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ABSTRACT: For centuries, the flexibility to hire and train apprentices has been an important source of successful implementation of innovations in production technologies. This paper shows that the input flexibility of apprenticeships in German firms is associated with product innovation. Even though R&D firms face higher costs to set up training facilities and are therefore less likely to start up apprenticeship training than non-R&D firms, conditional on having invested set up costs, R&D firms train more than non-R&D firms. R&D firms that train apprentices are more responsive to cyclical fluctuations. Against the trend of a 0.5 percentage points annual decline of new products introduced in the market, firms that train and expand their training activities through time are primarily responsible for an increase in product innovation. R&D firms also renew products 2.7 times more than non-R&D firms. All this emphasizes the prime role of firms that train apprentices in reinvigorating the economy.

JEL Classifications: J23, J24, M53
Keywords: Apprenticeship market, business climate, R&D, apprenticeship demand

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1. Introduction

For centuries, flexible apprenticeships have been an important source of the successful implementation of innovations in production technologies. Apprenticeship systems exist at least since the Middle Ages (Pirenne, 1936). In the presence of the Industrial Revolution's technological shock Britain's apprenticeship institution was the source of advantage in skilled mechanical labor and critical to its economic success (Zeev *et al.*, 2017). The post-war US market for apprentices was marked by a highly elastic supply of engineering students that changed rapidly with economic prospects and changing market conditions (Ryoo and Rosen, 2004), and apprenticeship contracts determine the rate of innovative diffusion (Mokyr, 2019).

[INSERT FIGURE 1A HERE]

Elasticity is characteristic for the apprenticeship system as a whole. Figure 1A illustrates the business cycle flexibility of apprenticeship contracts in Germany for the past two decades. Numbers rise in response to positive shocks and fall with changing prospects from negative shocks. In the last two decades the overall correlation between the number of newly concluded apprenticeship contracts and the Ifo Business Cycle Indicator is $\hat{\rho} = 0.62$. This flexibility is in strong contrast with regular employment dynamics, which are typically subject to adjustment costs based on wage, tenure and job protection rules.

For technological progress to enhance, new skills and knowledge are required to keep pace with the development of innovative production technologies (Bauerschuster *et al.*, 2009; Dostie, 2018; Mairesse, Hall and Mohnen, 2010; De la Croix et al., 2018). Just like hiring new workers, for many firms, training expenditures are investment decisions -- in human capital -- with fixed costs under uncertainty (Oi, 1962). But there are also differences. A contracted apprenticeship lasts between two and four years. In dual apprenticeship systems pre-determined pay raise at the contract's expiration date when matches are prolonged is a common feature. Such contracts optimally weigh the costs of training against the benefits of increased productivity. Skills apprenticed on-the-job are often tradable. Trained workers have better options to quit, and premature quitting renders training contracts inefficient, which results in fewer training opportunities and less training (Pfann, 2001; Malcomson, *et al.*, 2003). Unambiguously stating the length and the expected wage increase into the contract signals for both parties the expected productivity growth and the relevance of the ongoing employment relation (Acemoglu and Pischke, 1998).

Apprenticeships, or dual learning systems that combine on-the-job training and formal schooling are gaining popularity again in many countries (Steedman, 2010). Dearden *et al.* (2000) estimate that raising the proportion of trained industrial workers in the U.K. by 5 percentage points is associated with a 4 percentage point increase in value added per annum and a 1.6 percentage point annual wage increase. Governments expect substantial returns as well by means of improving employability, skills, and productivity (Wolter and Ryan, 2011). Large supply shocks of high-educated apprentices are easily cushioned by firms' excess demand for high-school educated apprentices (Muehlemann *et al.*, 2022). Innovative firms that face skill deficiencies embrace apprenticeship training (Lewis, 2020). Firms participating in apprenticeship training have higher innovation outcomes than do non-participating firms (Rupietta and Backes-Gellner, 2019).

The current role of apprenticeships in product innovation is the prime interest of this study.[1] Therefore, we will distinguish between R&D and non-R&D firms and look for answers to the question how these firms optimize the process of apprenticeship training in a dynamic setting while facing cyclical uncertainty and deal with the fact that trainees might quit prematurely.

