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ABSTRACT

R&D Decisions and Productivity Growth: Evidence from Switzerland and the Netherlands*

The fraction of R&D active firms decreased in Switzerland but increased in the Netherlands from 2000-2016. This paper examines reasons for this divergence and its impact on productivity growth. Our micro-data reveal R&D concentration among high-productivity firms in Switzerland. Innovation support sustains firms' R&D activities in both countries. Our structural growth model identifies the impact of innovation, imitation and R&D costs on firms' R&D decisions. R&D costs gained importance in Switzerland but not in the Netherlands, explaining the diverging R&D trends. Yet, counterfactual analyses show that policies should prioritize enhancing innovation and imitation success over cost reduction to boost productivity growth.

JEL Classification: E61, E65, D22, O31, O47, O52

Keywords: R&D, innovation, imitation, R&D costs, policy, productivity growth, traveling wave

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1. Introduction

The development of R&D activity in European countries is very different. We observe a sharply rising share of R&D active companies in the Netherlands or France and a declining share of R&D active companies in Germany or Switzerland over the period 2000-2016 [Eurostat, 2019]. At the same time, we see a similar development in productivity growth in both Switzerland and the Netherlands [OECD, 2023].

These empirical facts raise questions about the determinants of firms' R&D decision, the role of R&D decisions in explaining aggregate productivity growth and the effectiveness of innovation policies to revive productivity growth [cf. Goldin et al., 2024]. Can we expect lower growth rates if the share of R&D active companies declines in a country? And should governments consequently take policy action to counteract such decline?

To investigate these questions, our study focuses on two innovation leaders in Europe, Switzerland and the Netherlands, for which we have highly comparable firm-level datasets spanning the years 2000-2016. The selection of these countries is motivated by diverging trends in R&D activity but similar productivity growth trends and different approaches to innovation promotion. The Netherlands actively promotes engaging in R&D activities through a favorable corporate tax system (Innovation Box) and specific R&D incentives (R&D tax credit) that support innovation throughout the entire R&D life-cycle [Lokshin and Mohnen, 2012; Mohnen et al., 2017]. Switzerland, in contrast, predominantly uses indirect R&D measures such as the promotion of knowledge and technology transfer between universities and the private sector. Innovation grants are usually not awarded directly to private companies [SERI, 2020].[1]

We first provide descriptive evidence on R&D activity and firm productivity. We document that Swiss companies need increasingly higher productivity levels to stay R&D active whereas this productivity-innovation threshold decreases over time for Dutch companies. As such, fewer (more) but highly (less) productive innovators remain R&D active in Switzerland (the Netherlands). Moreover, we learn from a survival analysis that large, more productive, human-capital intensive and export-oriented firms are less likely to exit R&D in both countries. Innovation policy measures, either indirect ones such as public support for industry-science partnerships in Switzerland or direct ones such as the Innovation Box in the Netherlands, seem effective in keeping firms R&D active.

One could interpret the reduced-form effects of these policy instruments on firms' R&D investment decision through their impact on the difficulty of making innovations (in-house R&D success), R&D costs and technology diffusion (imitation). To disentangle the effects of these three fundamentals on firms' R&D decision and to solve potential endogeneity problems, we construct an endogenous growth model with random interactions (imitation) where firms decide to conduct in-house R&D or to imitate other firms by maximizing the expected profit in every period, following König et al. [2022]. We estimate the model using Simulated Method of Moments by targeting moments of the empirical distribution of R&D and productivity that are salient in the theory. Guided by the increasing

[1]Switzerland has only introduced a Patent Box promotion design in 2020. Innovation promotion is also pursued at the cantonal level. For example, most cantons offer tax relief for R&D expenditures. These measures were introduced after the period covered by this study.

number of R&D active companies in the Netherlands after 2008 and the timing of the introduction of the Innovation Box (2007), we compare estimates from the pre- and post-2008 period in both countries to quantify changes in the fundamentals driving the R&D decisions that firms make. We find that the importance of the estimated innovation and imitation success probabilities for the R&D decision has only slightly increased post-2008 in Switzerland. In contrast, the costs of doing R&D have increased significantly in the post 2008-period. This finding aligns with results from the Swiss Innovation Survey (see Spescha and Wörter [2022]), indicating a rising cost of innovation for Swiss firms. Higher R&D costs lower the expected profit from innovation and, hence, decrease the incentives and probability to conduct R&D, consistent with empirical observations. In the Netherlands, the estimated innovation and imitation success probabilities have decreased, contrary to Switzerland. Notably, the importance of the estimated costs for the R&D decision has decreased considerably in the post-2008 period, in contrast to Switzerland. Such lower importance of R&D costs makes innovation activities more attractive, ceteris paribus, inducing an increasing share of R&D firms over time, consistent with empirical observations. Hence, we observe a strikingly different evolution of the importance of R&D costs for R&D decisions in Switzerland and the Netherlands. This, in turn, contributes to the divergent patterns in the prevalence of R&D active companies in the two countries. The essential question is, however, to what extent this divergence affects productivity growth.

In order to examine the impact on productivity growth of the different developments in R&D costs and, consequently, the different shares of R&D active firms in the two countries, we use the estimated structural growth model to run counterfactual simulations. These simulations allow us to quantify the sensitivity of the growth rate with respect to changes in the fundamental parameters of the model. For both countries, we find that policies targeted towards increasing the success probabilities of innovation and/or imitation are the most effective in boosting the productivity growth rate. Increasing the in-house R&D success probability, however, also amplifies productivity dispersion, leading to larger inequality. Conversely, increasing the likelihood of successful imitation (indicating positive diffusion/spillover effects) reduces inequality. Policy instruments such as R&D subsidies or R&D tax credits are likely to reduce the innovation threshold by decreasing R&D costs. This leads to an increase in the number of R&D active, innovative companies, thereby weakly reducing productivity dispersion. However, such policies are found to contribute only moderately to increasing productivity growth. The latter can explain the situation in the Netherlands and in Switzerland. The innovation policy environment in the Netherlands has contributed to increasing the share of R&D active companies. However, this has not translated into a significant rise in productivity growth. In Switzerland, in contrast, where a comparable innovation support environment was absent, the share of R&D active firms has decreased. Yet, despite this decline, productivity growth in Switzerland has not been significantly lower than in the Netherlands throughout our observation period.

Finally, in our policy experiment we use the estimated model to quantify the growth impact of reducing R&D costs. We demonstrate that a decrease in R&D costs in Switzerland comparable to the change observed in the Netherlands after 2008 –a period characterized by the implementation of innovation support measures aimed at reducing innovation costs– could have led to a 1.64% increase in productivity growth. Conversely, if Dutch companies had experienced an environment without a reduction in innovation costs in the post-2008 period, the annual productivity growth rate would have been approximately 1.12% lower.

Related literature. Our study relates to several lines of literature. First, we contribute to the productivity growth literature, which has intensively investigated declining productivity growth rates and increasing productivity dispersion [e.g. Decker et al., 2020; Goldin et al., 2024; Gordon, 2018]. Such productivity development has led to a growing concentration of economic activity in a smaller number of firms [Autor et al., 2017, 2020]. The existing literature has proposed various underlying causes ranging from "winners-take-it-all" technologies [Autor et al., 2020], a lack of diffusion of newly generated knowledge [Akcigit and Ates, 2021; Andrews et al., 2015], a lack of complementary assets [Andrews et al., 2016], an increasing difficulty to create new knowledge [Bloom et al., 2020; Jones, 2009; Park et al., 2023], higher fixed costs of innovation [Rammer and Schubert, 2016], to a spread of highly efficient firms over multiple markets [Aghion et al., 2023]. We add to this line of research by examining the impact of R&D activities on productivity growth and dispersion. Our model allows us to disentangle whether the difficulty of creating knowledge, innovation costs or knowledge spillovers are responsible for the divergent developments in Switzerland and the Netherlands.

Second, we contribute to the discussion on effective policy instruments for increasing the productivity effects of R&D activities. Bloom et al. [2019] evaluate the effectiveness of several policies aimed at promoting technological innovation. They find that R&D tax credits, skilled immigration, and trade and competition are highly effective. In contrast, direct R&D grants and augmenting local human capital are reported to be less effective, with Patent Boxes being considered the least effective. Except for skilled immigration and augmenting local human capital, all these policies tend to increase inequality across firms. Acemoglu et al. [2018] consider re-allocation effects of scarce R&D resources and find that R&D subsidies to incumbent firms do not necessarily increase welfare because they prevent less productive firms from leaving the R&D market, which would free up scarce innovation inputs for more productive firms. As a result, overall productivity growth falls. Akcigit et al. [2022] examine effective tax policy approaches to encourage firm innovation behavior, taking into account the allocation effects of scarce resources. To support companies that are more productive in the R&D process, R&D subsidies should be non-linear and decreasing in the level of firms' R&D expenditures. Dechezleprêtre et al. [2023] exploit a change in size-based eligibility thresholds for R&D tax relief in the UK and find significant effects of tax relief on R&D, patenting and productivity. Choi and Levchenko [2023] investigate the long-term impact of a large-scale industrial policy in South Korea. The policy subsidized the allocation of foreign credit to Korean heavy and chemical industry firms. The authors find that subsidized firms grew faster than those never subsidized for 30 years after subsidies ended. However, the vast majority of this long-term impact stems from the benefits of learning-by-doing rather than the relaxation of financial constraints. König et al. [2022] find that the level of R&D subsidies is important: subsidies resulting in a moderate increase in R&D investment accelerate productivity growth, whereas excessively high subsidies slow down productivity growth. The latter is due to inducing many firms to innovate, which would benefit more from imitation and the adoption of technologies.[2] We contribute to this strand of literature by estimating the effective-

[2]König et al. [2022] use a similar structural model as we do here but they focus on the Chinese economy while we analyze two technologically leading European countries (e.g. in terms of patents per capita), Switzerland and the Netherlands. Moreover, while R&D measurement error might play a dominant role in the Chinese data, this issue is less of a concern in our survey micro-data. Furthermore, unlike König et al. [2022], we use multiple waves of the survey data. This allows us to estimate a panel data model without making strong assumptions about stationarity of the underlying data generating process.

ness of policy measures aimed at fostering innovation implemented in the Netherlands and we apply this specific setting to Switzerland.

Finally, the magnitudes of the effect on the productivity growth rate that we identify when comparing the two policy environments in Switzerland and the Netherlands are comparable with previous studies in the literature. For example, Akcigit [2009] documents that an optimal homogeneous R&D subsidy rate in the US could boost growth up to 2.1%. Kogan et al. [2017] report that a one-standard-deviation increase in the innovation index would result in a 3.4% rise in aggregate productivity growth over a 5-year period in the US. König et al. [2019] find that providing a subsidy to R&D expenditures for firms engaged in R&D collaboration could lead to welfare gains between 1% and 4%. Moreover, König et al. [2022] show that the introduction of an industrial policy that supports more productive firms in China could increase the growth rate by 2 percentage points. Relatedly, Van Reenen and Yueh [2012] find that if China had not implemented its international joint venture policy with the aim of facilitating technology transfer (diffusion), the country's annual GDP growth would have been reduced by between half a percentage point to over one percentage point over the past 30 years. Hence, our findings regarding the growth impact of an innovation-supportive environment do not exceed the estimates obtained in the existing literature.

Organization of the paper. The paper is structured as follows. Section 2 discusses the data, descriptive evidence on R&D activity and productivity, and descriptive evidence on factors that keep firms R&D active. Section 3 introduces a structural model for the three fundamentals –in-house R&D success (innovation), R&D costs and technology diffusion (imitation)– that affect a firm's decision to conduct R&D. The estimation results are provided in Section 4. Section 5 analyzes the productivity growth effects of the fundamental parameters of the model. Section 6 concludes. Additional relevant material can be found in the Supplementary Appendix.

2. Data and Descriptive Evidence

2.1. Data

Production and innovation data. We use highly comparable micro-data sets that are sourced from different surveys. For Switzerland, we use nine waves of the Swiss Innovation Survey (SIS) covering the period 2001-2016. The survey is collected by the KOF Swiss Economic Institute of ETH Zurich. The SIS is the equivalent of the well-known Community Innovation Survey (CIS) of the European Union. Between 2001 and 2010, the survey waves were conducted at three-year intervals. From 2010 onward, the survey waves have been carried out in two-year intervals in order to synchronize with the CIS. The SIS is based on a stratified random sample of firms with more than 5 employees, drawn from the Swiss business census. It is representative of the Swiss economy. The SIS includes all relevant industries in manufacturing, construction and services. Stratification is based on 2-digit industries and within each industry on three firm size classes. For this study, the SIS is restricted to the NACE Rev2 classification headings 10-33, 41-43 and 45-82. In addition to the common harmonized innovation indicators also present in the CIS, the SIS also asks firms about various other firm characteristics such as sales, number of employees, share of high-skilled employees, intermediate input costs and export activity.

For the Netherlands, we use several administrative data sets collected by Statistics Netherlands (CBS). The innovation variables stem from eight waves of the Dutch Community Innovation Survey covering the period 2000-2016. CIS enterprises are merged with data from the Production Surveys (PS). The latter contains data on production value, factor inputs and factor costs. The CIS and PS data are collected at the enterprise level. A combination of census and stratified random sampling is used for each wave of the CIS and PS. The stratification variables are the industry and the number of employees of an enterprise. A census is used for the population of enterprises with at least fifty employees and stratified random sampling is used for enterprises with fewer than fifty employees. This cut-off point of 50 employees is applied to each wave of the CIS and the PS. To define the skill type of each employee in Dutch firms, we use their education type reported in the Education database which comes from the Polis Administration and the Labour Force Survey ("Enquête BeroepsBevolking, EBB"). The Education database provides the highest level of education attained by an individual on October 1st of the year.[3] The education type is based on a 2-digit SOI-code (Dutch education classification, "Standaard Onderwijsindeling") and is converted to the ISCED classification (International Standard Classification of Education). To ensure comparability with the Swiss data, we only consider enterprises active in the manufacturing, construction and services industries. As such, we also use the NACE Rev2 classification headings 10-33, 41-43 and 45-82.

Innovation policy measure. To examine the impact of the main innovation policy instrument on R&D activity and productivity in the Netherlands, we match our PS-CIS data with data on Innovation Box usage collected by the tax office and supplied by Statistics Netherlands. The Innovation Box provides a reduced corporate income tax rate for profits generated from intangible assets. The idea is that lower taxes on future (expected) profits from R&D will make R&D investments more attractive. The policy measure started in 2007 as a Patent Box, lowering the corporate income tax rate from 20-25% to 5% for income derived from patented intangible assets. Throughout the years, several changes were introduced to make the policy more accessible to small and medium-sized firms. The largest change took place in 2010, when the Patent Box was turned into the Innovation Box as the formal patent requirement was removed. Since then, the reduced corporate income tax rate applies to profits arising from both patented and unpatented intangible assets. The most important eligibility criteria are conducting R&D activities that are formally recognized by the tax office and generating in-house R&D. Data on Innovation Box usage is defined at the level of tax units, which are legal entities used by tax authorities for the collection of corporate income tax. To match the Innovation Box usage data at the tax unit-year level to our firm-year panel, we use crosswalks provided by Statistics Netherlands. During the 2008-2016 period, about 14% of the firms that are in our matched PS-CIS sample are Innovation Box users. Among the Innovation Box users, 55% are

[3]While coverage of this dataset is increasing over time, its sample is skewed towards younger, more educated workers, especially at the beginning of our time period. We use an imputation method to predict the skill level of individuals whose education data is missing. More specifically, we estimate an inverse Mincer equation to predict education levels for workers for whom education information is missing based on individual and firm characteristics in our matched employer-employee micro-data for each year during the period 2000-2016. For the full procedure, we refer to Bartelsman et al. [2015].

manufacturing companies, 4% are construction companies and 41% are service companies.

The other innovation policy instruments in the Netherlands are the WBSO and the RDA,[4] for which we do not have data. These are two similar policy instruments. The WBSO was introduced in 1994 and reduces the wage costs of R&D workers through tax credits. The RDA was introduced in 2012 and is more general than the WSBO, as it encompasses tax credits for non-labor related R&D expenses. Thus, the Dutch innovation support environment that we measure in Section 4 extends beyond the scope of just the Innovation Box instrument. The WBSO improved the financial situation of firms already in the pre-2008 period. In contrast, the RDA, along with the Innovation Box, enhanced the financial situation of firms in the post-2008 period.

Estimation samples. For estimation purposes, we use information from the aforementioned SIS waves (Switzerland) and matched PS-CIS sample (the Netherlands). After some basic cleaning and deleting missing firm-year observations on real value added per worker (our main productivity measure) and engagement in R&D activity,[5] we end up with an unbalanced panel of 16,553 observations corresponding to 6,201 enterprises (48.2% in manufacturing, 9.5% in construction, and 42.1% in services) over the period 2000-2016 in Switzerland. For the Netherlands, we have an unbalanced panel of 43,341 observations corresponding to 21,624 enterprises (29.4% in manufacturing, 9.2% in construction and 61.4% in services) over the period 2000-2016.

2.2. Descriptive Information on R&D Activity and Productivity

In the following, we present descriptive evidence on the fraction of R&D active companies, the development of the productivity distribution and the innovation (R&D) decision of firms in Switzerland and the Netherlands.

Figure 1 shows the share of R&D active firms in Switzerland (left panel) and the Netherlands (right panel), where R&D active companies are defined as those engaging in either in-house or outsourced R&D activities.[6] In Switzerland, the number of R&D active firms sharply decreases from more than 41% at the beginning of the 2000s to less than 30% in 2016. In the Netherlands, we observe a completely different development: the share of R&D active firms ranges between 20-25%

[4]WBSO is an acronym for "The Wage Tax and Social Insurance Act" ("Wet Bevordering Speur- en Ontwikkelingswerk" and RDA stands for R&D tax Allowance.

[5]Similar to König et al. [2022], we take reported R&D expenditures as an indicator for the innovation decision of the firm. We focus on the extensive margin for R&D not only because this is consistent with the discrete choice model we estimate (and this model will be necessary to perform our counterfactual simulation experiments) but also because the intensive margin tends to be subject to more severe measurement error, tax evasion or manipulation. Further, only a small fraction of firms perform any R&D and the R&D expenditures distribution is highly skewed. This can lead to difficulties in the estimation of the intensive margin.

[6]The composition of R&D activities has remained relatively stable over time in both countries. The relationship between domestic R&D and R&D conducted abroad has remained steady for the past 20 years in Switzerland [Spescha and Wörter, 2022].

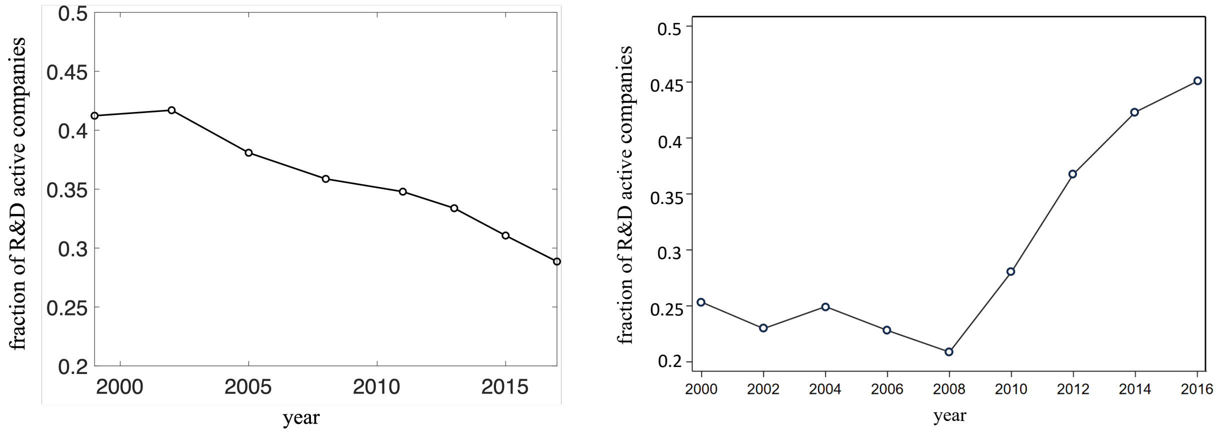

Figure 1: Fraction of R&D active firms over the years 2000-2016 in Switzerland (left panel) and the Netherlands (right panel).

during the 2000-2008 period but sharply increases afterwards and reaches 45% in 2016.[7,8]

Contrary to the development of R&D activity, productivity (measured as real value added per employee) develops in a similar way in both countries during our considered time span. Figure 2 shows the log-productivity distribution in Switzerland (left panel) and the Netherlands (right panel), respectively.[9] The distribution is computed for different years using a Kernel smoothing procedure. In both countries, the distribution has the shape of a "traveling wave" [cf. König et al., 2022, 2016], with the peak of the distribution moving to the right, indicating an increase in the average productivity level over time. This is consistent with Figure 3 which shows the yearly variation of the average and median log productivity in Switzerland (left panel) and the Netherlands (right panel), respectively. In both countries, average and median productivity levels slightly increase over time. In the Netherlands, we observe a slightly steeper increase in the post-2008 period, while in Switzerland we see a decline in productivity growth after 2008.[10] We will examine potential causes for these

[7]The observed differences in the share of R&D performing firms in the two countries could be related to different industrial structures. For example, countries with a substantial high-tech sector may experience a lower likelihood of reduced rates of R&D diffusion than countries with a large service sector. This is indeed crucial for making cross-sectional descriptive comparisons between countries. However, it is less important for the analysis presented in this paper, where our primary focus is on studying variations over time within a country. Furthermore, the industrial structure in Switzerland and the Netherlands did not change significantly during our observation period.

[8]Moreover, the share of R&D expenditures in sales shows an upward trend in both countries. This implies an increasing concentration of more R&D expenditures in an ever smaller number of R&D active firms in Switzerland while firms in the Netherlands are not only more frequently pursuing R&D but are also increasing their respective R&D expenditures.

[9]For a more accurate comparison, log productivity in the Netherlands has been adjusted by a constant to align with average log productivity in Switzerland at the beginning of our observation period.

[10]Note that there are minor differences compared to the official statistics of the respective countries, see for example "OECD (2023), GDP per hour worked (indicator). doi: 10.1787/1439e590-en (Accessed on 11 October 2023)". This

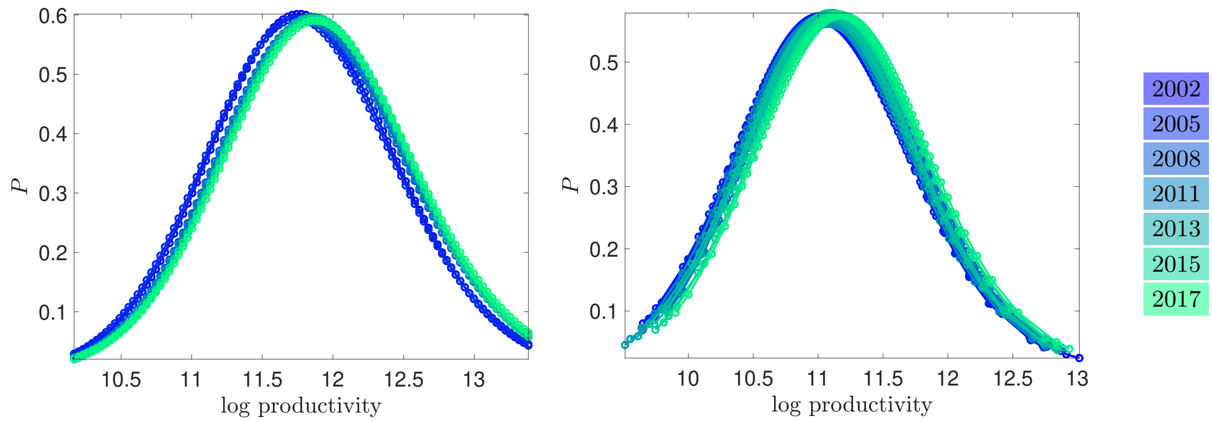

Figure 2: Log-productivity distribution (P) in Switzerland (left panel) and the Netherlands (right panel). Productivity is measured as real value added per employee (in full-time equivalents).

diverging trends in Section 3 and beyond.

Let us now look at the correlation between a firm's innovation decision (i.e. whether a firm conducts R&D or not) and its productivity level. The left panels of Figures 4 and 5 show firms' innovation decision plotted over their productivity levels in Switzerland and the Netherlands, respectively. In both countries, we see that firms with higher productivity tend to innovate more. The correlation between firms' innovation decision and productivity pooled across all years equals 0.75 in Switzerland and 0.90 in the Netherlands. The dashed line indicates the innovation-productivity 50%-threshold, that is, the lowest productivity level at which the likelihood of conducting R&D is more than 50%. The right panels of Figures 4 and 5 show the evolution of this innovation-productivity 50%-threshold over time in Switzerland and the Netherlands, respectively. The same evolution is depicted in Figure 6. The innovation-productivity threshold is increasing over time in Switzerland but decreasing in the Netherlands. This implies that Swiss (Dutch) companies need increasingly higher (lower) productivity levels to stay R&D active.

2.3. Descriptive Evidence on the Continuation of R&D Activities

In Section 2.2, we have documented that the decrease (increase) in the fraction of R&D active firms in Switzerland (the Netherlands) comes with an increasing (decreasing) productivity threshold above which firms engage in R&D. Let us now examine the factors (either firm characteristics or innovation policy instruments) that correlate with a firm's decision to continue doing R&D by running a survival analysis [Cleves et al., 2008]. These factors can be interpreted through the lens of three fundamentals

may be due to different samples. For example, for Switzerland, the KOF data refer to companies with more than 5 employees (in full-time equivalents) and the value added statistics on which the official data are based refer to companies with more than 3 employees (see Federal Statistical Office, Production and Value-Added Statistics, Factsheet). For the Netherlands, official figures based on the OECD database encompass very small businesses (see e.g. Grabska et al. [2017]). In contrast, our estimation sample is restricted to firms having at least 5 employees.

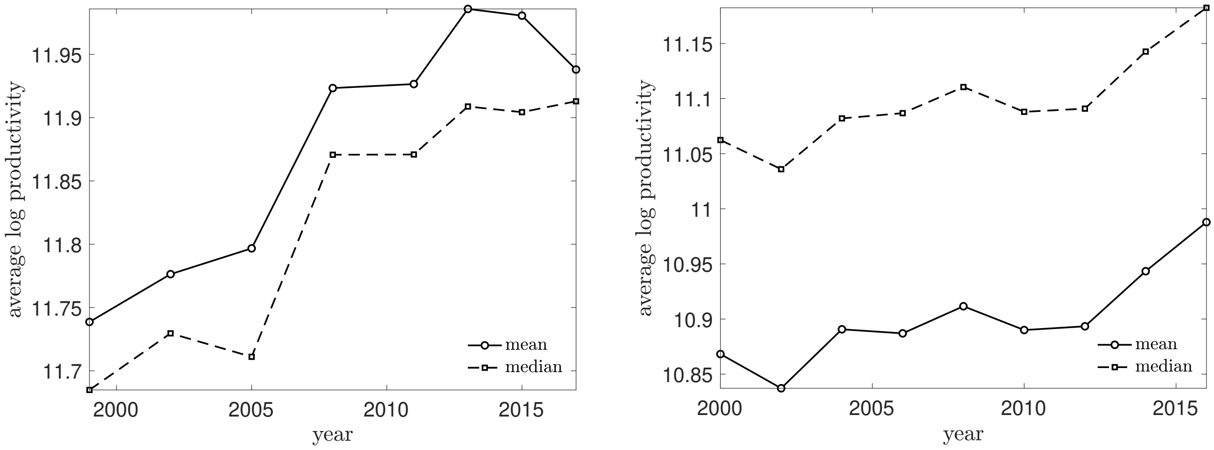

Figure 3: Evolution of average log productivity in Switzerland (left panel) and the Netherlands (right panel). The arithmetic mean and the median are shown. Productivity is measured as real value added per employee (in full-time equivalents).

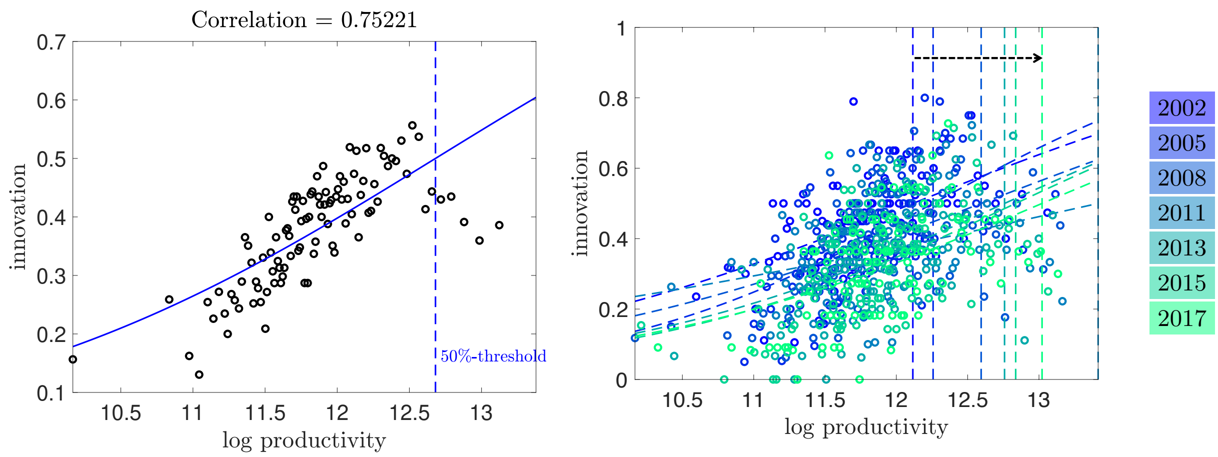

Figure 4: (Left panel) The innovation decision over productivity pooled across all years of observation in Switzerland. Productivity is measured as real value added per employee. The solid line shows the fit of a logistic function, $f(x) = 1/(1+\exp(-\beta_1(x-\beta_2)))$. The threshold is given by $x^* = \beta_2$ such that $f(\beta_2) = 1/2$. The 50%-threshold (dashed line) indicates the lowest productivity level at which the likelihood of doing R&D is more than 50%. (Right panel) The innovation decision over productivity across different years. The arrow indicates an upward shift of the 50%-threshold (see also the left panel of Figure 6).

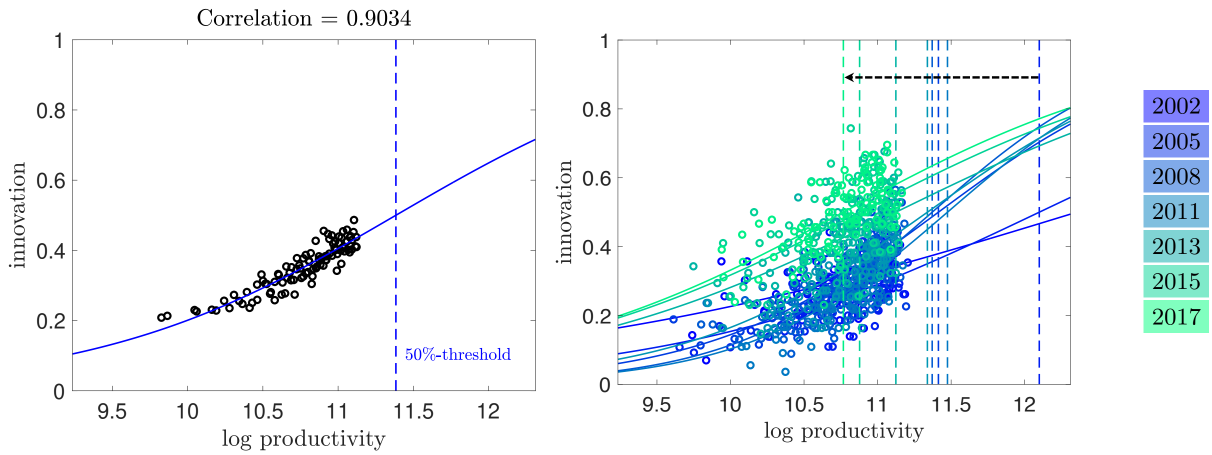

Figure 5: (Left panel) The innovation decision over productivity pooled across all years of observation in the Netherlands. Productivity is measured as real value added per employee. The solid line shows the fit of a logistic function, $f(x) = 1/(1 + \exp(-\beta_1(x - \beta_2)))$. The threshold is given by $x^* = \beta_2$ such that $f(\beta_2) = 1/2$. The 50%-threshold (dashed line) indicates the lowest productivity level at which the likelihood of doing R&D is more than 50%. (Right panel) The innovation decision over productivity across different years. The arrow indicates a downward shift of the 50%-threshold (see also the right panel of Figure 6).

