* idiosyncratic components in fixed and sunk costs does *not* imply that the switching cost between R&D modes is independent across modes. We incorporate potential correlations via the common component of the mode-switching costs $\tilde{F}^{x,x'}$, maintaining the independence assumption only for the idiosyncratic component.

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 as defined in equation (6). Under the distributional assumption for $\iota_{i,t}^{x'}$, the probability of a firm switching from R&D mode x to R&D mode x' is given by:

$$m_t^{x,x'}(\mathbf{s}_{i,t}) = \frac{\exp\left(\frac{1}{\nu}V_t^{x'}(\mathbf{s}_{i,t}) - \frac{1}{\nu}\widetilde{F}^{x,x'}\right)}{\sum_{x''\in X}\exp\left(\frac{1}{\nu}V_t^{x''}(\mathbf{s}_{i,t}) - \frac{1}{\nu}\widetilde{F}^{x,x''}\right)}. \tag{10}$$

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

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

where the subscript of each variable denotes the dimension of the variable. $\mathbf{1}$ is a 5 by 1 vector of ones; $\mathbf{f} = (f^0, f^N, f^{NI}, f^{NF}, f^{NIF})$ is 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 $\mathbf{F}$, 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, and 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

$$\mathbf{F} = \begin{bmatrix} 0 & F^N & F^N + F^I & F^N + F^F & F^N + F^I + F^F - F^{IF} \\ 0 & 0 & F^I & F^F & F^I + F^F - F^{IF} \\ 0 & F^{I0} & 0 & F^F + F^{I0} & F^F - F^{IF} \\ 0 & F^{F0} & F^I + F^{F0} & 0 & F^I \\ 0 & F^{I0} + F^{F0} & F^{F0} & F^{I0} & 0 \end{bmatrix}, \tag{11}$$

where each row and each column correspond to one 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 each R&D input type. 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 a particular source from the entire set of R&D tasks could be costly because the rest of the R&D team may need to be reorganized to accommodate the change.[21] Last but not least, the reduced-form facts presented in Section 2 suggest that it

[21]Since in the data, virtually all R&D-active firms hire native researchers, we assume that when a firm stops employing native researchers for any R&D task, it shuts down R&D altogether. In this case, there is no need to pay the

might be easier for firm with immigrant researchers than other firms to add offshore R&D into the R&D. Moreover, Appendix A.2 shows a strong connection between the origin country of immigrant researchers and the destination for offshore R&D. Motivated by these results, as well as the extensive literature that documents the importance of immigrants in facilitating international business (e.g., Rauch and Trindade, 2002; Burchardi, Chaney and Hassan, 2019), our specification of $\tilde{\mathbf{F}}$ allows the presence of immigrant researchers to potentially reduce the cost of offshore R&D through two components: in the sunk cost if $F^{IF} > 0$ and in the fixed cost if $f^{NIF} < f^{NF}$. We will let the data tell whether these inequalities are satisfied and which component is more important.

Discussion. In summary, our model incorporates static and dynamic interactions between firms' decisions to use different R&D inputs. Before turning to the estimation, we discuss the rationale underlying the four key aspects of firms' dynamic decisions.

First, at the center stage of our model are firms *in Denmark* looking to optimally source input for each R&D task μ. While this setup aligns with the measure of offshore R&D in our data, it does not explicitly account for the fact that some firms in the sample are the Danish affiliates of foreign MNCs, whose R&D both inside and outside Denmark might be driven by the incentive of their foreign headquarters. As a robustness check, we show in Appendix A.3 that the empirical patterns are similar when Danish affiliates of foreign MNCs are excluded.

Second, in the model, only immigrant researchers, not other immigrant workers, can reduce the cost of offshore R&D. This choice is motivated by the data: as shown in Appendix A.2, in regressions that include indicators for both immigrant researchers and other immigrant workers, only the indicator for researchers exhibits a robust correlation with offshore R&D.

Third, we assume that each firm makes only binary decisions of whether to hire immigrant researchers 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 it may appear too restrictive. However, it is worth noting that, in our data, most firms source R&D from only one foreign region.[22] Even among firms with more than 250 employees, the average number of offshore R&D destination regions is only 1.6. Our model can thus be viewed as a special case of a more general model with a two-step R&D decision: firms first choose whether to hire immigrant R&D workers and/or whether to offshore R&D and then select *one* foreign region to do so.

Finally, our model implies that, conditional on the current productivity $\omega_{i,t}$, how firms engaged in R&D in the past affects their R&D choice only through their current mode. This setup rules out the possibility that firms relying more heavily on a certain R&D input type (e.g., I) in the past might be more inclined to use the same input in the future and hence less likely to switch. We note that, with a generic matrix for the cost of switching modes ($\tilde{\mathbf{F}}$), our model can, in fact, speak to this channel. For example, one can enrich the cost of switching from mode x to mode x' to capture the cost associated with reorganizing the research team originally formed

reorganization cost required to continue R&D, so we assume the cost of dropping the input type N to be zero.

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

for mode x to function under mode x'. Following this insight, we show in Appendix B.7 that by adding such re-organization cost to $\tilde{\mathbf{F}}$, our model can be mapped into a model where firms accumulate source-specific R&D input and different inputs interact dynamically.[23]

4 Model Estimation

This section explains our model estimation approach, which follows a two-tiered strategy. The first tier estimates the production function, along the way recovering the dynamic impacts of both R&D investment and R&D modes on productivity. In the second tier, we recover all structural parameters necessary for counterfactual exercises by using an indirect inference approach, leveraging the first-tier estimates and firms' optimal R&D choice.

4.1 Tier I: R&D and the Evolution of Productivity

In the first tier, we estimate the production function and evaluate the impacts of R&D mode on productivity. This estimation does not require solving the Bellman equation (9), thus allowing for a relaxation of some assumptions in the structural model. For example, we can introduce dynamic production inputs. As explained later in this subsection, our estimation can also accommodate some variations in $A^{\tilde{x}}$ and $p^{\tilde{x}}$ across firms. In this sense, the estimates in this subsection can be consistent with more general models and are not strictly bound by the R&D sourcing model developed in the previous section.

We estimate the parameters governing the evolution of firms' productivity characterized by equations (5). As productivity is unobserved, we apply a two-step control function approach, which recovers $\omega_{i,t}$ jointly with the law of motion for productivity.

Step 1. The first step is to come up with a control function for productivity $\omega_{i,t}$. We start by expanding the general notation for production inputs, $o_{i,t}$ in equation (2), to allow for various inputs measured in the data. We write firms' measured revenues as a function of input use and the structural parameters of the production function:

$$
\begin{aligned}
\tilde{y}_{i,t} &\equiv \tilde{q}_{i,t} + \tilde{p}_{i,t} + \tilde{\epsilon}_{i,t} \\
&= \frac{\eta+1}{\eta}\omega_{i,t} + \tilde{\beta}_k \tilde{k}_{i,t} + \tilde{\beta}_l \tilde{l}_{i,t} + \tilde{\beta}_m \tilde{m}_{i,t} + \tilde{P} - \frac{1}{\eta}\tilde{Q} + \tilde{\epsilon}_{i,t}, \\
&\text{where } \tilde{\beta}_k \equiv \frac{\eta+1}{\eta}\beta_k,\ \tilde{\beta}_m \equiv \frac{\eta+1}{\eta}\beta_m,\ \tilde{\beta}_k \equiv \frac{\eta+1}{\eta}\beta_m.
\end{aligned} \tag{12}
$$

In the equation above, $\tilde{y}_{i,t}$ is the log measured revenue of firm i in t; $\tilde{q}_{i,t}$ and $\tilde{p}_{i,t}$ are log output quantity and log output price, respectively; $\tilde{k}_{i,t}$, $\tilde{l}_{i,t}$, and $\tilde{m}_{i,t}$ denote the log of capital, labor, and

[23] In quantification, we use data on the patterns of transition between modes to pin down $\tilde{\mathbf{F}}$. Since our model matches the transitions well, to the extent that such reorganization cost is important, they are implicitly incorporated in the quantification.

materials, respectively; $\tilde{\beta}_o,\ o \in \{m,k,l\}$ is the revenue elasticity of input o that takes into account the demand elasticity of consumers; $\tilde{\epsilon}_{i,t}$ is a mean-zero measurement error in log revenue.

Given the realization of productivity, firms choose capital, labor, material, and output quantity to maximize profit. Following the insight of Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2015), we assume that materials are a static input chosen after firms observe $\omega_{i,t}$ and have decided $\tilde{k}_{i,t}$ and $\tilde{l}_{i,t}$. This assumption implies that conditioning on $\tilde{k}_{i,t}$ and $\tilde{l}_{i,t}$, material use contains all information available to a firm on productivity and that it is monotonic in productivity. It can therefore be inverted to serve as a control function for productivity.

Formally, we express material use as a generic function of $z_{i,t}$, as well as $\tilde{k}_{i,t}$, $\tilde{l}_{i,t}$, and $\omega_{i,t}$, i.e., $\tilde{m}_{i,t} = m_t(\omega_{i,t}, \tilde{k}_{i,t}, \tilde{l}_{i,t}, z_{i,t})$. Included in $z_{i,t}$ are various firm-level controls that might affect firms' material use but are absent from our structural model. The first set of controls is on firms' participation in international trade. On the import side, importers might have better access to foreign suppliers, which reduces the overall price of materials; on the export side, exporters are likely to face a larger demand than non-exporters and therefore may choose to produce more for any given level of capital and labor inputs. This motivates us to include firms' lagged 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 older ones. We include the investment rate in $z_{i,t}$ to control for the potentially higher efficiency of more recent capital installations.

We invert $m(\cdot, \tilde{k}_{i,t}, \tilde{l}_{i,t}, z_{i,t})$ to express $\omega_{i,t}$ as a 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 (12) delivers:

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

The log measured revenue is now written as a function of an idiosyncratic measurement error, $\tilde{\epsilon}_{i,t}$, and a generic function h_t of $\tilde{k}_{i,t}, \tilde{l}_{i,t}, \tilde{m}_{i,t}$, and $z_{i,t}$. We specify $h_t(\cdot)$ as the sum of the following components: a cubic function of materials, dcapital, 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 of the control function approach comes down to estimating $h_{i,t}(\cdot)$ using OLS, separating $h_{i,t}(\cdot)$ 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 the law of motion for productivity in equation (5), we obtain:

$$
\begin{aligned}
&(\tilde{h}_{i,t} - \tilde{\beta}_k \tilde{k}_{i,t} - \tilde{\beta}_l \tilde{l}_{i,t} - \tilde{\beta}_m \tilde{m}_{i,t}) - \rho \cdot (\tilde{h}_{i,t-1} - \tilde{\beta}_k \tilde{k}_{i,t-1} - \tilde{\beta}_l \tilde{l}_{i,t-1} - \tilde{\beta}_m \tilde{m}_{i,t-1}) \\
&- \frac{\eta+1}{\eta} \cdot \gamma \cdot \mathbb{I}(rd_{i,t-1} > 0) \cdot \log(rd_{i,t-1}) - (1-\rho)(\tilde{P} - \frac{1}{\eta}\tilde{Q}) \\
&= \frac{\eta+1}{\eta} \zeta_{i,t},
\end{aligned} \tag{13}
$$

where we express the innovation in productivity ($\zeta_{i,t}$) as a function of firm choices and structural parameters. All firm choice variables on the left-hand side of equation (13) are now observable except for the effective R&D unit, $rd_{i,t-1}$, which depends on the firm's R&D spending and R&D mode. Firms' mode of R&D matters because, as discussed in Section 3, firms can improve R&D efficiency by using diverse inputs. We capture this effect with two specifications.

In the first specification, we adopt a parsimonious parametrization for the effect of R&D on productivity by replacing $\gamma \cdot \mathbb{I}(rd_{i,t-1} > 0) \cdot \log(rd_{i,t-1})$ in equation (13) with $\tilde{\gamma}_0 \mathbb{I}(x_{i,t-1} = N) + \tilde{\gamma}_1 \mathbb{I}(x_{i,t-1} \in \{NI, NF, NIF\})$. This simple reduced-form specification separately captures the average improvement in productivity from R&D with only domestic researchers and that from R&D with foreign inputs. We estimate these reduced-form coefficients, $\tilde{\gamma}_0$ and $\tilde{\gamma}_1$, along with other coefficients on the left-hand side of equation (13).

Our second specification for the effect of R&D on productivity is derived from the sourcing model presented in Section 3.1. Let $e_{i,t-1} > 0$ denote the R&D *expenditures* that firm i spends at time $t-1$ within Denmark, i.e., on domestic researchers and/or immigrant researchers. We show in Appendix B.2 that in our sourcing model, the period-t productivity of firm i with positive R&D investment in $t-1$ is given by:

$$
\begin{aligned}
\omega_{it} =& \rho\omega_{it-1} + \gamma \log(e_{it-1}) - \gamma \log(c^N) \\
&+ \begin{cases}
\zeta_{i,t}, \ \text{if } x_{i,t-1} = N \\
\gamma \left[\log(c^N) - \log(c^{NI})\right] + \zeta_{i,t}, \ \text{if } x_{i,t-1} = NI \\
\gamma(\theta+1) \left[\log(c^N) - \log(c^{NF})\right] + \zeta_{i,t}, \ \text{if } x_{i,t-1} = NF \\
\gamma \left[(\theta+1)\left(\log(c^{NI}) - \log(c^{NIF})\right) + \left(\log(c^N) - \log(c^{NI})\right)\right] + \zeta_{i,t}, \ \text{if } x_{i,t-1} = NIF,
\end{cases}
\end{aligned} \tag{14}
$$

where $c^{\tilde{x}}$ is the cost of the R&D input bundle for firms with mode $\tilde{x}$, as defined in (8); $x_{i,t-1}$ denotes firm i's R&D mode choice. Each line in the curly bracket of this equation corresponds to an R&D mode. The first line in the curly bracket states that for firms in R&D mode N, the effective R&D bundle is given by $\log(rd_{i,t-1}) = \log(e_{it-1}) - \log(c^N)$. The second through the fourth lines in the curly bracket express the productivity for firms in modes NI, NF, and NIF, respectively. As discussed in Section 3.2, $c^{NI}, c^{NF} < c^N$ and $c^{NI}, c^{NF} > c^{NIF}$ hold. This implies that conditional on $e_{i,t-1}$, firms in modes NI, NF, and NIF will see a higher future productivity gain than firms in mode N, which is captured by the terms inside the curly bracket. For firms in the NI mode, the larger productivity effect reflects that because $c^{NI} < c^{N}$, the same spending translates into more effective R&D investment. For firms in NIF and NF modes, an additional channel also contributes to the larger productivity effect—conditional on the total spending on R&D in Denmark ($e_{i,t-1}$), these firms also incur expenditures on offshore R&D.[24]

Following this discussion, our second specification replaces $\gamma \cdot \log(rd_{i,t-1})$ in (13) with

$$\tilde{\gamma}_0 \log(e_{i,t-1}) + \tilde{\gamma}_1 \mathbb{I}(x_{i,t-1} = NI) + \tilde{\gamma}_2 \mathbb{I}(x_{i,t-1} = NF) + \tilde{\gamma}_3 \mathbb{I}(x_{i,t-1} = NIF), \tag{15}$$

in which $\tilde{\gamma}_m$ for $m = 0, 1, 2, 3$ are functions of the structural parameters of the model, as shown in equation (14).[25] Alternatively, one can also view $\tilde{\gamma}_m$ for $m = 0, 1, 2, 3$ as reduced-form coefficients capturing how R&D modes affect firm productivity, which can be consistent with other models for the interactions between R&D inputs.

GMM Sample and Identification. We estimate specification (13) using the generalized method of moments (GMM), applying the two specifications discussed above separately. Since the production function specified in (12) is most appropriate for the manufacturing industry, we restrict our sample to manufacturing firms (here and in the indirect inference discussed in the next subsection). To form the moment conditions, we assume that $\tilde{k}_{i,t}$, $e_{i,t-1}$, and $x_{i,t-1}$ are determined before the innovation term in productivity $\zeta_{i,t}$ is realized, so they are independent of $\zeta_{i,t}$. Labor use, on the other hand, may respond 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 $(1-\rho)(\tilde{P} - \frac{1}{\eta}\tilde{Q})$ captures 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. We estimate $\tilde{\beta}_m$ by exploiting firms' first-order condition for materials (see e.g., Griliches, 1979; Gandhi, Navarro and Rivers, 2020).