[INSERT FIGURE 1B HERE]

Figure 1B shows the development of new and improved products brought to the market by R&D and non-R&D firms in Germany between 2008 and 2021. R&D firms are the prime contributors to product innovation, but new products brought to the market by R&D firms display a significant negative trend[2]. This may coincide with the recent slowdown in labor productivity in modern economies (*cf.* Goldin *et al.* 2024).

Due to high set-up costs, the likelihood to postpone training apprentices is probably more pertinent for R&D firms than non-R&D firms. Uncertainty results from unpredictable cyclicality and unexpected shocks. Combined with - sunk - costs of setting up training facilities, the variance of predicted returns increases with apprenticeship duration. A second source of uncertainty is related to the unpredictability of quit behavior of trainees. These two sources of uncertainty are not necessarily correlated with each other, although just like apprenticeship input demand, the quit behavior of workers is pro-cyclical as well (Weiss, 1984).

[1] Product innovation is measured according to the Oslo Manual (OECD, 2018) and includes a) completely new product, and b) an improved product.

[2] The estimated slope of the trendline is -0.0046 with a p-value smaller than 0.05. This implies a reduction of new products brought to the market by R&D firms in Germany has declined by half a percentage point per year during the period from 2008 until 2021.

The combination of set-up costs and both sources of uncertainty prompts discontinuity in the stream of expected returns to training expenses. The unpredictability of returns to training investments renders the net present value evaluation inappropriate. The value to postpone spending on training costs is a worthy option and an integral part of the training firm's decision process. Treating cyclical uncertainty and the bad news principle -- of an apprentice who decides to quit while being contracted by the firm for training – distinctively opens up the possibility to model the separate effects of the two sources of uncertainty on a firm's propensity to train apprentices.

The differences in the cyclical demand of apprenticeship training of R&D and non-R&D firms underline the importance of the relationship of innovation and apprenticeship training, as well as the leading role of R&D firms to revitalize the economy. The theoretical model used in this paper has a closed form solution, which provides an optimal apprenticeship input rule that is helpful to analyze differences in the input demand for apprenticeship trainees during good and bad economic times.

The paper is organized as follows. Section 2 presents the theoretical model and derives four testable hypotheses about the cyclicality of apprenticeship training, the difference between firms that do or do not invest in R&D to start apprenticeship training, and the responsiveness to cyclical fluctuations of R&D and non-R&D firms. Section 3 discusses the pro-cyclicality of apprenticeship input demand and presents tests based on macroeconomic data. Section 4 discusses the role of apprenticeships for R&D and non-R&D firms. Empirical evidence is presented using firm-level data of apprenticeship input demand for both types of firms. Section 5 quantifies the role of innovative training firms in reinvigorating the economy over the business cycle. Section 6 concludes.

2. Deriving testable hypotheses focusing on training costs and uncertainty

A risk-neutral firm values the productivity stream of an untrained worker as W_0 at time $t = 0$. Meanwhile, the firm considers investing k to set up apprenticeship training facilities and values the productivity stream of a trained worker as V_0, with $P_0 \equiv V_0 - W_0$. The firm is uncertain about the future development of the expected differences between trained and untrained workers productivity streams. The optimal decision to train comes down to the right timing. Uncertainty over the expected returns P_t to the set-up costs creates an incentive to either act directly or postpone the decision to train until later. Uncertainty about P_t gets larger the further t lies into the distant future. Waiting for relevant new information to arrive is a precious strategy, especially when set-up costs are also high. The stochastic process for P_t can be written as a mixed Poisson–Wiener process

$$(1) \quad dP = \alpha P dt + \sigma P dz - P dn$$

where $\alpha > 0$ is the expected growth of the stream of value differences between a worker's trained and untrained productivity through time; σ is the per unit of time variance of α, dt is the evolution of the training prospect through time; and dz is the random change in the training prospect assumed to come from a standard Wiener diffusion process z. We assume that quitting ruins the firm's returns on investment in apprenticeship training. The probability of quitting is represented by dn, the increment of a Poisson process with mean arrival rate $\pi \geq 0$, such that

$$(2) \quad dn = \begin{cases} -1 & with\,probability \quad \pi dt \\ 0 & with\,probability\ (1-\pi)dt. \end{cases}$$