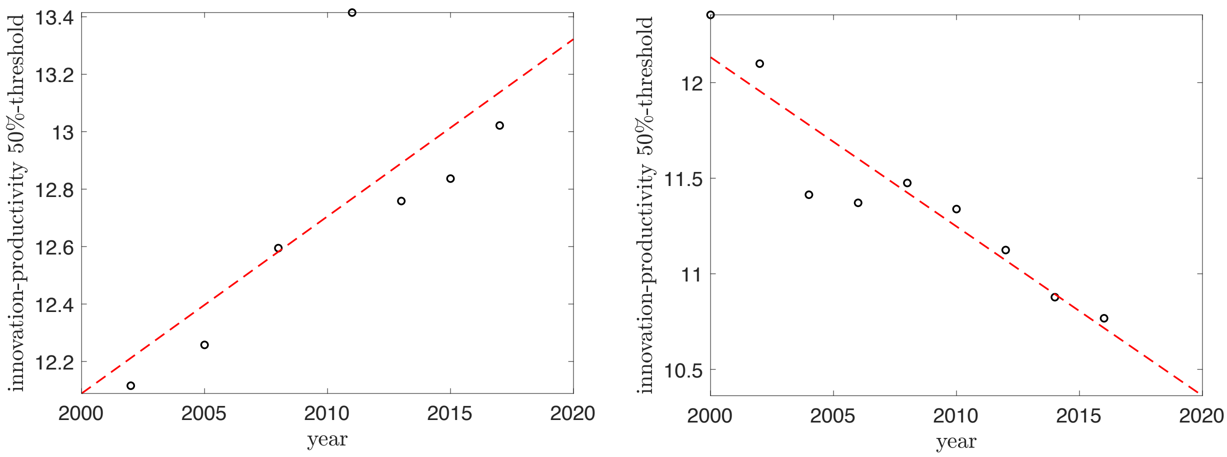

Figure 6: The innovation-productivity 50%-threshold for Switzerland (left panel) and the Netherlands (right panel). Productivity is measured as real value added per employee. Dashed lines indicate a linear regression fit.

that affect a firm's R&D decision: how likely it is for an innovation to succeed (innovation success probability), how costly it is to pursue an innovation strategy (R&D costs) and how easy it is to imitate others (imitation success probability).[11]

Survival analysis estimation samples. In the survival analysis, we include all R&D active firms that can either continue or exit R&D. Given these R&D active firms, we investigate whether they exit R&D and if so how long they lasted until they exit. Non-R&D active firms and firms entering R&D are not part of the analysis. The Swiss estimation sample consists of 1,669 firms that have been at risk for exiting from R&D activities. In total, we observe 809 exits between 2000 and 2016. The Dutch estimation sample consists of 3,720 firms, which result in 1,579 exits from R&D between 2000 and 2016. From the Kaplan-Meier estimates, we find that the probability that a Swiss (Dutch) company which conducted R&D in 2000, still conducts R&D in 2010 is 45.9% (40.1%), whereas it drops to 24.9% (27.3%) in 2016.[12]

Baseline Cox model. In the baseline Cox proportional hazard model, we examine the role of firm size (measured by employment in full-time equivalents), firm productivity (measured by real value added per worker), absorptive capacity (measured by the employment share of academics and the share of employees with higher education in Switzerland, and the share of employees with tertiary education in the Netherlands) and access to international markets (measured by export status) in affecting the risk of exit from R&D. In all specifications, we include 2-digit industry dummies to control for unobserved time-invariant heterogeneity at the industry level. Tables 1 and 2 show the coefficients for the explanatory variables of the estimated baseline Cox model for Switzerland and the Netherlands, respectively. These coefficients are exponentiated, indicating the extent to which the explanatory variables shift the hazard of exiting from R&D. For example, the hazard ratio of employment of 0.775 in the first column of Table 1 means that a one percent increase in employment reduces the hazard rate of exiting from R&D by 0.225%. For both countries, all firm covariates of our baseline model are statistically significant and negatively correlated with the hazard rate. Ceteris paribus, large, productive, human-capital intensive and export-oriented companies experience a lower hazard rate of exiting from R&D in both countries.

[11] In the current section, we examine partial correlations. In Section 3, we introduce a structural growth model derived from these fundamentals and analyze their impact on aggregate productivity growth.

[12] Results not reported but available upon request.

Table 1: Baseline Cox proportional hazard model: Exit from R&D in Switzerland.

	(1)	(2)	(3)	(4)
Ln(Employment)	0.775***	0.781***	0.773***	0.786***
	(0.018)	(0.018)	(0.019)	(0.018)
Ln(Value added/employee)		0.769***	0.800***	0.825**
		(0.053)	(0.053)	(0.053)
Share of academics			0.985***	0.988***
			(0.003)	(0.003)
Share of employees with higher education			0.991***	0.991***
			(0.003)	(0.002)
Export (0/1)				0.697***
				(0.049)
Observations	3,307	3,250	3,250	3,250
Industry fixed effects	Yes	Yes	Yes	Yes

Notes: ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 2: Baseline Cox proportional hazard model: Exit from R&D in the Netherlands.

	(1)	(2)	(3)	(4)
Ln(Employment)	0.832***	0.839***	0.840***	0.848***
	(0.018)	(0.018)	(0.018)	(0.019)
Ln(Value added/employee)		0.767***	0.779***	0.751***
		(0.043)	(0.044)	(0.043)
Share of high-skilled employees			0.611***	0.618***
			(0.108)	(0.113)
Export (0/1)				0.886**
				(0.052)
Observations	6,299	6,299	6,273	6,109
Industry fixed effects	Yes	Yes	Yes	Yes

Notes: ***/**/* denotes statistical significance at the 1%/5%/10% level.

Competitive vs. less competitive firms. To examine how the survival of competitive firms differs from less competitive ones, we distinguish three types of firms based on the explanatory variables in Tables 1 and 2. We consider firms with low values for the respective firm characteristics (that is, values in the 10% quantile of the distribution of the variables), firms with values lying at the median and firms with high values (that is, values in the 90% quantile of the distribution). Firms with high values (that is, large, productive, export-oriented firms with a high-skilled workforce) are generally considered to be more competitive than firms with low values. Figures 7 and 8 plot the survivor functions of the three types of firms in Switzerland and the Netherlands, respectively. In both countries, we observe that more competitive firms are significantly less likely to exit R&D compared to less competitive firms. For example, by the end of our analysis period, Swiss companies scoring high on the aforementioned firm characteristics have about a 62% probability of remaining R&D active, compared to a 43% probability for Dutch companies. In contrast, firms with low scores on these characteristics have less than a 5% probability of continuing R&D activities. Swiss (Dutch) firms at the median of the firm characteristics have a probability of about 30% (20%) to continue conducting R&D. Comparing the development of the survivor functions in the two countries highlights two differences, though. First, we observe a flattening of the survivor function from 2010 onward in the Netherlands for all firm types, which is not the case in Switzerland. Second, Dutch competitive firms show a more pronounced decline in the probability to remain R&D active compared to Swiss competitive firms. This suggests that Swiss competitive companies exhibit greater resistance to discontinuing R&D than their Dutch counterparts. One possible reason for this divergence is that there is more formal support for innovation activities in the Netherlands, to which we turn now.

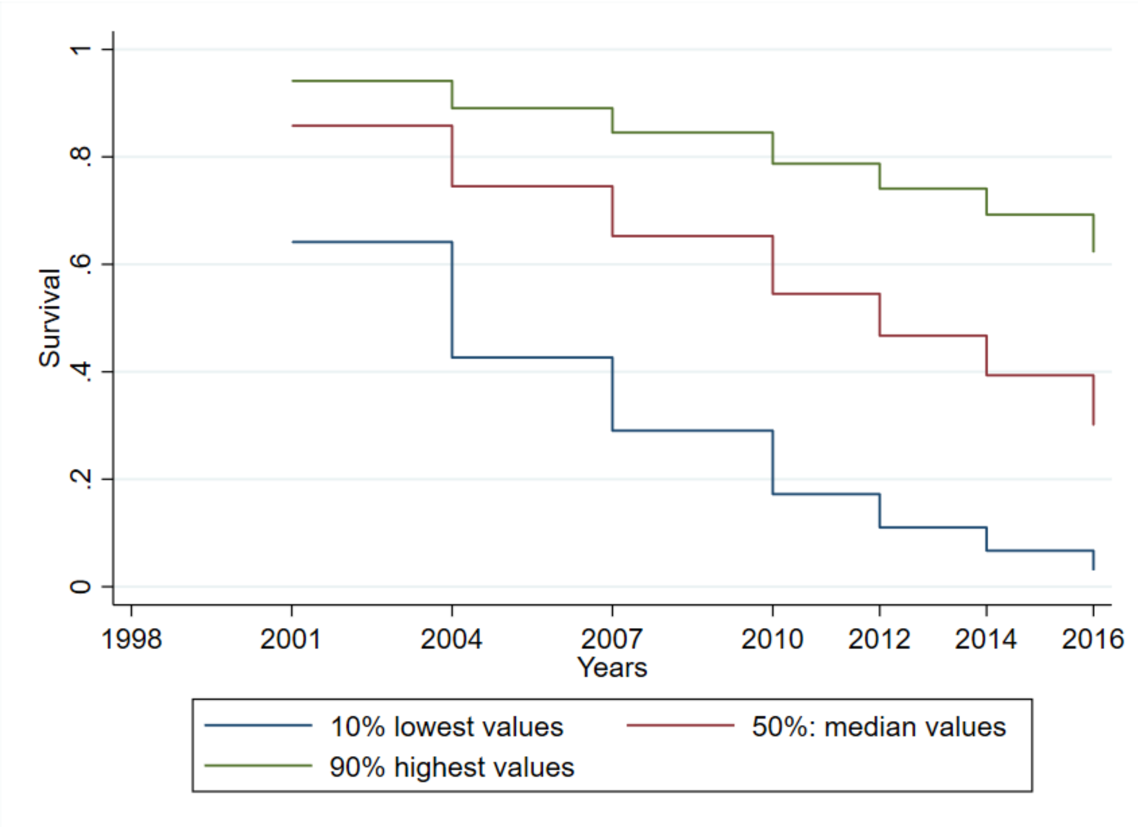

Figure 7: Survivor functions: Competitive vs. less competitive firms in Switzerland.

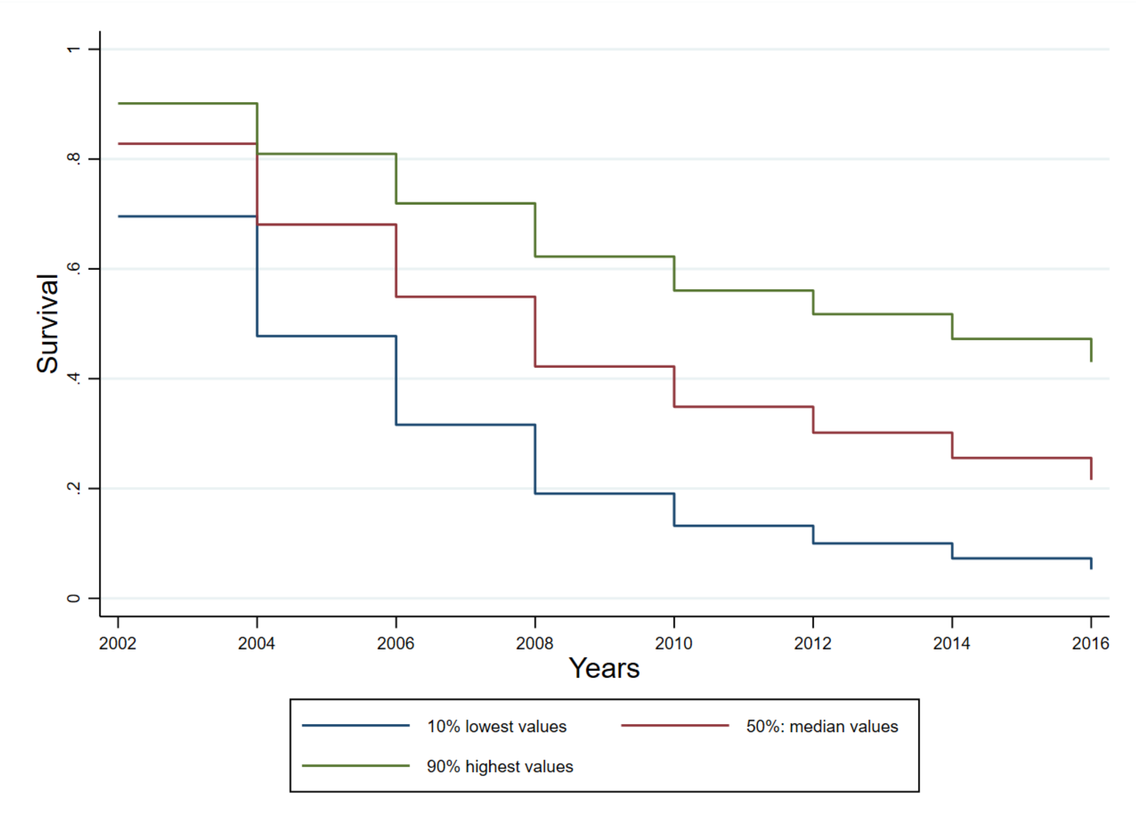

Figure 8: Survivor functions: Competitive vs. less competitive firms in the Netherlands.

Extended Cox model with innovation input/support. To investigate partial correlations between explanatory variables that measure the innovation input as well as the innovation support of firms and the hazard rate of exiting from R&D, we enrich our baseline model specification (specification (4) in Tables 1 and 2) and retain the firm covariates from the baseline estimations as control variables. As reported in Table 3, we include R&D expenditures, R&D cooperation with universities, R&D cooperation with other research institutes, and domestic and international innovation support when estimating this extended model on the Swiss micro-data. These variables are all negatively associated with the hazard rate of exiting R&D. Except for the coefficients of R&D cooperation with other research institutes and international innovation support, the exponentiated coefficients are statistically significant and below the value of one. For example, the coefficient of R&D expenditures is 0.859, indicating that a one percent increase in R&D expenditures reduces the hazard of exiting R&D by 0.141%. Domestic innovation support shows a coefficient of 0.425, which implies that the hazard of exiting R&D is only half as large for firms enjoying domestic innovation support than for firms without such support. Innovation support in Switzerland does not include any financial contribution to the R&D activities of the company. Instead, the funding is directed exclusively to the university partner of the project. The company must bear its own share of the costs associated with the cooperation project. This suggests that even "soft" measures of public innovation promotion, focusing primarily on supporting knowledge and technology transfer between the public research sector and industry rather than contributing financially to R&D activities of companies, are effective in keeping Swiss firms R&D active.

To estimate the extended model on the Dutch micro-data, we include R&D expenditures, R&D cooperation, government funding (excluding Patent/Innovation Box), funding from the EU (framework program) and being a Patent/Innovation Box user, in addition to the explanatory variables from the baseline estimation. Table 4 shows that Dutch firms engaging intensively in R&D activities (either through innovation input or cooperation) and Dutch firms receiving financial support from the government display a much lower hazard of exiting R&D. Dutch firms spending the same amount on R&D are much less likely to exit from R&D than their Swiss counterparts (see exponentiated coefficient of 0.761 as compared to 0.859 in Table 3). Table 4 suggests that the Innovation Box policy instrument might be quite effective in keeping firms R&D active: being a Patent/Innovation Box user decreases the hazard of exiting R&D by 64%.

Receiving indirect innovation policy support, such as promoting knowledge and technology transfer between universities and the private sector as in Switzerland, may influence the firm's R&D decision by enhancing the ease of generating innovations (innovation success probability). Receiving direct innovation policy support, such as lowering taxes on expected profits from R&D through the Innovation Box in the Netherlands, may influence the firm's R&D investment decision by reducing the cost associated with conducting R&D. Note, however, that the estimated coefficients from Cox proportional hazard models are simple, partial correlations. These estimates could potentially suffer from endogeneity problems arising from omitted variable bias and reverse causality. As such, we are not in a position to establish causal relationships. For example, firms that benefit from the Innovation Box might differ in observable and unobservable characteristics from those that cannot, extending beyond the measurable observables included in our estimations. These hidden characteristics might in fact cause the observed difference.

Table 3: Cox proportional hazard model with innovation input/support: Exit from R&D in Switzerland.

	(1)	(2)	(3)
Ln(R&D expenditures)	0.859***		
	(0.019)		
R&D Cooperation with universities		0.709***	
		(0.077)	
R&D Cooperation with other research institutes		0.918	
		(0.104)	
Innovation support domestic			0.425***
			(0.102)
Innovation support international			0.611
			(0.213)
Observations	3,175	3,224	1,807
Controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes

Notes: ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 4: Cox proportional hazard model innovation input/support: Exit from R&D in the Netherlands.

	(1)	(2)	(3)	(4)
Ln(R&D expenditures)	0.761***			
	(0.015)			
R&D Cooperation		0.725***		
		(0.037)		
Funding from government (excl. Patent/Innovation Box)			0.441***	
			(0.028)	
Funding from EU (excl. framework program)			0.975	
			(0.122)	
Funding from EU framework program			0.728*	
			(0.130)	
Patent/Innovation Box user				0.363***
				(0.061)
Observations	5,255	6,109	5,209	6,109
Control	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

Notes: ***/**/* denotes statistical significance at the 1%/5%/10% level.

3. Determinants of Firms' R&D Decisions

In Section 2.3, we have shown that size, productivity, human capital intensity and export status are factors that correlate with firms' decision to continue their R&D activities. These factors can impact the R&D decision by, on the one hand, increasing the likelihood of innovation success and, on the other hand, enhancing the ease with which other firms' technologies can be imitated. Moreover, we have documented that domestic and international innovation support are correlated with firms' R&D decision. While such measures can also affect innovation success, their main influence is on firms' R&D costs.

In this section, we jointly model the impact of these three fundamentals –the likelihood of innovation success (in-house R&D success), the innovation or R&D costs and the likelihood of imitation success (resulting in technology diffusion)– on the R&D decision of a firm. Such a model allows us to take into account potential endogeneity concerns. The goal is to disentangle the effects of these three fundamentals, which underlie every firm's R&D decision problem. To this end, we introduce a model of endogenous technological change, productivity growth and technology spillovers where firms' choice between in-house R&D and imitation is endogenous and based on firms' profit maximization motive. The model follows König et al. [2022]. The structural model will further allow us to perform counterfactual simulations to examine the productivity growth effects of R&D policies in Section 5.

3.1. Firms' Profits and R&D Costs

We assume that firm i's profits at time $t \geq 0$ are given by

$$\pi_i(t) = \psi A_i(t)^{\eta-1} - c_i(t) \tag{1}$$

with a proportionality factor $\psi > 0$ that is inversely related to the strength of competition in the market,[13] demand elasticity $\eta > 1$ and $A_i(t)$ denoting the productivity of firm i at time t. A derivation of the profit function in Equation (1) can be found in Acemoglu et al. [2006] and König et al. [2022, 2016] and we omit the details here for brevity. Further, following König et al. [2022], we assume that the cost of innovation is given by:[14]

$$c_i(t) = \begin{cases} \kappa \left(\overline{A}(t)^{\theta} A_i(t)^{1-\theta} \right)^{\eta-1} & \text{if} \quad i \text{ innovates,} \\ \\ 0 & \text{if} \quad i \text{ imitates.} \end{cases} \tag{2}$$

In Equation (2), $\overline{A}(t)$ denotes average productivity at time t, and $\kappa > 0$ and $\theta \in [0, 1]$ are cost parameters. We assume R&D costs to be a function of the geometric combination of A_i and $\overline{A}$.[15] If $\theta = 1$, R&D costs are independent of productivity. If $\theta < 1$, R&D costs vary across firms, being higher for high-productivity firms that are closer to the technological frontier.[16] When bringing the model to the data, we will estimate the value of θ that is most appropriate for the empirical application under consideration.

3.2. Innovation vs. Imitation

Productivity is measured along a quality ladder, $A_i \in \{\widetilde{A}, \widetilde{A}^2, \widetilde{A}^3, \ldots\}$. Firms can increase their productivity by a factor $\widetilde{A}$ along the ladder via two alternative channels: through imitating other firms' technologies (diffusion) or through conducting costly in-house R&D (innovation). Let P_a denote the probability mass function of the fraction of firms with log-productivity $a = \log(A)$ and let the cumulative distribution function be $F_a = \sum_{b=1}^{a} P_b$.

[13] According to Equation (1), in a more competitive market with a smaller ψ, ceteris paribus, firms enjoy lower profits.

[14] For a similar cost specification, see also Benhabib et al. [2014] and Chen et al. [2021]. In particular, Chen et al. [2021] note that any homothetic production function with Hicks neutral productivity admits this representation. For empirical support, see e.g. Cohen [2010], where it is shown that internal R&D funds increase with firm size and thus also with productivity.

[15] König et al. [2022] show that average productivity ($\overline{A}$) is proportional to the average wage rate in the economy.

[16] Arora et al. [2018], Bloom et al. [2020] and Griliches [1998] demonstrate that it has become more expensive to innovate. This is especially true for companies at the technological frontier. Arora et al. [2018] find that "more research effort may be necessary to produce one unit of scientific output if producing scientific breakthroughs (or 'climbing over the shoulders of giants') is getting harder." Bloom et al. [2020] document that it has become difficult for firms with higher productivity to generate new ideas. There might be several reasons for this. For example, more productive firms could be forced to devote management and labor resources to R&D, which has higher opportunity costs [cf. König et al., 2022].

Imitation. A firm pursuing the imitation strategy is randomly matched with another firm in the empirical distribution. If the firm is matched with a more productive firm, its productivity increases by one notch with probability $q \in [0,1]$ and remains constant with probability $1-q$. If the firm is matched with a less productive firm, it retains its initial productivity. Because of random matching, the probability that an imitating firm with log-productivity a moves up the productivity ladder equals $q\sum_{b=1}^{\infty} P_{a+b} = q(1-F_a)$.

Innovation. A firm can discover something genuinely new that is unrelated to the knowledge set of other firms with probability $p_i \in [0,1]$ (in-house R&D success). The realization of p_i is observed at the beginning of each period t, before firms choose whether to innovate or imitate.

3.3. Innovation Decision and Threshold

We assume that firms choose whether to innovate through in-house R&D or to imitate other firms based on a standard value-maximization objective. In our environment, this is equivalent to maximizing the expected profit in every period t. In turn, Equation (1) shows that the profit is linearly increasing in the productivity level.

Let $\mathbb{E}_i^{\text{in}}[\pi_i(t+\Delta t)|\cdot]$ and $\mathbb{E}_i^{\text{im}}[\pi_i(t+\Delta t)|\cdot]$ denote the expected profit for firm i from choosing in-house R&D or imitation, respectively. The probability of success in innovating through in-house R&D is given by $p_i(t) \in [\underline{p}, \overline{p}]$, with $0 \le \underline{p} \le \overline{p} \le 1$. The probabilities $p_i(t)$ are i.i.d. and realized at the beginning of each period t.

Firm i chooses innovation whenever, conditional on its current productivity $A_i(t)$ and the state of $p_i(t)$, we have that

$$\mathbb{E}_i^{\text{in}}[\pi_i(t+\Delta t)|\, A_i(t), p_i(t), P(t)] = \mathbb{E}_i^{\text{in}}\left[\psi A_i(t+\Delta t)^{\eta-1} - \kappa\left(\overline{A}(t)^{\theta} A_i(t)^{1-\theta}\right)^{\eta-1} \middle|\, A_i(t), p_i(t), P(t)\right] >$$
$$\mathbb{E}_i^{\text{im}}\left[\pi_i(t+\Delta t)|\, A_i(t), P(t)\right] = \mathbb{E}_i^{\text{im}}\left[\psi A_i(t+\Delta t)^{\eta-1}\middle|\, A_i(t), P(t)\right]. \quad (3)$$

The expected profit in Equation (3) from imitation is given by

$$\mathbb{E}_i^{\text{im}}\left[\pi_i(t+\Delta t)|\, A_i(t), P(t)\right] = q\left(1-F_{a_i(t)}(t)\right)\psi A_i(t)^{\eta-1}\widetilde{A}^{\eta-1} + \left(1-q\left(1-F_{a_i(t)}(t)\right)\right)\psi A_i(t)^{\eta-1},$$

while the expected profit from innovation is given by

$$\mathbb{E}_i^{\text{in}}[\pi_i(t+\Delta t)|\, A_i(t), p_i(t), P(t)] = p_i(t)\psi A_i(t)^{\eta-1}\widetilde{A}^{\eta-1} - \kappa\left(\overline{A}(t)^{\theta} A_i(t)^{1-\theta}\right)^{\eta-1} + (1-p_i(t))\psi A_i(t)^{\eta-1}. \quad (4)$$

In terms of log-productivities $a_i(t) = \log A_i(t)$, $\overline{a}(t) = \log \overline{A}(t)$ and $\log \widetilde{A} = \widetilde{a}$,[17] we can write

$$\begin{aligned}\mathbb{E}_i^{\text{in}}[\pi_i(t+\Delta t)|\, a_i(t), p_i(t), P(t)] = p_i(t)\psi e^{(\eta-1)(a_i(t)+\widetilde{a})} - \kappa e^{(\eta-1)\theta\overline{a}(t)} e^{(\eta-1)(1-\theta)a_i(t)} \\ + (1-p_i(t))\psi e^{(\eta-1)a_i(t)},\end{aligned}$$

and

$$\mathbb{E}_i^{\text{im}}\left[\pi_i(t+\Delta t)|\, a_i(t), P(t)\right] = \psi e^{(\eta-1)a_i(t)} \left(1 + q\left(1 - F_{a_i(t)}(t)\right)\left(e^{(\eta-1)\widetilde{a}} - 1\right)\right).$$

In the following, we denote by $\overline{\pi}_i^{\text{im}}(a_i(t), P(t)) \equiv \mathbb{E}_i^{\text{im}}[\pi_i(t+\Delta t)|\, a_i(t), P(t)]$ and $\overline{\pi}_i^{\text{in}}(a_i(t), p_i(t), P(t)) \equiv \mathbb{E}_i^{\text{in}}[\pi_i(t+\Delta t)|\, a_i(t), p_i(t), P(t)]$. The indicator function for whether firm i pursues imitation can then be written as $\chi^{\text{im}}(a,p,P) = \mathbb{1}_{\{\overline{\pi}_i^{\text{im}}(a,P) > \overline{\pi}_i^{\text{in}}(a,p,P)\}}$. We also define the indicator function for innovation as $\chi^{\text{in}}(a,p,P) \equiv 1 - \chi^{\text{im}}(a,p,P)$. Further, we define

$$\widetilde{\kappa} = \frac{\kappa}{\psi(e^{(\eta-1)\widetilde{a}} - 1)},$$

which is a measure for the relative cost (κ) over the monopoly power of firms (ψ). We can then write

$$\chi^{\text{im}}(a,p,P) = 1 - \chi^{\text{in}}(a,p,P) = \begin{cases} 1 & \text{if } p < q(1-F_a) + \widetilde{\kappa} e^{\theta(\eta-1)(\overline{a}-a)}, \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

3.4. Innovation Decision and Comparative Statics

Based on Equation (5), if we denote by

$$D_i = \underbrace{p_i}_{\substack{\text{innovation}\\ \text{potential}}} \; \underbrace{-\widetilde{\kappa} e^{\theta(\eta-1)(\overline{a}-a_i)}}_{\substack{\text{competition/cost}\\ \text{effect}}} \; \underbrace{-q(1-F_{a_i})}_{\substack{\text{imitation}\\ \text{potential}}}, \tag{6}$$

then, firm i conducts innovation ($\chi_{a_i}^{\text{in}}(p,P) = 1$) if $D_i > 0$ and chooses imitation ($\chi_{a_i}^{\text{im}}(p,P) = 1$) if $D_i \leq 0$. From a comparative statics analysis, we find that

$$\begin{aligned}
\frac{\partial D_i}{\partial a_i} = \theta \widetilde{\kappa} e^{\theta(\eta-1)(\overline{a}-a_i)} + q f_{a_i} > 0, &\qquad \text{(size)}, \\
\frac{\partial D_i}{\partial p_i} = 1 > 0, &\qquad \text{(in-house R\&D success probability)}, \\
\frac{\partial D_i}{\partial \widetilde{\kappa}} = -e^{\theta(\eta-1)(\overline{a}-a_i)} < 0, &\qquad \text{(competition / R\&D cost)}, \\
\frac{\partial D_i}{\partial q(1-F_{a_i})} < 0, &\qquad \text{(imitation success probability / laggards)}.
\end{aligned}$$

[17] Observe that $A_i \in \{\widetilde{A}, \widetilde{A}^2, \widetilde{A}^3, \ldots\} = \{e^{\widetilde{a}}, e^{2\widetilde{a}}, e^{3\widetilde{a}}, \ldots\}$.

In particular, firms with a higher log-productivity a_i tend to be larger and, according to Equation (6), have a higher probability of conducting R&D ($\frac{\partial D_i}{\partial a_i} > 0$). A higher value of the in-house R&D success probability p_i –due to e.g. a higher technological potential of the firm from industry-university collaborations– leads to a higher probability of engaging in R&D ($\frac{\partial D_i}{\partial p_i} > 0$), consistent with empirical observations. More intense competition can be captured by a higher value of the competition parameter $1/\psi$ and, according to Equation (6), leads to a lower probability of doing R&D ($\frac{\partial D_i}{\partial \widetilde{\kappa}} < 0$, where $\widetilde{\kappa} = \kappa/(\psi(e^{(\eta-1)\widetilde{a}}-1))$ is increasing in $1/\psi$). Note also that the term $e^{\theta(\eta-1)(\overline{a}-a_i)}$ is smaller the further the firm's log-productivity is above the average log-productivity $\overline{a}$, which in turn diminishes the competition effect through $\widetilde{\kappa}$. Less costly R&D investments (decrease in κ) lead to a higher probability of pursuing R&D ($\frac{\partial D_i}{\partial \widetilde{\kappa}} < 0$), consistent with empirical observations. Finally, the term $q(1-F_{a_i})$ reduces the likelihood of the firm conducting R&D, which is increasing in the imitation success probability q and is higher for firms lagging further behind in their log-productivity due to higher values of $1-F_{a_i}$ [cf. Aghion et al., 2005; Hashmi, 2013].

3.5. Failed In-house R&D and Passive Imitation

So far, we have assumed that a firm will not be able to enhance its productivity if it fails to innovate. This is a very strict assumption and excludes the possibility that a firm alters its strategy and shifts its focus to imitation instead of innovation when the latter proves unsuccessful. In an extended version of our model, we assume that if innovation fails, the firm gets a second chance to improve its technology via (passive) imitation. However, in such case, the probability of success is different from that of a firm actively pursuing imitation, being equal to $\delta q(1-F_a)$, with δ the passive imitation success probability. Thus, the total probability of success of a firm pursuing innovation is $p_i + (1-p_i)\delta q(1-F_a)$. The expected profit from innovation can then be computed by expanding Equation (4) as follows

$$\begin{aligned}\mathbb{E}_i^{\text{in}}[\pi_i(t+\Delta t)|\, A_i(t), p_i(t), P(t)] &= p_i(t)\psi A_i(t)^{\eta-1}\widetilde{A}^{\eta-1} - \kappa\left(\overline{A}(t)^{\theta}A_i(t)^{1-\theta}\right)^{\eta-1} + (1-p_i(t)) \\ &\times\left\{\delta\left[q\left(1-F_{a_i(t)}(t)\right)\psi A_i(t)^{\eta-1}\widetilde{A}^{\eta-1} + \left(1-q\left(1-F_{a_i(t)}(t)\right)\right)\psi A_i(t)^{\eta-1}\right] + (1-\delta)\psi A_i(t)^{\eta-1}\right\}.\end{aligned} \tag{7}$$

In terms of log-productivities (where we have defined $a_i(t) = \log A_i(t)$, $\overline{a}(t) = \log \overline{A}(t)$ and $\log \widetilde{A} = \widetilde{a}$), we can write this as

$$\begin{aligned}\mathbb{E}_i^{\text{in}}[\pi_i(t+\Delta t)|\, a_i(t), p_i(t), P(t)] &= p_i(t)\psi e^{(\eta-1)(a_i(t)+\widetilde{a})} - \kappa e^{(\eta-1)\theta\overline{a}(t)}e^{(\eta-1)(1-\theta)a_i(t)} + (1-p_i(t)) \\ &\times\left\{\delta\left[q\left(1-F_{a_i(t)}(t)\right)\psi e^{(\eta-1)(a_i(t)+\widetilde{a})} + \left(1-q\left(1-F_{a_i(t)}(t)\right)\right)\psi e^{(\eta-1)a_i(t)}\right] + (1-\delta)\psi e^{(\eta-1)a_i(t)}\right\}.\end{aligned}$$

With passive imitation, the indicator function for whether firm i pursues imitation in Equation (5) then needs to be modified as follows

$$\chi^{\text{im}}(a,p,P) = 1-\chi^{\text{in}}(a,p,P) = \begin{cases} 1 & \text{if } p < \frac{(1-\delta)q(1-F_a)+\widetilde{\kappa}e^{\theta(\eta-1)(\overline{a}-a)}}{1-\delta q(1-F_a)}, \\ 0 & \text{otherwise.}\end{cases} \tag{8}$$

3.6. Law of Motion of the Productivity Distribution

We consider an environment in which firms decide to conduct in-house R&D or to imitate other firms by maximizing the expected profit in every period t (see Sections 3.3 to 3.5). These decisions determine how the distribution of productivity evolves over time t. The following proposition provides a complete characterization of the evolution of the productivity distribution with heterogeneous firms in terms of their in-house R&D success probabilities, $p_i(t) \in [\underline{p}, \overline{p}]$.

Proposition 1. *The evolution of the* log*-productivity distribution $P_a(t)$, $a \in \mathcal{A}$, is given by the following system of integro-differential equations*

$$\begin{aligned}\frac{\partial P_a(t)}{\partial t} = \int_{[\underline{p},\overline{p}]} g(dp) \Big[& \left(\chi^{im}(a-1,p,P) + \delta(1-p)\chi^{in}(a-1,p,P)\right) q(1-F_{a-1}(t))P_{a-1}(t) \\ & - \left(\chi^{im}(a,p,P) + \delta(1-p)\chi^{in}(a,p,P)\right) q(1-F_a(t))P_a(t) \\ & + \chi^{in}(a-1,p,P)pP_{a-1}(t) - \chi^{in}(a,p,P)pP_a(t) \Big], \end{aligned} \tag{9}$$

where $g : [\underline{p}, \overline{p}] \to [0,1]$ is the density function of a random variable over the interval $[\underline{p}, \overline{p}]$ and

$$\chi^{im}(a,p,P) = 1 - \chi^{in}(a,p,P) = \begin{cases} 1 & \text{if } p < \frac{(1-\delta)q(1-F_a)+\tilde{\kappa}e^{\theta(\eta-1)(\overline{a}-a)}}{1-\delta q(1-F_a)}, \\ 0 & \text{otherwise,} \end{cases} \tag{10}$$

with $F_a = \sum_{b=1}^{a} P_b$ and average log*-productivity given by $\overline{a} = \sum_{a=1}^{\infty} F_a$.*

The proof of Proposition 1 can be found in Supplementary Appendix B. We can compute the evolution of the productivity distribution $P_a(t)$ by numerically solving the system of ordinary differential equations provided in Equation (9) for a given initial condition $P_a(0)$. This will be important for estimating the model in Section 4.1. In Supplementary Appendix A, we simplify Equation (9) by assuming a uniform distribution for in-house R&D success probabilities (as in König et al. [2022]), consistent with the assumption we make when estimating the structural model.