Specifically, we show in Appendix B.3 that the first-order condition for material use implies:

$$\log \Bigg(\underbrace{\frac{P_{m,t} \cdot \exp(\tilde{m}_{i,t})}{\exp(\tilde{y}_{i,t})}}_{\text{measured material/revenue ratio}} \Bigg) - \log(\tilde{\beta}_m) = -\tilde{\epsilon}_{i,t}, \tag{16}$$

in which $P_{m,t}$ is the price for materials. The first term on the left-hand side is the (log of) measured revenue share of materials. The second term is the log of the structural parameter of interest $\tilde{\beta}_m$. The right-hand side is the negative of the revenue measurement error $\tilde{\epsilon}_{i,t}$ in equation (12), which is assumed to be mean-zero. We use the method of moments to estimate $\tilde{\beta}_m$ from equation (16). In the baseline analysis, we assume that $\tilde{\beta}_m$ is common across industries and estimate it by pooling all firms in the sample while including industry fixed effects. In a robustness exercise reported in Appendix B.4, we allow for industry-specific $\tilde{\beta}_m$. In both cases, we plug in the estimated

[24]This channel is captured by the coefficient $\theta + 1$, which appears for firms in the NIF and NF modes but not for firms in the NI mode.

[25]Concretely, $\tilde{\gamma}_0 = \gamma$; $\tilde{\gamma}_1 = \gamma \cdot \log \frac{c^N}{c^{NI}}$; $\tilde{\gamma}_2 = \gamma(\theta+1) \cdot \log \frac{c^N}{c^{NF}}$; $\tilde{\gamma}_3 = \gamma \left((\theta+1) \cdot \log \frac{c^{NI}}{c^{NIF}} + \log \frac{c^N}{c^{NI}} \right)$.

Table 4: R&D and Productivity Evolution

	GMM estimation of (13)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\omega_{i,t-1}$	0.467***	0.476***	0.478***	0.472***	0.483***	0.486***
	(0.146)	(0.138)	(0.142)	(0.137)	(0.135)	(0.129)
$\log(e_{i,t-1})$				0.002***	0.002***	0.002***
				(0.001)	(0.001)	(0.001)
$\mathbb{I}(x_{i,t-1} = N)$	0.010**	0.010**	0.009**			
	(0.004)	(0.004)	(0.004)			
$\mathbb{I}(x_{i,t-1} = NI)$				0.023***	0.022***	0.022***
				(0.008)	(0.008)	(0.008)
$\mathbb{I}(x_{i,t-1} = NF)$				-0.003	-0.003	-0.004
				(0.007)	(0.007)	(0.007)
$\mathbb{I}(x_{i,t-1} = NIF)$				0.041***	0.042***	0.042***
				(0.015)	(0.015)	(0.015)
$\mathbb{I}(x_{i,t-1} \in \{NI, NF, NIF\})$	0.023***	0.023***	0.023***			
	(0.008)	(0.008)	(0.008)			
Revenue elasticities						
$\tilde{\beta}_l$	0.491***	0.490***	0.489***	0.487***	0.486***	0.486***
	(0.018)	(0.017)	(0.017)	(0.012)	(0.017)	(0.016)
$\tilde{\beta}_k$	0.115***	0.114***	0.114***	0.113***	0.112***	0.111***
	(0.015)	(0.014)	(0.016)	(0.014)	(0.014)	(0.013)
$\tilde{\beta}_m$	0.421***	0.421***	0.421***	0.421***	0.421***	0.421***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Lag import dummy		yes	yes		yes	yes
Lag export dummy			yes			yes
Number of observations	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 based on IDA; $\mathbb{I}(x_{i,t-1} = NF)$ is an indicator for offshore R&D, measured based on offshore R&D expenditures in the R&D survey; $\mathbb{I}(x_{i,t-1} = NIF)$ 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 (16). 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

value for $\tilde{\beta}_m$ into equation (13) and estimate all remaining parameters jointly. To account for the uncertainty in generated regressors $\tilde{h}_{i,t}$ and $\tilde{\beta}_m$, we calculate standard errors by bootstrapping the entire estimation procedure.

Results. Columns 1-3 in Table 4 report the estimates under the first specification, in which the effect of R&D is captured parsimoniously by two indicators, $\mathbb{I}(x_{i,t-1} = N)$ and $\mathbb{I}(x_{i,t-1} \in \{NI, NF, NIF\})$. In column 1, the results indicate that productivity is moderately persistent, with an autocorrelation of 0.47. R&D participation leads to on average a 1% productivity gain. Conditional on participating in R&D, sourcing from foreign sources results in an additional 2.3% productivity gain. Column 2 includes an indicator for firms' importing status in both the control function $h(\cdot)$ and the law of motion for productivity. As such, this specification allows import participation to affect productivity in two ways: directly, and indirectly by altering the firm's R&D sourcing efficiency and use of intermediate goods. The result from this specification shows that the positive effect of using foreign R&D inputs is not due to its correlation with importing.

Column 3 further includes exporting status in both the control function and the law of motion for productivity. The estimated coefficients are similar.

Columns 4-6 in Table 4 report the estimates when we adopt the second specification based on equation (15). Industry fixed effects are included in all three columns, and indicators for participation in international trade are included following the same order as presented in Columns 1-3. The estimated coefficient for the intensive margin of R&D is statistically significant in all cases, albeit relatively small—a finding consistent with our observations in Section 2. As widely acknowledged, firm-level R&D expenditures are difficult to measure or define accurately. Thus, the relatively small estimates may be attributed to a potential downward bias stemming from measurement errors in R&D expenditures.[26] Alternatively, this could stem from potentially heterogeneous effects of intensive margin R&D across firms with different sizes, leading to an overall small average effect.[27] More importantly to our purpose, in addition to the effect of R&D expenditures, we find statistically significant and economically sizable effects ($\approx$ 2.3%) from employing immigrant researchers on firm productivity. Employing immigrant researchers and using imported R&D services at the same time increases productivity by even more ($\approx$ 4.2%). 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 4 reports the estimates for revenue elasticities of capital, labor, and materials. All estimates are of reasonable values and stable across specifications.

Heterogeneity in R&D Sourcing Cost. Recall that our model maintains that the cost and efficiency shifters of R&D input types, $p^{\tilde{x}}$ and $A^{\tilde{x}}$, are common to all firms. If $p^{\tilde{x}}$ and $A^{\tilde{x}}$ are heterogeneous across firms, then firms with different costs or efficiency shifters would follow different productivity processes, meaning that the coefficients in equation (14) would differ across firms. As firms choosing a particular R&D mode likely face shifters that make that mode more attractive, such heterogeneity could introduce a selection bias.

Our estimation strategy accommodates several important sources of heterogeneity, under which it recovers the average effects of choosing an R&D mode on productivity. The first case is when these shifters are i.i.d. across firms and periods, and they are realized after firms' mode choice. Intuitively, if firms' selection into R&D or a particular R&D mode does not depend on the shifters, the difference in productivity evolution between firms in different modes captures the average causal effect of choosing a mode *among all firms*. The second potential source of heterogeneity arises when these shifters systematically vary by mode—i.e., both $p^{\tilde{x}}$ and $A^{\tilde{x}}$ are mode-specific. For example, A^I for firms in the NIF mode could be higher than for firms in the NI mode due to the synergy between immigrant researchers and offshore suppliers. In such cases, the effect of choosing an alternative R&D mode on productivity depends on the firm's

[26] In addition to conventional measurement errors, another factor affecting the structural interpretation of the estimates is that $e_{i,t-1}$ can include fixed and sunk costs of R&D. To address this concern, rather than interpreting the coefficient for $e_{i,t-1}$ as a structural parameter, we will conduct indirect inference, as described in the next subsection.

[27] Our estimate is in line with existing estimates. For example, focusing on Norway, Bøler, Moxnes and Ulltveit-Moe (2015) estimate heterogeneous R&D returns by firm size. They find a positive coefficient for large firms, larger in absolute value than ours, and a negative coefficient for small firms, implying an average return that is similar to ours.

current mode. The estimation described above recovers the average effect of a mode compared to not doing R&D *only for the firms choosing that mode*. As a corollary of the first two cases, the shifters may have two components—one that is specific to the firm's current mode, and the other that is i.i.d. In this scenario, we estimate the average effect of a mode for the firms that choose it as in the second case. Last but not least, these shifters can vary due to differences in productivity or other observable components across firms or over time. For example, importers and exporters may face different shifters from non-traders. This concern is alleviated by the fact that controlling for importing and exporting status does not materially change any estimates.

Robustness and Summary. We conduct five sets of robustness exercises for Table 4 and report the results in Appendix B.4. First, one may be concerned that measurement errors in R&D expenditures might bias the estimates for the coefficients of the indicators in columns 4-6. We show that replacing the continuous R&D measure in these columns with the indicator for doing R&D only with domestic researchers (i.e., $\mathbb{I}(x_{i,t-1} = N)$) does not change the coefficients for other indicators materially. Second, in the baseline analysis, we classify firms as participating in R&D activities 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, Roberts and Xu, 2011; Doraszelski and Jaumandreu, 2013; Bøler, Moxnes and Ulltveit-Moe, 2015), one might be concerned about a potential inconsistency between this measure and our definition of mode NI that hinges on occupation. We show that the results are robust if we define mode N based on occupation as well. Third, 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 rely on a specific assumption about firms' optimal output choice. Fourth, we allow the cost share of materials to vary by industry. Finally, we exclude R&D workers from the measurement of labor, thereby alleviating the concern that firms doing more R&D have bigger measurement errors for employment.

Results from these exercises show that productivity gains associated with using foreign R&D inputs are a robust feature of the data that does not rely on many of the model's assumptions. In the rest of this section, we use the structure of the model on R&D to recover all the structural parameters that are necessary for conducting counterfactual exercises.

4.2 Tier II, Step I: The Distribution of Idiosyncratic Cost Shocks

In the second tier of the estimation, we recover all structural parameters required for counterfactual exercises. This process unfolds in two steps. A key part of our structural estimation involves recovering the matrix of fixed and sunk costs for R&D modes, $\tilde{\mathbf{F}}$. An intuitive approach to identify $\tilde{\mathbf{F}}$ is by using the observed transition patterns between R&D modes in the data. A challenge for this approach, however, is that because $\tilde{\mathbf{F}}$ enters firms' mode choice jointly with the reciprocal of ν, as shown in equation (10), transition patterns alone do not separately identify $\tilde{\mathbf{F}}$ and ν. The first step of Tier II in our estimation procedure addresses this challenge and identifies ν.

We take advantage of a natural experiment in Denmark—the introduction of an R&D subsidy policy in 2011—for identification. 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, encourages more firms to conduct R&D. We can therefore identify ν by examining how the subsidy changes the probability of switching R&D modes among eligible firms.

Consider the choice of the firms entering period t with R&D mode $x \in \{N, NI, NF, NIF\}$ and productivity $\omega_{i,t}$, i.e., $\mathbf{s}_{i,t} = (\omega_{i,t}, x)$. Combining equations (9) and (10) gives us the log of the ratio between the share of these firms quitting R&D and the share staying in the current mode x:

$$\log\left(\frac{m_t^{x,0}(\mathbf{s}_{i,t})}{m_t^{x,x}(\mathbf{s}_{i,t})}\right) = \frac{1}{\nu}\underbrace{\left[c^x \times rd^*_{i,t}(\omega_{i,t}, x) + f^x\right]}_{\equiv e^*_{i,t}(\omega_{i,t},x) \text{ (i.e., R\&D expenses)}} + \frac{\delta}{\nu}\underbrace{\left[E_t V_{t+1}\left(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t} = 0\right) - E_t V_{t+1}\left(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t} = rd^*_{i,t}(\omega_{i,t}, x)\right)\right]}_{\text{Improvement in continuation value from optimally chosen R\&D}}. \tag{17}$$

In the above expression, $rd_{i,t} = rd^*_{i,t}(\omega_{i,t}, x)$ is the optimal effective R&D for firm i with productivity $\omega_{i,t}$ if R&D is carried out under mode x.[28] The expression shows that the log odds ratio is the sum of two components—R&D expenses, and dynamic gains due to the improvement in expected future productivity—with each component divided by ν.

With the aforementioned R&D subsidy policy in place, firms' R&D choice also depends on whether they are eligible for the subsidy, i.e., whether they make a positive accounting profit. For loss-making firms, both R&D mode and R&D spending can change, affecting both components of the log-odds ratio.[29] 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 future value function in the post-policy world to be similar to that before the policy.[30] Under this assumption and by invoking the Envelope Theorem, we show in Appendix B.5 that, up to the first-order, the difference in the log odds ratio between otherwise similar loss-making firms—with the subsidy

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

[29] In our model, when making R&D decisions, firms already know their *current* productivity, which allows them to calculate $\pi(\omega)$. Therefore, firms know whether they would be eligible for the policy if they opt to carry out R&D. While $\pi(\omega)$ is always positive, we can assume that there is an idiosyncratic fixed overhead cost that firms have to pay, in which case a firm would incur an operation loss if its productivity is low or if the realization of the operation cost is high. Since our model does not focus on exits, we do not include this cost for simplicity.

[30] 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 are met: 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 holding in the future. We also note that our assumption is not that firms perceive their continuation values to be the same as before with certainty. Instead, the assumption is that the perceived continuation value, *given* the chosen R&D mode and the realized productivity in the next period, remains the same as in the absence of the policy.

in effect ($\log\left(\frac{m_t^{\prime x,0}(\mathbf{s}_{i,t})}{m_t^{\prime x,x}(\mathbf{s}_{i,t})}\right)$) and without it ($\log\left(\frac{m_t^{x,0}(\mathbf{s}_{i,t})}{m_t^{x,x}(\mathbf{s}_{i,t})}\right)$)—is:

$$\underbrace{\log\left(\frac{m_t^{\prime x,0}(\mathbf{s}_{i,t})}{m_t^{\prime x,x}(\mathbf{s}_{i,t})}\right)}_{\text{with subsidy}} - \underbrace{\log\left(\frac{m_t^{x,0}(\mathbf{s}_{i,t})}{m_t^{x,x}(\mathbf{s}_{i,t})}\right)}_{\text{without subsidy}} \approx -\frac{1}{\nu} \times \tau \times e_{i,t}^*(\omega_{i,t}, x), \tag{18}$$

where $e_{i,t}^*(\omega_{i,t}, x)$ is the firm's optimal R&D spending *in the absence of* the subsidy, as defined in equation (17). Expression (18) shows that the change in the propensity of a loss-making firm's continuing R&D due to the R&D subsidy depends on the amount of the subsidy $\tau \times e_{i,t}^*(\omega_{i,t}, x)$, and the parameter ν which governs firms' responsiveness to the subsidy. In the model, firms' characteristics are uniquely determined by their current productivity and participation in R&D in the previous period. Equation (18) suggests that we can determine ν by checking if, conditional on firms' R&D mode and other characteristics, loss-making firms are less likely to quit doing R&D after the policy is introduced.

Table 5 takes a first look at the transition of loss-making firms between doing R&D with any mode and quitting R&D. The left side presents the patterns in 2011 (pre-policy), whereas the right side presents the patterns in 2012 (post-policy). Each period includes approximately 600 loss-making firms. In 2011, 26% of the firms that were active in R&D in the previous year stopped doing R&D. This percentage decreased to 14% in 2012 following the implementation of the policy. These shifts are further confirmed by Panel B, which focuses on loss-making manufacturing firms.

To account for the role of R&D mode and other dimensions of firm heterogeneity in shaping the transition pattern described in Table 5, we conduct a regression analysis. We divide the observations for each year (2011 and 2012) according to the firm's beginning-of-period R&D mode. We assess, within each group, whether the observations from 2012 exhibit a higher likelihood of discontinuing R&D compared to those from 2011. We control for industry fixed effects, employment, lagged productivity, and the interaction between productivity and firms' R&D mode. According to the model, productivity and R&D mode characterize a firm's state. In effect, we use firms in 2011 with similar observed characteristics as a comparison group for firms in 2012. We estimate the following linear probability model:

$$\mathbb{I}(i \text{ quits R\&D in } t) = \beta_0 \mathbb{I}(t = 2012) + \beta_x \cdot X_{i,t} + \epsilon_{i,t},$$

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 according to the R&D expenses in the R&D survey; $\mathbb{I}(t = 2012)$ is an indicator for the year when the R&D subsidy policy was implemented; and $X_{i,t}$ is the vector of control variables mentioned above. β_0 is the key coefficient of interest, capturing the effect of the policy.