Over each time interval dt, P will drop to zero with probability π. The expected percentage change in P is $\alpha - \pi$. An increase in π reduces the expected return P of investing in training. The optimal training rule $P^*(\pi)$ is the analytical solution of this dynamic optimization problem for the demand of apprenticeship training for a firm with set-up cost k and a risk-free interest rate ρ. It yields[3]

$$(3) \quad P^*(\pi) = \left(\frac{\beta(\pi)}{\beta(\pi)-1}\right) k \quad \text{with} \quad \beta(\pi) = \frac{1}{2} - \frac{\alpha}{\sigma^2} + \left(\left(\frac{\alpha}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(\rho+\pi)}{\sigma^2}\right)^{\frac{1}{2}}.$$

A high $P^*(\pi)$ implies a high value of future information, longer optimal waiting time, and lower likelihood to set up a training scheme today, when $t = 0$.

Uncertainty of future productivity growth.

The optimal training rule depends on the uncertainty of the expected growth rate σ. From equation (3) we find that $\partial P^*/\partial\beta(\pi) < 0$ and $\partial\beta(\pi)/\partial\sigma < 0$, such that $\partial P^*/\partial\sigma = \partial P^*/\partial\beta(\pi) * \partial\beta(\pi)/\partial\sigma > 0$. When the volatility or uncertainty of the expected productivity growth rate increases, then P^* gets larger. This means that the option value to wait spending on training costs increases during times of increased uncertainty ($\sigma_2 > \sigma_1$), when current apprenticeship contracts are less profitable than future contracts ($P_2^* > P_1^*$).

[3] The analytical solution is widely available in the real options literature. The positive root of the fundamental second-order homogeneous differential equation derived from *Bellman's Principle of Optimality* lies outside the unit circle, such that $\beta(\pi) > 1$ (*cf.* Dixit and Pindyck (1994), footnote 16, p.171).

This lowers the firm's propensity to train at present and causes apprenticeship training to be highly pro-cyclical. This gives rise to *prediction 1*: *The demand for apprenticeship training is pro-cyclical.*

[INSERT FIGURE 2 ABOUT HERE]

The rationale behind prediction 1 is explained graphically in Figure 2. It compares a period 1 of low uncertainty with a period 2 of high uncertainty $(\sigma_2 > \sigma_1)$. *Ceteris paribus*, in times of high uncertainty current apprenticeship contracts are less profitable than future contracts, such that $P_2^* > P_1^*$. Therefore, when uncertainty increases it lowers the firm's propensity to train. Downturns are periods of high uncertainty and incentivize decision maker to put more weight on their private signals (Zohar, 2024). When σ is high, a change in training activity shall induce a larger response of disagreement in the firm than in times of low uncertainty.

Differences in set-up costs of training.

The optimal training rule depends on fixed costs k, the costs to set-up a training facility, which form an entry barrier to become an apprenticeship training firm. Firms differ in k, and k is sunk as soon as the option to spend the set-up costs of apprenticeship training facilities is exercised. It holds that $\partial P^*/\partial k > 0$, such that firms, which are facing higher set-up costs, are less likely to train. Although k is difficult to measure, it is reasonable to assume that k for R&D firms exceeds k for non-R&D firms. When, indeed, $k_{R\&D} > k_{non-R\&D}$, it holds that $\partial P^*/\partial k_{R\&D} > \partial P^*/\partial k_{non-R\&D} > 0$. This gives *prediction 2: R&D firms are less likely to start up apprenticeship training than non-R&D firms*, which is at the same time an indirect measure of set-up cost differences between R&D and non-R&D firms.

Differences in expected productivity growth.