3.7. Traveling Wave, Threshold and Identification

It can be shown that the stationary productivity distribution $P_a(t)$ arising from Equation (9) is a "traveling wave" with power law tails and a threshold log-productivity level $a^*(t) = \{\max a \in \mathcal{A} : \chi^{\mathrm{im}}(a) = 1\}$ such that all firms above the threshold conduct in-house R&D while all firms below the threshold do imitation.[18] The shape of the productivity distribution (such as the dispersion and skewness), the growth rate and the threshold of the R&D profile (the probability to conduct R&D as a function of productivity) are closely related to the parameters of the structural model. This enables a distribution-based identification strategy of the structural parameters [Lewbel, 2019].

[18]For a proof, we refer to König et al. [2016] and König et al. [2022]. However, note that unlike König et al. [2022], we do not require stationarity of the distribution for estimating the model in Section 4.

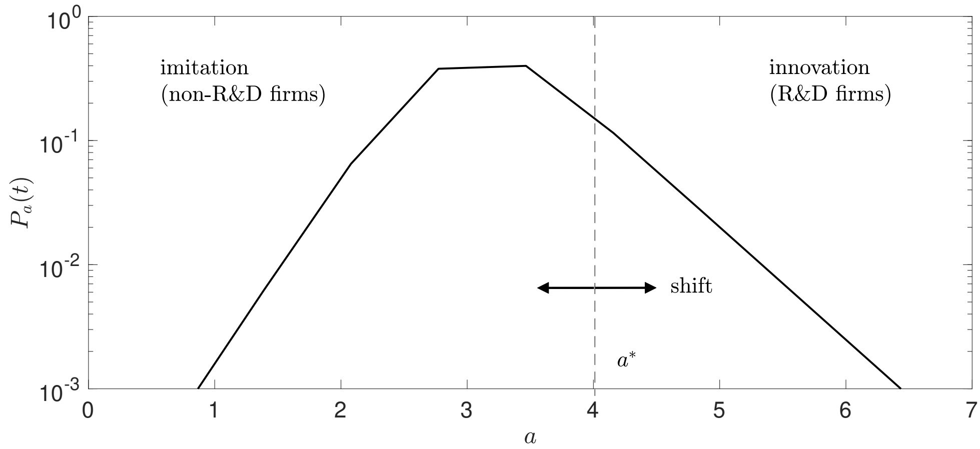

Figure 9: An illustration of the threshold a^*.

The productivity growth rate ν is increasing in the parameters p, q, δ and decreasing in the cost parameter $\widetilde{\kappa}$ (see also Section 5). This implies that higher innovation success (p), an increased rate at which ideas diffuse (q and δ) and lower R&D costs ($\widetilde{\kappa}$) have a positive impact on aggregate productivity growth. Consequently, they would shift the productivity distribution to the right over time, as illustrated in Figure 2. Further, a shift to the right of the threshold a^*, as illustrated in Figure 9, results in a reduction in the number of R&D active firms. The threshold increases if the in-house R&D success probability p decreases, the imitation success probability q increases, the passive imitation success probability δ decreases or R&D costs rise. Conversely, a reduction in R&D costs (e.g. due to a subsidy) would lower the threshold and increase the fraction of firms doing R&D. An increasing dispersion of the productivity distribution P_a, as illustrated in Figure 10, can be due to an increase in the in-house R&D success probability p, as the technological frontier moves up leaving laggard firms behind, or due to lower imitation success probabilities q or δ preventing laggard firms from catching up with technological leaders. Moreover, a higher value of the in-house R&D success probability p increases the skewness of the distribution. As firms become more successful in conducting R&D, the upper tail of the productivity distribution becomes heavier, with some firms at the technological frontier leaving the bulk of laggard firms further behind through a sequence of successful innovations. Finally, note that depending on the location of the threshold a^* on the productivity ladder, the fraction of R&D and non-R&D firms will vary, and with this the impact of changes in the imitation success probability q of non-R&D firms and the imitation success probability δ of R&D firms, respectively, on the productivity distribution and the growth rate.

We will use the sensitivity of the productivity growth rate, the productivity distribution, the threshold and the R&D profile discussed above to identify the parameters of the model in the following section.

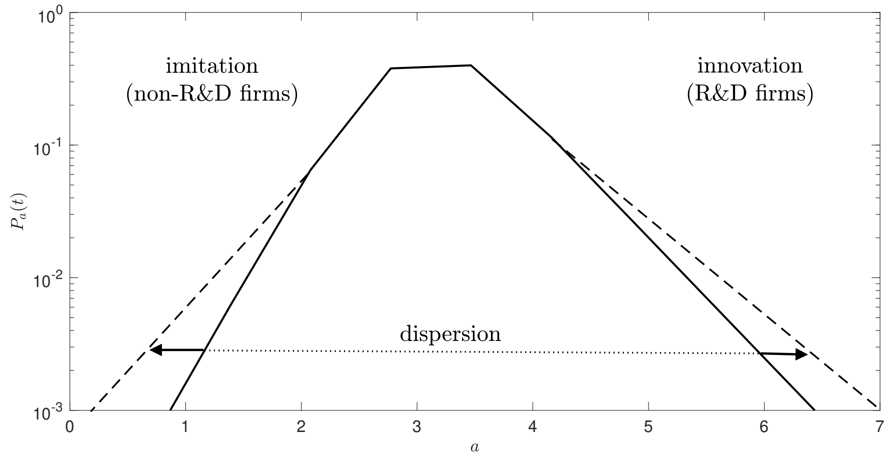

Figure 10: An illustration of the dispersion of the productivity distribution $P_a(t)$.

4. Estimation

In the following, we estimate the structural model introduced in Section 3 that takes into account the endogenous evolution of firms' productivity from their innovation and imitation decisions. Guided by the increase of R&D activity in the Netherlands after 2008 and the timing of the introduction of the Innovation Box (2007), we compare estimates from the pre- and post-2008 period when estimating the structural model.[19]

4.1. Structural Estimation: Productivity distribution and R&D decision

In order to estimate the parameters of the structural model introduced in Section 3, we choose the parameters in such a way as to fit the distributions predicted by the model to the empirical distributions. More precisely, we consider a set of moments (measuring the absolute differences between the model and the data) constructed from the log-productivity distribution and the R&D profile, i.e. the fraction of firms conducting R&D for a given log-productivity level. We then search for the parameters that minimize the distance between the targeted empirical moments and the

[19]In Supplementary Appendix C, we also estimate a linear probability model based on Equation (6) using Ordinary Least Squares (OLS) giving us correlations between the underlying fundamentals of firms' choice to either innovate or imitate and firms' actual R&D decision. Analogously, we can estimate the decision variable in Equation (8) where we allow for imitation of firms that fail to do successful in-house R&D ("passive imitation") using Nonlinear Least Squares (NLS). However, these reduced-form estimates might suffer from endogeneity bias (reverse causality) due to productivity (and other variables) being affected by the innovation decision (and vice versa). Moreover, the application of such regression models to a binary dependent variable can yield inefficient, inconsistent and biased coefficient estimates [cf. e.g. Long, 1997]. These reduced-form estimates will only be used to initialize the Metropolis-Hastings simulated moments minimization algorithm discussed in Section 4.1.

stationary distribution of the model. This estimation approach is referred to as the Simulated Method of Moments (SMM) procedure [McFadden, 1989] and the identification of the parameters is also referred to as distribution-based identification [Lewbel, 2019].

From Equation (2), we estimate the cost elasticity parameter θ from a linear regression of de-meaned log R&D expenditures on de-meaned log productivities in every period.[20] Moreover, following König et al. [2022] and Song et al. [2011], we set the demand elasticity parameter η to 5. The step size $\widetilde{a}$ is set to 0.05. For the remaining parameters of the model, we target a set of moments derived from the data and our model. The first set of moments derives from the productivity distribution P_a. The second set of moments is constructed from the fraction $H(a, P)$ of firms conducting R&D for a given log-productivity level a. Following the innovation decision in Equation (10) and assuming uniform draws of p in the interval $[0, \overline{p}]$, this is given by

$$H(a, P) \equiv \int_{[0,\overline{p}]} \chi^{\text{in}}(a, p, P) dp = \int_{[0,\overline{p}]} \mathbb{1}_{\{p > C(a,P)\}} dp, \tag{11}$$

where we have denoted by (cf. Equation (8))

$$C(a, P) \equiv \frac{(1-\delta)q(1-F_a) + \widetilde{\kappa} e^{\theta(\eta-1)(\overline{a}-a)}}{1 - \delta q (1-F_a)}.$$

The moments for our SMM approach are constructed from

$$\widehat{\mathbf{m}}(P, H|\boldsymbol{\theta}) = \begin{bmatrix} \vdots \\ P(a,t) \\ \vdots \\ H(a,t) \\ \vdots \end{bmatrix}, \quad \mathbf{m}(P_{\text{obs}}, H_{\text{obs}}) = \begin{bmatrix} \vdots \\ P_{\text{obs}}(a,t) \\ \vdots \\ H_{\text{obs}}(a,t) \\ \vdots \end{bmatrix},$$

with the error function given by $\mathbf{e}(P, H, P_{\text{obs}}, H_{\text{obs}}|\boldsymbol{\theta}) = \widehat{\mathbf{m}}(P, H|\boldsymbol{\theta}) - \mathbf{m}(P_{\text{obs}}, H_{\text{obs}})$, where $\boldsymbol{\theta} \in \boldsymbol{\Theta}$ denotes the vector of parameters, $(P_{\text{obs}}(a, t))_{a \geq 0}$ is the observed empirical productivity distribution at time t and $(H_{\text{obs}}(a, t))_{a \geq 0}$ is the observed empirical R&D profile at time t for the time periods $t = 0, \ldots, T$. The distributions $P(a, t)$ and $H(a, t)$ are the corresponding theoretical predictions from the solution to Equations (9) and (11) with the previous time period $t - 1$ as initial condition. The SMM estimator is then given by

$$\widehat{\boldsymbol{\theta}}_{SMM} = \text{argmin}_{\boldsymbol{\theta} \in \boldsymbol{\Theta}} \, \mathbf{e}(P, H, P_{\text{obs}}, H_{\text{obs}}|\boldsymbol{\theta})^\top \, \mathbf{W} \, \mathbf{e}(P, H, P_{\text{obs}}, H_{\text{obs}}|\boldsymbol{\theta}). \tag{12}$$

We use the identity matrix as weighting matrix $\mathbf{W}$ to avoid a potential small-sample bias [Altonji and Segal, 1996]. Moreover, we implement the moments minimization in Equation (12) with a

[20]Note that Equation (2) implies $\log c_i(t) - \overline{\log c(t)} = (\eta - 1)(1 - \theta)(a_i(t) - \overline{a}(t))$, where $c_i(t)$ is measured by the R&D expenditure level of firm i at time t, $a_i(t)$ by its log-productivity level and over-lined variables correspond to averages across firms.

Table 5: Pre- and post-2008 sample SMM estimation results for Switzerland and the Netherlands.

		Sample period 2000-2008		Sample period 2010-2016		Sample period 2012-2016	
		Switzerland SMM (1)	the Netherlands SMM (2)	Switzerland SMM (3)	the Netherlands SMM (4)	Switzerland SMM (5)	the Netherlands SMM (6)
Innovation	($\bar{p}$)	0.6034***	0.5685***	0.6199***	0.5496***	0.6297***	0.5782***
		(0.0505)	(0.0267)	(0.0625)	(0.0228)	(0.0625)	(0.0179)
Cost	($\tilde{\kappa}$)	0.0064***	0.0399***	0.0410***	0.0002***	0.0322***	0.0004***
		(0.0068)	(0.0118)	(0.0206)	(0.0000)	(0.0159)	(0.0002)
Imitation	(q)	0.1161***	0.2375***	0.1669***	0.1830***	0.1268***	0.1251***
		(0.0418)	(0.0457)	(0.0540)	(0.0455)	(0.0396)	(0.0305)
Passive Imitation	(δ)	0.0757***	0.1614***	0.7589***	0.4005***	0.0727***	0.0744***
		(0.0206)	(0.0295)	(0.0312)	(0.0350)	(0.0132)	(0.0150)
Firms		4,231	15,659	3,593	10,233	2,944	6,864
Observations		6,940	25,992	7,290	17,349	5,056	11,858
$R^2_{\mathrm{KL}}(P\|P_{\mathrm{obs}})$		0.8427	0.8637	0.9123	0.8720	0.9128	0.8955
$R^2_{\mathrm{KL}}(H\|H_{\mathrm{obs}})$		0.9353	0.9655	0.9163	0.9863	0.9192	0.9874
Change: 2000-2008 to 2010-2016							
Innovation	($\Delta\bar{p}/\bar{p}$)			+2.73%	-3.32%		
Cost	($\Delta\tilde{\kappa}/\tilde{\kappa}$)			+540.62%	-99.49%		
Imitation	($\Delta q/q$)			+43.75%	-22.94%		
Passive Imitation	($\Delta\delta/\delta$)			+902.50%	+148.14%		
Change: 2000-2008 to 2012-2016							
Innovation	($\Delta\bar{p}/\bar{p}$)					+4.35%	+1.70%
Cost	($\Delta\tilde{\kappa}/\tilde{\kappa}$)					+403.12%	-98.99%
Imitation	($\Delta q/q$)					+9.21%	-47.32%
Passive Imitation	($\Delta\delta/\delta$)					-3.96%	-53.90%

Notes: For each year and within each NACE Rev. 2 1-digit code, the data has been trimmed at the top and bottom 1% productivity percentiles at the industry-year level. Columns (1) to (6) are based on the Simulated Methods of Moments (SMM) estimation algorithm discussed in Section 4.1 for which we set $\tilde{a} = 0.05$ with 100 bootstrap samples. For Switzerland, the estimate for the cost parameter θ is 0.701 in the period 2000-2008 (column (1)), 0.740 in the period 2010-2016 (column (3)) and 0.802 in the period 2012-2016 (column (5)). For the Netherlands, the estimate for the cost parameter θ is 0.536 in the period 2000-2008 (column (2)), 0.526 in the period 2010-2016 (column (4)) and 0.648 in the period 2012-2016 (column (6)). Standard errors in parentheses. The asterisks *** (**,*) indicate that a parameter's 99% (95%, 90%) highest posterior density interval does not cover zero [Kruschke, 2015]. The R-squared measure $R^2_{\mathrm{KL}}(\cdot|\cdot)$ follows Cameron and Windmeijer [1997] and is defined as $R^2_{\mathrm{KL}}(\cdot|\cdot) = 1 - D_{\mathrm{KL}}(\cdot|\cdot)$, where $D_{\mathrm{KL}}(\cdot|\cdot)$ is the Kullback-Leibler divergence. The Kullback-Leibler divergence, $D_{\mathrm{KL}}(H|H_{\mathrm{obs}}) = \sum_a H(a)\log\left(\frac{H(a)}{H_{\mathrm{obs}}(a)}\right)$, measures the difference between the predicted (H) and the observed (empirical) distribution (H_{obs}) [Song, 2002]. The reported R-squared measures are averages across time periods.

Metropolis-Hastings MCMC algorithm following Chernozhukov and Hong [2003] and starting parameter values obtained from the reduced-form regression of Equation (8) using Nonlinear Least Squares (NLS). The estimates for the latter can be found in Supplementary Appendix C. Point estimates, standard errors and significance levels are computed using the bootstrap method with 100 bootstrap samples.[21]

[21] In all SMM model specifications, we assume that firms get a random draw from a uniform distribution with support $[0, \bar{p}]$ for their in-house R&D success probabilities every period (cf. Supplementary Appendix A).

Estimation results for Switzerland. The SMM estimates for Switzerland for the years 2000-2008 and 2010-2016 are reported in columns (1) and (3) of Table 5, respectively. We observe an increase in the in-house R&D success probability ($\bar{p}$) of 2.73% when comparing the pre- and post-2008 period (2000-2008 to 2010-2016).[22] We further observe an increase in the imitation success probability among non-R&D firms (q) of 43.75% in the post-2008 period. The estimate for the passive imitation success probability of R&D firms (δ) shows a nine-fold increase in the post-2008 period. These results highlight the increasing importance of imitation and technology diffusion for both non-R&D and R&D firms in the post-2008 period for Switzerland in order to fit the theoretical model to the empirical data. Moreover, the estimate of the relative cost parameter ($\widetilde{\kappa}$) increased by more than a factor of five (comparing 2000-2008 to 2010-2016).[23] This indicates that R&D costs have gained importance for a Swiss firm's decision to engage in R&D in the post-2008 period. An increase in R&D costs has also been documented in the empirical literature. For example, Bloom et al. [2020] and Pammolli et al. [2011] report a significant rise in R&D costs in the pharmaceutical sector. This sector is particularly large in Switzerland. At the same time, survey data for Switzerland indicate that competition has increased in Switzerland post-2008. Both of these effects could have contributed to the large increase in the estimated cost parameter ($\tilde{\kappa}$).[24] Our results suggest that the rise in R&D costs could be one of the driving forces behind the productivity growth decline observed for Switzerland in the post-2008 period (cf. Figure 3 in Section 2.2).

The goodness-of-fit of the SMM model specification is shown in Figures D.1-D.4 and E.1-E.2 in Supplementary Appendix D. Across the different years considered, the SMM model fits the data well.

Estimation results for the Netherlands. The SMM estimates for the Netherlands for the years 2000-2008 and 2010-2016 are reported in columns (2) and (4) of Table 5, respectively. We find a decrease in the in-house R&D success probability ($\bar{p}$) in the post-2008 period. This decrease is relatively small, however (about 3%). Technology diffusion among non-R&D firms has declined in the post-2008 period, as evidenced by a decrease in the imitation success probability (q) of 23%. In contrast, we observe that the passive imitation success probability of R&D firms (δ) more than doubled. The differences in the changes of the imitation success probabilities of non-R&D vs. R&D firms could be related to the increase in the fraction of R&D firms in the post-2008 period. Further, we observe a collapse of the relative R&D cost parameter ($\widetilde{\kappa}$) when comparing the pre- and post-2008 period. This significant decline may be attributed to public support measures aimed at reducing innovation costs in the Netherlands post-2008 (cf. Section 2.1).

[22]The corresponding estimated average in-house R&D success probability is given by $\bar{p}/2$.

[23]To account for the observed empirical fact that even firms with higher productivity stop doing R&D in the post-2008 period in Switzerland, the estimate for $\widetilde{\kappa}$ has to increase significantly for the model to be able to fit the data. To see this, note that for a firm with a log-productivity a much higher than the average $\bar{a}$, the terms $1 - F_a$ and $e^{\theta(\eta-1)(\bar{a}-a)}$ in Equation (8) governing the R&D decision will be very small. To deter such a firm from engaging in R&D, $\widetilde{\kappa}$ must be substantial.

[24]The increase in competition could be interpreted as a decrease in ψ and the increase in R&D costs as an increase in κ resulting in an overall increase in $\tilde{\kappa} \propto \kappa/\psi$. The combined effect could then be higher than the increase in the R&D cost-related parameter κ alone. An illustration of a shock affecting competition could be an exchange rate shock, which is particularly relevant for the Swiss economy.

The goodness-of-fit of the SMM model specification is shown in Figures D.5-D.8 and E.3-E.4 in Supplementary Appendix D. Across the different years considered, the SMM model fits the data well.

4.2. Robustness

In the following, we provide a series of robustness checks of the benchmark estimation results reported in Table 5.[25] We first consider an alternative post-sample period, excluding the immediate aftermath of the financial crisis, as this crisis may have simultaneously influenced productivity and innovation or imitation decisions. Additionally, one might be concerned about omitted unobserved firm heterogeneity that could bias the R&D decision and thus the estimation results. The robustness checks that we further consider in this section use a more homogeneous sample where such heterogeneity is less of a concern.[26] In particular, we consider a balanced panel which comprises mainly larger firms. Moreover, we estimate the model for the manufacturing sector only and also employ an alternative productivity measure (revenue total factor productivity, based on Ackerberg et al. [2015]). In all cases considered, we obtain qualitatively similar results as in the baseline specification in columns (1) to (4) in Table 5.

Alternative sample period. Columns (5) and (6) in Table 5 show the estimates of the model for an alternative post-sample period covering the years 2012 to 2016.[27] For Switzerland, we find that the R&D cost parameter estimate ($\widetilde{\kappa}$) is lower in the sample covering the years 2012 to 2016 than in the sample covering the years 2010 to 2016. This could be due to adjustment processes during more recent years that allowed firms to lower their R&D costs. For the Netherlands, we observe that the estimate of the R&D cost parameter ($\widetilde{\kappa}$) remains low in the post-sample period covering the years 2012 to 2016. However, the estimate of the passive imitation parameter (δ) is much smaller in the post-sample period covering the years 2012 to 2016. This could indicate an increased difficulty of technology diffusion and adoption of R&D firms in more recent years in the Netherlands.

Balanced panel. In columns (1) and (2) in Table 6, we re-estimate the model for a "balanced" panel where only firms with at least one observation in the pre- as well as in the post-sample period are included.[28] In the balanced sample for Switzerland, we do not see a drastic increase in the estimate of the R&D cost parameter ($\widetilde{\kappa}$). However, the estimate of the in-house R&D success probability ($\bar{p}$) is now smaller in the post-2008 period than in the pre-2008 period. This suggests that for firms in the balanced panel –which are typically larger– R&D costs became less of a concern, while the ability to successfully conduct in-house R&D became more challenging in the post-2008 period. For the Netherlands, we observe that the R&D cost parameter ($\widetilde{\kappa}$) also declined in the post-2008

[25]More detailed estimation results can be found in Supplementary Appendix E.

[26]Recall, however, that we already account for firm heterogeneity at the level of firm-specific productivity in our benchmark estimation results.

[27]Supplementary Appendix E.1 provides further details.

[28]Further details can be found in Supplementary Appendix E.2.

Table 6: Pre- and post-sample estimation results for Switzerland and the Netherlands using alternative samples.

		Balanced Panel		Manufacturing		Manufacturing with ACF	
		Switzerland	the Netherlands	Switzerland	the Netherlands	Switzerland	the Netherlands
		SMM	SMM	SMM	SMM	SMM	SMM
		(1)	(2)	(3)	(4)	(5)	(6)
Sample period: 2000-2008							
Innovation	$(\bar{p})$	0.6586***	0.5737***	0.6467***	0.6780***	0.6379***	0.5384***
		(0.0548)	(0.0431)	(0.0374)	(0.0260)	(0.0329)	(0.0269)
Cost	$(\widetilde{\kappa})$	0.0120***	0.0267***	0.0208***	0.1021***	0.0092***	0.0550***
		(0.0091)	(0.0084)	(0.0043)	(0.0291)	(0.0036)	(0.0071)
Imitation	(q)	0.1819***	0.2543***	0.0911***	0.2177***	0.0734***	0.2189***
		(0.0635)	(0.0473)	(0.0298)	(0.0481)	(0.0187)	(0.0085)
Passive Imitation	(δ)	0.0930***	0.2313***	0.0699***	0.4347***	0.0623***	0.7531***
		(0.0186)	(0.0532	(0.0160)	(0.0463)	(0.0045)	(0.0290)
Firms		2,148	4,268	2,123	4,311	1,496	3,420
Observations		4,016	9,378	3,533	7,750	2,268	6,297
$R^2_{\text{KL}}(P\|P_{\text{obs}})$		0.8822	0.8655	0.9086	0.9063	0.9008	0.8172
$R^2_{\text{KL}}(H\|H_{\text{obs}})$		0.9375	0.9433	0.9622	0.9583	0.9417	0.9374
Sample period: 2010-2016							
Innovation	$(\bar{p})$	0.4871***	0.6105**	0.6065***	0.7466***	0.5920***	0.6621***
		(0.0462)	(0.0290)	(0.0229)	(0.0183)	(0.0370)	(0.0317)
Cost	$(\widetilde{\kappa})$	0.0081***	0.0156***	0.0230***	0.0213***	0.0115***	0.0410***
		(0.0051)	(0.0058)	(0.0057)	(0.0084)	(0.0030)	(0.0130)
Imitation	(q)	0.1185***	0.1342***	0.1398***	0.1106***	0.0946***	0.4851***
		(0.0228)	(0.0519)	(0.0360)	(0.0216)	(0.0189)	(0.0540)
Passive Imitation	(δ)	0.6952***	0.3536***	0.7856***	0.3854***	0.6455***	0.9168***
		(0.0274)	(0.0624)	(0.0249)	(0.0469)	(0.0544)	(0.0125)
Firms		2,240	4,268	1,643	2,688	1,425	1,734
Observations		4,862	9,343	3,367	4,978	2,871	3,269
$R^2_{\text{KL}}(P\|P_{\text{obs}})$		0.8754	0.9114	0.9096	0.9146	0.9207	0.9538
$R^2_{\text{KL}}(H\|H_{\text{obs}})$		0.9002	0.9627	0.8914	0.9775	0.9141	0.9800
Change: 2000-2008 to 2010-2016							
Innovation	$(\Delta\bar{p}/\bar{p})$	-26.04%	+6.41%	-6.21%	+10.11%	-7.19%	+22.97%
Cost	$(\Delta\widetilde{\kappa}/\widetilde{\kappa})$	-32.50%	-41.57%	+10.57%	-79.13%	+25.00%	-25.45%
Imitation	$(\Delta q/q)$	-34.85%	-47.23%	+53.45%	-49.19%	+28.88%	+121.60%
Passive Imitation	$(\Delta\delta/\delta)$	+647.52%	+52.88%	+1,023%	-11.34%	+936.11%	+8.45%

Notes: For each year and within each NACE Rev. 2 1-digit code, the data has been trimmed at the top and bottom 1% productivity percentiles at the industry-year level. Columns (1) to (6) are based on the Simulated Methods of Moments (SMM) estimation algorithm discussed in Section 4.1 for which we set $\tilde{a} = 0.05$ with 50 bootstrap samples. For the balanced panel for Switzerland (column (1)), the estimate for the cost parameter θ is 0.688 in the period 2000-2008 and 0.648 in the period 2010-2016. For the balanced panel for the Netherlands (column (2)), the estimate for the cost parameter θ is 0.536 in the period 2000-2008 and 0.526 in the period 2010-2016. For the manufacturing sector (2-digit NACE codes 10-38) for Switzerland (column (3)), the estimate for the cost parameter θ is 0.688 in the period 2000-2008 and 0.800 in the period 2010-2016. For the manufacturing sector for the Netherlands (column (4)), the estimate for the cost parameter θ is 0.536 in the period 2000-2008 and 0.526 in the period 2010-2016. For the manufacturing sector using the alternative productivity measure (revenue total factor productivity) introduced in Ackerberg et al. [2015] (ACF) for Switzerland (column (5)), the estimate for the cost parameter θ is 0.688 in the period 2000-2008 and 0.796 in the period 2010-2016. For the manufacturing sector using the alternative productivity measure for the Netherlands (column (6)), the estimate for the cost parameter θ is 0.536 in the period 2000-2008 and 0.526 in the period 2010-2016. Standard errors in parentheses. The asterisks *** (**,*) indicate that a parameter's 99% (95%, 90%) highest posterior density interval does not cover zero [Kruschke, 2015]. The R-squared measure $R^2_{\text{KL}}(\cdot|\cdot)$ follows Cameron and Windmeijer [1997] and is defined as $R^2_{\text{KL}}(\cdot|\cdot) = 1 - D_{\text{KL}}(\cdot|\cdot)$, where $D_{\text{KL}}(\cdot|\cdot)$ is the Kullback-Leibler divergence. The Kullback-Leibler divergence, $D_{\text{KL}}(H|H_{\text{obs}}) = \sum_a H(a) \log\left(\frac{H(a)}{H_{\text{obs}}(a)}\right)$, measures the difference between the predicted (H) and the observed (empirical) distribution (H_{obs}) [Song, 2002]. The reported R-squared measures are averages across time periods.

period in the balanced panel, albeit to a lesser extent than in the full sample. The estimate of the passive imitation parameter (δ) increased in the post-2008 period in both the balanced and the full panel. However, contrary to the full sample, the estimate of the in-house R&D success probability ($\bar{p}$) increased in the post-2008 period in the balanced panel. This contrasts with our finding for Switzerland, where firms in the balanced panel experienced a lower ability to conduct successfully in-house R&D in the post-2008 period.

Manufacturing sector. Columns (3) and (4) in Table 6 present the estimation results for the manufacturing sector only (2-digit NACE codes 10-38).[29] For Switzerland, we observe an increase in R&D costs ($\widetilde{\kappa}$) in the post-2008 period for manufacturing firms, which is, however, less pronounced than in the full sample. Moreover, in contrast to the full sample, we find a decrease in the in-house R&D success probability ($\bar{p}$) in the post-2008 period. In the Netherlands, we observe a significant decrease in R&D costs in the post-2008 period for both the manufacturing sector and the full sample. However, unlike the full sample, we find a decrease in the passive imitation success probability (δ) in the post-2008 period. This suggests that technology diffusion among R&D firms has declined in the Dutch manufacturing sector.

Alternative productivity measure. In columns (5) and (6) in Table 6, we estimate the model for the manufacturing sector using an alternative productivity measure (revenue total factor productivity) introduced in Ackerberg et al. [2015] (ACF).[30] In Switzerland, we observe an increase in R&D costs ($\widetilde{\kappa}$) in the post-2008 period for both the manufacturing sector using the ACF productivity measure and the full sample. This increase is far less pronounced, though, when using the ACF productivity measure. Contrary to the full sample, the in-house R&D success probability ($\bar{p}$) is lower in the post-2008 period. These results resemble the ones for the real value added per worker based productivity measure for the Swiss manufacturing sector (column (3) in Table 6). For the Netherlands, we observe a decrease in R&D costs in the post-2008 period for both the manufacturing sector using the ACF productivity measure and the full sample. This decrease is less pronounced, though, when using the ACF productivity measure. Moreover, the in-house R&D success probability ($\bar{p}$) is higher in the post-2008 period. This resembles the results for the real value added per worker based productivity estimates for the Dutch manufacturing sector (column (4) in Table 6).

When comparing the estimation results for Switzerland and the Netherlands across the different specifications shown in Tables 5 and 6, respectively, the most striking and robust difference between the pre- and post-2008 period is an increase of the R&D cost parameter ($\widetilde{\kappa}$) for Switzerland and a decrease of this parameter for the Netherlands.[31] This discrepancy is likely attributable to the distinct innovation support environments in these two countries in the post-2008 period. In the following section, we analyze counterfactual scenarios in which we quantify in more detail the effect

[29]See Supplementary Appendix E.3 for further details.

[30]See Supplementary Appendix E.4 for more details.

[31]Except for the balanced panel for Switzerland where R&D costs are declining as well. However, this is a sample dominated by larger firms for which R&D costs seem to be less important.

of these innovation support environments on the productivity growth rates in both countries.

5. Counterfactuals

Our estimated structural growth model allows us to analyze how the productivity growth rate (ν) depends on the in-house R&D success probability ($\bar{p}$), R&D costs ($\widetilde{\kappa}$) and the imitation success probabilities of non-R&D and R&D firms (q and δ, respectively).

We first provide a comparative statics analysis in which we compute the difference of the productivity growth rate ν from a simulation of the model with the estimated value $\hat{\theta}$ of a parameter $\theta \in \{\bar{p}, \widetilde{\kappa}, q, \delta\}$ from Table 5 compared to a counterfactual simulation where this parameter is set to zero ($\theta = 0$), holding all other parameters constant at their estimated values. We report the relative difference $((\nu(\theta = \hat{\theta}) - \nu(\theta = 0))/\nu(\theta = \hat{\theta}))$ in Table 7 for the 2000-2008 period and the 2010-2016 period, respectively. Column (1) shows the results for Switzerland and column (2) the corresponding results for the Netherlands. Table 7 shows that in both countries by far the largest contribution to the relative change in the productivity growth rate comes from the in-house R&D success probability ($\bar{p}$). If firms were never to succeed in conducting successful R&D (i.e. $\bar{p} = 0$) in the 2000-2008 period, growth would be 80.61% lower in Switzerland over the same time period. In the Netherlands, the reduction in the productivity growth rate would be 62.26%. The productivity growth effect is much smaller for the other fundamental parameters.

These magnitudes and their relative importance remain relatively stable in the pre- and post-2008 period. In particular, when comparing the pre- and post-2008 period for Switzerland, the reduction in the productivity growth rate is 5.2 percentage points (p.p.) lower for the innovation success probability ($\bar{p}$) and 7.1p.p., respectively, 9.1p.p. higher for the imitation (q) and passive imitation (δ) success probabilities in the post-2008 period. The increase of the productivity growth rate from setting R&D costs ($\widetilde{\kappa}$) to zero is 1.5p.p. higher in the post-2008 period. The sign of the changes when comparing the pre- and post-2008 period are the same for the imitation parameters in the Netherlands. In contrast, the importance of the in-house R&D success probability ($\bar{p}$) increased in the Netherlands but decreased in Switzerland while the opposite holds for the importance of R&D costs ($\tilde{\kappa}$). The latter mirrors the increasing (decreasing) importance of R&D costs in Switzerland (the Netherlands) as documented in Section 4.1.

For both countries, Table 7 illustrates that a lack of success with in-house R&D would be most detrimental to productivity growth, followed by a lack of imitation success (technology diffusion). This is consistent with the trivial observation that a deficiency of innovation would bring growth to a halt in the long run in our model. The smallest impact on growth results from reducing R&D costs. Consequently, policies that are effective in supporting firms' capabilities to successfully innovate or imitate could boost productivity growth the most.

To get a better understanding of the sensitivity of the productivity growth rate to changes in the fundamental parameters over a broader range of admissible values, Figure 11 shows the relative changes in the productivity growth rate (ν) when varying the in-house R&D success probability ($\bar{p}$), the imitation success probability (q), the passive imitation success probability (δ) and the R&D cost parameter ($\widetilde{\kappa}$), respectively, over a whole range of parameter values for the post-2008 period for

Table 7: The percentage change of the productivity growth rate from the parameter estimate to the parameter being set to zero.