In Table 6, column 1 reports the results from this specification, indicating a decrease of approximately 10.5% in the probability of firms discontinuing R&D after the policy. In column 2, we conduct a placebo test focusing on profit-making firms that were ineligible for the subsidy.

Table 5: R&D Decisions of Loss-Making Firms

Panel A: all industries

Loss-making firms in 2011		2011 R&D	2011 no R&D	Loss-making firms in 2012		2012 R&D	2012 no R&D
2010	R&D	113	39	2011	R&D	144	24
	no R&D	27	427		no R&D	37	373

Panel B: manufacturing

Loss-making firms in 2011		2011 R&D	2011 no R&D	Loss-making firms in 2012		2012 R&D	2012 no R&D
2010	R&D	52	17	2011	R&D	67	11
	no R&D	15	135		no R&D	19	116

Notes: The sample consists of loss-making firms in 2011 and 2012 with at least 10 employees in all industries (Panel A) and manufacturing only (Panel B). '*R&D*' denotes firms reporting positive R&D expenditures, regardless of the mode, while 'no *R&D*' refers to firms doing no R&D.

Table 6: R&D Subsidy and R&D Participation

	Linear Probability Model		Logistic Model	
	Loss-making firms	Placebo: profitable firms	All industries	Manufacturing
	(1)	(2)	(3)	(4)
β_0	-0.105**	-0.027	-0.147***	-0.196**
	(0.048)	(0.024)	(0.049)	(0.081)
Observations	277	893	201	83
Firm size$_{i,t-1}$	Yes	Yes	Yes	Yes
Productivity$_{i,t-1}$	Yes	Yes	Yes	Yes
R&D mode$_{i,t-1}$# Productivity$_{i,t-1}$	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Notes: The first two columns report results from a linear probability model; the last two columns report results from a logistic model on loss-making firms. All specifications control for lagged log firm size, a quadratic function of lagged firm productivity (defined as log valued-added per worker), lagged R&D mode interacted with a quadratic function of lagged firm productivity, and industry fixed effects. The sample consists of firms in the entire private sector or manufacturing in 2011 and 2012 with at least 10 employees. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The finding suggests that the results in column 1 are not attributed to broader macroeconomic conditions affecting all firms simultaneously between 2011 and 2012.[31]

Estimates based on the linear probability model do not easily translate into the structural parameter of interest $\frac{1}{\nu}$. To address this, we estimate a logistic specification with the independent variable being the *log of R&D expenditures*, as shown below:

$$\mathbb{I}(i \text{ quits R\&D in } t) = \begin{cases} 1, & \text{if } \beta_0 \cdot \mathbb{I}(t = 2012) \cdot \log(e^*_{i,t}) + \beta_x \cdot X_{i,t} + \epsilon_{i,t} > 0 \\ 0, & \text{otherwise,} \end{cases} \tag{19}$$

in which $e^*_{i,t}$ is the optimal R&D expenditures for firm i if it chooses to continue R&D. Assuming $\epsilon_{i,t}$ is drawn from a standard logistic distribution, this specification serves as the reduced-form

[31] The difference between the estimates in the first two columns essentially constitutes a difference-in-differences estimate for the effect of the policy.

counterpart of the structural equation (18).[32] We estimate the elasticity from equation (19) and subsequently convert it to semi-elasticity $\frac{\tau}{\nu}$.[33] For firms continuing R&D, we use their R&D expenditures to measure $e^*_{i,t}$. For the firms that quit doing R&D in period t, we do not observe the actual R&D expenditures, so we use their lagged R&D expenditures as a proxy.

Columns 3 and 4 of Table 6 report the results from the logistic regression. The estimated coefficient for all firms is around -0.15, and it is larger in absolute terms for manufacturing firms. Since our productivity estimation and counterfactual simulations will focus on the manufacturing sector, we convert the estimate for manufacturing firms, -0.196, into the semi-elasticity given in equation (18), $-\frac{\tau}{\nu}$. For a typical firm (the median firm) that incurs 0.374 million USD in expenditures on R&D, our semi-elasticity estimate implies $-\frac{\tau}{\nu} = \frac{-0.196}{0.374}$. Plugging in the actual subsidy rate $\tau = 0.25$ delivers $\nu = 0.477$.

4.3 Tier II, Step II: Indirect Inference of the Remaining Structural Parameters

The final step of our estimation is to pin down the remaining structural parameters. We adopt the indirect inference method in this step to jointly identify different sets of parameters while maintaining a clear connection between the parameters and the targeted moments.

With the estimate of ν in hand, there are three sets of parameters remaining to be determined. The first set includes the parameters that govern the evolution of firm productivity: ρ, γ, the standard deviation σ_ζ of the error term in equation (5), and the unit cost of R&D for each mode (c^x for each R&D mode $x \in \{N, NI, NF, NIF\}$). These costs are composite parameters that depend on the efficiency $A^{\tilde{x}}$ and the price $p^{\tilde{x}}$ of each type of R&D input $\tilde{x} \in \{N, I, F\}$. However, as equation (14) shows, the impact of $A^{\tilde{x}}$ and $p^{\tilde{x}}$ on productivity is summarized entirely by the elasticity of productivity with respect to domestic R&D investment and the marginal contribution of each R&D mode, i.e., $\tilde{\gamma}_i$ for $i = 0, 1, 2, 3$ in equation (15). Moreover, as we show in the next section, counterfactuals that change the availability of foreign inputs can be implemented by altering $\tilde{\gamma}_i$'s directly. Therefore, conditional on $\tilde{\gamma}_i$'s, we do not need to separately identify $A^{\tilde{x}}$ and $p^{\tilde{x}}$. We collect ρ, σ_ζ, and $\tilde{\gamma}_i$ for $i = 0, 1, 2, 3$ in $\boldsymbol{\lambda} = (\tilde{\rho}, \tilde{\boldsymbol{\gamma}}, \sigma_\zeta)$ as the first set of parameters.[34]

The second set of parameters is about the macroeconomic environment that determines the size of the market, i.e., P_t, W_t, Q_t. These parameters enter the model only through the aggregate demand shifter Φ_t. The third set of parameters are the fixed and sunk costs of R&D modes, $\widetilde{\mathbf{F}}$.

[32] The logistic assumption in equation (19) implies that the pre- and post-policy log odds ratios are $\log\left(\frac{m_t^{x,0}(\mathbf{s}_{i,t})}{m_t^{x,x}(\mathbf{s}_{i,t})}\right) = \beta_x \cdot X_{i,t}$ and $\log\left(\frac{m_t'^{x,0}(\mathbf{s}_{i,t})}{m_t'^{x,x}(\mathbf{s}_{i,t})}\right) = \beta_0 \log(e^*_{i,t}) + \beta_x \cdot X_{i,t}$, respectively. The difference between the two yields the elasticity specification in equation (18).

[33] An alternative is to use the level of R&D expenditures as the explanatory variable to directly estimate $-\frac{\tau}{\nu}$. We do not adopt this alternative approach because with the distribution of R&D expenditures being skewed, specifications with the level of expenditures as the explanatory variable are heavily influenced by a small number of big firms. Nevertheless, using a level specification gives qualitatively similar results.

[34] In estimating structural parameters and conducting counterfactuals, we assume that all production inputs are flexible. This allows us to circumvent having capital and employment as state variables and to avoid solving numerically for investment and employment decisions. These benefits appear larger than the cost of this abstraction given that our counterfactual exercises focus on steady-state outcomes.

We stack these three sets of parameters in $(\boldsymbol{\lambda}, \Phi_t, \widetilde{\mathbf{F}})$ and estimate them jointly. We focus on manufacturing firms as in productivity estimation. Below, we describe the moments that identify each parameter and our estimation procedures in detail.

Parameters about the Evolution of Firm Productivity. We use the estimates reported in Table 4 to identify $\boldsymbol{\lambda}$. Ideally, we would like to directly assign the estimates in columns 4-6 to $\tilde{\gamma}_i$. However, as discussed earlier, the difficulty in accurately measuring intensive-margin R&D expenditures, e_{it}, may introduce biases into these estimates. To circumvent this problem, we use the estimates of column 3, which uses indicators and is therefore less susceptible to such biases. We take three estimates from column 3: the autocorrelation coefficient, the coefficients on the R&D indicator, and the diverse R&D 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 (1.44). We collect these moments in a vector as below

$$\hat{\boldsymbol{\alpha}} = (0.478, 0.009, 0.023, 0.903, 0.558, 1.44). \tag{20}$$

$\hat{\boldsymbol{\alpha}}$ will be the target in the indirect inference procedure to pin down the parameters in $\boldsymbol{\lambda}$.

The intuition for identification is as follows. The standard deviation of log firm sales pins down σ_ζ. s^N_{NI} and s^N_{NIF} contain the information needed to identify the cost difference between different R&D modes (e.g., $\log \frac{c^N}{c^{NI}}$ and $\log \frac{c^N}{c^{NF}}$). As demonstrated in Appendix B.6, when paired with the estimated coefficients for the indicators in column 3 of Table 4, these shares separately identify $\tilde{\gamma}_i$ for $i = 0, 1, 2, 3$, and are sufficient for our counterfactual exercises.[35]

Aggregate Demand Shifter. Φ_t in equation (4) represents the aggregate demand shifter that affects the scale of all firms. Focusing on the steady state of the model, we assume that $\Phi_t = \Phi$ is a constant and choose Φ such that the median sales among the model firms match the value of 25.6 million USD, the median sales among manufacturing firms in our empirical sample.

Fixed and Sunk Costs of R&D Modes. The matrix $\widetilde{\mathbf{F}}$ directly determines the probability of a given firm transitioning from one R&D mode to another. We pin down $\widetilde{\mathbf{F}}$ by using the observed transition matrix between R&D modes. Since each row of the transition matrix sums to 1, we have 20 independent moments to pin down the 10 parameters in $\widetilde{\mathbf{F}}$, as specified in equation (11).

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 the number of 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

[35]Note from equation (13) that the R&D coefficient estimated with GMM is the product of the true R&D coefficients governing the evolution of firms' productivity and $\frac{\eta+1}{\eta}$, where η is the demand elasticity of the product market. For consistency, in generating the model counterpart of $\hat{\boldsymbol{\alpha}}$, we also scale the regression coefficients from the simulated data by $\frac{\eta+1}{\eta}$, in which η is externally assigned, as shown in Table 7.

following constrained optimization problem:

$$\min_{(\boldsymbol{\lambda},\Phi,\widetilde{\mathbf{F}})\in\Lambda} \sum_{x,x'} n(x)\cdot\left(m^{x,x'}(\boldsymbol{\lambda},\Phi,\widetilde{\mathbf{F}})-\hat{m}^{x,x'}\right)^2 \tag{21}$$
$$s.t.\ \boldsymbol{\alpha}(\boldsymbol{\lambda},\Phi,\widetilde{\mathbf{F}})=\hat{\boldsymbol{\alpha}},$$

where the variables with a hat denote empirical moments and those without a hat are model-implied values under a particular choice of $(\boldsymbol{\lambda},\Phi,\widetilde{\mathbf{F}})\in\Lambda$. 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; $n(x)$ 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 weight reflects that the empirical moments $\hat{m}^{x,x'}$ converge to their asymptotic value as n increases, so modes with a smaller number of observations have more noisy moments and should be weighted less.

The constraint of this optimization problem ensures all the moments that just-identify the parameters $\boldsymbol{\lambda}$ and Φ, are matched exactly. The first three elements of $\hat{\boldsymbol{\alpha}}$ in the constraint, as defined in equation (20), are the first three estimated coefficients reported in column 3 of Table 4. 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 under parameters $(\boldsymbol{\lambda},\Phi,\widetilde{\mathbf{F}})$.[36]

In implementing the estimation, for any given set of values of $(\boldsymbol{\lambda},\Phi,\widetilde{\mathbf{F}})$, we simulate the model. With the simulated data, we calculate the transition matrix between R&D modes, the standard deviation of log sales, and the domestic R&D shares s^N_{NI} and s^N_{NIF}. We also estimate the coefficients following the specification in column 3 of Table 4 with the simulated data. Subsequently, we choose $(\boldsymbol{\lambda},\Phi,\widetilde{\mathbf{F}})$ to solve the optimization problem outlined above.[37]

Estimation Results and the Model Fit. Panel A of Table 7 reports the parameters that we take as given in the indirect inference. We estimated $\nu = 0.477$ from the previous step. We set the demand elasticity η to be -6.56. This choice follows the estimate of Aw, Roberts and Xu (2011) and implies a constant markup of around 18%. Finally, the discount rate is set to 0.95.

Panel B of Table 7 summarizes the results from the indirect inference procedure. The estimate for $\tilde{\rho}$ is 0.473, which is very close to the moment that pins it down (0.478). $\tilde{\gamma}_0$ from the joint estimation is almost three times the estimated coefficient in column 4 of Table 4, which is consistent with a downward bias due to measurement errors in R&D expenditures. Likely because intensive margin returns pick up a larger fraction of the total returns to R&D, the estimates for $\tilde{\gamma}_1$ and

[36] An alternative view of the constrained optimization problem is that the moments in the constraint represent macro moments (those reflecting the average outcomes of firms) and that the moments in the objective function are micro moments specific to firms in a particular mode. Our estimation aims to fit all macro moments and as many micro moments (weighted according to their informativeness) as possible.

[37] Appendix B.6 shows that, for a given guess of $\tilde{\boldsymbol{\gamma}}$ and without 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. It also shows that the problem in (21) identifies the parameters relevant for firm's R&D decisions without having to first estimate $A^{\tilde{x}}$ or $p^{\tilde{x}}$ for $\tilde{x}\in\{N,I,F\}$.

Table 7: Summary of Structural Parameters

Parameters	Descriptions	Source/Target	Value	(s.e.)
A. Estimated in Tier II - Step 1 / Independently Calibrated				
ν	scale parameter for the idiosyncratic cost in R&D	Table 6	$\nu = 0.477$	(-)
η	demand elasticity	Aw, Roberts and Xu (2011)	-6.56	(-)
δ	discount rate	-	0.95	(-)
B. Jointly Estimated in Tier II - Step 2				
Φ	aggregate demand	median sales: 16.9 million USD	-	
$\tilde{\rho}$	autocorrelation in productivity	Table 4 Column 3	0.473	(1.ee-2)
$\tilde{\boldsymbol{\gamma}}$	return to R&D	Table 4 Column 3, S^N_{NI}, and S^N_{NIF}	$\tilde{\gamma}_0 = 0.0057$	(6.7e-4)
			$\tilde{\gamma}_1 = 0.0017$	(3.6e-4)
			$\tilde{\gamma}_2 = 0.016$	(1.7e-2)
			$\tilde{\gamma}_3 = 0.013$	(2.1e-3)
σ_{ξ}	sd. of the innovation term in productivity	sd(log(*sales*))=1.268	0.20	(1.3e-3)
$\widetilde{\mathbf{F}}$	fixed and sunk costs in R&D	Table 8	Table 8	

Notes: Panel A reports the parameters estimated in Step 1 of Tier II of our estimation procedure and those externally calibrated. Panel B reports the outcome from Tier II - Step 2 of 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 (21).

$\tilde{\gamma}_3$ from indirect inference are smaller than their counterparts in the specification in column 4 of Table 4. Finally, we estimate a positive value for $\tilde{\gamma}_2$. The contrast between this estimate and the negative and statistically insignificant estimates in columns 4-6 in Table 4 stems from the difference in the source of identification: in this joint estimation, $\tilde{\gamma}_2$ is identified from the diversified R&D indicator in combination with the R&D expenditure shares s^N_{NI} and s^N_{NIF}, whereas in Table 4, it is primarily identified from a small number of observations in the *NF* mode.

We show in Appendix B.6 that our estimate of $\tilde{\boldsymbol{\gamma}}$ implies $\theta = 0.32$ as the Fréchet shape parameter, implying a large heterogeneity in the efficiency across ideas from different sources. This estimate is tightly connected to the large estimated gains from using diverse R&D modes in Table 4. It also suggests that an important reason for firms to access foreign R&D inputs is to exploit better ideas for some of the R&D tasks.[38]

Panel A of Table 8 reports the empirical transition matrix for manufacturing firms and the model counterpart. Our model fits the transition patterns reasonably well, with a mean difference between the model and the data being 0.014. The fit of the *NF* row is worse than that of other rows, 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 R&D 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 in $\widetilde{\mathbf{F}}$. 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 other values in the same *column*, suggesting that sunk costs play an important role. In terms of magnitude, we find that the average startup cost of doing R&D with mode N is 1.61 million USD. Compared to the average R&D expenditures of 1.78 million USD in the data, this

[38]Our estimate is lower than that of Antràs, Fort and Tintelnot (2017), who estimate a heterogeneity parameter of 1.8 among different suppliers of the same *good*. This difference could reflect the distinct nature of *ideas* versus *goods*.