The optimal training rule depends on α, the expected growth of the stream of value differences between a trained and an untrained worker's productivity. Since $\partial\beta(\pi)/\partial\alpha < 0$, it holds that $\partial P^*/\partial\alpha = \partial P^*/\partial\beta(\pi) * \partial\beta(\pi)/\partial\alpha < 0$. This means that other things equal the larger the expected growth in productivity difference between trained and untrained workers, the more likely it is that a firm will train. Naturally, the parameter α can also be interpreted as the *ceteris paribus* productivity difference between workers that receive training in R&D compared to non-R&D firms. When $\alpha_{R\&D} > \alpha_{non-R\&D}$, it holds that $\partial P^*/\partial\alpha_{R\&D} < \partial P^*/\partial\alpha_{non-R\&D} < 0$. Or, stated differently, R&D firms that expect higher productivity gains from training face lower option values to wait and are, therefore, more likely to train. *Prediction 3* is that *conditional on being a training firm R&D firms train more than non-R&D firms*.

Cyclical differences in apprenticeship demand between R&D and non-R&D firms.

When k is sunk and $\alpha_{R\&D} > \alpha_{non-R\&D}$, it also holds that $\partial P^*_{non-R\&D}/\partial\sigma > \partial P^*_{R\&D}/\partial\sigma$, and $P^*_{non-R\&D} > P^*_{R\&D}$. Thus, the model foretells that R&D firms are more responsive to fluctuations in uncertainty than non-R&D firms. *Prediction 4* is that *R&D firms that train are more responsive to cyclical fluctuations than non-R&D firms*.

The probability of quitting in R&D and non-R&D firms

There is little evidence of existing differences in the likelihood of apprentices quitting from training in R&D versus non-R&D firms. Suppose that $\pi_{non-R\&D} > \pi_{R\&D}$. Then according to equation (3), the discount rate of future returns on investment, $\rho + \pi$ is larger for non-R&D

firms than for R&D firms. Quitting only hurts those firms that actually train. They have already invested k, and have hired apprentices. This implies a modification of prediction 3 in the following sense. If training firms are faced with a higher propensity of premature quitting they are less likely to train apprentices.

3. Pro-cyclicality of input demand for apprenticeships

The cyclicality of the number of newly concluded training contracts has been studied extensively. Procyclicality as shown in Figure 1 also holds for practically all countries with apprenticeship training programs[4]. Procyclicality is present in the data for Germany regardless of the measure of cyclical economic activity is used, such as unemployment, gross domestic product, company expectations, or business climate.

The data used in this paper for testing the hypotheses are obtained from two data sources. The first source is aggregated data of the yearly register of all German apprenticeship contracts (Rohrbach-Schmidt and Uhly, 2016). The regional chambers of commerce collect the contract information and send it to the Federal Statistical Office, which then processes it and passes it on to the Federal Institute for Vocational Education and Training (BIBB). The register covers all apprenticeships in Germany, as regional chambers of industry and commerce are required to report them. The data contain attributes of apprentices (contract holders) and details about the occupation and region. This information is used to create a panel data set that includes the number of new contracts in a given occupation, the state

[4] See Muehlemann and Wolter (2021) for a comprehensive overview. For Switzerland: Goller and Wolter (2021); Great Britain: Ventura (2020); Canada: Skof (2006); Norway: Brunello (2009); Denmark: Rasmussen and Westergaard-Nilsen (1999); USA: Farber (1967).

(*Bundesland*), and the year when a contract was concluded. To account for regional demographic changes, the number of school leavers at the state-year level are also controlled for in our empirical analysis. Finally, we match information from the Federal Employment Agency on the number of unfilled apprenticeship positions at the state occupation level for each year, which allows us to create our main dependent variable of interest, the firm's demand for apprentices.

Some additional variables are sampled to capture the effects of the business cycle. Firstly, the Ifo Business Climate Index is published monthly by the Ifo Institute and is based on the subjective responses of establishments to the current business situation and their business expectations (see Figure 1). Moreover, statistics of the German GDP growth as an alternative measure of the business cycle are used as well. These data are used to test prediction 1.