		Switzerland (1)	the Netherlands (2)
Sample period: 2000-2008			
Innovation	$(\bar{p}=0)$	-80.61%	-62.26%
Cost	$(\widetilde{\kappa}=0)$	+0.03%	+1.01%
Imitation	$(q=0)$	-1.33%	-6.87%
Passive Imitation	$(\delta=0)$	-0.27%	-2.00%
Sample period: 2010-2016			
Innovation	$(\bar{p}=0)$	-75.38%	-70.01%
Cost	$(\widetilde{\kappa}=0)$	+1.56%	$+1.73\times10^{-5}$%
Imitation	$(q=0)$	-8.43%	-7.14%
Passive Imitation	$(\delta=0)$	-9.39%	-5.64%
Change: 2000-2008 to 2010-2016			
Innovation	(p.p.)	+5.23	-7.74
Cost	(p.p.)	+1.51	-1.01
Imitation	(p.p.)	-7.10	-0.27
Passive Imitation	(p.p.)	-9.12	-3.64

Notes: The relative difference in the productivity growth rate (ν) from the estimated parameter $\hat{\theta}$ to the parameter being set to zero ($\theta=0$) is computed as $(\nu(\theta=\hat{\theta})-\nu(\theta=0))/\nu(\theta=\hat{\theta})$ where $\theta\in\{\bar{p},\widetilde{\kappa},q,\delta\}$. Column (1) shows the results for Switzerland for the pre- and post-2008 period with the parameter estimates from Table 5. Column (2) shows the corresponding results for the Netherlands.

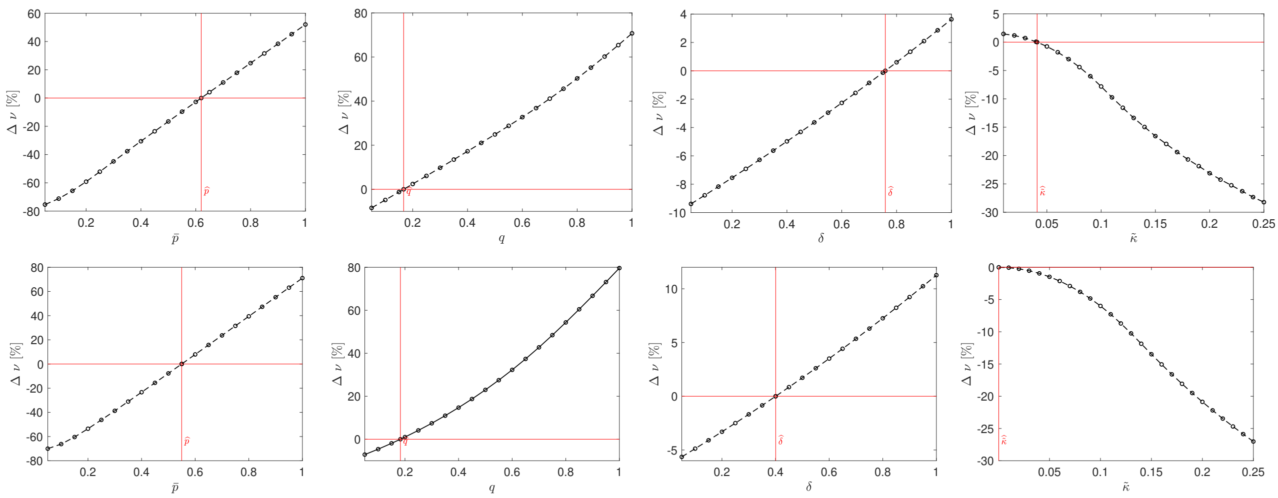

Figure 11: Changes in the productivity growth rate (ν) in Switzerland (top panels) and the Netherlands (bottom panels) when changing the in-house R&D success probability $\bar{p}$ (first column), the imitation success probability q (second column), the passive imitation success probability δ (third column) and the R&D cost parameter $\widetilde{\kappa}$ (last column), respectively, relative to their estimated values post-2008, with the remaining parameters set to their post-2008 estimates. The estimates can be found in column (3) in Table 5 for Switzerland and column (4) for Netherlands in Table 5. Vertical lines correspond to the estimated values.

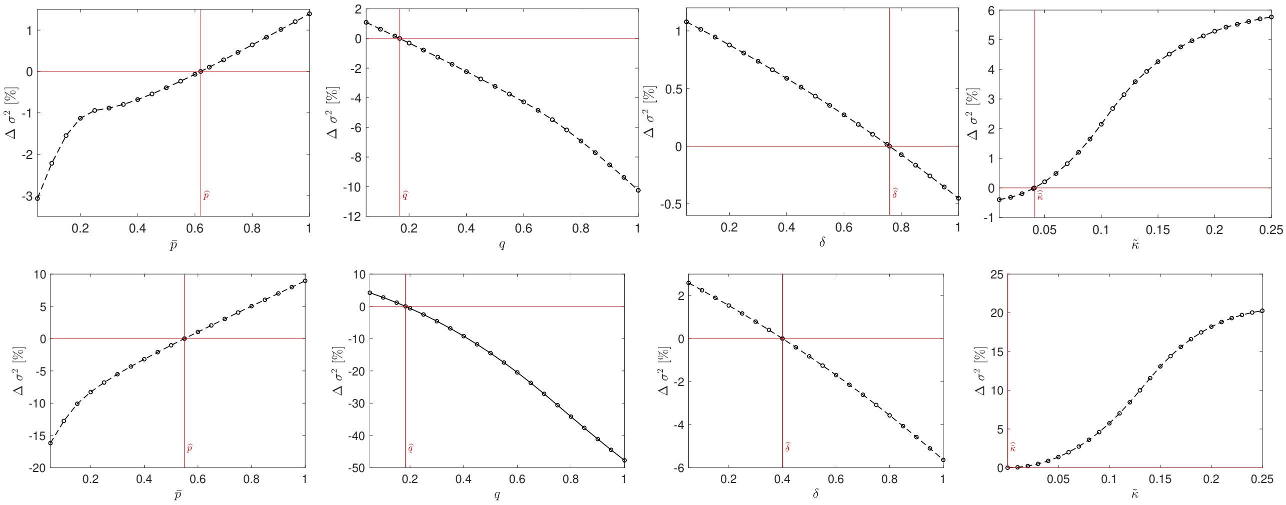

Figure 12: Changes in the productivity variance (σ^2) in Switzerland (top panels) and the Netherlands (bottom panels) when changing the in-house R&D success probability $\bar{p}$ (first column), the imitation success probability q (second column), the passive imitation success probability δ (third column) and the R&D cost parameter $\widetilde{\kappa}$ (last column), respectively, relative to their estimated values post-2008, with the remaining parameters set to their post-2008 estimates. The estimates can be found in column (3) in Table 5 for Switzerland and column (4) for Netherlands in Table 5. Vertical lines correspond to the estimated values.

Switzerland (top panels) and the Netherlands (bottom panels). The changes are computed relative to a benchmark scenario in which the parameters are set to their estimated values post-2008 in column (3) in Table 5 for Switzerland and column (4) in Table 5 for the Netherlands. We find that the productivity growth rate ν is monotonically increasing in $\bar{p}$, q and δ, while it is decreasing in the R&D cost parameter $\widetilde{\kappa}$. Figure 11 corroborates the results of Table 7 and shows that by far the highest increase in productivity growth can be achieved by increasing the success probabilities of innovation ($\bar{p}$) or imitation of non-R&D firms (q).

How do the fundamental parameters affect productivity dispersion? Figure 12 shows the relative changes in the productivity variance (σ^2) when varying the in-house R&D success probability ($\bar{p}$), the imitation success probability (q), the passive imitation success probability (δ) and the R&D cost parameter ($\widetilde{\kappa}$) for Switzerland and the Netherlands, respectively. For both countries, the variance (σ^2) is increasing in the in-house R&D success probability ($\bar{p}$) and the R&D cost parameter ($\widetilde{\kappa}$), while it is decreasing in the imitation success probabilities (q and δ), respectively. This illustrates that policies that increase the innovation success probability ($\bar{p}$) and/or decrease R&D costs ($\widetilde{\kappa}$) not only increase the productivity growth rate but also increase inequality in the economy.

Finally, we simulate a counterfactual for Switzerland in which we impose the change in the R&D cost parameter ($\widetilde{\kappa}$) that we observed in the Netherlands from the pre- to the post-2008 period. In particular, for the Netherlands we find that $\widetilde{\kappa}$ decreased by 99.5%. Applying the same relative change to Switzerland and leaving the in-house R&D success ($\bar{p}$), imitation (q) and passive imitation (δ) parameters at their post-2008 level, yields an increase in the productivity growth rate by 1.64% for the counterfactual relative to the benchmark (the latter given in column (3) in Table 5). We interpret this comparison of the benchmark and the counterfactual as indicating a potential (moderate) increase in the annual productivity growth rate had Switzerland experienced the same change in the R&D cost parameter as the Netherlands.

Similarly, we simulate a counterfactual for the Netherlands in which we set the estimated parameter for the R&D cost parameter ($\widetilde{\kappa}$) in the post-2008 period to the pre-2008 estimate (the latter given in column (2) in Table 5) and leave the in-house R&D success ($\bar{p}$), imitation (q) and passive imitation (δ) parameters at their post-2008 level. This simulation exercise mimics a counterfactual where the Netherlands did not experience an environment of extended innovation support. We find that the productivity growth rate in the counterfactual is 1.12% lower than in the benchmark scenario. We interpret this as evidence of the heightened innovation support having contributed to a modest increase of approximately 1.12% in the annual productivity growth rate in the Netherlands.

6. Conclusion

We analyze the distribution of productivity and the innovation decision of firms in two innovation leaders in Europe, Switzerland and the Netherlands, across a panel of almost 20 years of observations. These countries are characterized by diverging trends in R&D activity (a decrease in Switzerland and an increase in the Netherlands) but similar productivity trends and different approaches to innovation promotion (indirect R&D promotion in Switzerland but active support in the Netherlands). At the descriptive level, we document that more competitive firms in Switzerland are less likely to discontinue R&D activities compared to their Dutch counterparts. We further find that innovation support is effective in maintaining firms engaged in R&D activities in both countries.

To understand the nature and impact of these structural developments, where fewer but highly productive innovators stay R&D active in Switzerland and more but less productive innovators continue R&D activities in the Netherlands, we estimate a structural growth model and investigate the role of innovation success, R&D costs and technology spillovers (imitation success) in driving firms' R&D decision. Our structural model estimates indicate that higher R&D costs lead to a decline in the share of R&D active firms in Switzerland. In the Netherlands, in contrast, we observe sharply declining R&D costs, likely attributed to extensive innovation support. The significantly lower R&D costs result in an increase in the share of R&D active firms. Therefore, the divergent trend in R&D activity between Switzerland and the Netherlands is primarily a consequence of the divergent pattern in R&D costs.

We then use our estimated model to investigate how the productivity growth rate responds to changes in the success of innovation, the success of imitation and R&D costs. We find that the largest improvement in productivity growth can be achieved by enhancing the success probabilities of innovation or imitation among non-R&D firms (technology diffusion). While lower R&D costs lead to an increase in the number of R&D active firms, their contribution to productivity growth is relatively small. In a counterfactual, we show that if Switzerland had undergone a comparable reduction in the R&D cost parameter as observed in the Netherlands during the post-2008 period, the Swiss economy would have encountered only a modest rise in the productivity growth rate of 1.64%. Conversely, had the Netherlands not experienced a more innovation-supportive environment in the post-2008 period (assuming R&D costs remained at their pre-2008 level), it would have witnessed only a slight decline in the productivity growth rate of 1.12%. These findings indicate that boosting the share of R&D active firms contributes positively to growth. However, the effectiveness of increasing the probability of R&D success and imitation, in terms of enhancing productivity growth, is much more substantial. Consequently, economic policy should prioritize these latter two fundamentals.

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Supplementary Appendix for "R&D Decisions and Productivity Growth: Evidence from Switzerland and the Netherlands"

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Contents

A. Uniformly Distributed R&D Success Probability

Assuming a uniformly distributed in-house R&D success probability allows us to simplify Equation (9) in Section 3.6 as follows:

Lemma 1. *Assuming a uniform distribution of the in-house R&D success probability with support*

$[0,\overline{p}]$ *allows us to write Equation (9) as follows*

$$\frac{\partial P_a(t)}{\partial t} = \frac{1}{\overline{p}}\Big[q(1-F_{a-1}(t))P_{a-1}(t)\left(\min\{C(a-1,P),\overline{p}\}\right.$$
$$\left.+\delta\frac{1}{2}\left(\overline{p}(2-\overline{p})-C(a-1,P)(2-C(a-1,P))\right)\mathbb{1}_{\{C(a-1,P)<\overline{p}\}}\right)$$
$$-q(1-F_a(t))P_a(t)\left(\min\{C(a,P),\overline{p}\}+\delta\frac{1}{2}\left(\overline{p}(2-\overline{p})-C(a,P)(2-C(a,P))\right)\mathbb{1}_{\{C(a,P)<\overline{p}\}}\right)$$
$$-\frac{1}{2}P_a(t)\left(\overline{p}^2-C(a,P)^2\right)\mathbb{1}_{\{C(a,P)<\overline{p}\}}+\frac{1}{2}P_{a-1}(t)\left(\overline{p}^2-C(a-1,P)^2\right)\mathbb{1}_{\{C(a-1,P)<\overline{p}\}}\Big], \tag{A.1}$$

where we have denoted by

$$C(a,P)\equiv\frac{(1-\delta)q(1-F_a)+\widetilde{\kappa}e^{\theta(\eta-1)(\overline{a}}-a)}{1-\delta q\,(1-F_a)}. \tag{A.2}$$

Note that $C(a,P)$ is non-negative and decreasing in a. Let the threshold productivity be defined as $a^*=\{\min a\in\mathcal{A}:C(a,P)<\overline{p}\}=\{\max a\in\mathcal{A}:C(a,P)\geq\overline{p}\}$. Then for all $a\leq a^*$, we have that $\min\{C(a-1,P),\overline{p}\}=\min\{C(a,P),\overline{p}\}=\overline{p}$ and $\mathbb{1}_{\{C(a,P)<\overline{p}\}}=\mathbb{1}_{\{C(a-1,P)<\overline{p}\}}=0$ so that we can write Equation (A.1) for all $a\leq a^*$ as follows

$$\frac{\partial P_a(t)}{\partial t}=q(1-F_{a-1}(t))P_{a-1}(t)-q(1-F_a(t))P_a(t).$$

Then for $a=a^*+1$, we have that $\min\{C(a-1,P),\overline{p}\}=\overline{p}$ but $\min\{C(a,P),\overline{p}\}=C(a,P)$ and $\mathbb{1}_{\{C(a,P)<\overline{p}\}}=1$ but $\mathbb{1}_{\{C(a-1,P)<\overline{p}\}}=0$ so that for $a=a^*+1$, we can write Equation (A.1) as follows

$$\frac{\partial P_a(t)}{\partial t}=\frac{1}{\overline{p}}\Big[q(1-F_{a-1}(t))P_{a-1}(t)\overline{p}-q(1-F_a(t))P_a(t)\Big(C(a,P)+\delta\frac{1}{2}\big(\overline{p}(2-\overline{p})$$
$$-C(a,P)(2-C(a,P))\big)\Big)-\frac{1}{2}P_a(t)\left(\overline{p}^2-C(a,P)^2\right)\Big],$$

For all $a>a^*+1$, we have that $\min\{C(a-1,P),\overline{p}\}=C(a-1,P)$ and $\min\{C(a,P),\overline{p}\}=C(a,P)$ and $\mathbb{1}_{\{C(a,P)<\overline{p}\}}=\mathbb{1}_{\{C(a-1,P)<\overline{p}\}}=1$ so that Equation (A.1) for all $a>a^*+1$ can be written as

$$\frac{\partial P_a(t)}{\partial t}=\frac{1}{\overline{p}}\Big[q(1-F_{a-1}(t))P_{a-1}(t)\left(C(a-1,P)+\delta\frac{1}{2}\left(\overline{p}(2-\overline{p})-C(a-1,P)(2-C(a-1,P))\right)\right)$$
$$-q(1-F_a(t))P_a(t)\left(C(a,P)+\delta\frac{1}{2}\left(\overline{p}(2-\overline{p})-C(a,P)(2-C(a,P))\right)\right)$$
$$-\frac{1}{2}P_a(t)\left(\overline{p}^2-C(a,P)^2\right)+\frac{1}{2}P_{a-1}(t)\left(\overline{p}^2-C(a-1,P)^2\right)\Big]. \tag{A.3}$$

We can compute the evolution of the productivity distribution $P_a(t)$ by numerically solving the system of ordinary differential equations provided in Equation (A.3) for a given initial condition $P_a(0)$.

B. Proofs

Proof of Proposition 1. For simplicity, we consider the case in which all firms have the same in-house R&D success probability p. The generalization to heterogeneous probabilities is straightforward. The evolution of the log-productivity distribution $P_a(t)$ can be written as

$$\begin{aligned} P_a(t+\Delta t) - P_a(t) = & \left(\chi^{\text{im}}(a-1,p,P) + \delta\chi^{\text{in}}(a-1,p,P)(1-p)\right) q(1-F_{a-1}(t))P_{a-1}(t) \\ & - \left(\chi^{\text{im}}(a,p,P) + \delta\chi^{\text{in}}(a,p,P)(1-p)\right) q(1-F_a(t))P_a(t) \\ & + \chi^{\text{in}}(a-1,P)pP_{a-1}(t) - \chi^{\text{in}}(a,P)pP_a(t), \end{aligned} \tag{B.1}$$

where δ is the passive imitation probability, and

$$\chi^{\text{im}}(a,p,P) = 1 - \chi^{\text{in}}(a,p,P) = \begin{cases} 1 & \text{if } p < \frac{(1-\delta)q(1-F_a)+\widetilde{\kappa}e^{\theta(\eta-1)(\overline{a}-a)}}{1-\delta q(1-F_a)}, \\ 0 & \text{otherwise,} \end{cases} \tag{B.2}$$

with the average log-productivity given by $\bar{a} = \sum_{a=1}^{\infty} F_a$. The first term in Equation (B.1) corresponds to the case that a firm with log-productivity $a-1$ is selected, times the indicator that it wants to imitate, $\chi^{\text{im}}(a-1,p,P) = 1$, or that it wants to innovate, failed to do so and then engages in passive imitation, $\chi^{\text{in}}(a-1,p,P)(1-p)\delta$, times the probability that it draws a firm with log-productivity larger than $a-1$ and successfully improves its log-productivity by one unit with probability q. The second term corresponds to the event that a firm with log-productivity a is selected and successfully imitates. The third term corresponds to the case that a firm with log-productivity $a-1$ is selected, wants to innovate, $\chi^{\text{in}}(a-1,p,P) = 1 - \chi^{\text{im}}(a-1,p,P) = 1$, and succeeds to improve its log-productivity by one unit with probability p. The fourth term corresponds to the case that a firm with log-productivity a is selected, wants to innovate, $\chi^{\text{in}}(a,p,P) = 1 - \chi^{\text{im}}(a,p,P) = 1$, and succeeds with probability p. Finally, one can check from Equation (B.1) that for all $t \geq 0$: $\sum_{a=1}^{\infty}(P_a(t+\Delta t) - P_a(t)) = 0$. $\square$

Proof of Lemma 1. Assuming a uniform distribution of the in-house R&D success probability allows us to write Equation (9) as follows

$$\begin{aligned} \frac{\partial P_a(t)}{\partial t} = & \frac{1}{\overline{p}-\underline{p}} \int_{[\underline{p},\overline{p}]} \Big[\left(\chi^{\text{im}}(a-1,p,P) + \delta(1-p)\chi^{\text{in}}(a-1,p,P)\right) q(1-F_{a-1}(t))P_{a-1}(t) \\ & - \left(\chi^{\text{im}}(a,p,P) + \delta(1-p)\chi^{\text{in}}(a,p,P)\right) q(1-F_a(t))P_a(t) + \chi^{\text{in}}(a-1,p,P)pP_{a-1}(t) - \chi^{\text{in}}(a,p,P)pP_a(t) \Big] \, dp. \end{aligned}$$

Using the fact that

$$\int_{[\underline{p},\overline{p}]} \chi^{\text{im}}(a,p,P)dp = \int_{[\underline{p},\overline{p}]} \mathbb{1}_{\{p<C(a,P)\}}dp = (\min\{C(a,P),\overline{p}\} - \underline{p})\mathbb{1}_{\{C(a,P)>\underline{p}\}},$$

and

$$\int_{[\underline{p},\overline{p}]} p\chi^{\text{in}}(a,p,P)dp = \int_{[\underline{p},\overline{p}]} p\mathbb{1}_{\{p>C(a,P)\}}dp$$
$$= \int_{[\max\{\underline{p},C(a,P)\},\overline{p}]} pdp\mathbb{1}_{\{C(a,P)<\overline{p}\}}$$
$$= \frac{1}{2}\left(\overline{p}^2 - (\max\{\underline{p},C(a,P)\})^2\right)\mathbb{1}_{\{C(a,P)<\overline{p}\}},$$

and

$$\int_{[\underline{p},\overline{p}]} (1-p)\chi^{\text{in}}(a,p,P)dp = \int_{[\underline{p},\overline{p}]} (1-p)\mathbb{1}_{\{p>C(a,P)\}}dp$$
$$= \int_{[\max\{\underline{p},C(a,P)\},\overline{p}]} (1-p)dp\mathbb{1}_{\{C(a,P)<\overline{p}\}}$$
$$= \frac{1}{2}\, p(2-p)|_{\max\{\underline{p},C(a,P)\}}^{\overline{p}}\, \mathbb{1}_{\{C(a,P)<\overline{p}\}}$$
$$= \frac{1}{2}\left(\overline{p}(2-\overline{p}) - \max\{\underline{p},C(a,P)\}(2-\max\{\underline{p},C(a,P)\})\right)\mathbb{1}_{\{C(a,P)<\overline{p}\}},$$

where we have denoted by

$$C(a,P) \equiv \frac{(1-\delta)q(1-F_a) + \widetilde{\kappa}e^{\theta(\eta-1)(\overline{a}-a)}}{1-\delta q\,(1-F_a)}, \tag{B.3}$$

we can write

$$\begin{aligned}
\frac{\partial P_a(t)}{\partial t} = \frac{1}{\overline{p}-\underline{p}} \Big[& q(1-F_{a-1}(t))P_{a-1}(t)\Big((\min\{C(a-1,P),\overline{p}\}-\underline{p})\mathbb{1}_{\{C(a-1,P)>\underline{p}\}} \\
& + \delta\frac{1}{2}\left(\overline{p}(2-\overline{p}) - \max\{\underline{p},C(a-1,P)\}(2-\max\{\underline{p},C(a-1,P)\})\right)\mathbb{1}_{\{C(a-1,P)<\overline{p}\}}\Big) \\
& -q(1-F_a(t))P_a(t)\Big((\min\{C(a,P),\overline{p}\}-\underline{p})\mathbb{1}_{\{C(a,P)>\underline{p}\}} \\
& + \delta\frac{1}{2}\left(\overline{p}(2-\overline{p}) - \max\{\underline{p},C(a,P)\}(2-\max\{\underline{p},C(a,P)\})\right)\mathbb{1}_{\{C(a,P)<\overline{p}\}}\Big) \\
& -\frac{1}{2}P_a(t)\left(\overline{p}^2 - (\max\{\underline{p},C(a,P)\})^2\right)\mathbb{1}_{\{C(a,P)<\overline{p}\}} \\
& +\frac{1}{2}P_{a-1}(t)\left(\overline{p}^2 - (\max\{\underline{p},C(a-1,P)\})^2\right)\mathbb{1}_{\{C(a-1,P)<\overline{p}\}}\Big].
\end{aligned} \tag{B.4}$$

From Equation (B.3), we see that $C(a,P) \geq 0$. Further, assuming $\underline{p} = 0$ allows us to write

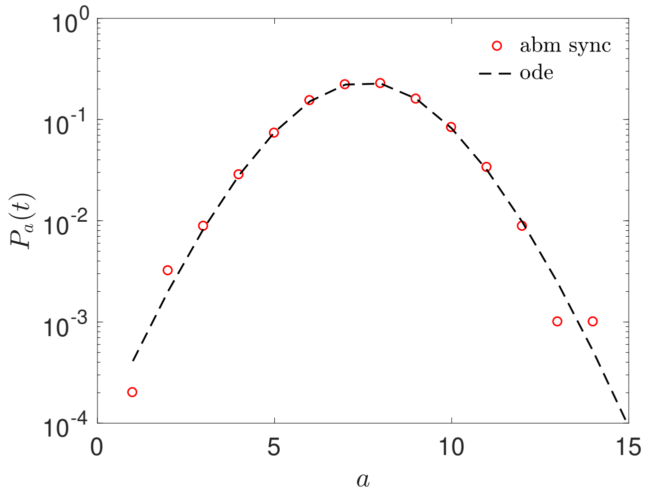

Figure B.1: The log-productivity distribution $P_a(t)$ from a Monte Carlo simulation of the stochastic process indicated with circles. The dashed line indicates the solution of the ordinary differential equation of Equation (B.5).

$$
\begin{aligned}
\frac{\partial P_a(t)}{\partial t} = \frac{1}{\overline{p}} & [q(1 - F_{a-1}(t))P_{a-1}(t) \left(\min\{C(a-1,P), \overline{p}\} \right. \\
& \left. + \ \delta \frac{1}{2} \left(\overline{p}(2-\overline{p}) - C(a-1,P)(2 - C(a-1,P))\right) \mathbb{1}_{\{C(a-1,P)<\overline{p}\}} \right) \\
& -q(1 - F_a(t))P_a(t) \left(\min\{C(a,P), \overline{p}\} \right. \\
& \left. + \ \delta \frac{1}{2} \left(\overline{p}(2-\overline{p}) - C(a,P)(2 - C(a,P))\right) \mathbb{1}_{\{C(a,P)<\overline{p}\}} \right) \\
& -\frac{1}{2} P_a(t) \left(\overline{p}^2 - C(a,P)^2\right) \mathbb{1}_{\{C(a,P)<\overline{p}\}} \\
& \left. +\frac{1}{2} P_{a-1}(t) \left(\overline{p}^2 - C(a-1,P)^2\right) \mathbb{1}_{\{C(a-1,P)<\overline{p}\}} \right] . \qquad \text{(B.5)}
\end{aligned}
$$

□

Figure B.1 shows the log-productivity distribution $P_a(t)$ from a numerical solution of Equation (B.5).

C. Reduced-Form Estimation of the R&D Decision

The OLS estimates of the linear probability model without passive imitation ($\delta = 0$) from a regression of Equation (6) and the NLS estimates of the model with passive imitation ($\delta \neq 0$) from a regression of Equation (8) are reported in columns (1)-(3) of Table C.1 for Switzerland and in columns (4)-(6) of Table C.1 for the Netherlands. In both cases, the upper panel reports the estimates for the pre-2008 period and the lower panel for the post-2008 period.

Estimation results for Switzerland. We observe a decrease in the in-house R&D success probability ($\bar{p}$) from the pre-2008 to the post-2008 period across all model specifications. According to the LPM estimates (column (1) in Table C.1) and the NLS estimates (columns (2)-(3)), the decrease in $\bar{p}$ is about 15%. In contrast, the cost of doing R&D ($\widetilde{\kappa}$) does not change significantly in neither the LPM model nor the two NLS models. The NLS estimates also show that for Swiss R&D firms that fail to innovate, the success probability of improving their technology via passive imitation (δ) increased in the post-2008 period when firm heterogeneity is not taken into account (see column (2)) but decreased when firm heterogeneity is taken into account (column (3)). This indicates the importance of including firm-specific random effects in the estimation. Moreover, and not surprisingly, the goodness-of-fit, measured by $R^2_{\mathrm{KL}}(H|H_{\mathrm{obs}})$ in Table C.1, improves when introducing random effects in the NLS model.

Comparing the LPM estimates with the NLS estimates allows us to analyze the bias that is introduced by estimating a model without passive imitation ($\delta = 0$) if the true data generating process is one with passive imitation ($\delta \neq 0$). We observe that estimating a misspecified model –assuming no passive imitation ($\delta = 0$)– results in an upward-biased estimate of the imitation parameter (q). However, when we allow for passive imitation, we find a considerable decrease in q. Such finding signals greater difficulties to benefit from technology spillovers among non-R&D firms and highlights the importance of distinguishing between R&D and non-R&D firms in the imitation process. However, there is only a slight improvement in the goodness-of-fit of the R&D profile of the NLS model without passive imitation over the LPM model.

We can further contrast the LPM and NLS estimation results with the ones obtained from the SMM approach in Table 5 of Section 4.1. Taking into account the endogenous evolution of firms' productivities from their innovation and imitation decisions in the SMM model shows that the passive imitation success probability (δ) exhibits a strong increase across sample periods, in contrast to the conclusion drawn from the NLS estimates. Further, we observe that the estimates for the innovation success probability ($\bar{p}$) and R&D cost ($\widetilde{\kappa}$) tend to be higher in the SMM models than in the OLS and NLS models. This bias is likely attributed to the fact that the OLS and NLS models only consider firms' R&D decisions but do not take into account the effect of $\bar{p}$ and $\widetilde{\kappa}$ on the aggregate productivity distribution, which results in an underestimation of the dispersion and skewness of the productivity distribution.

Estimation results for the Netherlands. In contrast to Switzerland, we find that it became easier for Dutch firms to generate innovations over time: the in-house R&D success probability ($\bar{p}$) increased by about 40% in the post 2008-period according to the estimates of the LPM model without passive imitation (see column (4) in Table C.1) and the estimates of the NLS models with passive imitation (see columns (5) and (6)). The NLS estimates, but not the LMP estimates, also point to an increase in the imitation success probability (q), indicating an increasing importance of imitation opportunities for a firm's R&D decision. Estimating the model with passive imitation shows that the success probability of Dutch R&D firms passively pursuing imitation increased in the post-2008 period: δ increased by 58% when firm heterogeneity is not taken into account and by 27% when it is taken into account. Estimating a misspecified model, assuming no passive imitation ($\delta = 0$), would lead us to the conclusion that R&D costs ($\widetilde{\kappa}$) remained stable across the two sample periods. However, accounting for passive imitation reveals a substantial decrease in these costs during the post-2008

Table C.1: Pre- and post-sample LPM and NLS regression estimation results for Switzerland and the Netherlands.

		Switzerland			the Netherlands		
		LPM	NLS		LPM	NLS	
		w/o passive imitation	w/o random effects	with random effects	w/o passive imitation	w/o random effects	with random effects
		$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$	$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$
		(1)	(2)	(3)	(4)	(5)	(6)
Sample period: 2000-2008							
Innovation	$(\bar{p})$	0.4915***	0.4595***	0.4726***	0.3765**	0.3696***	0.3408***
		(0.0061)	(0.0032)	(0.0007)	(0.0560)	(0.0004)	(0.0001)
Cost	$(\widetilde{\kappa})$	0.0003	0.0000	0.0023***	0.0003	0.0003***	0.0002***
		(0.0002)	(0.0000)	(0.0001)	(0.0002)	(0.0001)	(0.0000)
Imitation	(q)	0.2188***	0.7414***	0.3565***	0.2030***	0.3637***	0.4464***
		(0.0109)	(0.0272)	(0.1145)	(0.0080)	(0.0047)	(0.0420)
Passive Imitation	(δ)		0.8848***	0.4621***		0.5535***	0.6994***
			(0.0120)	(0.2038)		(0.0138)	(0.0418)
Observations		6,940	6,940	6,940	25,992	25,992	25,992
$R^2_{\text{KL}}(H\|H_{\text{obs}})$		0.9272	0.9273	0.9525	0.9430	0.9495	0.9670
Sample period: 2010-2016							
Innovation	$(\bar{p})$	0.4270***	0.3945***	0.4099***	0.5280***	0.5080***	0.4720***
		(0.0082)	(0.0013)	(0.0010)	(0.0089)	(0.0016)	(0.0003)
Cost	$(\widetilde{\kappa})$	0.0004	0.0000	0.0000	0.0003	0.0001***	0.0000***
		(0.0002)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)
Imitation	(q)	0.2217***	0.8303***	0.2609***	0.2145***	0.7315***	0.6395***
		(0.0027)	(0.0063)	(0.0499)	(0.0048)	(0.0242)	(0.0540)
Passive Imitation	(δ)		0.9145***	0.2662***		0.8730***	0.8561***
			(0.0039)	(0.1533)		(0.0098)	(0.0279)
Observations		7,290	7,290	7,290	17,349	17,349	17,349
$R^2_{\text{KL}}(H\|H_{\text{obs}})$		0.8875	0.8893	0.9221	0.9677	0.9680	0.9839

Notes: Models (1) and (4) correspond to the Linear Probability Model (LPM) discussed in Section 3.4. Models (2), (3), (5) and (6) correspond to a Nonlinear Least Squares (NLS) estimation procedure with an innovation decision variable as in Equation (8) as the dependent variable, with and without firm (random) effects in the in-house R&D success probability, respectively. For each year and within each NACE Rev. 2 1-digit code, the data has been trimmed at the top and bottom 1% productivity percentiles at the industry-year level. For the random effects, we use a Metropolis Hastings Bayesian maximum likelihood estimation algorithm in which we propose new random effects from a normal distribution (truncated to the unit interval), with mean equal to their previous MCMC draw values and variance computed from the previous MCMC draws using the so called "Adaptive Metropolis" (AM) algorithm [Haario et al., 2001]. Standard errors in parentheses. The asterisks *** (**,*) indicate that a parameter's 99% (95%, 90%) highest posterior density interval does not cover zero [Kruschke, 2015]. The R-squared measure $R^2_{\text{KL}}(\cdot|\cdot)$ follows Cameron and Windmeijer [1997] and is defined as $R^2_{\text{KL}}(\cdot|\cdot) = 1 - D_{\text{KL}}(\cdot|\cdot)$, where $D_{\text{KL}}(\cdot|\cdot)$ is the Kullback-Leibler divergence. The Kullback-Leibler divergence, $D_{\text{KL}}(H|H_{\text{obs}}) = \sum_a H(a) \log\left(\frac{H(a)}{H_{\text{obs}}(a)}\right)$, measures the difference between the predicted (H) and the observed (empirical) distribution (H_{obs}) [Song, 2002]. The reported R-squared measures are averages across time periods.

period. Only the latter is consistent with the more favorable innovation support environment in the Netherlands in the post-2008 period (cf. Section 2.1).