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	0.897	0.061	0.075	0.033	0.015	0.005	0.008	0.011	0.005
N	0.276	0.245	0.592	0.576	0.082	0.114	0.042	0.039	0.008	0.027
NI	0.115	0.119	0.059	0.061	0.684	0.682	0.011	0.003	0.131	0.134
NF	0.140	0.119	0.380	0.284	0.033	0.058	0.407	0.342	0.040	0.196
NIF	0.049	0.044	0.011	0.022	0.252	0.251	0.021	0.019	0.667	0.663
SS dist.	0.582	0.587	0.134	0.144	0.171	0.157	0.021	0.019	0.092	0.094
Panel B: The estimated cost matrix and breakdowns										
$\widetilde{\mathbf{F}}$	0		N		NI		NF		NIF	
0	0	-	1.613	(0.047)	2.838	(0.11)	4.073	(1.23)	4.652	(0.21)
N	0	-	0.001	(0.003)	1.225	(0.105)	2.460	(1.23)	3.039	(0.22)
NI	0	-	0.714	(0.10)	0.001	(2e-4)	3.173	(1.24)	1.815	(0.17)
NF	0	-	0.005	(0.003)	1.230	(0.10)	1.118	(1.25)	1.785	(0.20)
NIF	0	-	0.718	(0.10)	0.005	(0.001)	1.831	(1.25)	0.560	(0.13)
Breakdown	f^N	f^{NI}	f^{NF}	f^{NIF}	F^N	F^I	F^F	F^{IF}	F^{I0}	F^{F0}
	0.001	0.001	1.118	0.560	1.613	1.225	1.342	0.087	0.713	0.004
	(0.003)	(2e-4)	(1.24)	(0.13)	(0.047)	(0.11)	(0.14)	(0.008)	(0.10)	(9e-4)

Notes: Panel A of the table reports the transition probability between modes in the steady state of the estimated model and that in the data, averaged among manufacturing firms with more than 10 employees over the sample period. The steady-state distribution for the data represents firms' frequency distribution across modes over the same period. Panel B reports the estimates for the cost parameter matrix $\widetilde{\mathbf{F}}$ and its breakdown 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.

average estimate implies that a significant portion of R&D expenses is allocated to fixed and sunk cost components.[39]

Second, our estimates exhibit $\tilde{F}^{N,NF} - \tilde{F}^{NI,NIF} > 0$, which is statistically significant at 10%. Firms with immigrant R&D workers face 30% lower costs in starting offshore R&D compared to firms without any immigrant R&D workers. This finding suggests that the higher propensity for starting offshore R&D among firms with immigrant researchers in the data cannot be solely attributed to the increased R&D efficiency generated by static interactions between offshore R&D and high-skill immigrants. Reduced fixed and sunk costs of offshore R&D due to immigrant researchers are also an important source of such complementarity.[40]

The last row of Panel B breaks down the composite cost matrix by mode-specific fixed costs and the sunk costs associated with mode switching. Decomposing $\tilde{F}^{N,NF} - \tilde{F}^{NI,NIF}$ into the sunk cost component F^{IF} and the fixed cost component $f^{NF} - f^{NIF}$ reveals that both components

[39] The average masks substantial heterogeneity. Under the estimated value of ν, the two-standard-deviation range of $F^N + \iota^N_{i,t}$ is $(1.61 - 0.89, 1.61 + 0.89)$.

[40] One might be concerned that the key elements in the transition matrix identifying $\tilde{F}^{N,NF} > \tilde{F}^{NI,NIF}$, e.g., a higher frequency of the $NI \to NIF$ switch than that of the $NI \to NF$ switch, are entirely driven by large and productive firms doing more of all activities. If so, our estimation could be imposing a size-driven effect on the information values of immigrant researchers. We note that, first, as shown in Appendix A.2, the transition pattern remains 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 $\widetilde{\mathbf{F}}$ picks up what cannot be explained by firm size alone.

matter, with the fixed component playing a relatively larger role.

5 Counterfactuals

We use the estimated model to conduct counterfactual experiments, with two primary objectives: first, to understand what determines firms' choice to use foreign R&D inputs and the importance of these foreign inputs for overall R&D; second, to examine how these inputs influence the outcomes of policies targeting either overall R&D or the use of specific foreign R&D inputs.

5.1 Benefits from Diverse Ideas and the Information Value of Immigrant Researchers

In the model, a key motive for using foreign R&D inputs arises from the heterogeneity in the quality of ideas across input sources. With such heterogeneity, firms that obtain inputs from diverse sources can leverage superior ideas for each task, thereby achieving higher R&D efficiency. In addition to this incentive, as revealed by our structural estimation, employing immigrant researchers provides an extra benefit by facilitating communications with offshore R&D suppliers, thus reducing the cost of starting offshore R&D. For the sake of brevity, we refer to this as the "information channel" in this section.

In this subsection, we conduct two experiments to understand the importance of the information channel and idea heterogeneity 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, thereby removing the cost advantage in doing offshore R&D enjoyed by firms with immigrant researchers. In the second experiment, we shut down the heterogeneity in ideas for R&D tasks across sources by setting θ to infinity.[41] In this limit case, the only reason a firm would pay higher fixed and sunk costs to adopt foreign-sourced R&D inputs is that they have a favorable idiosyncratic cost draw ι for the R&D mode using foreign inputs. Thus, this experiment can also be viewed as shutting down the benefit from using foreign R&D inputs.

The first panel in Table 9 reports the distribution of firms across R&D modes in the benchmark and the two counterfactual economies. When the information channel is eliminated, the share of firms in mode NIF decreases by more than 90%. Interestingly, the share of firms in the NI mode also decreases by 46%, even though the firms that have chosen this mode are not *directly* affected by the change in fixed and sunk costs implemented in this experiment. This decline indicates that many firms selecting the NI mode in the benchmark economy are driven by the prospect of more easily transitioning into the NIF mode in the future. In total, the fraction of R&D-active firms decreases by 15 p.p., from 41% to 26%, underscoring the importance of the information channel in influencing R&D participation. When we eliminate the heterogeneity in ideas across

[41] Note from equations (8) that as $\theta \to \infty$, c^{NI}, c^{NIF}, and c^{NIF} all converge to c^N (and $\tilde{\gamma}_m \to 0$ for $m = 1, 2, 3$) if domestic researchers are, *on average*, more cost-efficient than foreign sources. This condition is satisfied in our setting given that firms in the NIF mode spend the highest fraction of expenditures on domestic researchers (recall $s^N_{NIF} = 0.558$). Therefore, modifying the law of motion for productivity by setting $\tilde{\gamma}_m \to 0$ for $m = 1, 2, 3$ implements the counterfactual of $\theta \to \infty$ without recovering the level of $A^{\tilde{x}}$ or $p^{\tilde{x}}$.

sources, as shown in the third column of panel (a), less than 18% of firms conduct R&D, 23 p.p. less than in the benchmark economy. Also, firms do R&D overwhelmingly in mode N, except for the firms that happen to have a favorable draw ι for using foreign inputs.

The shift in firms' R&D mode choices between the benchmark model and alternative specifications translates into a qualitatively similar shift in the distribution of R&D expenditures across modes, as reported in panel (b) of Table 9. 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 firm counts in these modes. This disparity demonstrates a compositional shift resulting from selection. For instance, when the information channel is absent, the average cost of transitioning to the NIF mode is higher than in the benchmark model. As a result, compared to the benchmark, firms opting for the NIF mode in the absence of the information channel are, on average, larger and more productive, leading them to outspend firms in other modes of R&D.

We now examine the impact of these model mechanisms on aggregate productivity. Reported in panel (c) of Table 9 is the sales-weighted average log productivity among all firms and by R&D mode. Eliminating the information channel reduces aggregate productivity by 0.5% from the benchmark, and shutting down the heterogeneity in ideas decreases aggregate productivity by 0.8%.[42] Intuitively, both experiments effectively increase the overall cost of R&D, leading to lower R&D participation. Somewhat unexpectedly, despite the decrease in aggregate productivity, the average productivity in all modes increases when the information channel is removed. This result is entirely driven by the shift in the composition of firms among R&D modes: as the entry into the NIF mode becomes more costly due to the removal of the information channel, the most productive firms remain in the NIF mode, while the less productive firms transition to other modes. Because the switchers are still more productive than existing firms in the less costly R&D modes, the average productivity in all modes increases. This finding highlights the importance of the selection mechanism in interpreting the productivity disparity across R&D modes evident in the data (see Table 2), a factor we account for through the structural model.

To assess the importance of foreign R&D inputs in the overall gains in aggregate productivity from R&D, we conduct an additional experiment that eliminates entirely the incentive to conduct R&D by assuming that doing R&D has no impact on firms' future productivity. In this experiment, aggregate productivity declines to 0.276, slightly lower than 0.278, which is the aggregate productivity when we eliminate the heterogeneity in ideas from the benchmark. The modest difference between these two numbers illustrates that, in a small open economy like Denmark, most of the productivity gains from R&D originate from access to foreign ideas. When forced to carry out R&D with only domestic inputs, most firms stop doing R&D and the economy reaps only 20% ($= \frac{0.278-0.276}{0.286-0.276} \times 100$) of the total returns from R&D.

In summary, the counterfactual results show that the heterogeneity in ideas accounts for 56% of firms' participation in R&D and 80% of the gains in aggregate productivity from R&D.

[42] The modest effects on overall productivity mirror the relatively small estimates for the returns to R&D presented in Table 4. Since our emphasis lies on the significance of foreign inputs and the interaction between them, we focus on the relative levels of aggregate productivity gains across counterfactuals.

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	$\theta \to \infty$	Benchmark	No info	$\theta \to \infty$	Benchmark	No info	$\theta \to \infty$
No R&D	58.67	73.50	82.24	-	-	-	0.257	0.263	0.270
N	14.36	15.63	14.17	37.11	59.89	79.84	0.280	0.291	0.312
NI	15.70	8.44	3.39	41.10	33.27	19.00	0.277	0.299	0.305
NF	1.90	1.97	0.09	3.41	5.44	0.53	0.420	0.443	0.312
NIF	9.37	0.45	0.11	18.38	1.40	0.63	0.364	0.409	0.305
All	100	100	100	100	100	100	0.286	0.281	0.278

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 '$\theta \to \infty$' report the results from the alternative specification where we set θ to infinity to shut down the heterogeneity in ideas. 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 firms in each R&D mode.

Moreover, firms' R&D choices crucially depend on the cost of doing R&D in different modes and the extent to which such costs can be mitigated by immigrant researchers. Incorporating these mechanisms is vital for explaining observed R&D choices and, as we will show in the subsequent subsections, for evaluating policy outcomes.

5.2 High-Skill Immigration and Offshore R&D Policies

Firms' access to immigrant researchers and offshore R&D services is heavily influenced by national policies, often sparking heated debates. We investigate the impacts of two policies—high-skill immigration liberalization and offshore R&D promotion—using the model. We model these policies as a 50% reduction in the sunk costs of hiring immigrant researchers and starting offshore R&D, F^I and F^F, respectively. The reduction in F^I can be viewed as a reform that eases friction in hiring foreign researchers. The decrease in F^F could represent advancements in information technology (IT) facilitating cross-border collaboration or an investment treaty that makes it easier for firms to set up R&D operations abroad. While these 50% adjustments might seem large, it is worth noting that the integration of new member states into the EU stands as one of the most significant liberalizations in immigration in recent decades, resulting in rapid migration increases in the region (Caliendo, Parro, Opromolla and Sforza, 2021). Furthermore, the advancement of IT over the last two decades has made cross-border communication easier than ever.

Table 10 presents the results from these experiments. The high-skill immigration liberalization increases the share of firms with immigrant researchers by 10.4 p.p. Approximately one-third of this increase occurs in mode NIF. The offshore R&D promotion increases the share of firms in NF or NIF modes by around 13.4 p.p., with the vast majority of this increase also happening in the NIF mode. As offshore R&D becomes less expensive, we also observe more firms opting for the NI mode, reflecting the information value of immigrant researchers.

We examine the impact of these two policies on aggregate productivity. As shown in the last row of panel (c) in Table 10, the immigration liberalization policy increases aggregate productivity by 0.2%, whereas the offshore R&D promotion policy results in a 0.5% increase in aggregate productivity. The average productivity in individual modes, on the other hand, declines from

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	58.67	46.67	35.93	-	-	-	0.257	0.252	0.248
N	14.36	15.62	12.85	37.11	31.20	22.17	0.280	0.272	0.266
NI	15.70	22.93	26.60	41.10	46.68	46.60	0.277	0.276	0.264
NF	1.90	2.20	3.09	3.41	2.97	3.54	0.420	0.404	0.389
NIF	9.37	12.58	21.53	18.38	19.15	27.69	0.364	0.362	0.347
All	100	100	100	100	100	100	0.286	0.288	0.291

Notes: Columns marked as 'Immigration' report the results from the counterfactual scenario of the immigration liberalization policy, and the columns marked as 'Offshoring' report the results from the counterfactual scenario of 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 firms in each R&D mode.

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	-12.00	1.27	7.23	0.30	3.20	-22.74	-1.51	10.90	1.19	12.16
without the information channel	-10.73	1.71	8.54	0.04	0.43	-6.65	2.06	1.40	2.46	0.73
II. *Changes* in aggregate productivity (overall, %)										
with the information channel	0.21					0.54				
without the information channel	0.12					0.23				

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 %) in 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.

the benchmark levels. Once again, the difference between the responses in aggregate and mode-specific productivity arises from a composition change: firms that switch from a less costly R&D mode to a more costly one are less productive than existing participants in the more costly mode but more productive than the firms remaining in the less costly mode. Consequently, their shift lowers the average productivity across all modes.

The results in Section 5.1 highlight the importance of the information channel in influencing firms' R&D choices. To understand how this channel interacts with the two policies, we simulate each policy using the alternative model without the information channel, as defined in Section 5.1. We then compare the effects of each policy between the benchmark and the alternative model. Table 11 reports the findings. For both policies, the information channel significantly amplifies the extent of changes in firms' R&D mode choices, pushing more firms to the NIF mode. The lower panel in the table reports the impacts of these two policies on aggregate productivity in the benchmark and the alternative model. It shows that approximately half of the productivity impact resulting from the immigration and offshore R&D liberalization policies is attributed 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	58.67	18.05	-	–	0.257	0.225
N	14.36	14.01	37.11	20.38	0.280	0.243
NI	15.70	19.82	41.10	29.52	0.277	0.251
NF	1.90	13.91	3.41	12.95	0.420	0.349
NIF	9.37	34.21	18.38	37.16	0.364	0.328
All	100	100	100	100	0.286	0.297

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

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

Many countries adopt direct subsidies or tax rebates to promote R&D investment. These policies, such as the one implemented in Denmark for loss-incurring firms, often cover a significant portion of firms' R&D costs. In the last set of exercises, we examine the significance of foreign inputs in assessing R&D policies. We consider a policy that reduces the fixed and sunk R&D costs by half from the baseline values.[43]

Table 12 summarizes the results of this experiment. With the subsidies, a significantly larger number of firms engage in R&D, particularly through the NF and NIF modes, leading to a shift in R&D expenditures towards these modes. Similar to the cases of the immigration policy and the offshoring policy in Section 5.2, aggregate productivity increases modestly by 1.1%, while the average productivity of each R&D mode decreases due to the compositional shift toward more diversified R&D modes.

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	-40.61	-0.34	4.12	12.00	24.83
$\theta \to 0$	-25.88	11.68	10.55	1.46	2.19
II. *Changes* in the aggregate productivity (overall, %)					
Benchmark	1.20				
$\theta \to 0$	0.19				

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, in the baseline model, and in an alternative model with $\theta \to 0$. Panel II reports changes (in %) in the overall aggregate productivity between the benchmark equilibrium and the new equilibrium under the R&D subsidy policy under these two model specifications.