For the estimation of cyclicality, we provide estimates of aggregated data at the state occupation level, where apprentice ***demand*** is our dependent variable of interest. We denote the demand for apprentices d in the occupational field o, state s, and year t as

(5) $$d_{ost} = \upsilon_{os} + \mathbf{x}'_{st}\beta + \mathbf{z}'_{st}\gamma + \varepsilon_{ost},$$

where υ_{so} accounts for unobserved time-invariant heterogeneity at the state and 2-digit occupation level, **x** contains measures for business cycle fluctuations, the average of the Ifo Business Climate Index of the first three quarters in period t ($\overline{\mathrm{BCI}}_{\mathrm{t,Jan-t,Sept}}$), the national GDP, or the vacancy/unemployment ratio at the 2-digit occupation and state level, and **z includes** state-level and occupation-level trends as well as the state-level number of school graduates by level of education. This results in the first-difference regression model

(6) $$d_{ost} - d_{ost,\,t-1} = \left(\mathbf{x}_{st} - \mathbf{x}_{st,t-1}\right)'\beta + (\mathbf{z}_{st} - \mathbf{z}_{st-1})'\gamma + (\varepsilon_{ost} - \varepsilon_{ost-1})$$

with $E\left[(\varepsilon_{ost} - \varepsilon_{ost-1})\middle|\left(\mathbf{z}_{st} - \mathbf{z}_{st,t-1}\right)\right] = 0$. Pro-cyclicality is found when $\beta > 0$ (*cf.* Barlevy, 2007).

[INSERT TABLE 1 ABOUT HERE]

Table 1 shows the results of the estimation of equation (6). Including additional lagged controls to obtain stationarity in the error term $\Delta\varepsilon_{ost}$, we find positive correlations between the demand for apprentices and all business cycle indicators. Labor market tightness is positively correlated with the demand for apprentices. An increase in the tightness ratio by 10 percent in the current period is associated with a 1.4 percent increase in apprentice demand. A 10-point increase in the Ifo BCI is associated with a 5.2% increase in the demand for apprentices. Unsurprisingly, all results clearly confirm the pro-cyclicality of input demand for apprentices.

4. Differences in apprenticeship demand between R&D and non-R&D firms

For the empirical investigation of predictions 2, 3 and 4 a second data source will be used, which is the IAB establishment panel (Ellguth et al. 2014).[5] Our sample includes representative information on the ***demand*** for apprentices at the establishment level, including unfilled training positions from 2007 to 2021. Analyzing the training behavior at the establishment level allows to account for observable and unobservable time-invariant

[5] Data access was provided during on-site guest visits at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) and/or via remote access. Annual waves of the establishment panel were combined following the procedure proposed by Umkehrer (2017).

characteristics of a firm as well as time-varying observable variables such as employment growth.

In the IAB establishment panel, a panel identifier is available with corresponding survey weights that account for panel attrition, allowing us to report weighted statistics for the two group of establishments that we use for our panel regressions (i.e., panel cases from 2007-2017, and 2012-2021, respectively).[6] We use these establishment level panel data to estimate regression models for testing the derived hypotheses.[7]

[INSERT TABLE 2A ABOUT HERE]

Table 2A shows the summary statistics of the variables used in the analysis for this data set. It is a representative sample that consists of nearly 15,500 establishments in each survey wave.[8] For our analysis, we exclude establishments with missing information about their training status, employment variables, business expectations, works councils, collective bargaining agreements, and skilled worker vacancies, ending up with just over 100,000 establishment-year observations that include information based on annual surveys conducted in the period 2007 to 2021. The average annual demand for new apprenticeships is 0.36 per firm; 24 percent of all observations in the sample are firms that train apprentices; 5 percent are R&D firms, and 1.6 percent are R&D firms that train apprentices.[9] The large majority (98 percent) of firms are small or medium sized enterprises. On average, 4.5 percent

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[6] For details on the calculation of panel weights see Bechmann et al. (2021), chapter 8. Note that while we apply the corresponding survey weights for the descriptive statistics, we follow the advice of Bechmann *et al.* (2021) and refrain from using weights in our regression models.