We can again compare the LPM and NLS estimation results with the ones obtained from the SMM approach in Table 5 in Section 4.1. In the SMM model (with passive imitation), we find a slight decrease in the in-house R&D success probability $\bar{p}$ (about 3%) in the post-2008 period. This contrasts with the significant increase (about 40%) indicated by the LPM and NLS estimates. However, similar to the LPM and NLS model estimates, we observe a collapse of R&D costs ($\widetilde{\kappa}$) when comparing the pre- and post-2008 periods using the SMM approach.

While the above LPM and NLS estimation results give insight into some basic correlations and trends, these reduced-form estimates might still suffer from endogeneity bias (reverse causality) due to productivity (and other variables) being affected by the innovation decision (and vice versa).[32] We therefore present in the main text in Section 4.1 the estimation results from a structural model that addresses this endogeneity by controlling for the reciprocal influence of productivity on the R&D decision and vice versa.[33]

D. Goodness-of-fit Statistics

Goodness-of-fit statistics for Switzerland. Figure D.1 shows a comparison of the empirical log-productivity distribution P_{obs} with the prediction by the model P_a in the pre-2008 period using the parameter estimates of column (1) in Table 5. Figure D.2 compares the empirical log-productivity innovation profile H_{obs} with the prediction by the model H_a in the pre-sample period using the parameter estimates of column (1) in Table 5. Both figures cover the years 2000 to 2008 for Switzerland. Figures D.3 and D.4 illustrate these comparisons for the years 2010-2016 for Switzerland using the parameter estimates of column (3) in Table 5.

[32] Moreover, note that estimating such regression models with a binary dependent variable can yield inefficient, inconsistent and biased coefficient estimates [cf. e.g. Long, 1997]. Therefore, we only rely on these estimates to inform us about the direction of correlations and to use them as initial values for the Metropolis-Hastings SMM estimation algorithm [Chernozhukov and Hong, 2003].

[33] Similar to the estimation approach in König et al. [2022].

Pre-sample for Switzerland: 2000–2008.

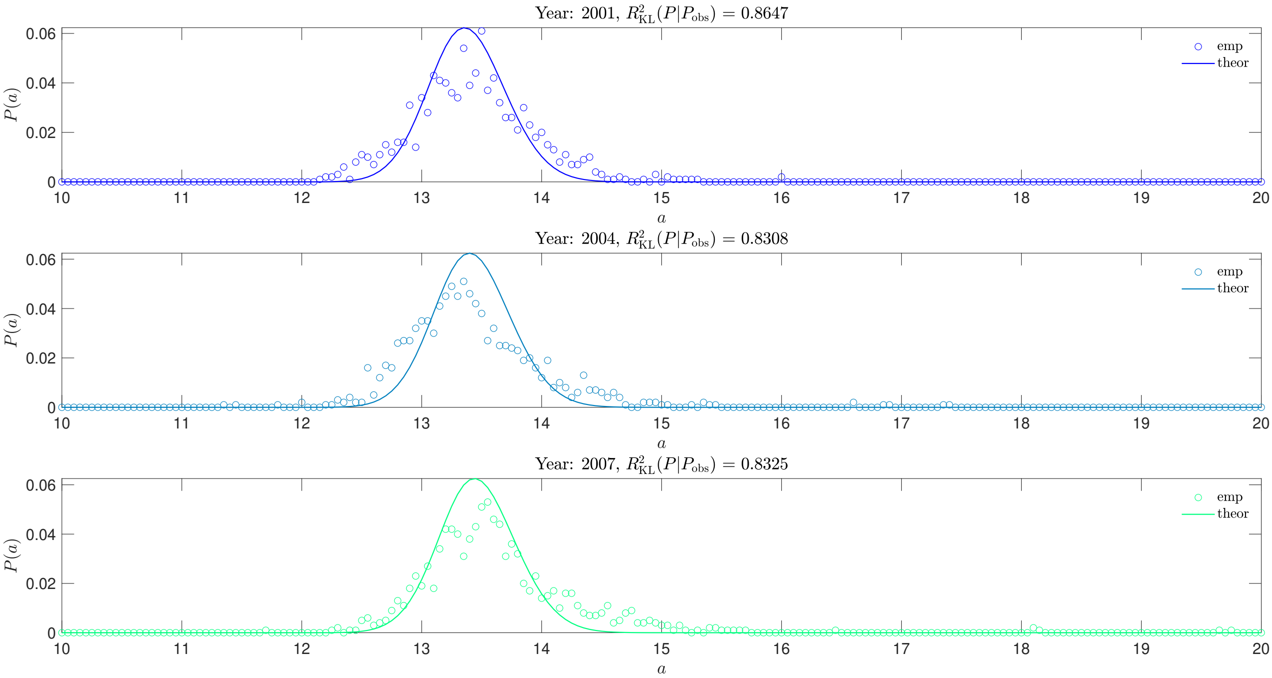

Figure D.1: Comparison of the empirical log-productivity distribution $P(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (1) in Table 5. The data cover the years 2000 to 2008 for Switzerland.

Pre-sample for Switzerland: 2000–2008.

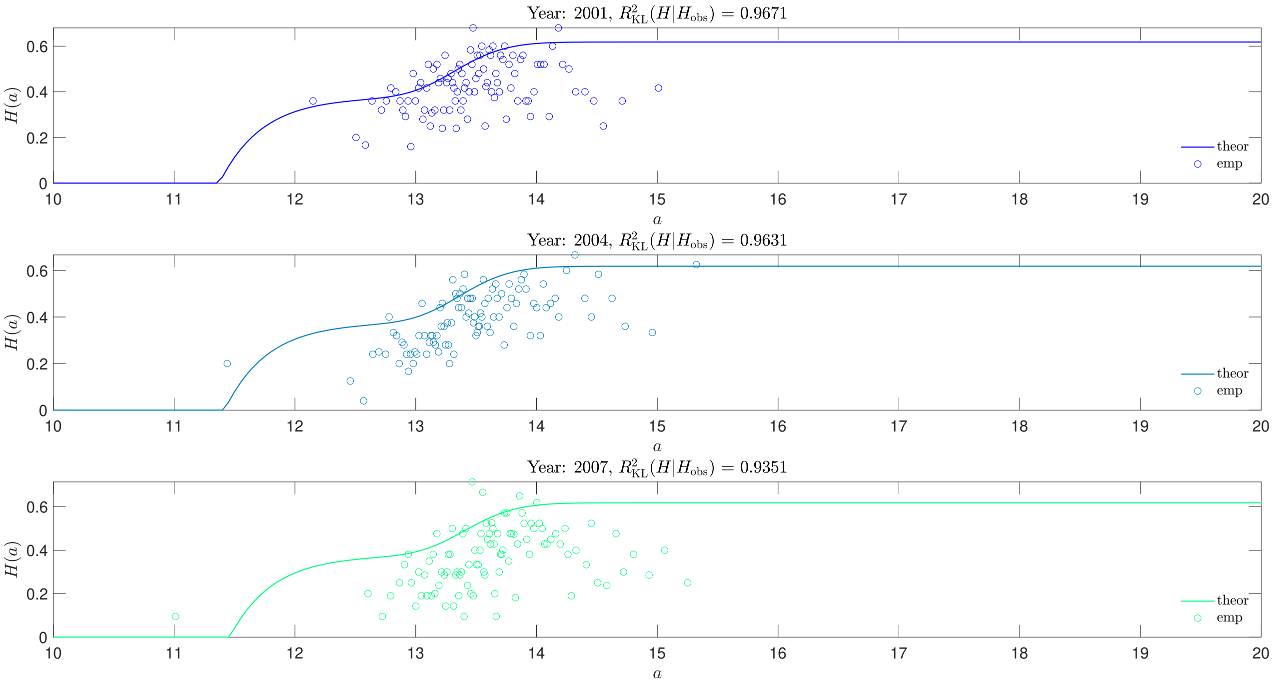

Figure D.2: Comparison of the empirical log-productivity innovation profile $H(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (1) in Table 5. The data cover the years 2000 to 2008 for Switzerland.

Post-sample for Switzerland: 2010–2016.

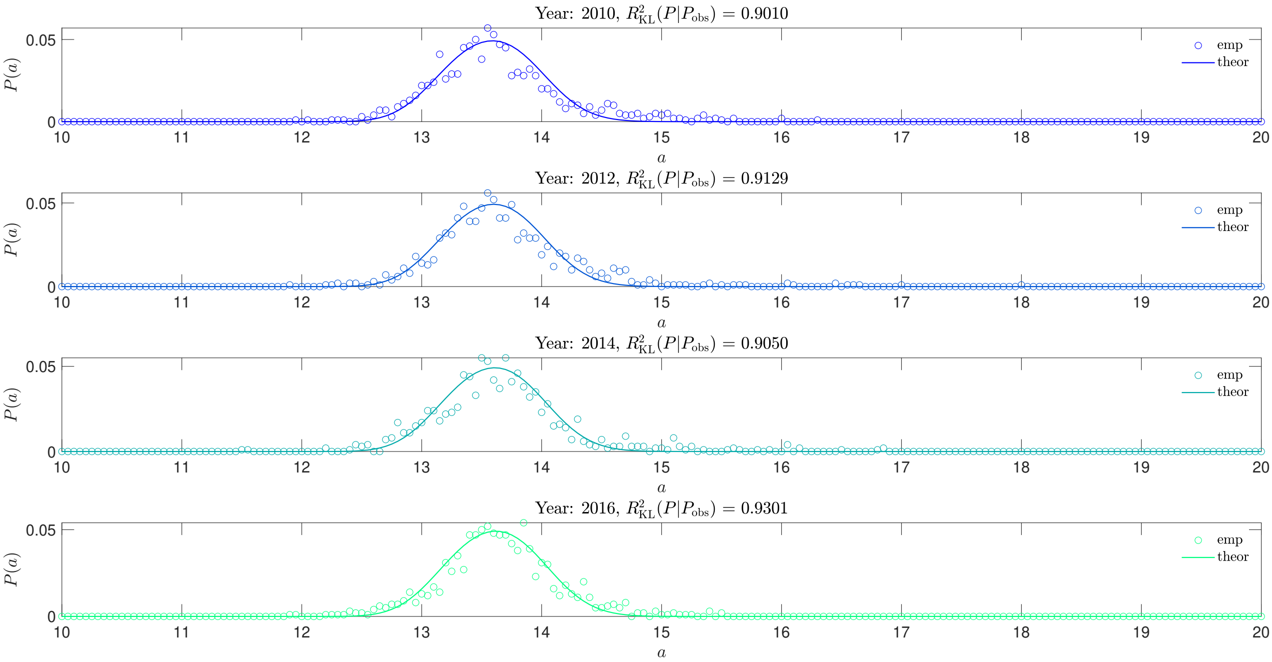

Figure D.3: Comparison of the empirical log-productivity distribution $P(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (3) in Table 5. The data cover the years 2010 to 2016 for Switzerland.

Post-sample for Switzerland: 2010–2016.

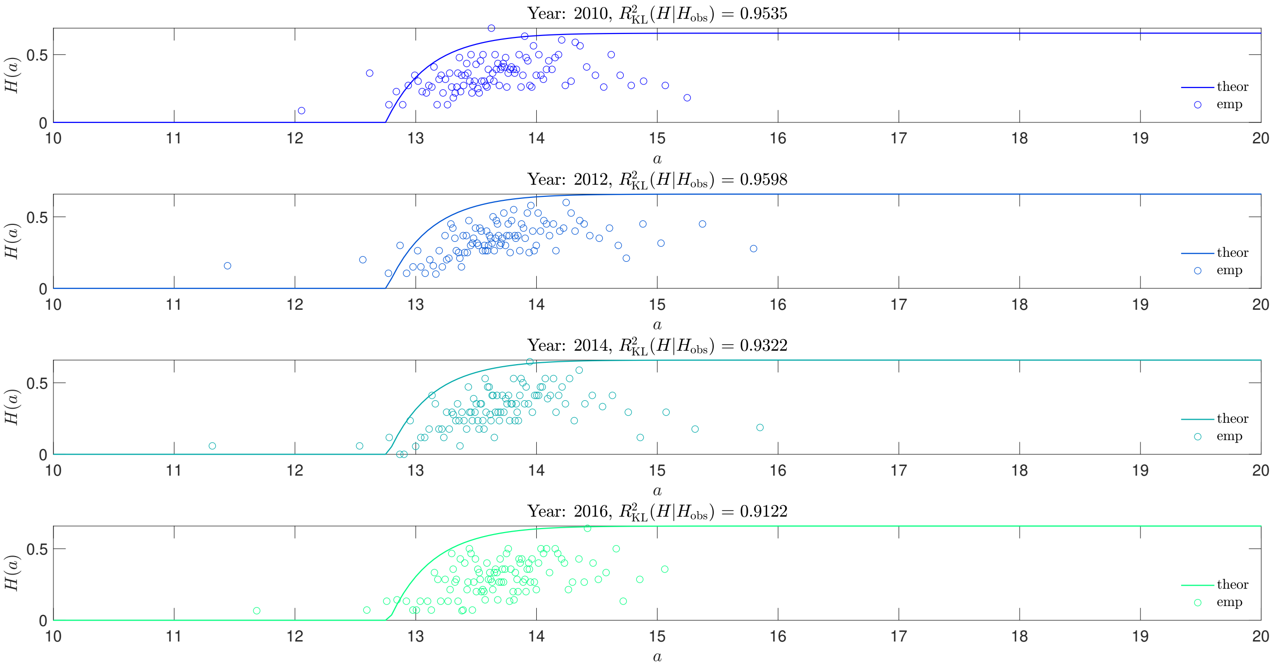

Figure D.4: Comparison of the empirical log-productivity innovation profile $H(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (3) in Table 5. The data cover the years 2010 to 2016 for Switzerland.

Goodness-of-fit statistics for the Netherlands. Figure D.5 shows a comparison of the empirical log-productivity distribution P_a with the prediction by the model using the parameter estimates of column (2) in Table 5. Figure D.6 compares the empirical log-productivity innovation profile H_a with the prediction by the model using the parameter estimates of column (2) in Table 5. Both figures cover the years 2000 to 2008 for the Netherlands. Figure D.7 illustrates a comparison of the empirical log-productivity distribution P_a with the prediction by the model using the parameter estimates of column (4) in Table 5. Figure D.8 compares the empirical log-productivity innovation profile H_a with the prediction by the model using the parameter estimates of column (4) in Table 5. Figures D.7 and D.8 encompass the years 2010 to 2016 for the Netherlands.

Pre-sample for the Netherlands: 2000–2008.

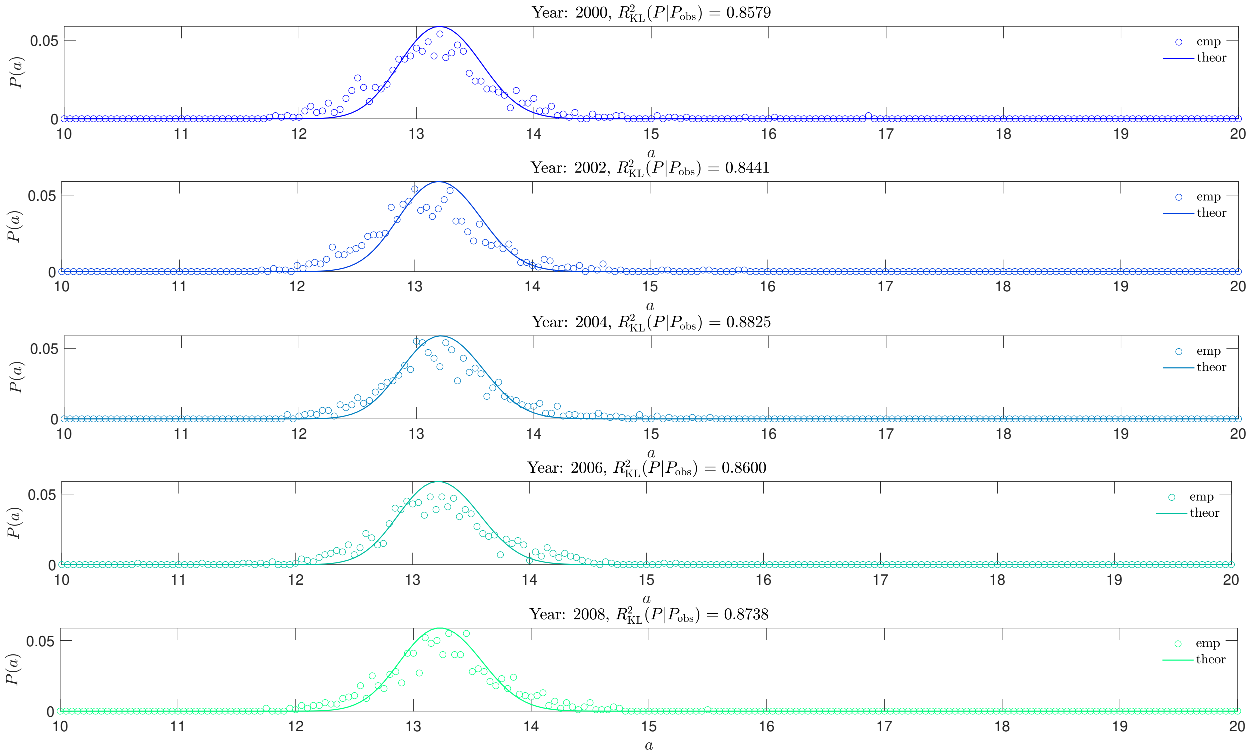

Figure D.5: Comparison of the empirical log-productivity distribution $P(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (2) in Table 5. The data cover the years 2000 to 2008 for the Netherlands.

Pre-sample for the Netherlands: 2000–2008.

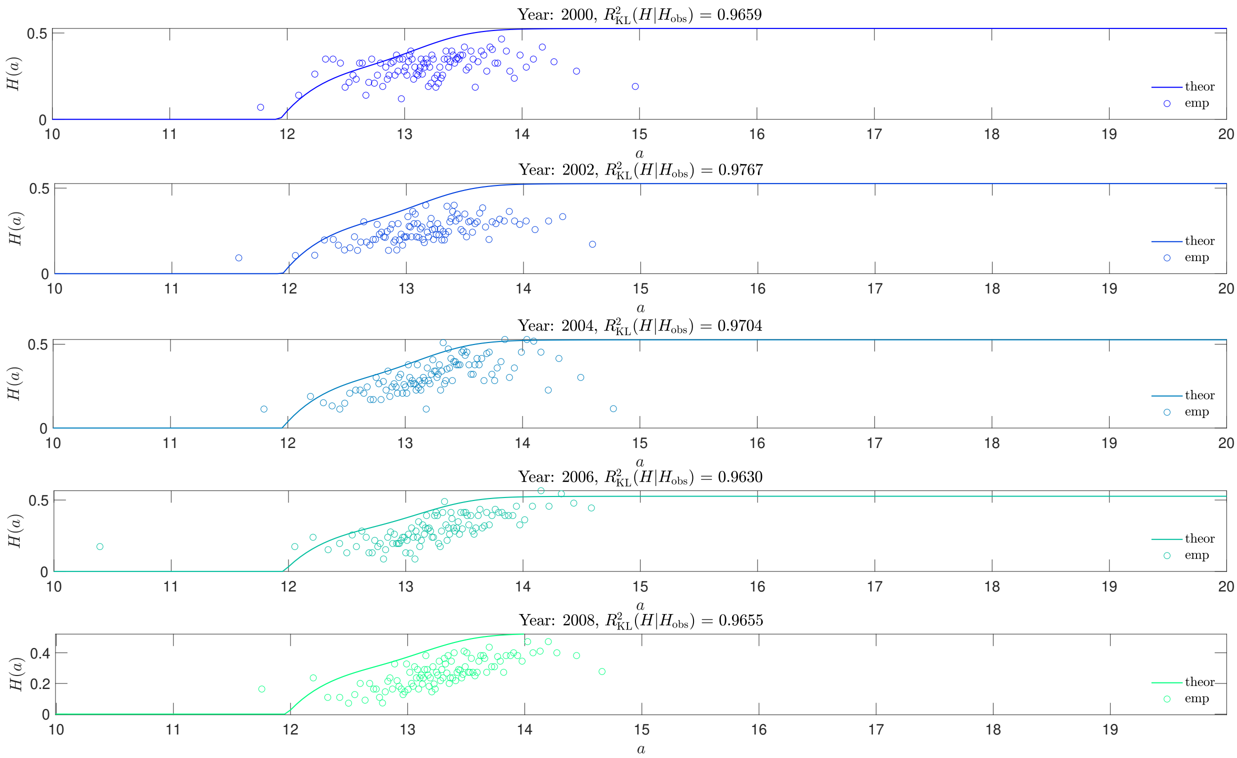

Figure D.6: Comparison of the empirical log-productivity innovation profile $H(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (2) in Table 5. The data cover the years 2000 to 2008 for the Netherlands.

Post-sample for the Netherlands: 2010–2016.

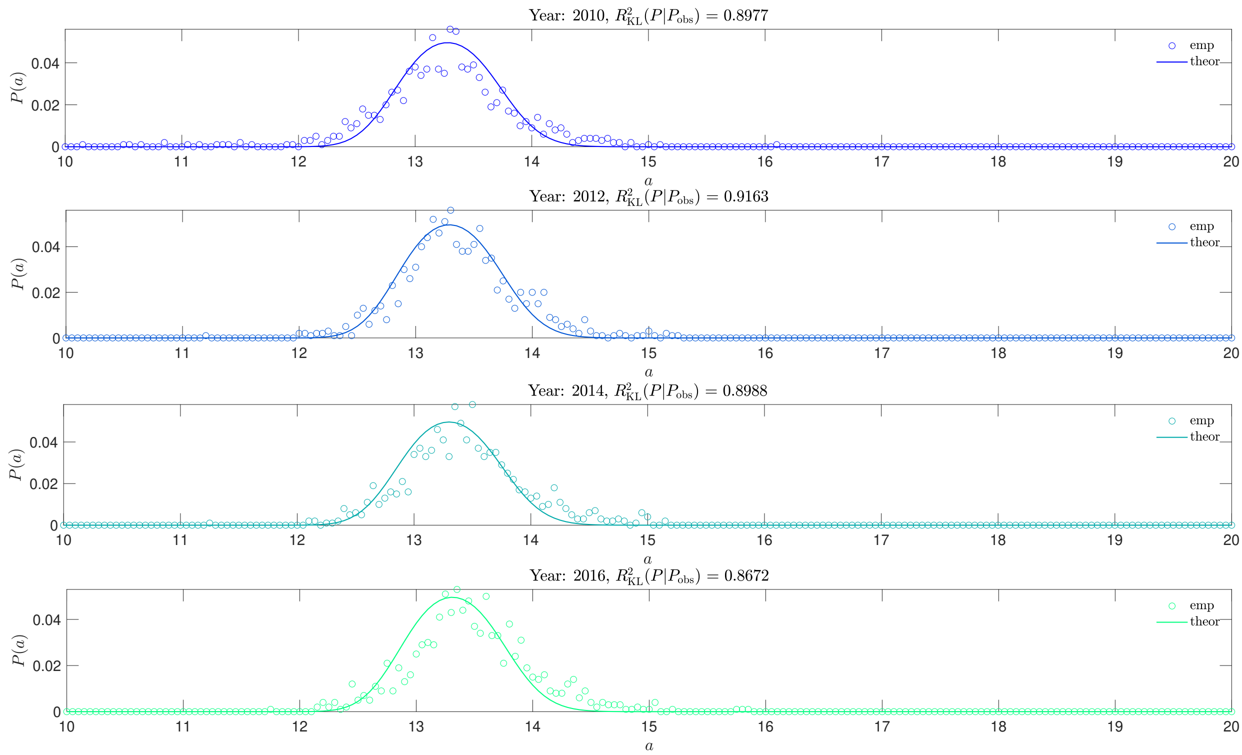

Figure D.7: Comparison of the empirical log-productivity distribution $P(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (4) in Table 5. The data cover the years 2010 to 2016 for the Netherlands.

Post-sample for the Netherlands: 2010–2016.

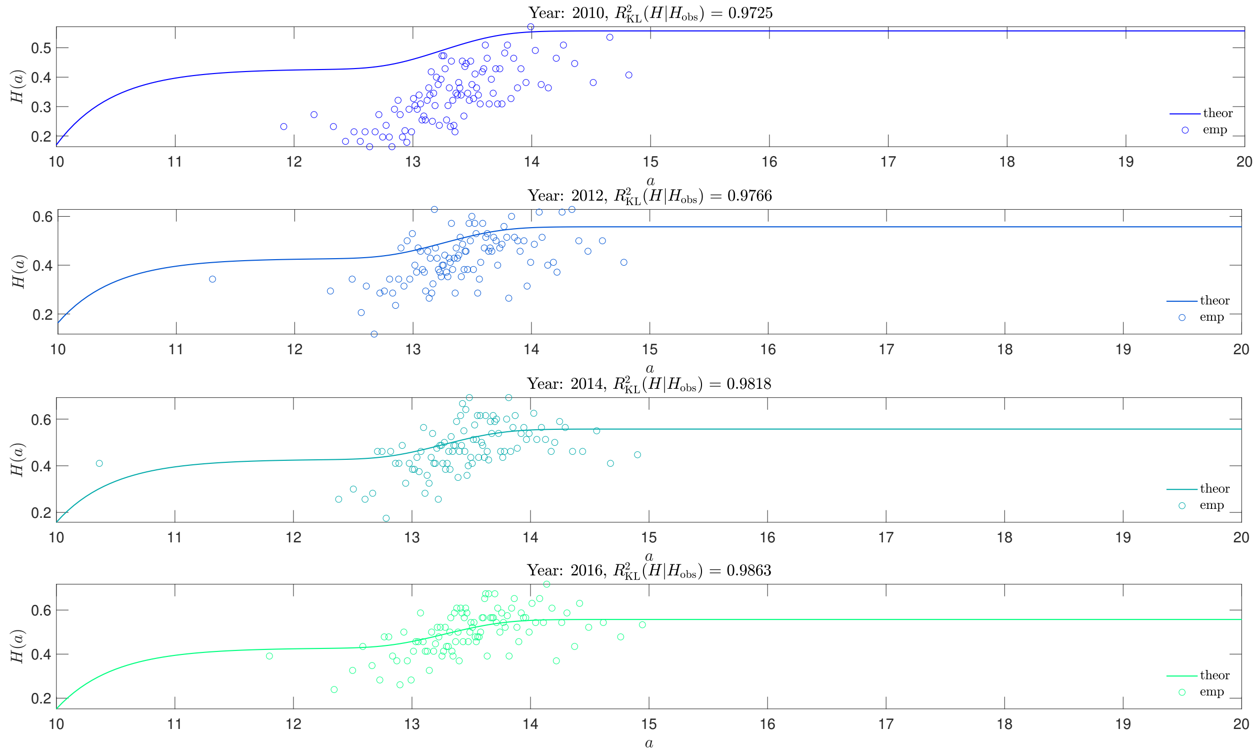

Figure D.8: Comparison of the empirical log-productivity innovation profile $H(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (4) in Table 5. The data cover the years 2010 to 2016 for the Netherlands.

E. Robustness Analyses

In the following sections, we provide a series of robustness checks of the benchmark estimation results presented in Section 4.1. Section E.1 estimates the model for an alternative post-sample period covering the years 2012 to 2016. Section E.2 re-estimates the model for a balanced panel. Section E.3 presents the estimation results for the manufacturing sector only (2-digit NACE codes 10-38). In Section E.4, we estimate the model with an alternative productivity measure (revenue total factor productivity) introduced in Ackerberg et al. [2015].

E.1. Alternative Post-Sample Period

Estimation results for Switzerland. The estimation results for the sample across the years 2012 to 2016 for Switzerland are reported in Table E.1. The goodness-of-fit of the SMM model in column (3) in Table E.1 is shown in Figures E.1 and E.2.

Comparing the SMM estimates in Table 5 with the ones in Table E.1 reveals that the estimate of the R&D cost parameter $\widetilde{\kappa}$ is lower in the sample covering the years 2012 to 2016 than in the sample covering the years 2010 to 2016. This may be attributed to adjustment processes in more recent years that enabled firms to reduce their R&D costs.

Table E.1: Post-sample estimation results for Switzerland and the Netherlands.

		Switzerland			the Netherlands		
		LPM	NLS	SMM	LPM	NLS	SMM
		w/o passive imitation	w/o random effects	with random effects	w/o passive imitation	w/o random effects	with random effects
		$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$	$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$
		(1)	(2)	(3)	(4)	(5)	(6)
Sample period: 2012-2016							
Innovation	$(\bar{p})$	0.4245***	0.3879***	0.6297***	0.5633***	0.5442***	0.5782***
		(0.0066)	(0.0013)	(0.0625)	(0.0087)	(0.0037)	(0.0179)
Cost	$(\widetilde{\kappa})$	0.0002	0.0000	0.0322***	0.0000	0.0000***	0.0004***
		(0.0002)	(0.0000)	(0.0159)	(0.0006)	(0.0000)	(0.0002)
Imitation	(q)	0.2391***	0.8446***	0.1268***	0.2008***	0.7543***	0.1251***
		(0.0136)	(0.0137)	(0.0396)	(0.0180)	(0.0142)	(0.0305)
Passive Imitation	(δ)		0.9154***	0.0727***		0.8908***	0.0744***
			(0.0035)	(0.0132)		(0.0074)	(0.0150)
Observations		5,056	5,056	5,056	11,858	11,858	11,858
$R^2_{\mathrm{KL}}(H \vert H_{\mathrm{obs}})$		0.8809	0.8826	0.9192	0.9651	0.9720	0.9874

Notes: Models (1) and (4) correspond to the Linear Probability Model (LPM) discussed in Section 3.4. Models (2) and (5) correspond to a Nonlinear Least Squares (NLS) estimation procedure with an innovation decision variable as in Equation (8) as the dependent variable. For each year and within each NACE Rev. 2 1-digit code, the data has been trimmed at the top and bottom 1% productivity percentiles at the industry-year level. Models (3) and (6) are based on the Simulated Methods of Moments (SMM) estimation algorithm discussed in Section 4.1 for which we set $\tilde{a} = 0.05$, using the estimates of Models (2) and (5) as initial conditions for the MCMC algorithm, respectively, and applying a bootstrap procedure with 50 bootstrap samples. For Switzerland, the estimate for the cost parameter θ is 0.541 in the period 2000-2008 and 0.790 in the period 2012-2016. For the Netherlands, the estimate for the cost parameter θ is 0.536 in the period 2000-2008 and 0.526 in the period 2010-2016. Standard errors in parentheses for Models (1)–(6). The asterisks *** (**,*) indicate that a parameter's 99% (95%, 90%) highest posterior density interval does not cover zero [Kruschke, 2015]. The R-squared measure $R^2_{\mathrm{KL}}(\cdot|\cdot)$ follows Cameron and Windmeijer [1997] and is defined as $R^2_{\mathrm{KL}}(\cdot|\cdot) = 1 - D_{\mathrm{KL}}(\cdot|\cdot)$, where $D_{\mathrm{KL}}(\cdot|\cdot)$ is the Kullback-Leibler divergence. The Kullback-Leibler divergence, $D_{\mathrm{KL}}(H|H_{\mathrm{obs}}) = \sum_a H(a) \log\left(\frac{H(a)}{H_{\mathrm{obs}}(a)}\right)$, measures the difference between the predicted (H) and the observed (empirical) distribution (H_{obs}) [Song, 2002]. The reported R-squared measures are averages across time periods.

Post-sample for Switzerland: 2012–2016.

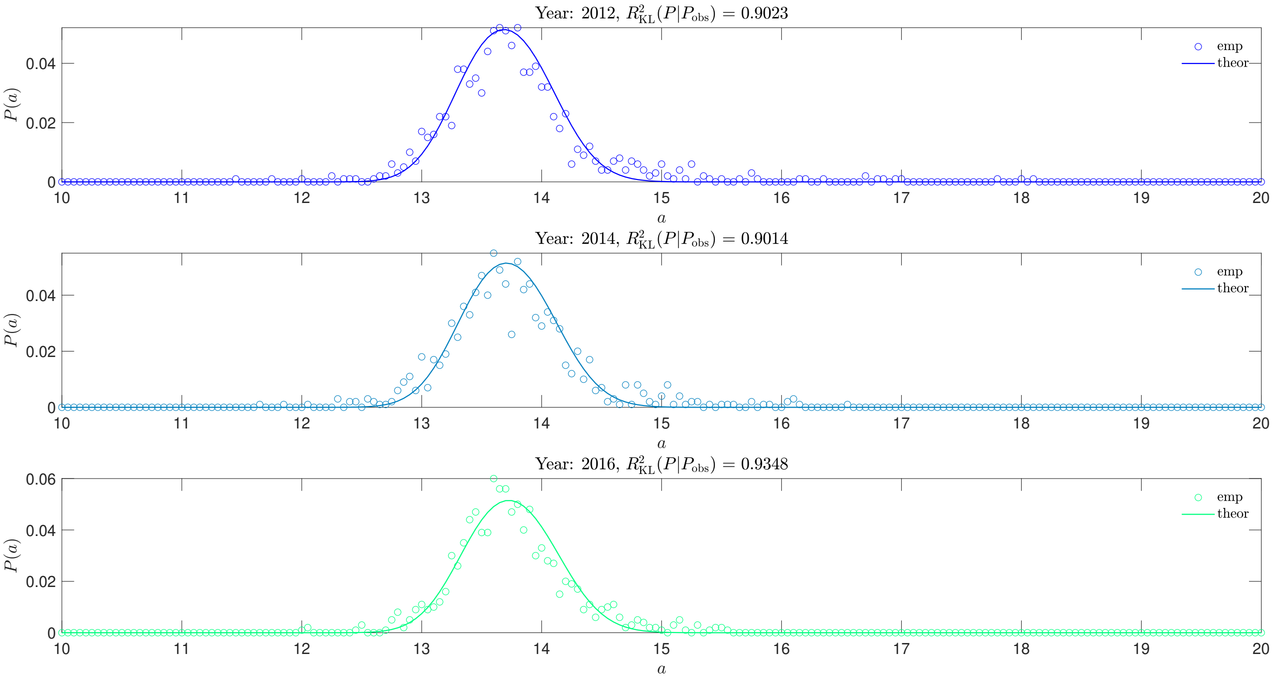

Figure E.1: Comparison of the empirical log-productivity distribution $P(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (3) in Table E.1. The data cover the years 2012 to 2016 for Switzerland.

Post-sample for Switzerland: 2012–2016.