Compared to existing studies estimating firms' return to R&D, the main innovation of this paper lies in allowing for the use of foreign-sourced R&D inputs. Does this feature matter in evaluating the effect of R&D subsidies on firms' R&D choices and aggregate productivity? To answer this question, Table 13 compares the effect of the same R&D subsidy policy between the

[43]To put this number in context, in 2021, among the OECD countries, the implied tax subsidy rates on R&D expenditures (both fixed *and* variable) for large firms exceeds 30% in Portugal, Slovakia, France, Spain, and Iceland.

benchmark model and an alternative model without the heterogeneity in ideas (i.e., $\theta \to \infty$). In this alternative model, the R&D subsidy leads to a much smaller increase in firms' participation in R&D compared to the increase demonstrated in the benchmark model. Moreover, this smaller increase in R&D participation is concentrated primarily among the N and NI modes, as opposed to the NIF mode. This difference results in a significantly different prediction for aggregate productivity: the same R&D subsidy policy generates only 0.19% aggregate productivity gains, less than one-sixth of the prediction of the benchmark model.

In the era of globalized R&D, foreign R&D inputs are playing an increasingly important role and have emerged as a principal source of returns to R&D. Our experiment suggests that overlooking the role of these inputs could substantially underestimate the effect of R&D policies.

6 Conclusion

While substantial progress has been made in understanding firms' foreign sourcing of production inputs, much less is known about their foreign sourcing of R&D inputs. Leveraging unique data from Denmark, this paper investigates firms' choices regarding two foreign R&D inputs—immigrant researchers and imported R&D services—and analyzes the consequences of these decisions on firm performance and aggregate productivity.

We provide evidence demonstrating that firms' use of immigrant researchers and imported R&D services interacts with each other, and that these foreign inputs enhance overall R&D effectiveness. We rationalize these findings through a model of firm dynamics with R&D sourcing. Our counterfactual experiments underscore the pivotal role of access to foreign-sourced ideas in firms' R&D returns and participation. Omitting these inputs or their interaction would lead to different assessments of the effectiveness of innovation, immigration, and offshoring policies.

This paper is a step toward a more comprehensive understanding of firms' global organization of R&D. Our model revolves around the R&D sourcing decision from the perspective of a firm operating in Denmark, leveraging uniquely suited data. However, it does not delve into how R&D sourcing affects the firm's global production. Understanding firms' decisions to carry out R&D in various locations, for both local and global purposes, and how these decisions interact with immigration policies, is an important avenue for future research.

While our findings are drawn from Denmark, an economy that may not be representative of other developed countries, we emphasize that the reliance on foreign ideas and talent in R&D extends beyond Denmark. As discussed in the introduction, the shares of patents invented by immigrants and the proportion of enterprise R&D conducted in offshore locations have both grown substantially over the past decades around the globe. Another important direction for future research involves assessing whether the significance of foreign R&D inputs generalizes to other larger economies and exploring the reasons behind potential heterogeneity across countries.

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Appendix For Online Publication
High-Skill Immigration, Offshore R&D, and Firm Dynamics

Jingting Fan
Pennsylvania State University

Eunhee Lee
Seoul National University

Valerie Smeets
Aarhus University and CEPR

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 the dataset from which each piece of information is obtained, and Table A.2 provides an overview of how each sample is constructed, linking samples to the corresponding tables in the paper. The remainder 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	**Contains the information on**	**Dataset**	**Contains the information on**
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		

Table A.2: Summary of Samples

Sample	Description (coverage and source)	Results using this sample
Baseline sample	For-profit private-sector firms with more than 10 employees, in both FIRE and the R&D survey	Table 1 Panels A and B, Table 2, Table 3, Panel A of Table 5 and parts of 6 (restricted to loss-making R&D-active firms), Appendix Tables A.6, A.7, A.9, A.10, A.11, A.12, A.13, A.14, A.15, A.16
Manufacturing sample	Manufacturing firms in the baseline sample	Table 4, Panel B of Table 5 and parts of 6 (restricted to loss-making R&D-active firms), Table 7, Panel A of Table 8, Appendix Tables B.2, B.3, B.4, B.5
Offshoring survey sample	Firms both in the baseline sample and in the Offshoring Survey	Panel C of Table 1, Table A.8

A.1.1 Detailed Description of Each Database

IDA. The Integrated Database for Labor Market Research (IDA) is a linked employer-employee database provided by Statistics Denmark (DST, hereafter), containing information on the universe of workers and firms in Denmark. The IDA database comprises four datasets with details on individuals, employment, workplaces, and firms, linked through common identifiers. The employment data represent a snapshot in November for each year, excluding workers out of the labor force during that month. In cases where workers report multiple employment spells in November, we retain 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 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. Our classification strategy follows Bernard, Fort, Smeets and Warzynski (2020), who classify occupations into four groups: R&D, management, production and manual work, and services and support activities.

Our empirical analysis focuses on the period between 2001 and 2015. A major change in the DISCO codes occurred in 2008. We classify occupations in the DISCO codes both before and after the change (DISCO88 and DISCO08, respectively). We carefully verify 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.3 reports occupations classified as R&D-related in both DISCO88 and DISCO08. We classify occupation based on the nature of required tasks instead of the skill or wage of the workers in an occupation. In general, occupations related to R&D activities form a subset of DISCO Groups 2 ('Work that requires knowledge at the highest level within the area in question') and 3 ('Work that requires intermediate level knowledge'). Occupations related to management (often associated with DISCO Group 1) are excluded. To minimize subjective judgment, we base classifications on 3-digit occupation codes. Doing so have some drawbacks. For example, we classify the 3-digit occupation 222—'Work on topics in medicine, dentistry, veterinary science and pharmacy'—as R&D-related because some workers in this occupation are doing R&D-related work. But there must also be some health care practitioners that do not engage in R&D at all. We think this concern is unlikely to impact our results for two reasons. First, our descriptive statistics focus on for-profit firms with more than 10 employees; in structural estimation, we further restrict the sample to manufacturing firms. Thus, major biology research institutes, hospitals, and most private healthcare practices are not included in our sample. Second, throughout extensive robustness checks, we consistently find that the key channels we document exist predominantly for, or are stronger among, R&D workers compared to non-R&D workers. If anything, a narrower definition of R&D than ours likely leads to even stronger empirical findings.

The dataset comprises approximately 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 million workers and 28,000 firms per year. Focusing on this sample, we construct workers' hourly wage and determine the municipality of their workplace. This information allows us to compute the primary (or modal) geographic location of each firm in Denmark.

BEF. We complement IDA with information from the national registers (BEF, provided by DST, covering the universe of individuals in Denmark) to identify immigrants. In the baseline analysis, we define immigrants as those born outside Denmark. In various robustness exercises reported in Appendix Section A.3, we also explore alternative definitions of immigrants, lever-

Table A.3: R&D-Related Occupations in DISCO88 and DISCO08 Classifications

DISCO 88 Classification (3-digit)	
Work that requires the highest level of skills in the field in question	
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
Work requiring intermediate skills	
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)	
Work that requires the highest level of skills in the field in question	
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
Work requiring intermediate skills	
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

aging the rich set of demographic information available in the data.

UDDA. We augment IDA with education information from the education register (UDDA, provided by DST). 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', and '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) from 2000 to 2015. FIRE provides accounting information such as revenues, value-added, investments, materials, wage bill, and employment. This dataset also includes information about the firm's primary industry, based on the NACE industry classification, concorded to NACE Rev.2.

The information in FIRE originates from the Tax Authorities, requiring companies with an annual turnover above 0.5 million Danish krone (DKK) and individually-owned companies with an annual turnover above 0.3 million DKK to report accounting information. Due to this sampling strategy, we exclude firms with an annual turnover of less than 0.3 million DKK. Additionally, we exclude government activities and public services firms, not-for-profit firms (determined by legal status, such as not-for-profit funds, associations, non-profit associations, government-owned, church-owned, and not specified), and firms in agriculture or extraction. After matching this FIRE sample with the IDA sample, we end up with approximately 95,000 firms per year. Restricting the sample further to firms with at least 10 employees leaves us with around 17,000

Table A.4: 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

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. The industry-specific deflators are at the NACE Rev.2 Intermediate Aggregation level (A*38 Codes, see Table A.4), and we define the industry of firms accordingly. In total, there are 25 industry groups for the entire private sector and 11 industry groups for the manufacturing sector.

We calculate firms' capital stock using 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 initial 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, an R&D Survey released by DST since 1991. The survey is the Danish equivalent of the European Community Innovation Survey, covering all firms with over 250 employees, more than 1 billion DKK in revenue, spending at least 5 million DKK on R&D activities, or operating in R&D industries (defined as NACE 2-digit Rev.2 industry 72). In addition, it includes a stratified sample of all 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 conducting domestic R&D in year t if they report positive domestic R&D expenditures that year. The survey also captures information on R&D expenditures sourced overseas, either via a foreign subsidiary, foreign consultants,

[1] To avoid biases arising from reporting errors in our structural estimation, we exclude observations exhibiting abnormal accounting statistics. Specifically, we exclude observations with revenue labor ratio, material labor ratio, or capital labor ratio falling outside the 1st to 99th percentile of their respective broad industry groups.

foreign unrelated firms, or foreign research institutes. This variable is available for the following years: 2001-2003, 2005 and 2007-2014. The survey question specifies 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 surveyed entity in Denmark during that year.

Finally, the survey also inquires whether firms have R&D workers present in their foreign affiliates, categorized by broad geographic locations. This information is available from 2009 to 2012 for four geographic areas (Europe, United States and Canada, China, Rest of the World) and from 2013 to 2016 for eight 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 consolidate the 2013-2016 geographic information into the four geographic areas of 2009-2012. We 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×FIRE×FUI sample, limited to firms with at least 10 workers, comprises approximately 47,000 firm-year observations spanning 2001-2015, which amounts to around 3,000 firms per year. This is the sample from which we derive descriptive statistics in Section 2 of the paper.

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

UHDI. We supplement our data with the information on firms' participation in international trade from 2001 to 2015 (UHDI, provided by DST). UHDI is derived from two main sources: Intrastat and Extrastat. Intrastat is based on reports to DST from approximately 7,000 companies per year about their trade in goods with companies in other EU countries. The reporting thresholds under Intrastat are set to ensure that the reporting companies' trade volume represents 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×year×product×country level, to either the firm×year or the firm×year×country level. From this, we determine whether firms are exporting or importing goods in a given year and identify the specific foreign regions with which firms are trading.

FATI. In a robustness exercise in Section A.3, we show that the information value of immigrant researchers in facilitating offshore R&D can be seen among firms that are not an affiliate of a foreign multinational. To this end, we augment the main data with FATI (provided by DST), which identifies foreign multinational firms in Denmark.

[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.'

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

A.1.2 Construction of the Key Variables

Table A.5 summarizes how each of the key variables is constructed with our data.

Table A.5: Summary of Variable Construction

Category	Variable	Notation	Empirical definition
R&D modes	R&D with only natives	N	Firms with positive domestic R&D spending from the R&D survey (Alternative definition in the appendix: Firms employing researchers according to IDA)
	R&D with natives and immigrants	NI	N and employing immigrant researchers according to IDA
	R&D with natives and offshore R&D services	NF	N and positive offshore R&D expenses from the R&D survey
	R&D with all input types	NIF	NI and NF
Indicators	R&D indicator	$\mathbb{I}(\text{R\&D}_{it-1})$	Firms with positive reported R&D expenditures in Denmark according to the R&D survey (Alternative definition in the appendix: Firms employing researchers according to IDA)
	Offshore R&D indicator	$\mathbb{I}(\text{off}_{it-1})$	Firms reporting to have offshore activities in R&D according to the R&D survey
	R&D immigrant indicator	$\mathbb{I}(\text{immi}_{it-1})$	Firms employing immigrant researchers according to IDA
R&D expenses	Total R&D spending	N.A.	Domestic + offshore R&D spending from the R&D survey
	Domestic R&D spending	$e_{i,t-1}$	Reported R&D expenditures in Denmark in the R&D survey

A.2 Regression Evidence on the Information Value of Immigrant Researchers

Table 2 in the text shows that a higher fraction of firms with immigrant researchers than those without immigrants start doing offshore R&D in the next period. This pattern is consistent with immigrant researchers reducing the frictions firms face in sourcing R&D services from abroad. One concern with this interpretation is that the observed pattern could be confounded by other firm characteristics, such as their industry or size. In this section, we present regression evidence to address these 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, enhancing the credibility of the role of employing immigrant researchers in helping firms start offshore R&D. Additionally, we employ a shift-share design that capitalizes on the increase in the supply of immigrant researchers from different foreign regions in Denmark to further address the concern of reverse causality—i.e., firms may hire immigrant researchers because establishing a foreign source of imported R&D services reduces the cost of hiring immigrant researchers.

A.2.1 Firm-Level Evidence

Our firm-level specification for the relationship between offshore R&D and having immigrant researchers is as below:

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

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 engages in offshore R&D in period t. To avoid confusion when exploring variations across foreign regions later, we split Denmark into 5 geographic regions and refer to each geographic region as a 'city'. The key explanatory variable is $\mathbb{I}(\text{immi}_{it-1})$, an indicator for whether firm i had an immigrant employee in R&D-related occupations in period $t-1$. $\tilde{v}_{d(i)j(i)t}$ represents city-industry-year fixed effects, ensuring that our estimate of β does not pick up a higher propensity of hiring immigrant researchers or offshoring R&D among firms in specific cities or industries. $\vec{X}_{it}$ is a vector of time-varying firm characteristics, including size, labor productivity, and lagged importing and exporting status.

Table A.6 reports the estimation results. The first column controls for 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 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 merely capturing the relationship documented in these studies, columns 4 and 5 control for firm-level import and export status, which has minimal impact on the point estimate of β. Column 5 represents our preferred specification, suggesting 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. Building on the specification in column 5, we include an indicator for whether a firm employs immigrants outside R&D-related occupations according to the IDA and report the results in column 6. We find a small negative coefficient for this indicator, $\mathbb{I}(\text{non-R\&D-immi}_{i,t-1})$, indicating that 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*.

The Role of the Firm's Past R&D Investment. Lastly, we investigate whether the empirical evidence concerning the effect of immigrant researchers on a firm's offshore R&D is driven by the firm's past R&D investment. While likely highly correlated with the existing controls in columns 2-5, we add the log of a firm's R&D investment from the previous period to the specifications reported in columns 5-6, respectively, and report the results in columns 7-8. To check if R&D investment strictly within Denmark has a different impact from total R&D investment, we also

[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.7), 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.

control for the log of domestic R&D investment from the previous period and report the results in columns 9-10. The strength of the effect of having immigrant researchers slightly diminishes when including firms' previous R&D investment, but a statistically significant effect persists.

Table A.6: Immigrant Researchers and Offshore R&D: Firm-Level Regressions

	OLS (2001-2014)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{I}(\text{immi}_{i,t-1})$	0.081***	0.041***	0.038***	0.038***	0.038***	0.038***	0.027***	0.027***	0.020***	0.020***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\mathbb{I}(\text{non-R\&D-immi}_{i,t-1})$						-0.011**		-0.010*		-0.008
						(0.004)		(0.006)		(0.005)
$\log(\text{R\&D}_{i,t-1})$							0.111***	0.111***		
							(0.008)	(0.008)		
$\log(\text{Domestic R\&D}_{i,t-1})$									0.018***	0.018***
									(0.001)	(0.001)
Observations	30,930	30,930	30,589	30,589	30,589	30,589	19260	19260	19260	19260
Firm size$_{i,t}$		yes	yes	yes	yes	yes	yes	yes	yes	yes
Productivity$_{i,t}$			yes	yes	yes	yes	yes	yes	yes	yes
Import status$_{i,t-1}$				yes	yes	yes	yes	yes	yes	yes
Export status$_{i,t-1}$					yes	yes	yes	yes	yes	yes
City×industry×year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The sample consists of private sector firms with at least 10 employees from 2001 to 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. Note that $\mathbb{I}(\text{immi}_{i,t-1})$ is based on immigrants working in R&D-related occupations, while $\mathbb{I}(\text{non-R\&D-immi}_{i,t-1})$ is an indicator for whether a firm has immigrants in non-R&D-related occupations. Firm size is measured by log employment, and productivity is measured by log value added per worker. Cities are defined as the five main geographic regions within Denmark, and industries are classified 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.6 indicates that, conditional on other characteristics, firms with immigrant researchers are more likely to engage in offshore R&D. One plausible mechanism driving this correlation is that, by hiring immigrant researchers, firms gain tacit knowledge about the home countries of these immigrants, thereby reducing the frictions in sourcing R&D services from these countries. This mechanism aligns with the reduced-form research on the network effect of immigrants on international business (Rauch and Trindade, 2002). If this channel is indeed the driving force, we would 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 additional advantage of using a firm-destination-level specification is the ability 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.