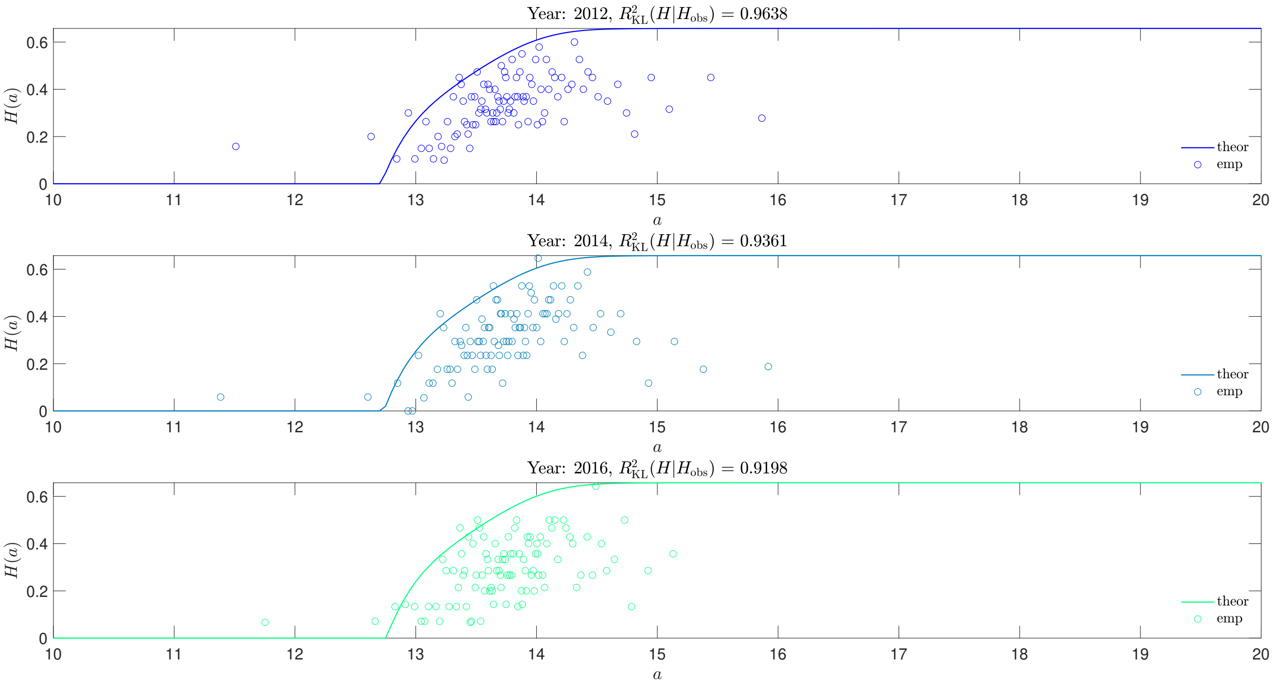

Figure E.2: Comparison of the empirical log-productivity innovation profile $H(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (3) in Table E.1. The data cover the years 2012 to 2016 for Switzerland.

Estimation results for the Netherlands. The estimation results for the sample across the years 2012 to 2016 for the Netherlands are reported in Table E.1. The goodness-of-fit of the SMM model in column (6) of Table E.1 is shown in Figures E.3 and E.4.

Comparing the SMM estimates in Table 5 with the ones in Table E.1 reveals that the estimate of the R&D cost parameter $\widetilde{\kappa}$ remains low in the sample covering the years 2012 to 2016. However, the passive imitation parameter estimate (δ) is much smaller in the sample covering the years 2012 to 2016. This points to a heightened challenge in the diffusion and adoption of technology among R&D firms in the Netherlands in recent years.

Post-sample for the Netherlands: 2012–2016.

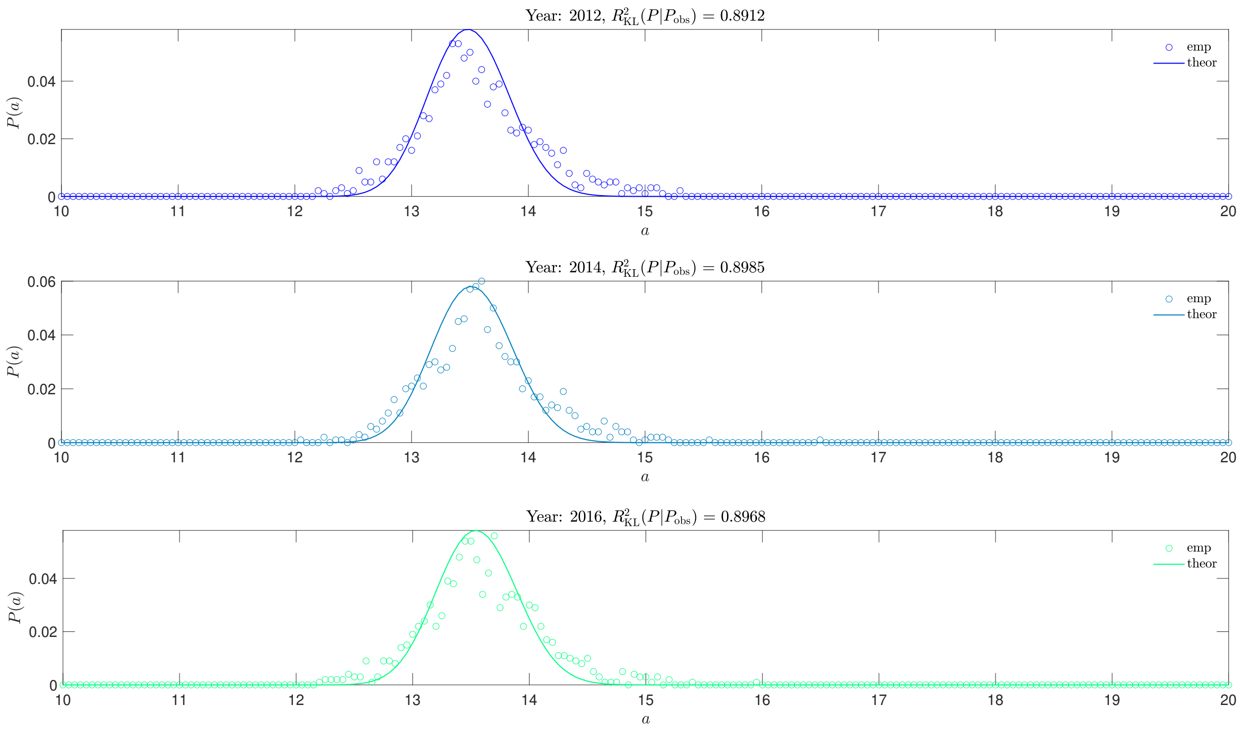

Figure E.3: Comparison of the empirical log-productivity distribution $P(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (6) in Table E.1. The data cover the years 2012 to 2016 for the Netherlands.

Post-sample for the Netherlands: 2012–2016.

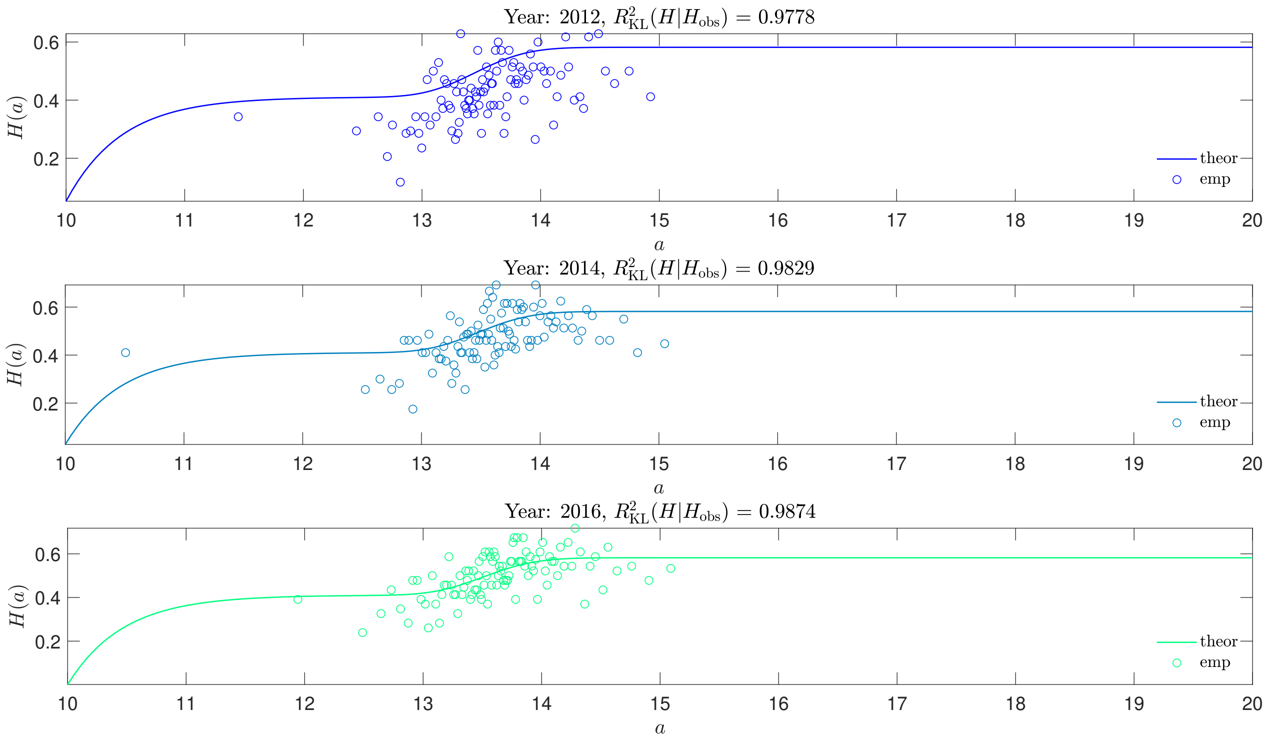

Figure E.4: Comparison of the empirical log-productivity innovation profile $H(a)$ (indicated with circles) and the prediction by the model (indicated with lines). The parameter estimates can be found in column (6) in Table E.1. The data cover the years 2012 to 2016 for the Netherlands.

E.2. Balanced Panel

Estimation results for Switzerland. The pre- and post-2008 estimation results for Switzerland using a balanced panel including only firms having at least one observation in the pre- as well as in the post-sample period are reported columns (1)-(3) in Table E.2.[34] The goodness-of-fit of the SMM model (column (3)) is shown in Figures E.5, E.6, E.7 and E.8.

Comparing the SMM estimates in Table 5 with the ones in Table E.2 shows that in the latter we do not see a drastic increase in the estimate of the R&D cost parameter $\widetilde{\kappa}$. The estimate of the in-house R&D success probability ($\bar{p}$) in the balanced sample covering the years 2010-2016 is now smaller than in the balanced sample covering the years 2000-2008. This suggests that for firms in the balanced panel –which are typically larger– R&D costs became less of a concern, while the ability to successfully conduct in-house R&D became more challenging in the post-2008 period.

[34] The estimation results for the 2012-2016 sample period can be obtained from the authors upon request.

Table E.2: Pre- and post-sample estimation results for Switzerland and the Netherlands using a balanced panel.

		Switzerland			the Netherlands		
		LPM	NLS	SMM	LPM	NLS	SMM
		w/o passive imitation	w/o random effects	with random effects	w/o passive imitation	w/o random effects	with random effects
		$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$	$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$
		(1)	(2)	(3)	(4)	(5)	(6)
Sample period: 2000-2008							
Innovation	$(\bar{p})$	0.5160***	0.4796***	0.6586***	0.4928***	0.4890***	0.5737***
		(0.0208)	(0.0044)	(0.0548)	(0.0529)	(0.0047)	(0.0431)
Cost	$(\widetilde{\kappa})$	0.0019*	0.0002***	0.0120***	0.0021	0.0006***	0.0267***
		(0.0010)	(0.0000)	(0.0091)	(0.0020)	(0.0005)	(0.0084)
Imitation	(q)	0.2223***	0.8706***	0.1819***	0.2472***	0.4174***	0.2543***
		(0.0813)	(0.0202)	(0.0635)	(0.0104)	(0.0100)	(0.0473)
Passive Imitation	(δ)		0.9306***	0.0930***		0.4975***	0.2313***
			(0.0115)	(0.0186)		(0.0206)	(0.0532)
Observations		4,016	4,016	4,016	9,378	9,378	9,378
$R^2_{\mathrm{KL}}(H\|H_{\mathrm{obs}})$		0.8840	0.8996	0.9375	0.9035	0.9022	0.9433
Sample period: 2010-2016							
Innovation	$(\bar{p})$	0.4199***	0.3809***	0.4871***	0.6118***	0.5809***	0.6105***
		(0.1192)	(0.0044)	(0.0462)	(0.0238)	(0.0051)	(0.0290)
Cost	$(\widetilde{\kappa})$	0.0011	0.0000	0.0081***	0.0044	0.0005***	0.0156***
		(0.0010)	(0.0000)	(0.0051)	(0.0036)	(0.0003)	(0.0058)
Imitation	(q)	0.1874***	0.9208***	0.1185***	0.3004***	0.6806***	0.1342***
		(0.0120)	(0.0243)	(0.0228)	(0.0174)	(0.0213)	(0.0519)
Passive Imitation	(δ)		0.9601***	0.6952***		0.7681***	0.3536***
			(0.0064)	(0.0274)		(0.0203)	(0.0624)
Observations		4,862	4,862	4,862	8,343	8,343	8,343
$R^2_{\mathrm{KL}}(H\|H_{\mathrm{obs}})$		0.8309	0.8431	0.9002	0.9448	0.9435	0.9627

Notes: Models (1) and (4) correspond to the Linear Probability Model (LPM) discussed in Section 3.4. Models (2) and (5) correspond to a Nonlinear Least Squares (NLS) estimation procedure with an innovation decision variable as in Equation (8) as the dependent variable. For each year and within each NACE Rev. 2 1-digit code, the data has been trimmed at the top and bottom 1% productivity percentiles at the industry-year level. Models (3) and (6) are based on the Simulated Methods of Moments (SMM) estimation algorithm discussed in Section 4.1 for which we set $\tilde{a} = 0.05$, using the estimates of Models (2) and (5) as initial conditions for the MCMC algorithm, respectively, and applying a bootstrap procedure with 50 bootstrap samples. For Switzerland, the estimate for the cost parameter θ is 0.688 in the period 2000-2008 and 0.6482 in the period 2010-2016. For the Netherlands, the estimate for the cost parameter θ is 0.536 in the period 2000-2008 and 0.526 in the period 2010-2016. Standard errors in parentheses for Models (1)–(6). The asterisks *** (**,*) indicate that a parameter's 99% (95%, 90%) highest posterior density interval does not cover zero [Kruschke, 2015]. The R-squared measure $R^2_{\mathrm{KL}}(\cdot|\cdot)$ follows Cameron and Windmeijer [1997] and is defined as $R^2_{\mathrm{KL}}(\cdot|\cdot) = 1 - D_{\mathrm{KL}}(\cdot|\cdot)$, where $D_{\mathrm{KL}}(\cdot|\cdot)$ is the Kullback-Leibler divergence. The Kullback-Leibler divergence, $D_{\mathrm{KL}}(H|H_{\mathrm{obs}}) = \sum_a H(a) \log\left(\frac{H(a)}{H_{\mathrm{obs}}(a)}\right)$, measures the difference between the predicted (H) and the observed (empirical) distribution (H_{obs}) [Song, 2002]. The reported R-squared measures are averages across time periods.

Pre-sample for Switzerland using a balanced panel: 2000–2008.

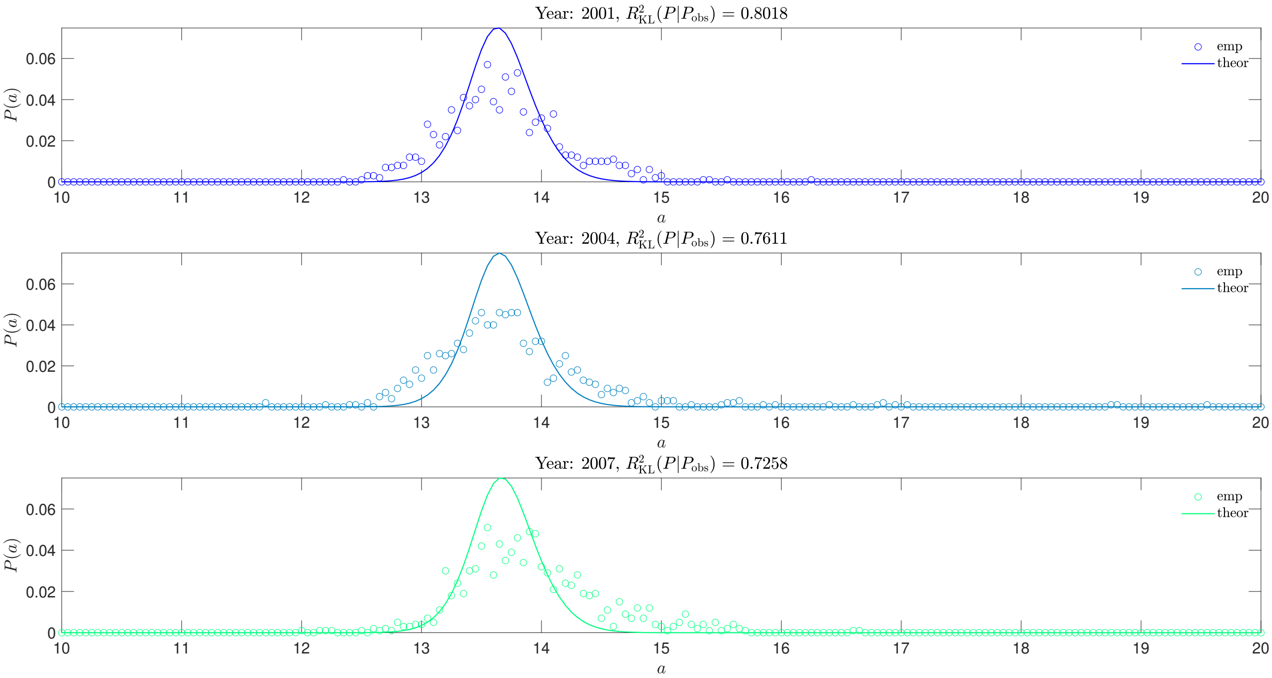

Figure E.5: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.2. The data cover the years 2000 to 2008 for Switzerland using a balanced panel.

Pre-sample for Switzerland using a balanced panel: 2000–2008.

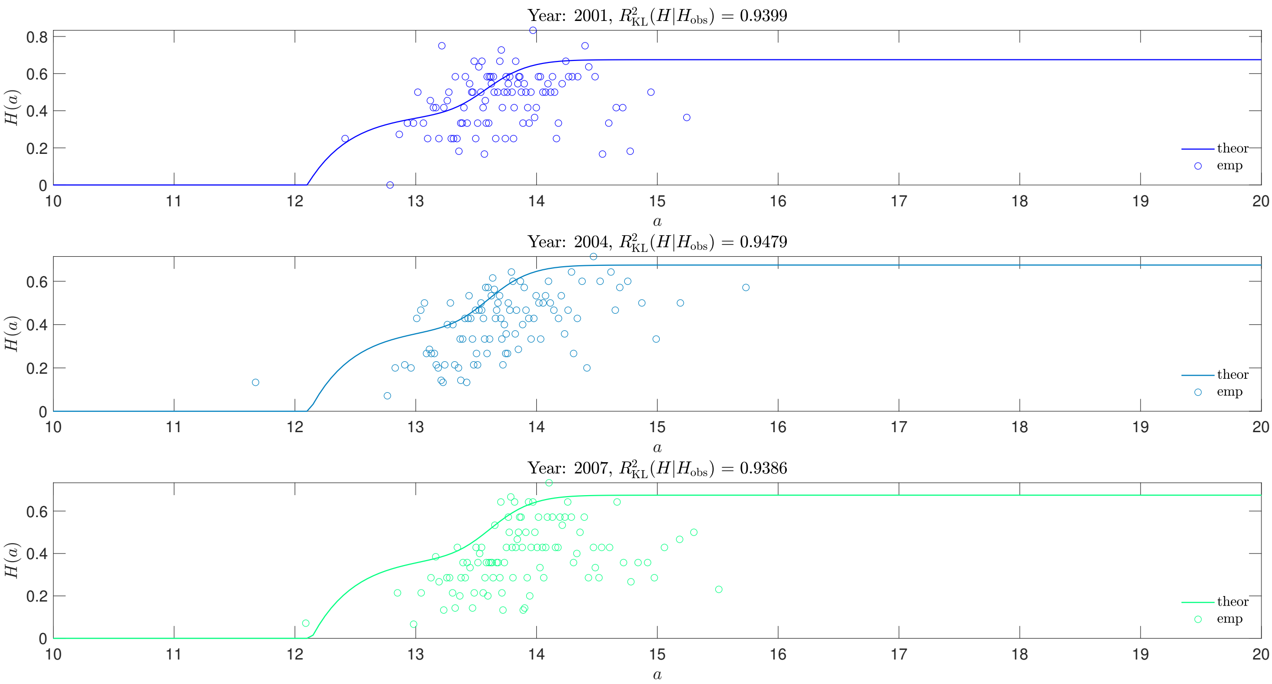

Figure E.6: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.2. The data cover the years 2000 to 2008 for Switzerland using a balanced panel.

Post-sample for Switzerland using a balanced panel: 2010–2016.

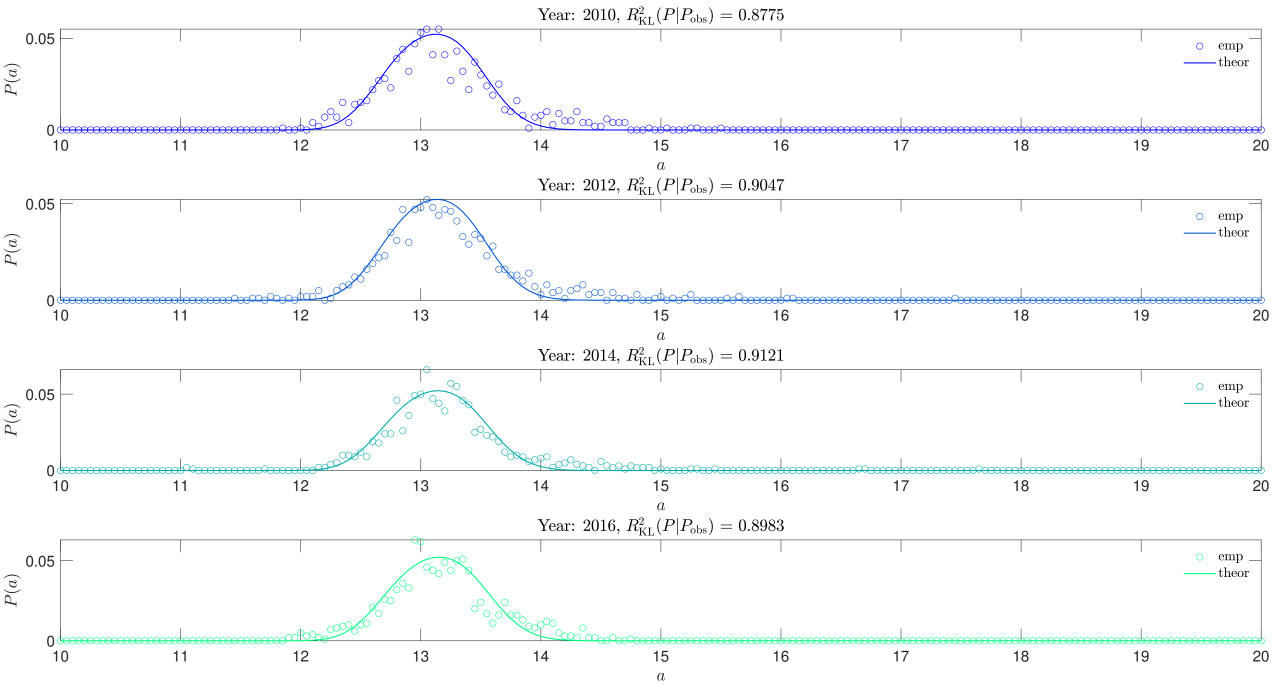

Figure E.7: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.2. The data cover the years 2010 to 2016 for Switzerland using a balanced panel.

Post-sample for Switzerland using a balanced panel: 2010–2016.

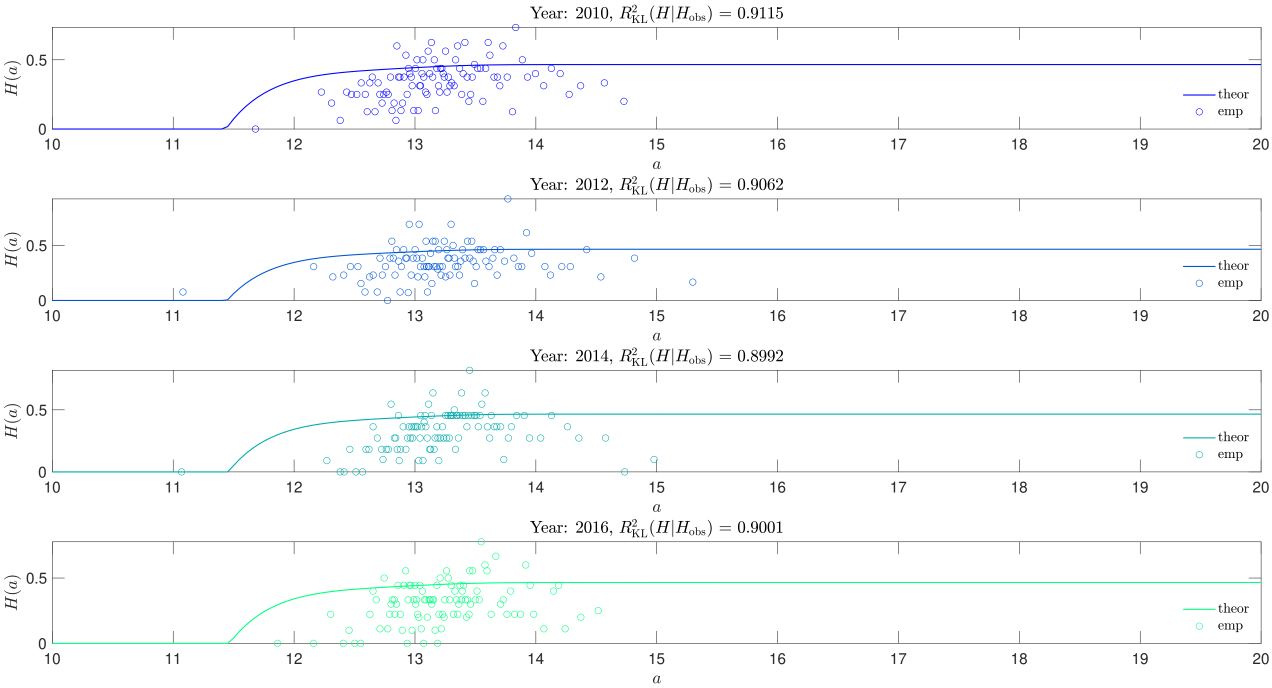

Figure E.8: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.2. The data cover the years 2010 to 2016 for Switzerland using a balanced panel.

Estimation results for the Netherlands. The pre- and post-2008 estimation results for the Netherlands using a balanced panel including only firms having at least one observation in the pre- as well as in the post-sample period are reported in columns (4)-(6) in Table E.2.[35] The goodness-of-fit of the SMM model in column (6) in Table E.2 is shown in Figures E.9, E.10, E.11 and E.12.

Comparing the SMM estimates in Table 5 with the ones in Table E.2 reveals that also for the balanced panel the R&D cost parameter $\widetilde{\kappa}$ declined in the post-2008 period, albeit to a significantly lesser extent. The passive imitation parameter estimate (δ) increased in the post-2008 period for both the full and the balanced panel. However, contrary to the full sample, the estimate of the in-house R&D success probability ($\bar{p}$) increased in the post-2008 period in the balanced panel. This is in contrast to our finding for Switzerland, where we observe that firms in the balanced panel experienced a lower ability to conduct successfully in-house R&D in the post-2008 period.

[35]The estimation results for the 2012-2016 sample period can be obtained from the authors upon request.

Pre-sample for the Netherlands using a balanced panel: 2000–2008.

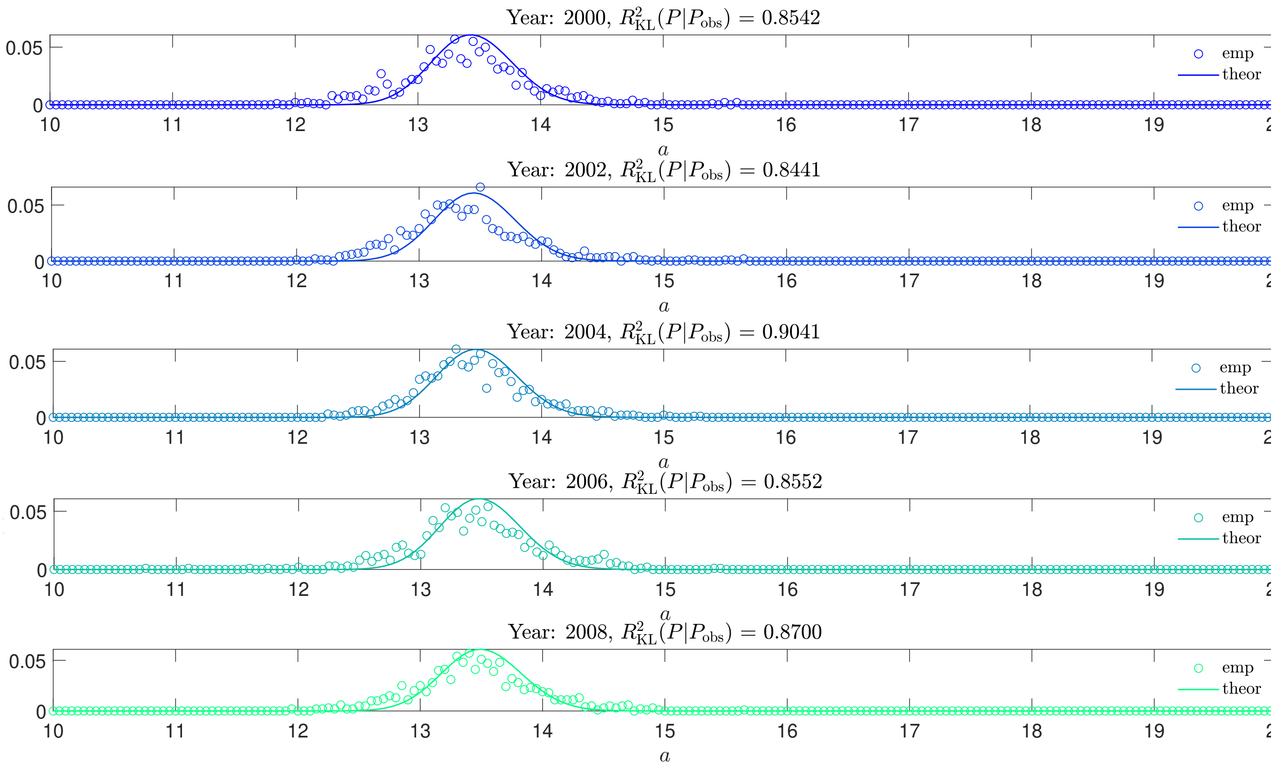

Figure E.9: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.2. The data cover the years 2000 to 2008 for the Netherlands using a balanced panel.

Pre-sample for the Netherlands using a balanced panel: 2000–2008.

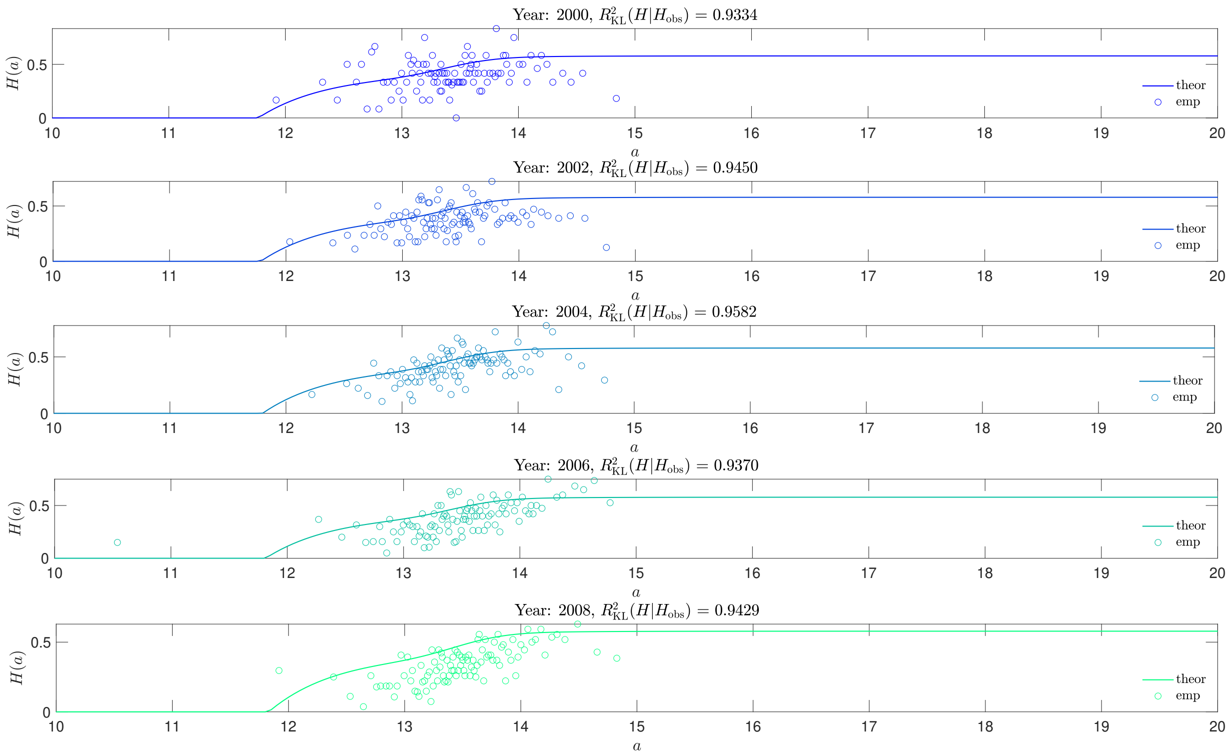

Figure E.10: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.2. The data cover the years 2000 to 2008 for the Netherlands using a balanced panel.

Post-sample for the Netherlands using a balanced panel: 2010–2016.

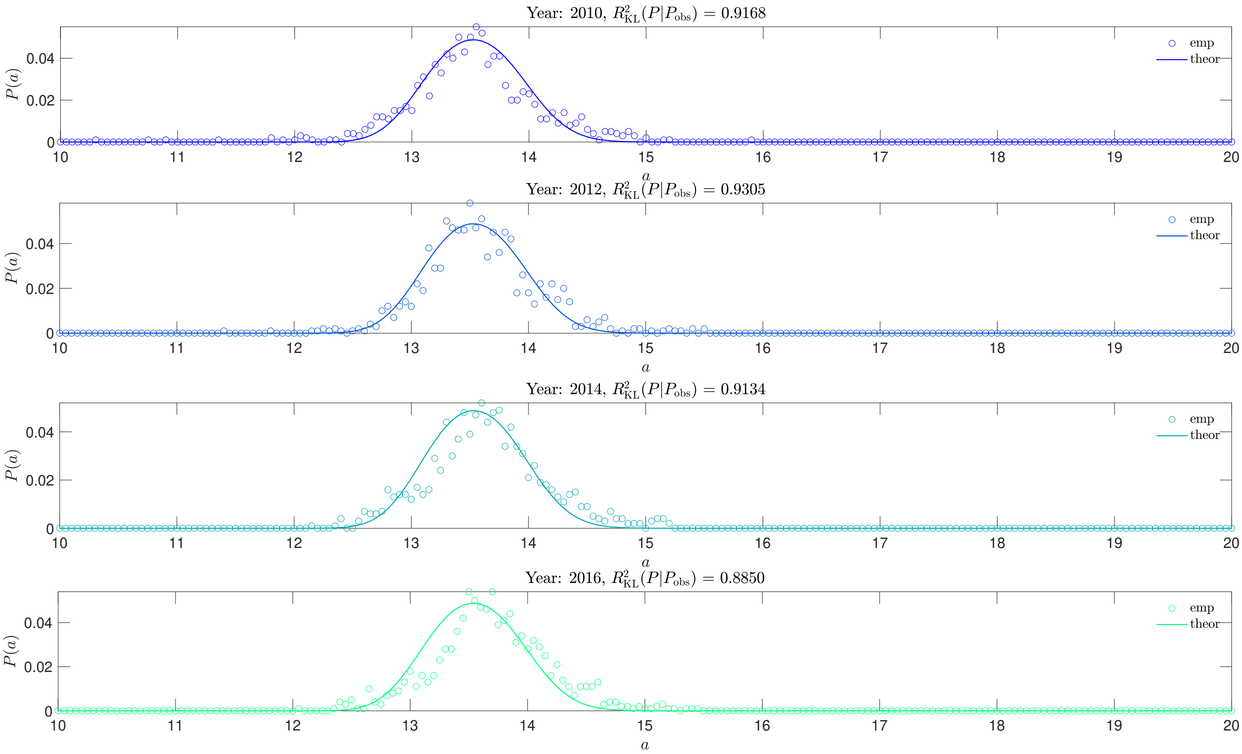

Figure E.11: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.2. The data cover the years 2010 to 2016 for the Netherlands using a balanced panel.

Post-sample for the Netherlands using a balanced panel: 2010–2016.

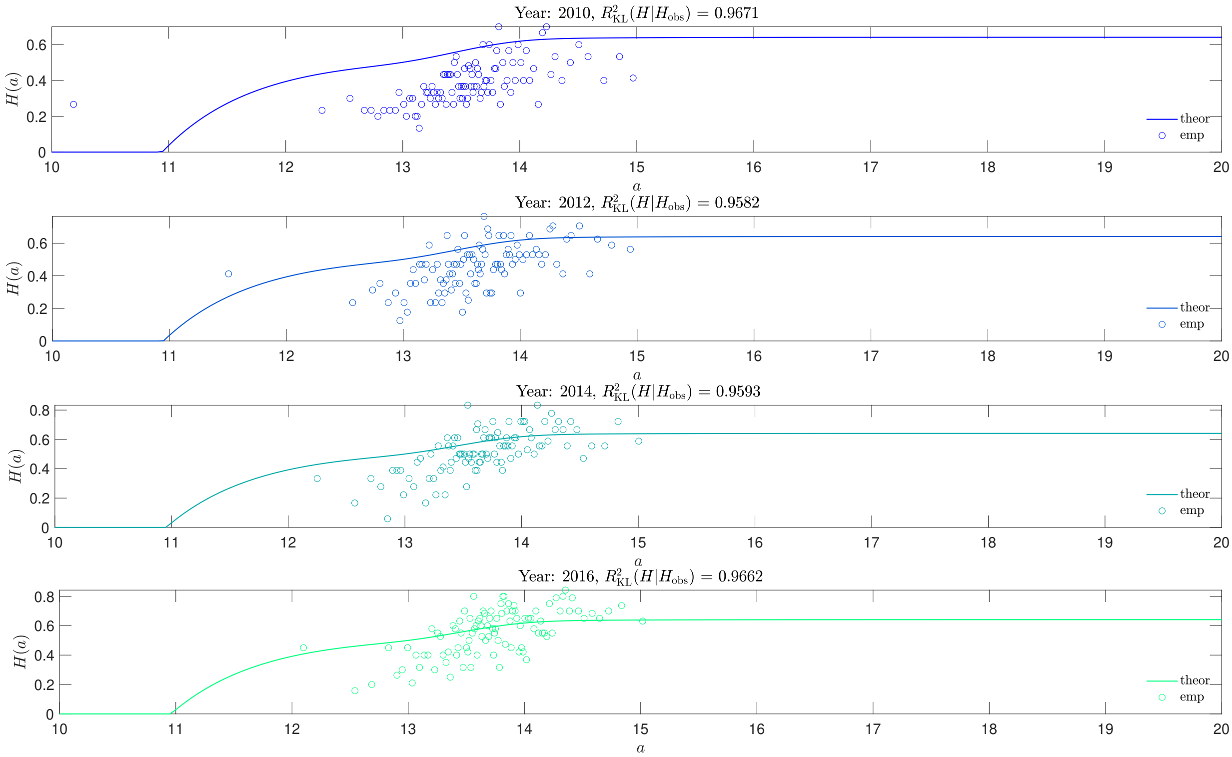

Figure E.12: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.2. The data cover the years 2010 to 2016 for the Netherlands using a balanced panel.

E.3. Manufacturing Sector

Estimation results for Switzerland. The pre- and post-2008 estimation results for the manufacturing sector (2-digit NACE codes 10-38) for Switzerland are reported in columns (1)-(3) in Table E.3.[36] The goodness-of-fit of the SMM model in column (3) in Table E.3 is shown in Figures E.13, E.14, E.15 and E.16.

Comparing the SMM estimates in Table 5 with the ones in Table E.3 shows that the increase in R&D costs ($\widetilde{\kappa}$) in the post-2008 period is much smaller for the firms in the manufacturing sector than for firms in the full sample. In contrast to the full sample, we find a decrease in the in-house R&D success probability ($\bar{p}$) in the post-2008 period in the manufacturing sector.

[36]The estimation results for the 2012-2016 sample period can be obtained from the authors upon request.

Table E.3: Pre- and post-sample estimation results for the manufacturing sector in Switzerland and the Netherlands.

		Switzerland			the Netherlands		
		LPM	NLS	SMM	LPM	NLS	SMM
		w/o passive imitation	w/o random effects	with random effects	w/o passive imitation	w/o random effects	with random effects
		$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$	$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$
		(1)	(2)	(3)	(4)	(5)	(6)
Sample period: 2000-2008							
Innovation	($\bar{p}$)	0.6866***	0.6703***	0.6467***	0.6722	0.6743***	0.6780***
		(0.0172)	(0.0152)	(0.0374)	(22.043)	(0.0060)	(0.0260)
Cost	($\tilde{\kappa}$)	0.0073	0.0090***	0.0208***	0.0000	0.0055***	0.1021***
		(0.0080)	(0.0029)	(0.0043)	(0.0445)	(0.0035)	(0.0291)
Imitation	(q)	0.2349***	0.2878***	0.0911***	0.3151	0.3250***	0.2177***
		(0.0483)	(0.0220)	(0.0298)	(7.5372)	(0.0083)	(0.0481)
Passive Imitation	(δ)		0.3758***	0.0699***		0.0670***	0.4347***
			(0.0841)	(0.0160)		(0.0344)	(0.0463)
Observations		3,533	3,533	3,533	7,750	7,750	7,750
$R^2_{\mathrm{KL}}(H\|H_{\mathrm{obs}})$		0.9360	0.9196	0.9622	0.9446	0.9394	0.9583
Sample period: 2010-2016							
Innovation	($\bar{p}$)	0.6489	0.6436***	0.6065***	0.7803	0.7648***	0.7466***
		(0.5714)	(0.0032)	(0.0229)	(0.9355)	(0.0059)	(0.0183)
Cost	($\tilde{\kappa}$)	0.0067	0.0067***	0.0230***	0.0000	0.0002***	0.0213***
		(0.0061)	(0.0000)	(0.0057)	(0.0491)	(0.0001)	(0.0084)
Imitation	(q)	0.2290	0.2377***	0.1398***	0.2329	0.5765***	0.1106***
		(0.3021)	(0.0059)	(0.0360)	(0.5748)	(0.0417)	(0.0216)
Passive Imitation	(δ)		0.1230***	0.7856***		0.7578***	0.3854***
			(0.0790)	(0.0249)		(0.0294)	(0.0469)
Observations		3,367	3,367	3,367	4,978	4,978	4,978
$R^2_{\mathrm{KL}}(H\|H_{\mathrm{obs}})$		0.8747	0.8748	0.8914	0.9572	0.9632	0.9775

Notes: Models (1) and (4) correspond to the Linear Probability Model (LPM) discussed in Section 3.4. Models (2) and (5) correspond to a Nonlinear Least Squares (NLS) estimation procedure with an innovation decision variable as in Equation (8) as the dependent variable. For each year and within each NACE Rev. 2 1-digit code, the data has been trimmed at the top and bottom 1% productivity percentiles at the industry-year level. Models (3) and (6) are based on the Simulated Methods of Moments (SMM) estimation algorithm discussed in Section 4.1 for which we set $\tilde{a} = 0.05$, using the estimates of models (2) and (5) as initial conditions for the MCMC algorithm, respectively, and applying a bootstrap procedure with 50 bootstrap samples. For Switzerland, the estimate for the cost parameter θ is 0.688 in the period 2000-2008 and 0.800 in the period 2010-2016. For the Netherlands, the estimate for the cost parameter θ is 0.180 in the period 2000-2008 and 0.368 in the period 2010-2016. Standard errors in parentheses for models (1)–(6). The asterisks *** (**,*) indicate that a parameter's 99% (95%, 90%) highest posterior density interval does not cover zero [Kruschke, 2015]. The R-squared measure $R^2_{\mathrm{KL}}(\cdot|\cdot)$ follows Cameron and Windmeijer [1997] and is defined as $R^2_{\mathrm{KL}}(\cdot|\cdot) = 1 - D_{\mathrm{KL}}(\cdot|\cdot)$, where $D_{\mathrm{KL}}(\cdot|\cdot)$ is the Kullback-Leibler divergence. The Kullback-Leibler divergence, $D_{\mathrm{KL}}(H|H_{\mathrm{obs}}) = \sum_a H(a) \log\left(\frac{H(a)}{H_{\mathrm{obs}}(a)}\right)$, measures the difference between the predicted (H) and the observed (empirical) distribution (H_{obs}) [Song, 2002]. The reported R-squared measures are averages across time periods.

Pre-sample for the manufacturing sector in Switzerland: 2000–2008.

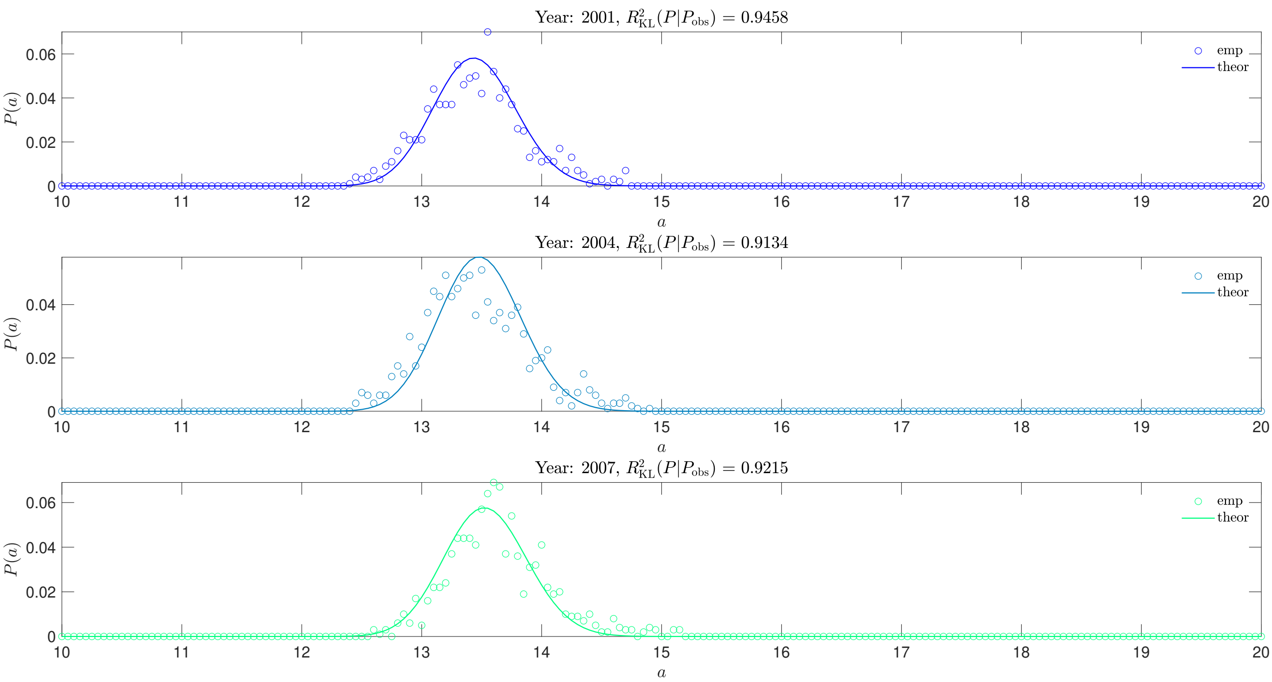

Figure E.13: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.3. The data cover the years 2000 to 2008 for the manufacturing sector in Switzerland.

Pre-sample for the manufacturing sector in Switzerland: 2000–2008.

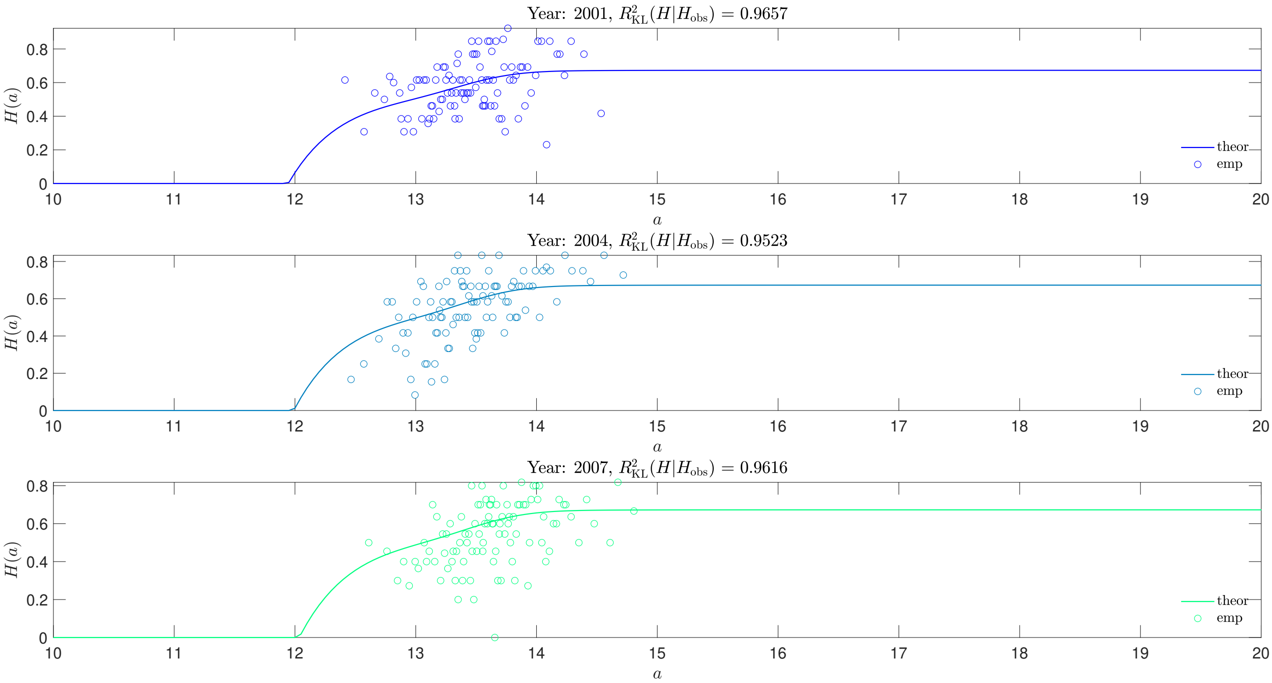

Figure E.14: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.3. The data cover the years 2000 to 2008 for the manufacturing sector in Switzerland.

Post-sample for the manufacturing sector in Switzerland: 2010–2016.

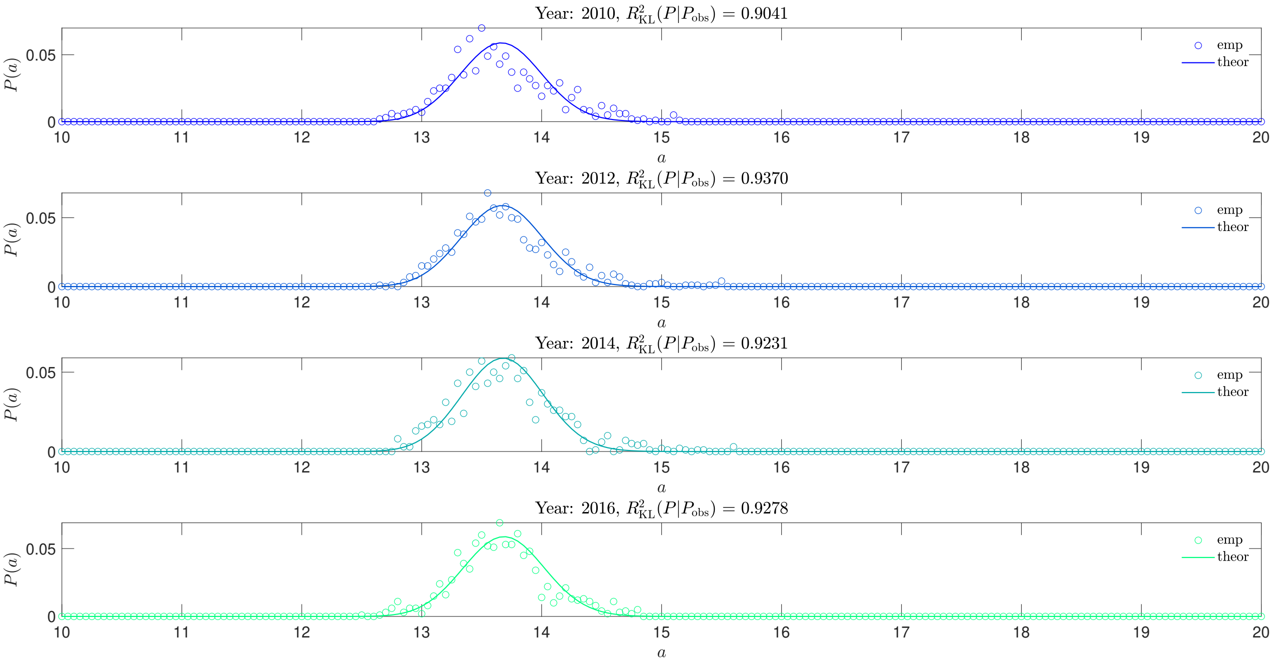

Figure E.15: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.3. The data cover the years 2010 to 2016 for the manufacturing sector in Switzerland.

Post-sample for the manufacturing sector in Switzerland: 2010–2016.

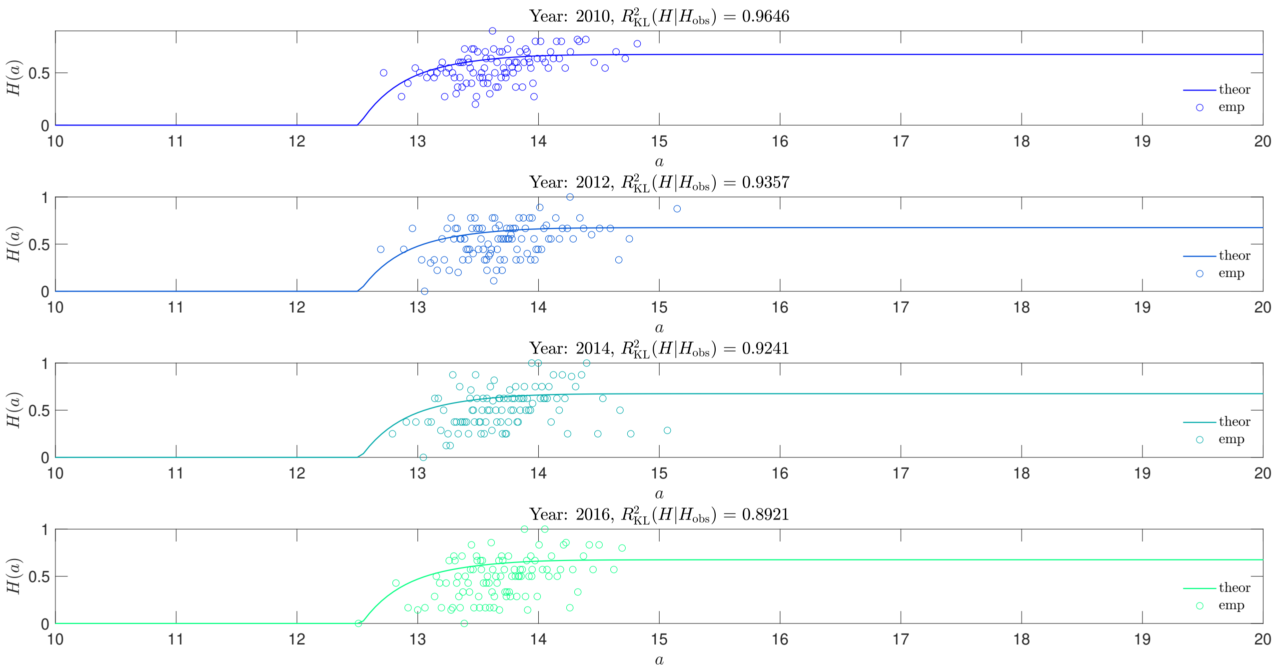

Figure E.16: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.3. The data cover the years 2010 to 2016 for the manufacturing sector in Switzerland.

Estimation results for the Netherlands. The pre- and post-2008 estimation results for the manufacturing sector (2-digit NACE codes 10-38) for the Netherlands are reported in columns (4)-(6) in Table E.3.[37] The goodness-of-fit of the SMM model in column (6) in Table E.3 is shown in Figures E.17, E.18, E.19 and E.20.

Comparing the SMM estimates in Table 5 with the ones in Table E.3 reveals a significant decrease in R&D costs in the post-2008 period for both the full sample and the manufacturing sector. However, contrary to the full sample, we find a decrease in the passive imitation success probability (δ) in the post-2008 period in the manufacturing sector.

[37]The estimation results for the 2012-2016 sample period can be obtained from the authors upon request.

Pre-sample for the manufacturing sector in the Netherlands: 2000–2008.

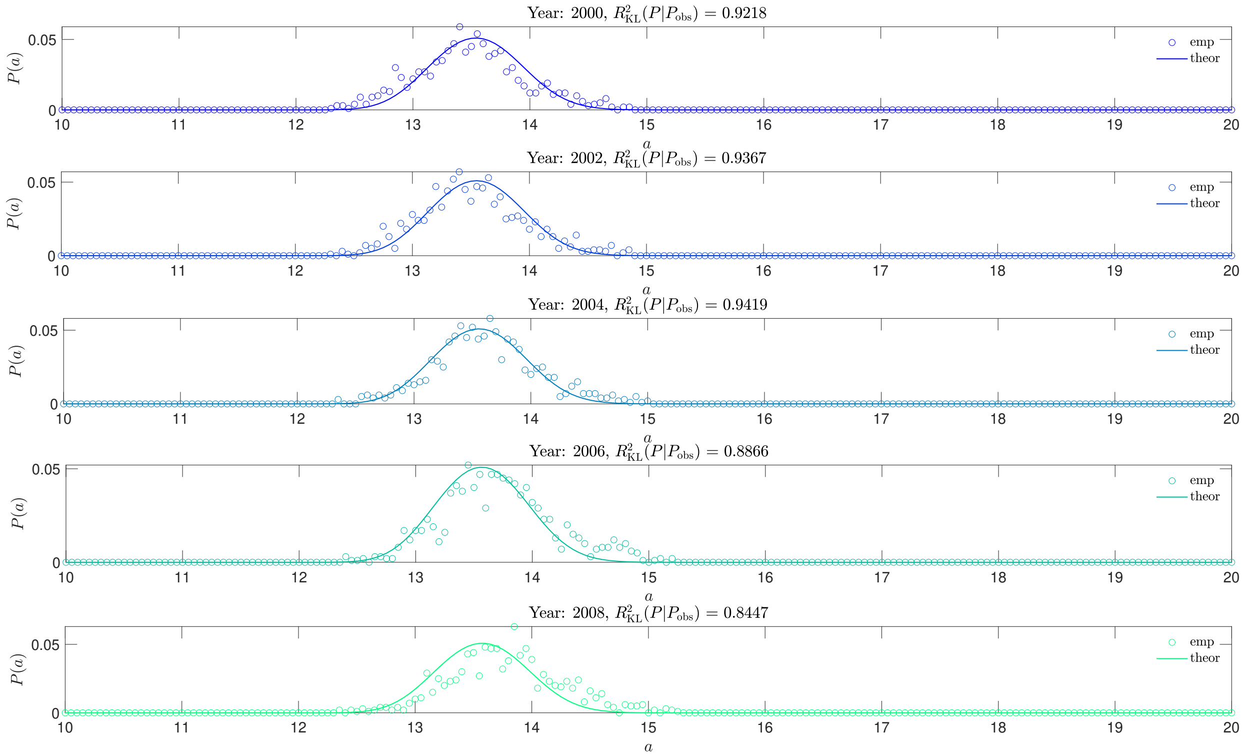

Figure E.17: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.3. The data cover the years 2000 to 2008 for the manufacturing sector in the Netherlands.

Pre-sample for the manufacturing sector in the Netherlands: 2000–2008.

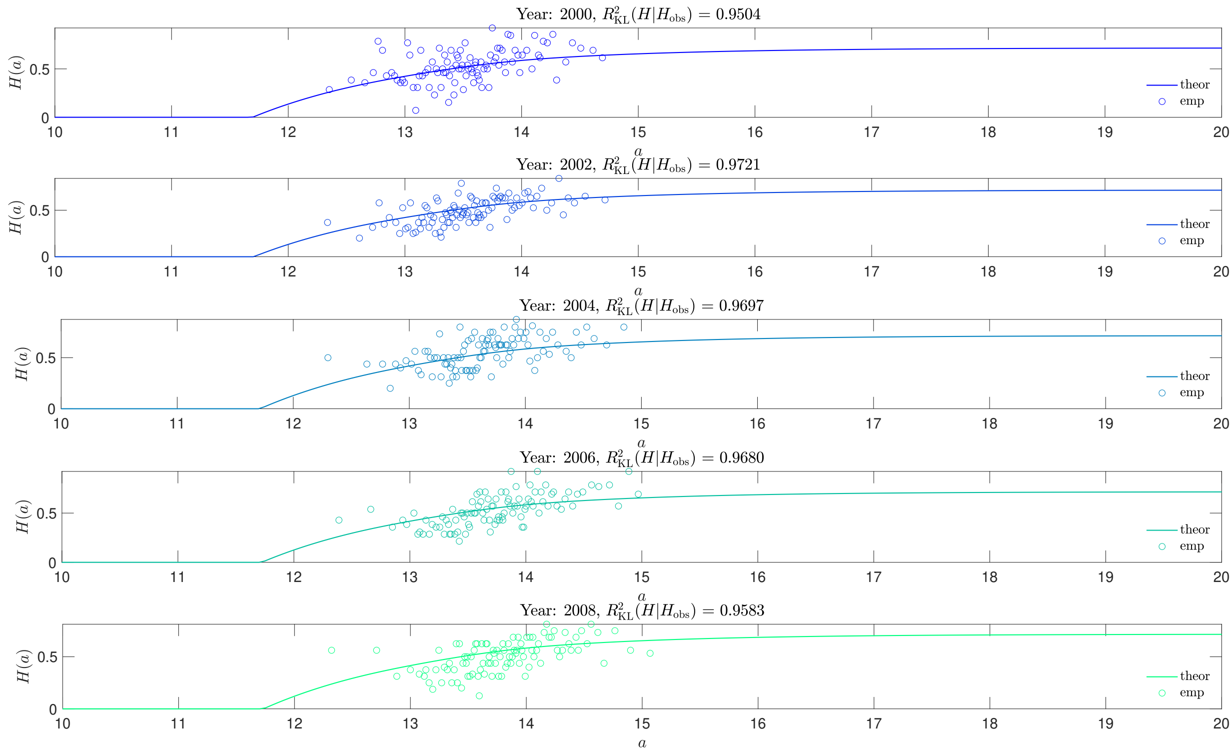

Figure E.18: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.3. The data cover the years 2000 to 2008 for the Netherlands for the manufacturing sector.

Post-sample for the manufacturing sector in the Netherlands: 2010–2016.

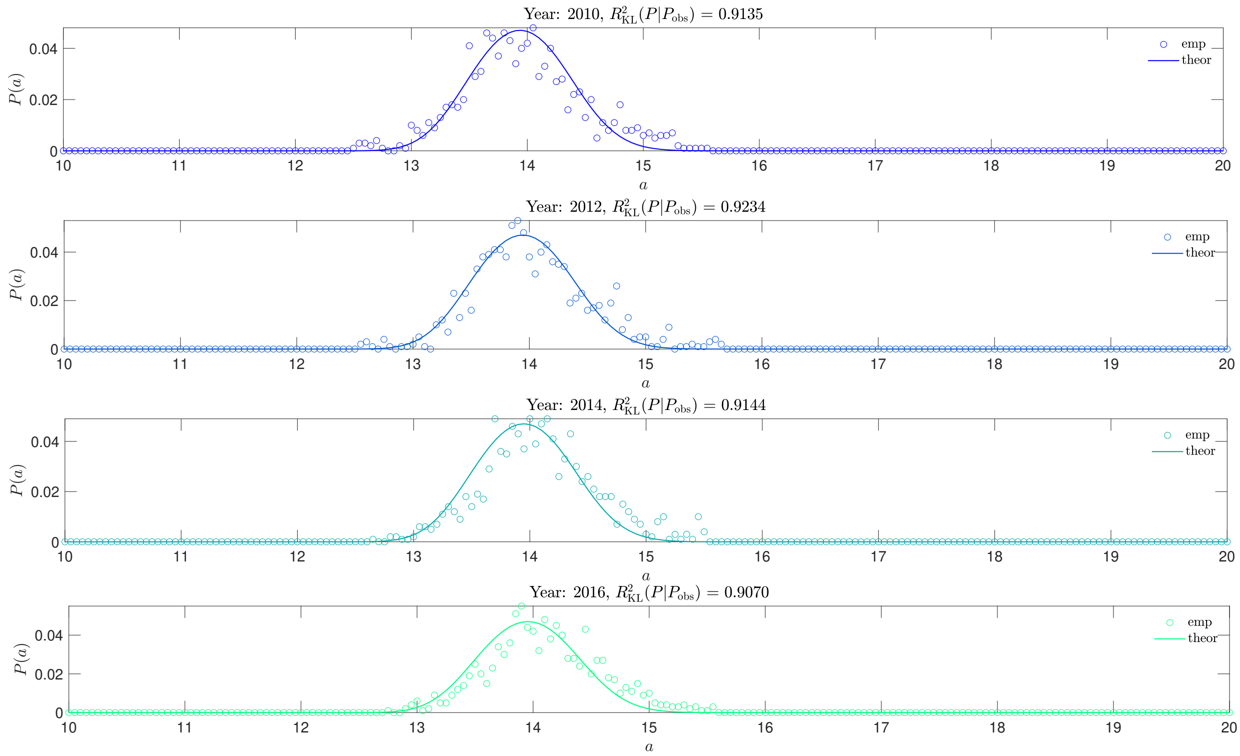

Figure E.19: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.3. The data cover the years 2010 to 2016 for the manufacturing sector in the Netherlands.

Post-sample for the manufacturing sector in the Netherlands: 2010–2016.