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

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

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

We use the R&D Survey to construct $\mathbb{I}(\text{off}_{it}^n)$. Between 2009 and 2015, the R&D Survey inquires about the foreign regions where a firm has affiliate R&D employment, providing 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 Rest of the World. Between 2013 and 2015, the survey divides foreign countries into eight 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 aggregate the latter eight regions into the four regions used in 2009-2012, ensuring consistency in defining foreign regions across 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. $\tilde{\phi}_{it}$ represents firm-year fixed effects, absorbing time-varying firm characteristics that might drive the correlation between $\mathbb{I}(\text{off}_{it}^n)$ and $\mathbb{I}(\text{immi}_{it-1}^n)$. Some firms may 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 $\mathbb{I}(\text{off}_{it}^n)$ and $\mathbb{I}(\text{immi}_{it-1}^n)$. To address this concern, we include industry-destination-time and city-destination-time fixed effects, denoted by $\tilde{v}_{d(i)t}^n$ and $\tilde{\eta}_{j(i)t}^n$. 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, $\tilde{X}_{it}^n$ comprises control variables which capture other potential connections between firm i and region n.

Columns 1 to 3 of Table A.7 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 persists when city-industry-destination-year fixed effects are controlled for. Furthermore, it is not attributable to the correlation between either of the two decisions and firms' importing/exporting relationship with region n. In column 3, we also control for whether the firm hires immigrants for non-research occupations from region n, and the point estimate for the coefficient on $\mathbb{I}(\text{immi}_{it-1}^n)$ changes very little. The point estimate indicates that firms hiring immigrant researchers from a foreign region n will experience 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%), possibly 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 immigrants and conduct offshore R&D due to firm-destination-specific factors unobserved by the econometrician. 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 based on a shift-share instrumental variable that exploits the variation in firms' exposure to immigrant researchers in their

[5] While this measure captures geographic variation, it does not encompass 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 the period 2013-2015 and use the 8-region grouping. This approach enables us to distinguish India and different parts of the EU from larger groups. The results are similar and available upon request.

[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.

Table A.7: Immigrant Researchers and Offshore R&D: Firm-Destination-Level Regressions

	OLS (2009-2015)			IV (2009-2015)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\text{immi}^n_{i,t-1})$	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 presents 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 consist of 4 groups: European Union, United States and Canada, China and the rest of the world. The indicators for immigrant R&D workers ($\mathbb{I}(\text{immi}^n_{i,t-1})$) and immigrant non-R&D workers ($\mathbb{I}(\text{Non-R\&D-immi}^n_{i,t-1})$) reflect immigrants from offshoring destination n. Cities and industries are defined as in Table A.6. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Danish location and industry. Specifically, we use the following as an instrument for $\mathbb{I}(\text{immi}^n_{it-1})$:

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

where $j(i)$ and $d(i)$ denote the industry and the (Danish) city of firm i, respectively; $\text{share}^n_{j(i),d(i),2000}$ 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 locations and industries with a high density of existing immigrants from the same origin. The exclusion restriction 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.7 report the IV estimation results. Our design exhibits a reason-

[8] For robustness, we use 1995 as the base year for constructing the instrument while excluding firms that hired immigrant researchers in 1995. This specification yields similar results. Due to differences in firms' industry classification prior to 2000 compared to 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.

ably strong first stage, with the expected sign and a K-P F statistics exceeding 20. The point estimate of the coefficient of interest is positive and statistically significant. Notably, the estimate is an order of magnitude larger than the OLS counterpart, possibly indicating that the IV approach helps address measurement errors. Perhaps more importantly, this could also arise from heterogeneous effects. The instrument leverages variations in the supply of immigrants from a particular origin in the local labor market. Firms operating in a local labor market with a greater presence of immigrants from a particular origin might reap more returns if the hired immigrants can provide valuable information through their connection to the home country within the local immigrant community. This finding resonates with results from the literature that uses regional and industry-level data, supporting the external values of immigrants.

The difference in magnitude notwithstanding, the OLS and the IV results offer complementary evidence—based on orthogonal variations—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 exhibit 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 pertains to in-house employment only. However, firms can also source R&D services from independent foreign suppliers. One concern is that if in-house employment crowds out outside suppliers, the results in Table A.7 might capture this substitution effect rather than implying 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.8: Immigrant Researchers and Offshore R&D: Evidence from the Offshoring Survey

	OLS (2011)			
	Firm-Level		**Firm-Destination-Level**	
	(1)	(2)	(3)	(4)
$\mathbb{I}(\text{immi}_{i,t-1})$	0.048***	0.048***	0.013*	0.012*
	(0.015)	(0.015)	(0.007)	(0.007)
$\mathbb{I}(\text{Non-R\&D-immi}_{i,t-1})$		-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×industry FE	yes	yes		
City×industry×destination FE			yes	yes

Notes: In this table, a firm is classified as offshoring if it reports having R&D activities abroad in the Offshoring Survey for the year 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), meaning that the two indicator functions as explanatory variables are also region-specific for columns 3 and 4. Foreign regions in columns 3 and 4 comprise 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.6 and Table A.7. Standard errors (in parentheses) are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[9] This concern does not apply to the results in Table A.6.

Table A.8 reports the estimation results. Columns 1 and 2 are at the firm-level as in Equation (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. In other words, the two explanatory variables reported in Table A.8 are $\mathbb{I}(\text{immi}^n_{i,t-1})$ and $\mathbb{I}(\text{Non-R\&D-immi}^n_{i,t-1})$ in columns 3 and 4. The results show that this alternative measure of offshore R&D yields 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 consistently observe that the coefficient of non-R&D immigrants has different signs, with or without statistical significance, across specifications. This suggests that the information value for offshore R&D is primarily associated with immigrants with R&D-related occupations.

A.3 Robustness Exercises for Reduced-Form Facts

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

A.3.1 Alternative Definitions of Immigrants

The first overarching concern pertains to the definition of immigrants. In our baseline analysis, immigrants are defined as individuals born outside Denmark. Our model highlights two key roles of immigrants: their possession of specific knowledge about their home country, contributing valuable information to the firm, and the additional value they bring to the R&D process through diverse backgrounds and expertise. However, not all researchers born outside Denmark can play these roles. For example, an immigrant who arrived in Denmark as an infant might not be able to speak the language of her home country, and having been educated in Denmark, might not provide the diversity of ideas to the R&D process. This concern also extends to immigrant researchers from other Scandinavian countries, who may be relatively more similar to Danish researchers. Consequently, our reduced-form findings might potentially reflect the close economic ties between Scandinavian countries rather than capturing the broader role that immigrants could play in their local economy.

We acknowledge that if such concerns are empirically relevant, our empirical analysis, which includes all immigrants rather than only those likely to fulfill the two roles outlined a priori, could potentially *underestimate* the role of immigrants. In this subsection, we present direct evidence demonstrating that excluding immigrants who may not differ significantly from native workers does not weaken our reduced-form results. Specifically, we explore alternative definitions of immigrants, including those who enter Denmark at age 18 or above, at age 22 or above, and after completing their highest level of education. Additionally, we exclude immigrants from Sweden and Norway.

Table A.9 reports evidence on the role of immigrant researchers in facilitating firms' offshore R&D under narrower definitions of immigrant researchers. For conciseness, we focus on the firm-level OLS specifications. Column 1 replicates our preferred specification from Table A.6 (column 5). The subsequent columns report results using various alternative definitions of immigrant researchers. Notably, we find that the impact of having immigrant researchers on offshore R&D is stronger when we focus on immigrant researchers likely to differ more from Danish researchers, as indicated by these alternative definitions.

Table A.10 reports robustness exercises for Table 3 from the paper, focusing on the sourcing of R&D inputs and firm performance. The first two columns reproduce our preferred specifications from Table 3 (columns 4 and 8). 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 either similar to or slightly larger than those in the baseline specification.

Table A.9: Immigrant Researchers and Offshore R&D: Alternative Definitions of Immigrants

	baseline	**> 18 yr**	**> 22 yr**	**completed education**	**non-Scandinavians**
	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}(\text{immi}_{i,t-1})$	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 relationship between employing immigrant researchers and offshore R&D based on different definitions of immigrants. Specifications follow column 5 of Table A.6. 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.10: R&D Input Sourcing 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 exercises 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 same specifications with alternative definitions for immigrant researchers. See the notes of Table A.9 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. In the reduced-form analysis, 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, potentially leading to biases in the inferred impact of having immigrant researchers on firm's offshore R&D.

We address the concern on reduced-form and structural estimation separately. Tables A.11 and A.12 report the evidence on the information value of immigrant researchers for offshore R&D and on the relationship between international sourcing of R&D and firm performance, with different cutoffs for the number of immigrant researchers used to classify firms as hiring immigrants for R&D. The results are consistent across specifications.

Table A.11: Immigrant Researchers and Offshore R&D: Alternative Mode Classifications

	baseline	**# of immi ≥ 2**	**# of immi ≥ 5**
	(1)	(2)	(3)
$\mathbb{I}(\text{immi}_{i,t-1})$	0.038***		
	(0.005)		
$\mathbb{I}(\text{immi}_{i,t-1} \geq 2)$		0.079***	
		(0.006)	
$\mathbb{I}(\text{immi}_{i,t-1} \geq 5)$			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.6. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.13, we report 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.13 replicates the transition matrix in Table 8 of the text. The middle and right panels correspond to the cases where at least two 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 direction of the effect of having immigrant researchers on offshore R&D, 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.14 both three- and five- year transition matrices. The qualitative patterns that identify the information value of immigrant researchers for offshore R&D are robust.

Table A.13: 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.14: 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 effect of having immigrant researchers on offshore R&D 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 necessarily be 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.15 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.6. Columns 3 and 4 replicate columns 2 and 3 of Table A.7. The sample shrinks by around 25%, but the estimates remain essentially the same.

Table A.15: Immigrant Researchers and Offshore R&D: 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$\times$industry$\times$ 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$\times$industry$\times$destination$\times$ year FE			Yes	yes

Notes: This table reports the robustness for the relationship between employing immigrant researchers and offshore R&D, excluding affiliates of foreign multinationals from the sample. Columns 1 and 2 follow the specifications in columns 5 and 6 of Table A.6; columns 3 and 4 follow the specifications in columns 2 and 3 of Table A.7. As defined previously, $\mathbb{I}(\text{immi}_{i,t-1})$ is an indicator function for immigrants in R&D-related occupations, and $\mathbb{I}(\text{Non-R\&D-immi}_{i,t-1})$ is the one for immigrants in non-R&D-related occupations. 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.16 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 engineering talent, 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, geographic proximity to Denmark, and EU membership.

Table A.16: 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 Deriving 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 Deriving Equation (14)

Let $s_x^{\tilde{x}}$ denote the share of R&D expenditures of a firm in mode $x \in X\{NI, NF, NIF\}$ that is spent on input $\tilde{x} \in \{N, I, F\}$. Analogous derivations to Eaton and Kortum (2002) deliver:

$$\begin{cases} s_{NI}^{N} = \left(\frac{c^N}{c^{NI}}\right)^{-\theta} \\ s_{NI}^{I} = 1 - s_{NI}^{N} \end{cases} \qquad \begin{cases} s_{NF}^{N} = \left(\frac{c^N}{c^{NF}}\right)^{-\theta} \\ s_{NF}^{F} = 1 - S_{NF}^{N} \end{cases} \qquad \begin{cases} s_{NIF}^{N} = \left(\frac{c^N}{c^{NIF}}\right)^{-\theta} \\ s_{NIF}^{I} = \left(\frac{c^{NI}}{c^{NIF}}\right)^{-\theta} - \left(\frac{c^N}{c^{NIF}}\right)^{-\theta}, \\ s_{NIF}^{I} = 1 - s_{NIF}^{N} - s_{NIF}^{I} \end{cases} \quad \text{(B.1)}$$

where $c^x,\ x \in \{N, NI, NF, NIF\}$, is defined in equation (8). Note here we follow the convention in the text to omit the i, t subscripts.

Let $e_{i,t-1}$ be the total R&D expenditures on inputs within Denmark. Then, the effective R&D investment (for all sources) for firms in mode $x \in \{N, NI\}$ is given by

$$rd_{i,t-1} = \begin{cases} \frac{e_{i,t-1}}{c^N}, \text{ if } x = N \\ \frac{e_{i,t-1}}{c^{NI}} = \frac{e_{i,t-1}}{c^N} \cdot \frac{c^N}{c^{NI}}, \text{ if } x = NI. \end{cases} \tag{B.2}$$

Using equation (B.1), the effective investment for firms in mode $x \in \{NF, NIF\}$ is given by

$$rd_{i,t-1} = \begin{cases} \frac{e_{i,t-1}}{s^N_{NF} \cdot c^{NF}} = \frac{e_{i,t-1}}{c^N} \cdot \frac{c^N}{c^{NF}} \cdot \left(\frac{c^{NF}}{c^N}\right)^{-\theta}, \text{ if } x = NF \\ \frac{e_{i,t-1}}{(s^N_{NIF} + s^I_{NIF}) \cdot c^{NIF}} = \frac{e_{i,t-1}}{c^N} \cdot \frac{c^N}{c^{NI}} \cdot \frac{c^{NI}}{c^{NIF}} \cdot \left(\frac{c^{NIF}}{c^{NI}}\right)^{-\theta}, \text{ if } x = NIF. \end{cases} \tag{B.3}$$

Plugging equations (B.2) and (B.3) into equation (5) delivers equation (14).

B.3 Estimating the Material Share

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 materials with $P_{m,t}$ being the price of material, 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:

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

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

$$\exp\left(\tilde{y}_{i,t}(\tilde{m}_{i,t}|\omega_{i,t}, \tilde{k}_{i,t}, \tilde{l}_{i,t})\right) \cdot \tilde{\beta}_m = P_{m,t} \cdot \exp(\tilde{m}_{i,t}). \tag{B.4}$$

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.4), we thus have:

$$\frac{P_{m,t} \cdot \exp(\tilde{m}_{i,t})}{\exp\left(\tilde{y}_{i,t}\right)} = \tilde{\beta}_m \exp(-\tilde{\epsilon}_{i,t}) \tag{B.5}$$
$$\Longleftrightarrow \log\left(\frac{P_{m,t} \cdot \exp(\tilde{m}_{i,t})}{\exp(\tilde{y}_{i,t})}\right) = \log(\tilde{\beta}_m) - \tilde{\epsilon}_{i,t}.$$

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 4), we pool all firms to estimate the average material share. For robustness, we also estimate equation (B.5) by industry to obtain industry-specific material shares, which we then plug into the GMM estimation. The main findings from this exercise, reported in Section B.4 of this appendix, are materially the same as the baseline results.

B.4 Robustness Exercise for Production Function Estimation

In this section, we conduct five sets of robustness exercises on the GMM estimation of the production function. In the first two exercises, respectively, we use only indicators for R&D modes rather than the log of R&D expenditures, and alternative definition of firms' R&D status; in the third and fourth exercises, 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. In the final exercise, we include only non-R&D labor when estimating equation (13). 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.4.1 Estimation with Discrete R&D Measure

In Columns 4-6 of Table 4 in the text, we use the log of R&D spending and indicators for the use of foreign R&D inputs to estimate the impacts of R&D on firm productivity. One may be concerned that measurement errors with R&D expenditures can lead to bias in our estimates. We replicate the results in Columns 4-6 of Table 4 using only indicators for firms' R&D modes. The results are reported in Table B.1 below. As the table shows, the input elasticities and the coefficients for indicator for using foreign R&D inputs are both similar to the results in Table 4.

B.4.2 Alternative Classification 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 domestic researchers, there are two options. As 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. However, some firms might report incurring R&D expenditures and 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

Table B.1: Specification with Discrete R&D Measure

	GMM estimation of (13)		
	(1)	(2)	(3)
$\omega_{i,t-1}$	0.472***	0.482***	0.485***
	(0.150)	(0.122)	(0.138)
$\mathbb{I}(x_{i,t-1} = N)$	0.010**	0.009**	0.009**
	(0.004)	(0.004)	(0.004)
$\mathbb{I}(x_{i,t-1} = NI)$	0.024***	0.024***	0.023***
	(0.008)	(0.008)	(0.008)
$\mathbb{I}(x_{i,t-1} = NF)$	0.000	-0.000	-0.000
	(0.007)	(0.007)	(0.008)
$\mathbb{I}(x_{i,t-1} = NIF)$	0.047***	0.048***	0.048***
	(0.017)	(0.015)	(0.015)
Revenue elasticities			
$\tilde{\beta}_l$	0.489***	0.487***	0.487***
	(0.017)	(0.016)	(0.015)
$\tilde{\beta}_k$	0.114***	0.113***	0.112***
	(0.016)	(0.013)	(0.014)
$\tilde{\beta}_m$	0.421***	0.421***	0.421***
	(0.002)	(0.002)	(0.002)
Industry fixed effects	yes	yes	yes
Lag import dummy		yes	yes
Lag export dummy			yes
Number of observations	9,320	9,320	9,320

Notes: This table replicates Columns 4-6 of Table 4 in the text, replacing the control $\log(e_{i,t-1})$ with an indicator variable for $\mathbb{I}(x_{i,t-1} = N)$. Bootstrapped standard errors are clustered by firm and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F, it also employs native researchers. Table B.2 reports the results, which follow the specifications in Table 4. The coefficients on R&D and different modes of R&D are similar to those in Table 4.

Table B.2: R&D and Productivity Evolution: Alternative Classification of R&D Modes

	GMM estimation of (13)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\omega_{i,t-1}$	0.472***	0.479***	0.480***	0.465***	0.476***	0.479***
	(0.129)	(0.110)	(0.116)	(0.146)	(0.131)	(0.125)
$\log(e_{i,t-1})$				0.002***	0.002***	0.002***
				(0.001)	(0.001)	(0.001)
$\mathbb{I}(x_{i,t-1} = N)$	0.013**	0.011**	0.011**			
	(0.006)	(0.006)	(0.006)			
$\mathbb{I}(x_{i,t-1} = NI)$				0.024***	0.023***	0.023***
				(0.008)	(0.008)	(0.008)
$\mathbb{I}(x_{i,t-1} = NF)$				-0.000	-0.001	-0.001
				(0.008)	(0.008)	(0.008)
$\mathbb{I}(x_{i,t-1} = NIF)$				0.042***	0.044***	0.044***
				(0.016)	(0.015)	(0.015)
$\mathbb{I}(x_{i,t-1} \in \{NI, NF, NIF\})$	0.038***	0.037***	0.036***			
	(0.012)	(0.010)	(0.011)			
Industry fixed effects	yes	yes	yes	yes	yes	yes
Lag import dummy		yes	yes		yes	yes
Lag export dummy			yes			yes
Number of observations	9,237	9,237	9,237	9,237	9,237	9,237

Notes: This table replicates Table 4 in the text using 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.4.3 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 is advantageous in maintaining compatibility with the monopolistic competition environment. As an alternative, we can focus on value-added, following the approach in the seminal works by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). This alternative implicitly treats materials as additive in the total revenue function.

Concretely, we assume that firms' log value-added is given by:

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

where $\tilde{\epsilon}_{i,t}$ represents a measurement error in revenue; $\tilde{l}_{i,t}$ and $\tilde{k}_{i,t}$ are log labor and capital, respectively; $\omega_{i,t}$ denotes total factor productivity for the value-added version of equation (13). Following the approach in Olley and Pakes (1996), firms make the investment decision in $t-1$, after the realization of $\zeta_{i,t-1}$.

We express 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 $z_{i,t}$ represents the set of controls that might affect a firm's investment decision, such as the firm's import/export status and average wage. Given our assumption on the evolution of productivity, strict monotonicity of $i_{i,t}$ in $\omega_{i,t}$ holds. Thus, we can invert the investment function to obtain 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 a two-step procedure similar to Olley and Pakes (1996). In the first step, we employ a flexible function of $i_{i,t}$, $\tilde{k}_{i,t}$, $\tilde{l}_{i,t}$, and $z_{i,t}$ to purge out 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.3 reports the results. Focusing on value-added, this approach yields a higher persistence in productivity compared to the baseline specifications. Reassuringly, the key coefficients of interest—those associated with R&D status—remain qualitatively similar to those in Table 4.

B.4.4 Industry-Specific Material Shares

By focusing on the value-added production function, the robustness exercise reported in Table B.3 allows individual firms to differ in their material use. In this subsection, we conduct an alternative robustness exercise by estimating a revenue production function, allowing for material shares to differ by industry.

To achieve this, we first estimate equation (B.5) by industry, obtaining industry-specific material shares. Subsequently, we plug these shares into equation (13) and estimate it via GMM, using the same set of instruments as in the baseline analysis. Table B.4 reports the results. The estimates remain robust even when applying industry-specific material shares to all firms.

B.4.5 Using Only Non-R&D Labor in Estimating the Production Function

As we consider potentially distinct roles played by researchers and non-researchers, one may think that the estimation of the production function should exclusively involve non-R&D workers. To address this concern, we replicate the analysis from Table 4 in the main text by excluding

Table B.3: R&D and Productivity Evolution: Value-Added Production Function

	GMM estimation of (13)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\omega_{i,t-1}$	0.679***	0.688***	0.692***	0.696***	0.707***	0.712***
	(0.089)	(0.089)	(0.090)	(0.096)	(0.097)	(0.098)
$\log(e_{i,t-1})$				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**			
	(0.004)	(0.004)	(0.004)			
$\mathbb{I}(x_{i,t-1} = NI)$				0.019***	0.019**	0.018**
				(0.007)	(0.007)	(0.008)
$\mathbb{I}(x_{i,t-1} = NF)$				-0.019*	-0.019*	-0.019*
				(0.011)	(0.010)	(0.011)
$\mathbb{I}(x_{i,t-1} = NIF)$				0.027**	0.028**	0.028**
				(0.011)	(0.012)	(0.012)
$\mathbb{I}(x_{i,t-1} \in NI \bigcup NF \bigcup NIF)$	0.018**	0.018**	0.018**			
	(0.007)	(0.007)	(0.007)			
Industry fixed effects	yes	yes	yes	yes	yes	yes
Lag import dummy		yes	yes		yes	yes
Lag export dummy			yes			yes
Number of observations	9,260	9,260	9,260	9,260	9,260	9,260

Notes: This table follows the same sample and specifications as in Table 4. In contrast to Table 4, where we estimate a revenue production function, this table focuses on estimating a value-added production function. Bootstrapped standard errors, clustered by firm, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: R&D and Productivity Evolution: Industry Specific Material Shares

	GMM estimation of (13)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\omega_{i,t-1}$	0.446***	0.464***	0.465***	0.452***	0.471***	0.474***
	(0.132)	(0.155)	(0.145)	(0.138)	(0.153)	(0.140)
$\log(e_{i,t-1})$				0.002***	0.002***	0.002***
				(0.001)	(0.001)	(0.001)
$\mathbb{I}(x_{i,t-1} = N)$	0.009**	0.008**	0.008**			
	(0.004)	(0.004)	(0.004)			
$\mathbb{I}(x_{i,t-1} = NI)$				0.026***	0.025***	0.025***
				(0.008)	(0.008)	(0.008)
$\mathbb{I}(x_{i,t-1} = NF)$				-0.002	-0.003	-0.004
				(0.008)	(0.007)	(0.007)
$\mathbb{I}(x_{i,t-1} = NIF)$				0.042***	0.044**	0.044**
				(0.016)	(0.018)	(0.017)
$\mathbb{I}(x_{i,t-1} \in \{NI, NF, NIF\})$	0.025***	0.025***	0.025***			
	(0.008)	(0.009)	(0.009)			
Industry fixed effects	yes	yes	yes	yes	yes	yes
Lag import dummy		yes	yes		yes	yes
Lag export dummy			yes			yes
Number of observations	9,320	9,320	9,320	9,320	9,320	9,320

Notes: This table replicates the results from Table 4 in the text, incorporating industry-specific material shares. Bootstrapped standard errors, clustered by firm, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

researchers. The results, presented in Table B.5, indicate that the estimation results closely align with the baseline results.

B.5 R&D Subsidy Estimating Equation: Deriving Equation (18)

With the R&D subsidy in place, the log odds ratio of a firm discontinuing R&D versus remaining in the same mode is

Table B.5: R&D and Productivity Evolution: Using Non-R&D Labor

	GMM estimation of (13)					
	(4)	(5)	(6)	(1)	(2)	(3)
$\omega_{i,t-1}$	0.488***	0.499***	0.499***	0.498***	0.511***	0.512***
	(0.131)	(0.141)	(0.131)	(0.133)	(0.140)	(0.135)
$\log(e_{i,t-1})$				0.003***	0.003***	0.003***
				(0.001)	(0.001)	(0.001)
$\mathbb{I}(x_{i,t-1} = N)$	0.013**	0.012**	0.012**			
	(0.006)	(0.006)	(0.006)			
$\mathbb{I}(x_{i,t-1} = NI)$				0.035***	0.034***	0.034***
				(0.007)	(0.007)	(0.007)
$\mathbb{I}(x_{i,t-1} = NF)$				-0.005	-0.006	-0.006
				(0.008)	(0.008)	(0.008)
$\mathbb{I}(x_{i,t-1} = NIF)$				0.052***	0.053***	0.053***
				(0.014)	(0.015)	(0.015)
$\mathbb{I}(x_{i,t-1} \in \{NI, NF, NIF\})$	0.035***	0.034***	0.034***			
	(0.011)	(0.012)	(0.011)			
Industry fixed effects	yes	yes	yes	yes	yes	yes
Lag import dummy		yes	yes		yes	yes
Lag export dummy			yes			yes
Number of observations	9,073	9,073	9,073	9,073	9,073	9,073

Notes: This table replicates Table 4 using non-R&D-labor as the labor input. Bootstrapped standard errors, clustered by firm, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$$\log\left(\frac{m_t^{\prime x,0}(\mathbf{s}_{i,t})}{m_t^{\prime x,x}(\mathbf{s}_{i,t})}\right) = (1-\tau)\times\frac{1}{\nu}[c^x \times rd_{i,t}^{*\prime}(\omega_{i,t},x) + f^x] + \frac{\delta}{\nu}\left[E_t V_{t+1}'\big(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=0\big) - E_t V_{t+1}'\big(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=rd_{i,t}^{*\prime}(\omega_{i,t},x)\big)\right], \tag{B.6}$$

where $'$ indicates variables in the presence of the subsidy (e.g. $rd_{i,t}^{*\prime}(\omega_{i,t},x)$, V_{t+1}'), and τ indicates the subsidy rate.

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 the policy, i.e., $V_{i,t}(\cdot) \approx V_{i,t}^{\prime}(\cdot)$.[10] Under this assumption, we can express firms' continuation value net of R&D investment as:

$$\begin{aligned}
&\delta E_t V'_{t+1}\big(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=rd_{i,t}^{*\prime}(\omega_{i,t},x)\big) - (1-\tau)\times[c^x \times rd_{i,t}^{*\prime}(\omega_{i,t},x) + f^x] \\
&= \max_{rd_{i,t}}\{\delta E_t V'_{t+1}\big(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}\big) - (1-\tau)\times(c^x \times rd_{i,t} + f^x)\} \\
&\approx \max_{rd_{i,t}}\{\underbrace{\delta E_t V_{t+1}\big(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}\big) - (1-\tau)\times(c^x \times rd_{i,t} + f^x)}_{\equiv f(rd_{i,t},\ \tau)}\} \\
&\approx \max_{rd_{i,t}}\{f(rd_{i,t},\ 0)\} + \tau\cdot\frac{\partial f(rd_{i,t},\ \tau)}{\partial\tau}\Big|_{rd_{i,t}=\arg\max_{rd_{i,t}}\{f(rd_{i,t},\ 0)\}} \\
&= \underbrace{\delta E_t V_{t+1}\big(\omega_{i,t+1}|\omega_{i,t}, rd_{i,t}=rd_{i,t}^{*}(\omega_{i,t},x)\big) - [c^x \times rd_{i,t}^{*}(\omega_{i,t},x) + f^x]}_{\max_{rd_{i,t}}\{f(rd_{i,t},\ 0)\}} + \tau\times[c^x \times rd_{i,t}^{*}(\omega_{i,t},x) + f^x].
\end{aligned} \tag{B.7}$$

[10] Assuming $V_{i,t}(\cdot) \approx V_{i,t}^{\prime}(\cdot)$ does not imply that firms perceive their continuation values to be the same as before because by adjusting R&D expenditures, firms can change the future states.

The first equality in (B.7) follows from the definition of $rd_{i,t}$ as the solution to the Bellman equation (9); the approximation in the second line stems from our assumption of $V_{i,t}(\cdot) \approx V'_{i,t}(\cdot)$; the third and fourth lines result from an application of the Envelope Theorem. Intuitively, in the absence of the subsidy, firms were optimally choosing R&D expenditures to maximize the net value $f(rd_{i,t}, 0)$. After the subsidy is introduced, firms' response in the R&D expenditures only has a second-order effect. Thus, the first-order effect of the subsidy on firms' net value is simply the subsidy rate times the optimal R&D expenditures in the absence of the subsidy.[11]

By combining equations (B.7) with equations (17) and (B.6), along with the earlier assumption that results in $V_{i,t}(\cdot) \approx V'_{i,t}(\cdot)$, we arrive at the expression described in the text.:

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

B.6 Identification of Structural Parameters from Problem (21)

In this section, we first show that, for a given $\tilde{\gamma}_i, i = 0, 1, 2, 3$, and without the knowledge of $A^{\tilde{x}}$ and $p^{\tilde{x}}$ for $\tilde{x} \in \{N, I, F\}$, we can verify whether the model-implied s^N_{NI} and s^N_{NIF} equal their empirical counterparts, $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$. We then proceed to show that $\tilde{\gamma}_i, i = 0, 1, 2, 3$, together with $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$, are sufficient to identify θ and conduct counterfactual exercises.

Checking $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$. Specifically, from equations (14) in the text, we have the following mapping from $\tilde{\gamma}_i, i = 0, 1, 2, 3$ to the structural parameters of the model:

$$
\begin{cases}
\tilde{\gamma}_0 = \gamma, \quad (1) \\
\tilde{\gamma}_1 = \gamma\left[\log(c^N) - \log(c^{NI})\right], \quad (2) \\
\tilde{\gamma}_2 = \gamma(\theta+1)\left[\log(c^N) - \log(c^{NF})\right], \quad (3) \\
\tilde{\gamma}_3 = \gamma\left[(\theta+1)\left(\log(c^{NI}) - \log(c^{NIF})\right) + \left(\log(c^N) - \log(c^{NI})\right)\right]. \quad (4)
\end{cases}
\tag{B.8}
$$

Using the first two lines of the equation, we have

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

Plug the above into line 4 of equation (B.8) and re-arrange it to obtain

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

[11] Note that firms' optimal R&D expenditures will change after the introduction of the subsidy. Still, the impact on firms' continuation value is captured by the original R&D expenditures.

Using the expressions of s^N_{NI} and s^N_{NIF} from equation (B.1), for the model to match $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$, it must be the case that

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

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

Combining the above equations, we obtain:

$$\begin{aligned} &-\frac{\tilde{\gamma}_1}{\tilde{\gamma}_0}\theta = \log(\hat{s}^N_{NI}) \\ &-\frac{\theta}{\tilde{\gamma}_0(\theta+1)}[\tilde{\gamma}_3 + \tilde{\gamma}_1\theta] = \log(\hat{s}^N_{NIF}). \end{aligned} \tag{B.9}$$

Thus, to verify whether a given guess of $\boldsymbol{\lambda}$ can match $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$, we first use the first line of equation (B.9) to back out θ. Subsequently, we substitute this θ into the second line of (B.9) and verify whether the equation holds. If the equality holds, it indicates that $\tilde{\gamma}_i, i = 0,1,2,3$ can satisfy both constraints. This result enables us to choose parameters that minimize the deviation of the model from the data on transition patterns, within the set of parameters matching both $\hat{s}^N_{NI}$ and $\hat{s}^N_{NIF}$, without estimating $A^{\tilde{x}}$ and $p^{\tilde{x}}$ for $\tilde{x} \in \{N, I, F\}$.

Solving the Firms' Problem without the Fundamentals. In solving problem (21), we need to simulate firms' decisions. For any given $\tilde{\gamma}_i, i = 0,1,2,3$, we solve the firms' optimization problem using equation (14) as their law of motion for productivity, allowing firms to choose both the mode of R&D and R&D spending $e_{i,t-1}$. An additional aspect of solving the firms' problem is that $e_{i,t-1}$ in equation (14) corresponds to firms' total R&D spending on factors within Denmark and does not include spending on offshore sources. However, it is the total spending on all sources that enters the Bellman equations (see equation (9)). Therefore, when solving for firms' decisions, we need to account for the fact that the R&D level governing the law of motion of productivity is not always the same as firms' total R&D spending.