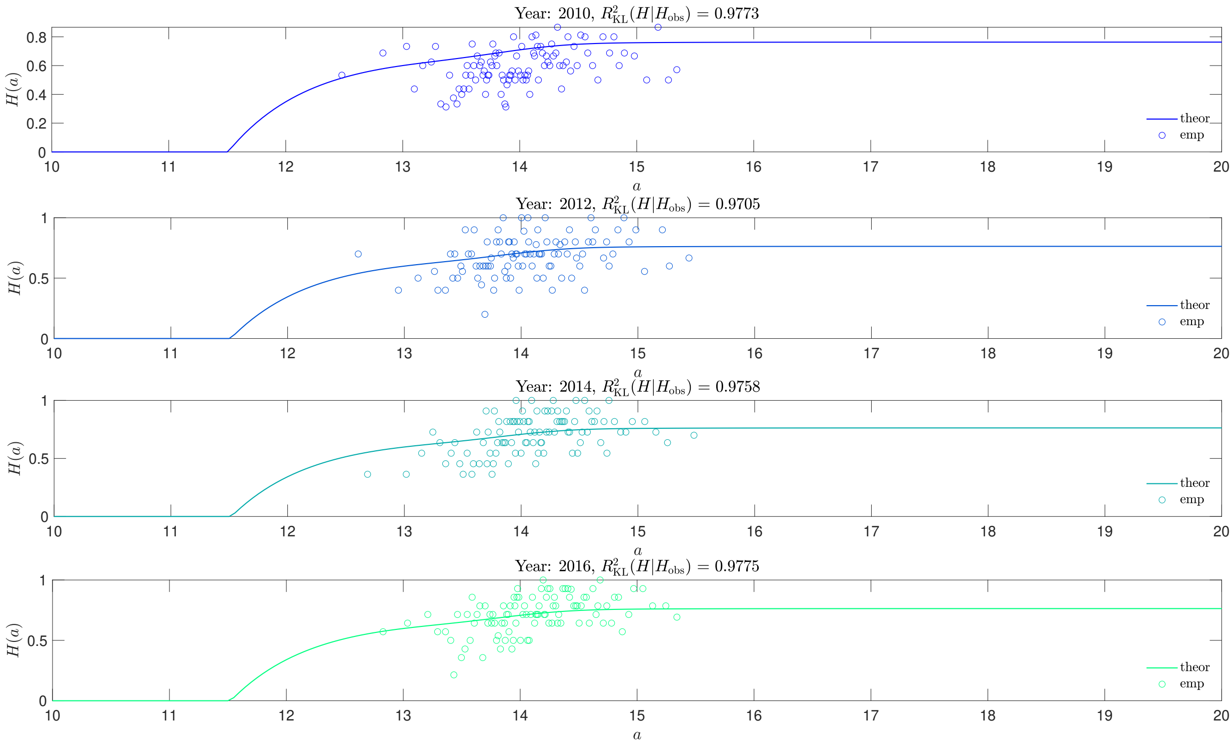

Figure E.20: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.3. The data cover the years 2010 to 2016 for the manufacturing sector in the Netherlands.

E.4. Alternative Productivity Measure

Estimation results for Switzerland. The pre- and post-2008 estimation results for the manufacturing sector in Switzerland using the ACF productivity measure (revenue total factor productivity) introduced in Ackerberg et al. [2015] are reported in columns (1)-(3) in Table E.4.[38] The goodness-of-fit of the SMM model in column (3) in Table E.4 is shown in Figures E.21, E.22, E.23 and E.24.

Comparing the estimates in Table 5 with the ones in Table E.4 for the SMM model (column (3)) reveals an increase in R&D costs in the post-2008 period for both the full sample and the manufacturing sector using the ACF productivity measure. In the latter case, this increase is less pronounced, though. Contrary to the results for the full sample using real value added per worker as productivity measure (Table 5), the in-house R&D success probability ($\bar{p}$) is lower in the post-2008 period for the manufacturing sector using revenue total factor productivity as productivity measure (Table E.4). This finding resembles the one for the for the manufacturing sector in Switzerland using the value added per worker based productivity measure (see Section E.3).

[38] The estimation results for the 2012-2016 sample period can be obtained from the authors upon request.

Table E.4: Pre- and post-sample estimation results for the manufacturing sector in Switzerland and the Netherlands using the ACF revenue total factor productivity measure [Ackerberg et al., 2015].

		Switzerland			the Netherlands		
		LPM	NLS	SMM	LPM	NLS	SMM
		w/o passive imitation	w/o random effects	with random effects	w/o passive imitation	w/o random effects	with random effects
		$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$	$\delta = 0$	$\delta \neq 0$	$\delta \neq 0$
		(1)	(2)	(3)	(4)	(5)	(6)
Sample period: 2000-2008							
Innovation	$(\bar{p})$	0.6932***	0.6811***	0.6379***	0.5342	0.5167***	0.5384***
		(0.0217)	(0.0152)	(0.0329)	(0.3783)	(0.0048)	(0.0269)
Cost	$(\widetilde{\kappa})$	0.0000	0.0015***	0.0092***	0.0260	0.0002***	0.0550***
		(0.0099)	(0.0009)	(0.0036)	(0.2572)	(0.0001)	(0.0071)
Imitation	(q)	0.1997***	0.1915***	0.0734***	0.0000	0.9497***	0.2189***
		(0.0679)	(0.0178)	(0.0187)	(0.0786)	(0.0397)	(0.0085)
Passive Imitation	(δ)		0.1468***	0.0623***		0.9944***	0.7531***
			(0.1138)	(0.0045)		(0.0015)	(0.0290)
Observations		2,268	2,268	2,268	6,297	6,297	6,297
$R^2_{\mathrm{KL}}(H\|H_{\mathrm{obs}})$		0.8929	0.9023	0.9417	0.9072	0.9098	0.9374
Sample period: 2010-2016							
Innovation	$(\bar{p})$	0.5840*	0.5872***	0.5920***	0.6896***	0.6834***	0.6621***
		(0.3282)	(0.0114)	(0.0370)	(0.0308)	(0.0044)	(0.0317)
Cost	$(\widetilde{\kappa})$	0.0148	0.0148***	0.0115***	0.0000	0.0002***	0.0410***
		(0.0174)	(0.0000)	(0.0030)	(0.0404)	(0.0001)	(0.0130)
Imitation	(q)	0.0317	0.0460***	0.0946***	0.0445	0.8777***	0.4851***
		(0.1095)	(0.0253)	(0.0189)	(0.0462)	(0.0764)	(0.0540)
Passive Imitation	(δ)		0.2074***	0.6455***		0.9879***	0.9168***
			(0.1502)	(0.0544)		(0.0057)	(0.0125)
Observations		2,871	2,871	2,871	3,269	3,269	3,269
$R^2_{\mathrm{KL}}(H\|H_{\mathrm{obs}})$		0.8667	0.8839	0.9141	0.9323	0.9295	0.9800

Notes: Models (1) and (4) correspond to the Linear Probability Model (LPM) discussed in Section 3.4. Models (2) and (5) correspond to a Nonlinear Least Squares (NLS) estimation procedure with an innovation decision variable as in Equation (8) as the dependent variable. For each year and within each NACE Rev. 2 1-digit code, the data has been trimmed at the top and bottom 1% productivity percentiles at the industry-year level. Models (3) and (6) are based on the Simulated Methods of Moments (SMM) estimation algorithm discussed in Section 4.1 for which we set $\tilde{a} = 0.05$, using the estimates of models (2) and (5) as initial conditions for the MCMC algorithm, respectively, and applying a bootstrap procedure with 50 bootstrap samples. For Switzerland, the estimate for the cost parameter θ is 0.688 in the period 2000-2008 and 0.796 in the period 2010-2016. For the Netherlands, the estimate for the cost parameter θ is 0.536 in the period 2000-2008 and 0.526 in the period 2010-2016. Standard errors in parentheses for models (1)–(6). The asterisks *** (**,*) indicate that a parameter's 99% (95%, 90%) highest posterior density interval does not cover zero [Kruschke, 2015]. The R-squared measure $R^2_{\mathrm{KL}}(\cdot|\cdot)$ follows Cameron and Windmeijer [1997] and is defined as $R^2_{\mathrm{KL}}(\cdot|\cdot) = 1 - D_{\mathrm{KL}}(\cdot|\cdot)$, where $D_{\mathrm{KL}}(\cdot|\cdot)$ is the Kullback-Leibler divergence. The Kullback-Leibler divergence, $D_{\mathrm{KL}}(H|H_{\mathrm{obs}}) = \sum_a H(a) \log\left(\frac{H(a)}{H_{\mathrm{obs}}(a)}\right)$, measures the difference between the predicted (H) and the observed (empirical) distribution (H_{obs}) [Song, 2002]. The reported R-squared measures are averages across time periods.

Pre-sample for the manufacturing sector in Switzerland using the ACF productivity measure: 2000–2008.

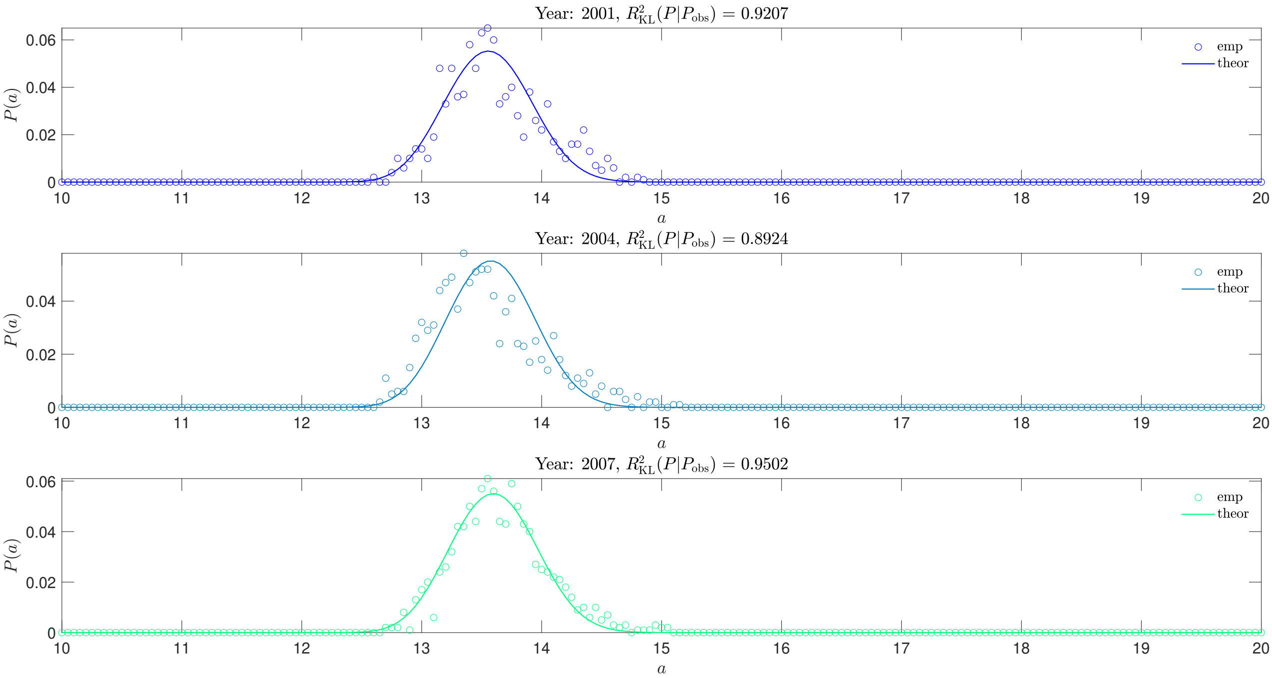

Figure E.21: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.4. The data cover the years 2000 to 2008 for the manufacturing sector in Switzerland using the ACF revenue total factor productivity measure [Ackerberg et al., 2015].

Pre-sample for the manufacturing sector in Switzerland using the ACF productivity measure: 2000–2008.

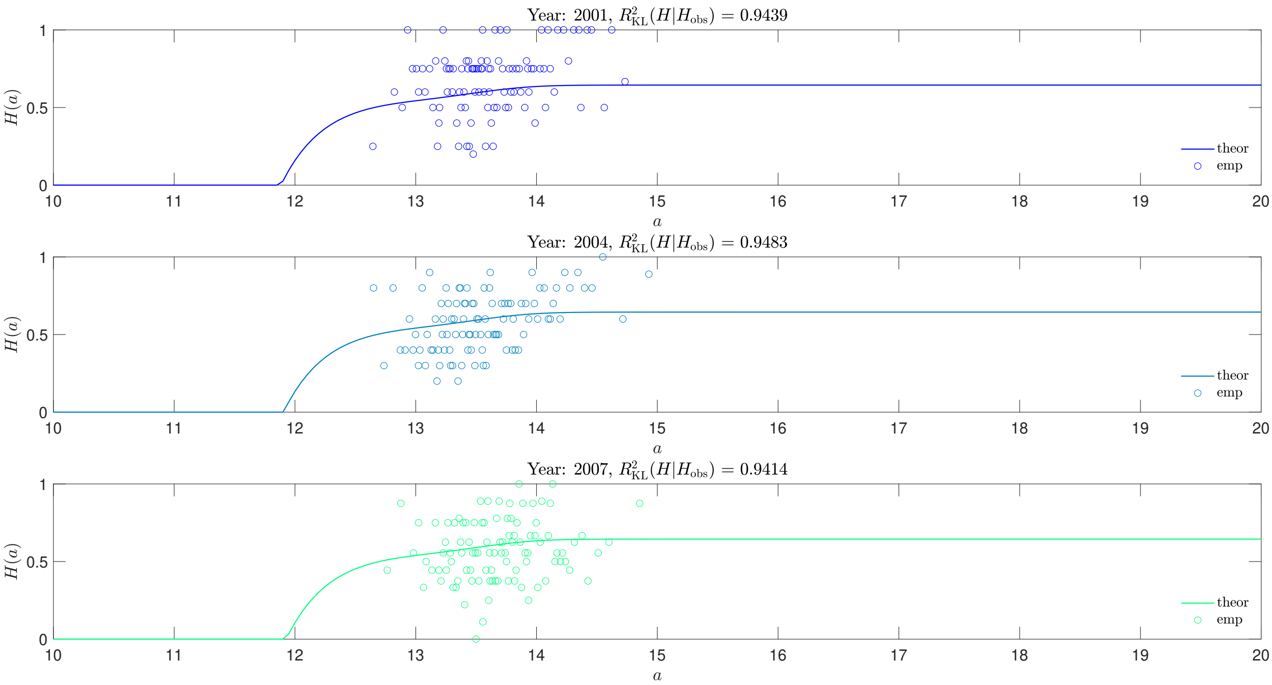

Figure E.22: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.4. The data cover the years 2000 to 2008 for the manufacturing sector in Switzerland using the ACF revenue total factor productivity measure [Ackerberg et al., 2015].

Post-sample for the manufacturing sector in Switzerland using the ACF productivity measure: 2010–2016.

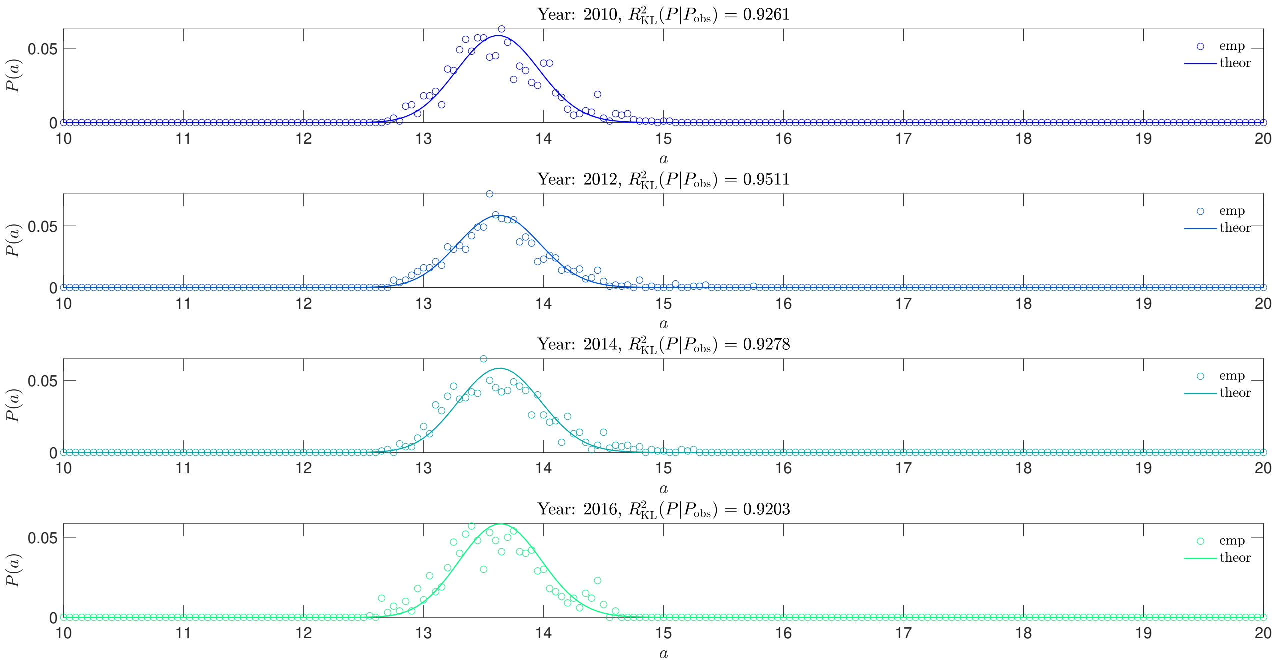

Figure E.23: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.4. The data cover the years 2010 to 2016 for the manufacturing sector in Switzerland using the ACF revenue total factor productivity measure [Ackerberg et al., 2015].

Post-sample for the manufacturing sector in Switzerland using the ACF productivity measure: 2010–2016.

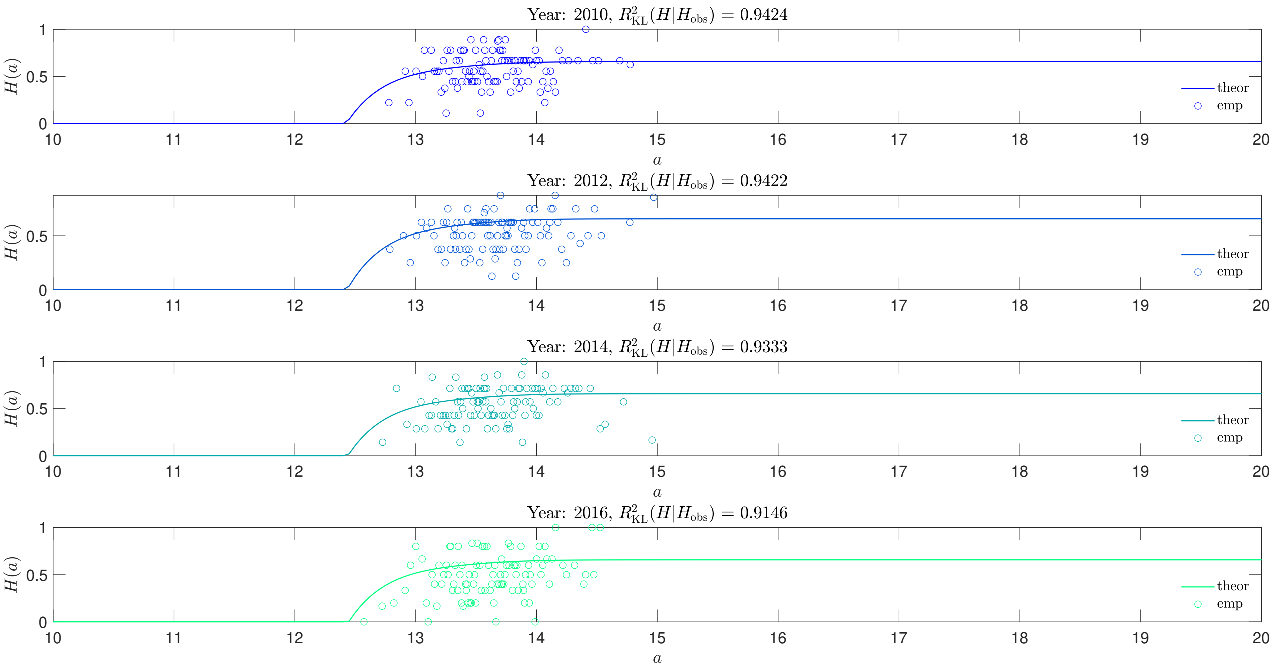

Figure E.24: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (3) in Table E.4. The data cover the years 2010 to 2016 for the manufacturing sector in Switzerland using the ACF revenue total factor productivity measure [Ackerberg et al., 2015].

Estimation results for the Netherlands. The pre- and post-2008 estimation results for the manufacturing sector in the Netherlands using the ACF productivity measure (revenue total factor productivity) introduced in Ackerberg et al. [2015] are reported in columns (4)-(6) in Table E.4.[39] The goodness-of-fit of the SMM model in column (6) in Table E.4 is shown in Figures E.25, E.26, E.27 and E.28.

Comparing the SMM estimates in Table 5 with the ones in Table E.4 reveals a decrease in R&D costs in the post-2008 period for both the full sample and the manufacturing sector using the ACF productivity measure. In the latter case, this decrease is much smaller, though. Contrary to the results for the full sample using real value added per worker as productivity measure (Table 5), the in-house R&D success probability ($\bar{p}$) is higher in the post-2008 period for the manufacturing sector using revenue total factor productivity as productivity measure (Table E.4). This finding resembles the one for the manufacturing sector in the Netherlands using the value added per worker based productivity measure (see Section E.3).

[39] The estimation results for the 2012-2016 sample period can be obtained from the authors upon request.

Pre-sample for the manufacturing sector in the Netherlands using the ACF productivity measure: 2000–2008.

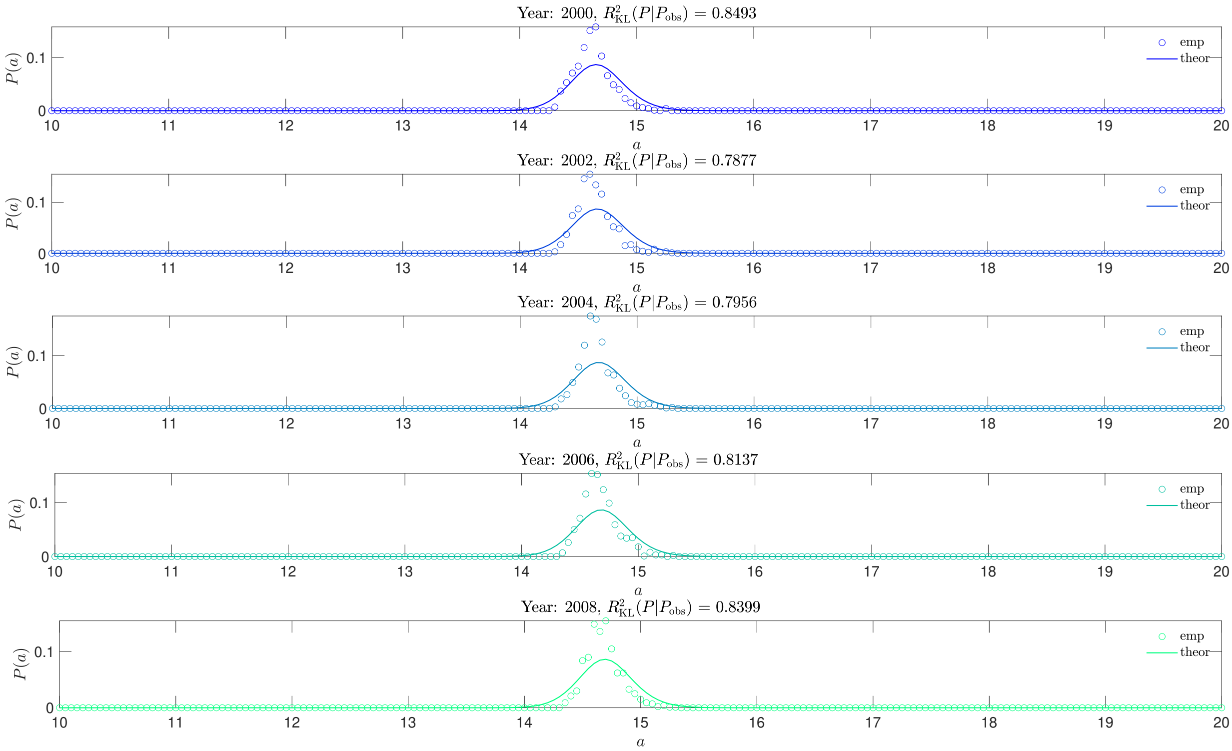

Figure E.25: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.4. The data cover the years 2000 to 2008 for the manufacturing sector in the Netherlands using the revenue total factor productivity measure [Ackerberg et al., 2015].

Pre-sample for the manufacturing sector in the Netherlands using the ACF productivity measure: 2000–2008.

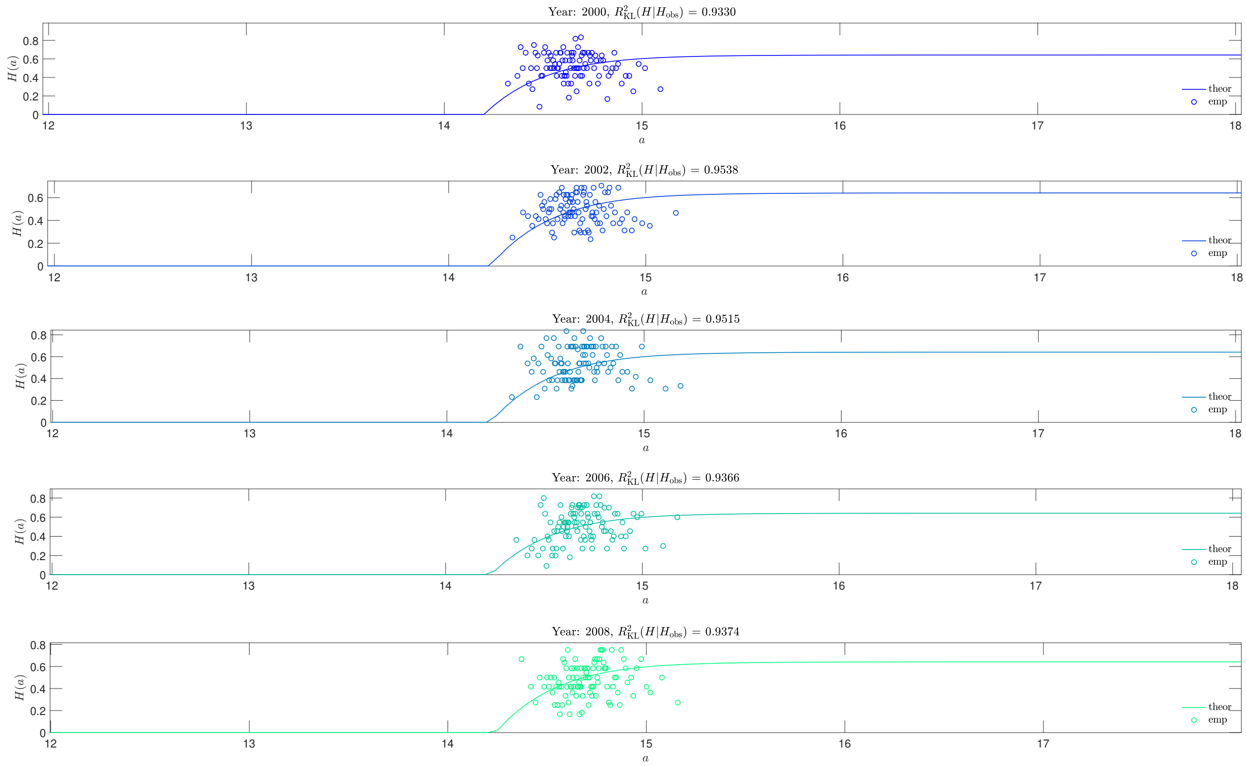

Figure E.26: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.4. The data cover the years 2000 to 2008 for the manufacturing sector in the Netherlands using the ACF revenue total factor productivity measure [Ackerberg et al., 2015].

Post-sample for the manufacturing sector in the Netherlands using the ACF productivity measure: 2010–2016.

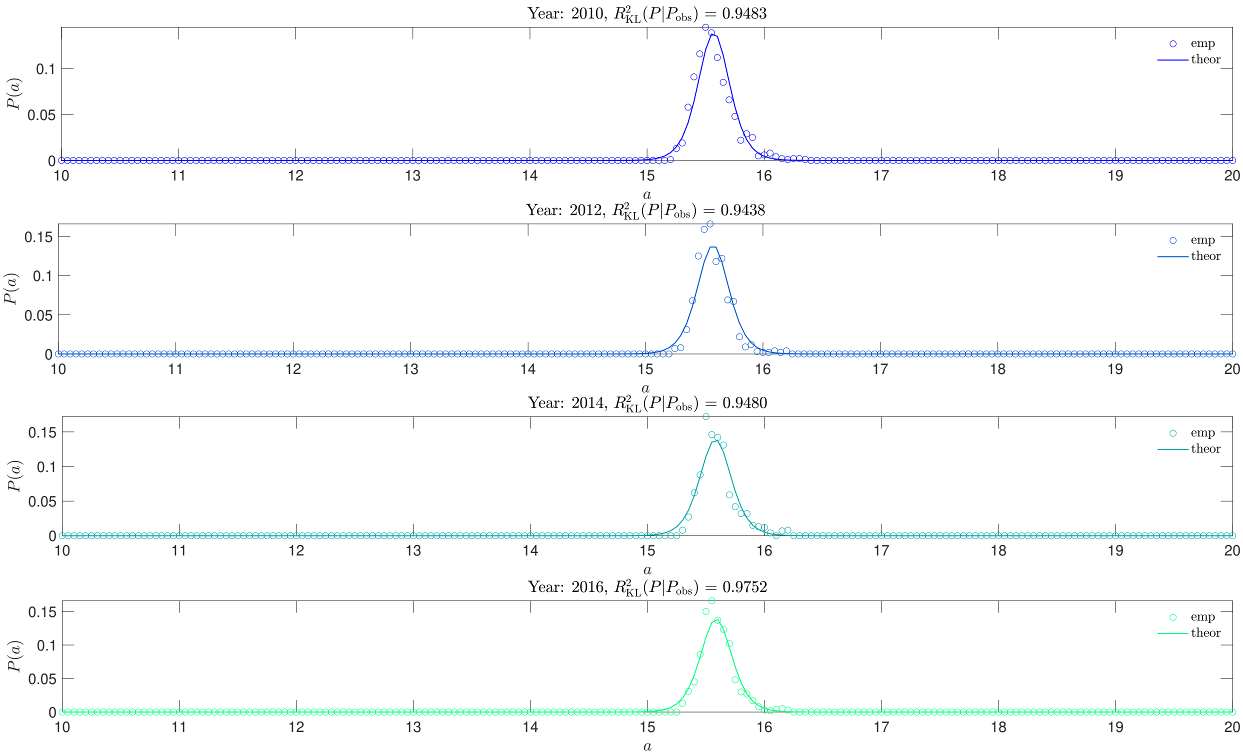

Figure E.27: Comparison of the empirical log-productivity distribution $P(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.4. The data cover the years 2010 to 2016 for the manufacturing sector in the Netherlands using the ACF revenue total factor productivity measure [Ackerberg et al., 2015].

Post-sample for the manufacturing sector in the Netherlands using the ACF productivity measure: 2010–2016.

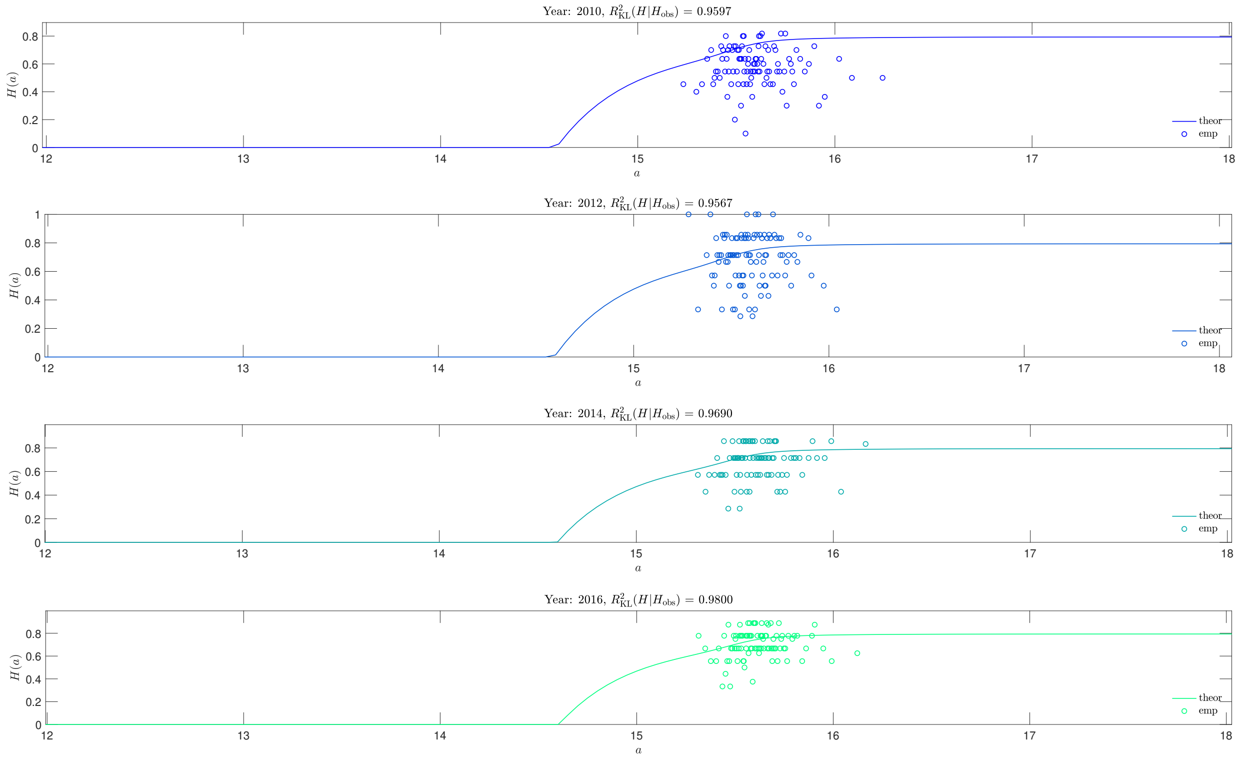

Figure E.28: Comparison of the empirical log-productivity innovation profile $H(a)$ and the prediction by the model. The parameter estimates can be found in column (6) in Table E.4. The data cover the years 2010 to 2016 for the manufacturing sector in the Netherlands using the ACF revenue total factor productivity measure [Ackerberg et al., 2015].