To account for this difference, we analytically derive the share of offshore R&D expenditures in total R&D expenditures for firms in mode $x = NF, NIF$ as a function of $\tilde{\gamma}_i, i = 0,1,2,3$. Recall from equation (B.1) that

$$s^N_{NIF} + s^I_{NIF} = \left(\frac{c_{NI}}{c_{NIF}}\right)^{-\theta}$$
$$s^N_{NF} = \left(\frac{c_N}{c_{NF}}\right)^{-\theta}.$$

Combining this with equation (B.8) delivers

$$\begin{aligned} s^N_{NF} &= \exp\Big(-\frac{\tilde{\gamma}_2\theta}{\tilde{\gamma}_0(\theta+1)}\Big) \\ s^N_{NIF} + s^I_{NIF} &= \exp\Big(-\frac{(\tilde{\gamma}_3 - \tilde{\gamma}_1)\theta}{\tilde{\gamma}_0(\theta+1)}\Big). \end{aligned} \tag{B.10}$$

Thus, for firms in mode NF, the total spending is given by $e_{i,t-1}/s^N_{NF}$. Similarly, for firms in mode NIF, the total spending is $e_{i,t-1}/(s^N_{NIF}+s^I_{NIF})$.

In solving the problem (21), for any given $\boldsymbol{\lambda}$, we solve the firm's decision in $t-1$ using the law of motion implied by $\tilde{\gamma}_i, i=0,1,2,3$. Firms choose the mode x and $e_{i,t-1}$ to maximize their value function. When calculating these values, we consider that the actual R&D expenses are the sum of $e_{i,t-1}$ and the offshore component. The relationship between the two is governed by equation (B.10), which can be readily calculated with $\tilde{\gamma}_i, i=0,1,2,3$ and θ.

Identification of Structural Parameters and Counterfactuals. The above discussion suggests that when the constraint in problem (21) is satisfied, we also recover θ from equation B.9. Plugging the recovered θ into equation (B.8) delivers $\left[\log(c^N)-\log(c^{NI})\right]$, $\left[\log(c^N)-\log(c^{NF})\right]$, and $\left[\log(c^N)-\log(c^{NIF})\right]$ as function of θ and $\tilde{\gamma}_i, i=0,1,2,3$.

Note that even though we do not identify $A^{\tilde{x}}$ and $p^{\tilde{x}}$ for $\tilde{x}\in\{N,I,F\}$, the differences in the effective cost of R&D investment between different modes are sufficient for the counterfactuals that we are interested in. For example, by setting $\left[\log(c^N)-\log(c^{NI})\right]$ to zero and setting $\left[\log(c^N)-\log(c^{NIF})\right]$ to be the same as $\left[\log(c^N)-\log(c^{NF})\right]$ and calculating the implied $\tilde{\gamma}_i, i=0,1,2,3$ using equation (B.8), we can conduct a counterfactual where foreign R&D inputs do not bring any additional gains in firm productivity.

B.7 A Model of R&D with Source-Specific Input Accumulation

In this section, we develop a model of R&D with source-specific R&D input accumulation and demonstrate how this model can be mapped to the benchmark model presented in Section 3 through a re-interpretation of the cost of switching R&D modes, $\widetilde{\mathbf{F}}$.

To establish a clear connection to the benchmark model, we begin by micro-founding the productivity law of motion (equation (5)) in the benchmark model, using a model of know-how accumulation via R&D.

Setup. We assume that the productivity of firm i in period t depends on two factors: the stock of accumulated intangible capital, encompassing factors such as production know-how and consumer brand loyalty, and an idiosyncratic term. Formally, we specify

$$\omega_{i,t}=\log(H_{i,t})+\zeta_{i,t},$$

where $H_{i,t}$ is the stock of intangible capital, and $\zeta_{i,t}$ is the idiosyncratic term. We assume that $H_{i,t}$ evolves with $H_{i,t-1}$ and the firm's effective R&D in $t-1$, $rd_{i,t-1}$, according to the following:

$$H_{i,t}=\begin{cases}(H_{i,t-1})^{\rho}(rd_{i,t-1})^{\gamma}, & rd_{i,t-1}>0\\ (H_{i,t-1})^{\rho}, & rd_{i,t-1}=0.\end{cases}$$

Then, this setup leads to a law of motion for productivity akin to equation (5) with the following mapping: the auto-correlation parameter ρ in equation (5) is converted into the (geometric) depreciation rate of intangible capital, and the return-to-R&D parameter γ in equation (5) is now the elasticity of period-t intangible capital stock to effective R&D investment in period $t-1$.

We now consider a more general setting, in which firms can accumulate intangible capital from different sources (N, I, and F), all of which will then be combined to form the overall intangible capital of the firm. Let $H^{\tilde{x}}_{i,t}$, denote the stock of intangible capital in firm i accumulated from source $\tilde{x}\in\{N,I,F\}$. The accumulation of $H^{\tilde{x}}_{i,t}$ is governed by

$$H^{\tilde{x}}_{i,t}=\mathbb{I}(rd^{\tilde{x}}_{i,t-1}>0)\cdot[H^{\tilde{x}}_{i,t-1}]^{\rho}[rd^{\tilde{x}}_{i,t-1}]^{\gamma}+\left(1-\mathbb{I}(rd^{\tilde{x}}_{i,t-1}>0)\right)\cdot[H^{\tilde{x}}_{i,t-1}]^{\rho},$$

in which $rd^{\tilde{x}}_{i,t-1}$ represents the *flow* investment in R&D input of type $\tilde{x}$ with a price of $p^{\tilde{x}}$. The source-specific stock is then combined into firm-wide intangible stock through the following technology

$$H_{it} = \left[(A^N)^{\frac{1}{\theta}}(H^N_{i,t})^{\frac{\theta-1}{\theta}} + (A^I)^{\frac{1}{\theta}}(H^I_{i,t})^{\frac{\theta-1}{\theta}} + (A^F)^{\frac{1}{\theta}}(H^F_{i,t})^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \tag{B.11}$$

where θ is the elasticity of substitution between different input types.

Steady-State R&D Input Composition. In this setup, the optimal mix of R&D flow for firms depends on the composition of their current stock. For example, for firms in mode NIF, the ratio between the optimal investment in input N and F, denoted by $\frac{rd^N_{i,t}}{rd^F_{i,t}}$, depends not only on the relative prices $\frac{p^N}{p^F}$ but also on $\frac{H^N_{i,t}}{H^F_{i,t}}$.

We consider a particular composition of intangible stocks in period t—what we call the 'steady-state composition', under which firms' optimal investment is such that the composition of the stock of different intangible inputs stays the same. For example, for a firm in mode NIF, under the steady-state input mix of this mode, we have:

$$\frac{H^N_{i,t}}{H^F_{i,t}} = \left(\frac{H^N_{i,t-1}}{H^F_{i,t-1}}\right)^{\rho}\left(\frac{rd^N_{i,t-1}}{rd^F_{i,t-1}}\right)^{\gamma} \implies \frac{H^N_{i,t}}{H^F_{i,t}} = \frac{H^N_{i,t-1}}{H^F_{i,t-1}} = \left(\frac{rd^N_{i,t-1}}{rd^F_{i,t-1}}\right)^{\frac{\gamma}{1-\rho}}, \tag{B.12}$$

and we can derive the steady-state ratio between $H^N_{i,t}$ and $H^I_{i,t}$ analogously.

We derive the steady-state composition of $H^{\tilde{x}}_{i,t}$ and $rd^{\tilde{x}}_{i,t}$ for $\tilde{x} \in \{N, I, F\}$ for firms in the NIF mode. First, suppose that firms are restricted to the NIF mode, in which case firms do not need to consider the value of different stocks when they switch to another R&D mode in the future.[12] Then, the R&D cost minimization problem in period $t-1$ is given by:

$$\begin{aligned}
& min_{rd^N_{i,t-1},\, rd^F_{i,t-1},\, rd^I_{i,t-1}} \left[P^N \cdot rd^N_{i,t-1} + P^F \cdot rd^F_{i,t-1} + P^I \cdot rd^I_{i,t-1}\right] \\
s.t. & \left[(A^N)^{\frac{1}{\theta}}(H^N_{i,t})^{\frac{\theta-1}{\theta}} + (A^I)^{\frac{1}{\theta}}(H^I_{i,t})^{\frac{\theta-1}{\theta}} + (A^F)^{\frac{1}{\theta}}(H^F_{i,t})^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \geq H_{i,t} \\
& H^N_{i,t} \geq (H^N_{i,t-1})^{\rho}(rd^N_{i,t-1})^{\gamma} \\
& H^F_{i,t} \geq (H^F_{i,t-1})^{\rho}(rd^F_{i,t-1})^{\gamma} \\
& H^I_{i,t} \geq (H^I_{i,t-1})^{\rho}(rd^I_{i,t-1})^{\gamma}.
\end{aligned}$$

Imposing that $\frac{H^N_{i,t}}{H^F_{i,t-1}} = \frac{H^N_{i,t-1}}{H^F_{i,t-1}}$ and that $\frac{H^N_{i,t}}{H^I_{i,t-1}} = \frac{H^N_{i,t-1}}{H^I_{i,t-1}}$, the first-order conditions of the problem

[12] We relax this assumption later and show that if the switching firms convert their existing stock of intangibles to the same composition as the steady-state composition of the new mode *by paying the cost of transitioning modes* $\widetilde{\mathbf{F}}$, then the cost minimization problem solved by the firm is isomorphic to the one discussed here.

satisfy:

$$
\frac{rd^N_{i,t-1}}{rd^F_{i,t-1}} = \left(\frac{A^N}{A^F}\right)^{\frac{1-\rho}{\theta(1-\rho)+\gamma(1-\theta)}} \cdot \left(\frac{p^N}{p^F}\right)^{\frac{-(1-\rho)\theta}{\theta(1-\rho)+\gamma(1-\theta)}} \tag{B.13}
$$

$$
\frac{rd^N_{i,t-1}}{rd^I_{i,t-1}} = \left(\frac{A^N}{A^I}\right)^{\frac{1-\rho}{\theta(1-\rho)+\gamma(1-\theta)}} \cdot \left(\frac{p^N}{p^I}\right)^{\frac{-(1-\rho)\theta}{\theta(1-\rho)+\gamma(1-\theta)}}
$$

$$
\frac{H^N_{i,t-1}}{H^F_{i,t-1}} = \left[\left(\frac{A^N}{A^F}\right)^{\frac{1-\rho}{\theta(1-\rho)+\gamma(1-\theta)}} \cdot \left(\frac{p^N}{p^F}\right)^{\frac{-(1-\rho)\theta}{\theta(1-\rho)+\gamma(1-\theta)}}\right]^{\frac{\gamma}{1-\rho}} \tag{B.14}
$$

$$
\frac{H^N_{i,t-1}}{H^I_{i,t-1}} = \left[\left(\frac{A^N}{A^I}\right)^{\frac{1-\rho}{\theta(1-\rho)+\gamma(1-\theta)}} \cdot \left(\frac{p^N}{p^I}\right)^{\frac{-(1-\rho)\theta}{\theta(1-\rho)+\gamma(1-\theta)}}\right]^{\frac{\gamma}{1-\rho}}.
$$

We can analogously derive the steady-state composition for firms restricted to R&D modes NI and NF, respectively. It follows immediately that for firms in the NI mode, the steady-state ratio between $H^N_{i,t}$ and $H^F_{i,t}$ is the same as for firms in the NIF mode; similarly, for firms in the NF mode, the steady-state ratio between $H^N_{i,t}$ and $H^I_{i,t}$ is the same as for firms in the NIF mode.

Incorporating Mode Switching. Now, we introduce mode switching. In addition to the fixed and sunk costs associated with entering a mode, we assume that, upon a mode switch, the switching firm incurs a one-time cost to adjust the *composition* of its intangible stocks to match the steady-state composition of the new mode, as derived in equation (B.14). This adjustment alters the composition of source-specific intangible while maintaining the overall intangible stock, as defined in equation (B.11). For example, suppose a firm is currently in mode N with only $H^N_{i,t}$ as its stock of intangibles; by paying the cost of switching to mode NIF, this firm adjusts its *composition* according to the equation (B.14) while maintaining its overall intangible.

The implication of this adjustment is twofold. First, the firm will have the same productivity immediately after mode switching (but before R&D is carried out). Second, each time a firm switches modes and undergoes this adjustment, its composition of intangible stocks aligns with the steady-state composition of the new mode. Consequently, firms in any R&D mode always exhibit the corresponding steady-state composition. By corollary, it means that firms in all modes make their flow R&D investment according to the steady-state R&D composition of that mode (see equation (B.13) for firms in the NIF mode).

Implications for Productivity Dynamics. We now discuss the implication of this alternative model for firms' productivity dynamics. Consider firms in the NIF mode. Following equation

(B.14), the combined intangible stock of the firms in this model satisfies

$$
\begin{aligned}
H_{it} &= \left[(A^N)^{\frac{1}{\theta}}(H^N_{i,t})^{\frac{\theta-1}{\theta}} + (A^I)^{\frac{1}{\theta}}(H^I_{i,t})^{\frac{\theta-1}{\theta}} + (A^F)^{\frac{1}{\theta}}(H^F_{i,t})^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \\
&\quad \text{(using equations (B.13) and B.14)} \\
&= (H_{i,t-1})^{\rho}\cdot(rd^N_{i,t-1})^{\gamma}\cdot\left[(A^N)^{\frac{1}{\theta}} + (A^I)^{\frac{1}{\theta}}\cdot\left(\frac{rd^N_{i,t-1}}{rd^I_{i,t-1}}\right)^{\frac{\gamma}{1-\rho}\cdot\frac{\theta-1}{\theta}} + (A^F)^{\frac{1}{\theta}}\cdot\left(\frac{rd^N_{i,t-1}}{rd^F_{i,t-1}}\right)^{\frac{\gamma}{1-\rho}\cdot\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}(1-\rho)} \\
&= (H_{i,t-1})^{\rho}\cdot(rd^N_{i,t-1})^{\gamma}\cdot \\
&\underbrace{\left[(A^N)^{\frac{1}{\theta}} + (A^I)^{\frac{1}{\theta}}\cdot\left(\frac{A^N}{A^I}\right)^{\frac{\gamma}{\theta(1-\rho)+\gamma(1-\theta)}\frac{\theta-1}{\theta}}\cdot\left(\frac{p^N}{p^I}\right)^{\frac{\gamma(\theta-1)}{\theta(1-\rho)+\gamma(1-\theta)}} + (A^F)^{\frac{1}{\theta}}\cdot\left(\frac{A^N}{A^F}\right)^{\frac{\gamma}{\theta(1-\rho)+\gamma(1-\theta)}\frac{\theta-1}{\theta}}\cdot\left(\frac{p^N}{p^F}\right)^{\frac{\gamma(\theta-1)}{\theta(1-\rho)+\gamma(1-\theta)}}\right]^{\frac{\theta(1-\rho)}{\theta-1}}}_{\equiv\exp(\gamma_{NIF})}.
\end{aligned}
\tag{B.15}
$$

It follows that the productivity of the firm evolves according to

$$\omega_{i,t} = \rho\omega_{i,t-1} + \gamma\log(rd^N_{i,t-1}) + \gamma_3\mathbb{I}(x_{i,t-1} = NIF) + \zeta_{i,t},$$

where γ_{NIF} is defined in equation (B.15). We can derive an analogous equation for firms in modes $0, N, NI, NF$, which leads to the same reduced-form specification as equation (14).

Discussion. The above derivation suggests that a model with mode-specific input accumulation can be mapped to the benchmark model developed in Section 3, provided that we generalize the cost of transitioning modes $\widetilde{\mathbf{F}}$ to incorporate the cost of adapting the intangible input composition of a firm from the current values to the steady-state value associated with the new mode. We think of such cost as being associated with reorganizing the research direction so that it is in line with the most efficient way of splitting the task across R&D input types according to their efficiencies $A^{\tilde{x}}$ and prices $p^{\tilde{x}}$.

This mapping indicates that the alternative model leads to the same reduced-form specification for the productivity dynamics, which we estimate in Section 4. Although the structural interpretation of the estimates differs between the two models, the alternative model implies the same counterfactual outcomes to the extent that many counterfactuals can be carried out using these reduced-form coefficients alone.[13]

[13] One such example is to set the coefficients for $\mathbb{I}(x_{i,t-1} = NI)$, $\mathbb{I}(x_{i,t-1} = NF)$, and $\mathbb{I}(x_{i,t-1} = NIF)$ to be zero, thereby eliminating the gains from R&D diversification.