[7] A caveat: The exact timing of a firm's training decision is not precisely recorded in the data. Many firms sign an apprenticeship contract several months before the official start of training in August or September depending on the state.

[8] See https://iab.de/en/the-iab/surveys/the-iab-establishment-panel/ for more information about the IAB establishment panel.

[9] Information on the R&D indicator variable was only surveyed every two years. We imputed the missing information with the reported value of the previous period.

of firms bring a completely new product to the market per calendar year, while 28 percent improve an existing product. To ensure that our results are not driven by only a specific shock, we restrict our analysis to firms that are observed 2007 and in subsequent years until 2017, which includes the Great Recession. Furthermore, we provide estimates for a second subsample of firms that are observed in 2012 and in subsequent years until 2021, which also includes Covid-19 as a large shock. The descriptive statistics show that both groups of firms are comparably similar in terms of their average demand for apprenticeships as well as for other observable characteristics.

[INSERT TABLE 2B ABOUT HERE]

Table 2B provides information on the probability of product innovation for R&D firms that also train apprentices. On average, R&D training firms employed between 6 and 8 apprentices in the years 2007 to 2020. The share of firms that bring completely new products to the market fluctuates between 0.13 (year 2011) and 0.31 (year 2020), while a large majority ranging from 0.67 (year 2011) and 0.86 (year 2018) improved an already existing product in any given calendar year.

P2: Are R&D firms less likely to start up apprenticeship training?

Set-up costs for training in R&D firms are considered to be higher than for non-R&D firms, such that $k_{R\&D} > k_{non-R\&D}$. The second theoretical prediction is that R&D firms that will train take longer to invest in setting up training facilities. We test this hypothesis rather straightforwardly and compare the waiting time to set up training facilities between the two types of firms, which is proxied by the time it takes to start contracting apprenticeship positions after the firm was founded. The observed waiting times are obviously censored on both sides of the sample. In the analysis, we disregard the censoring issue and include only those firms that offer apprenticeship positions at some point during the observation period. The sample consists of 3,515 firms that were founded after 2005, which includes all firms that offer at least one apprenticeship position during the observation period. Regressing the time in years it takes to first announce an apprenticeship position on a binary variable for firms with an R&D department, holding constant for all possible observable variations at the firm level available in our data set, we find a positive and significant parameter that is equal to 0.602 (s.e. = .255 ; p=.018). The average duration for non-R&D firms in the sample to contract an apprentice for the first time is 4.1 years, while for firms with R&D departments it lasts 7.2 months longer.

P3: Being a training firm, do R&D firms train more than non-R&D firms?

Table 3A shows that R&D firms on average train 8 percent more apprentices compared to non-R&D firms if training is possible. The German Vocational Training Act (§30) requires that a training firm is suitable for providing apprenticeship training if the professional skills, knowledge, and abilities required in the training regulations can be fully provided.[10] In particular, apprentice instructors must possess the professional as well as the pedagogical skills, knowledge, and abilities that are necessary for conveying the training content, which must be demonstrated during a standardized examination (*Ordinance on Aptitude of Instructors*) or signalled with a specialized *Meister*'s diploma. Furthermore, firms that -- will -- employ apprentices are required to have suitable training facilities. Thus, the variable indicating the possibility of training, that is, whether a firm is legally allowed to train apprentices in any given year, can also be interpreted as an indicator that a firm has already spent set-up costs to train apprentices. Table 3B also shows that conditional on employing at least one apprentice, the difference in the demand for apprenticeships in R&D firms is no longer statistically significant. The point estimate is 6 percent, similar compared to the

[10] For more details on a firm's training requirements see the website of the German Federal Institute for Vocational Education and Training: https://www.bibb.de/de/145848.php

results in Table 3A. In conclusion, we find evidence supporting prediction 3 that R&D firms train more conditional on having spent set-up costs to train apprentices.

And what about the quitting behavior of apprentices? There is very little information in the data about premature quitters, but we do have information on retention rates. Although this is of a slightly different order, and possibly requires a different kind of analysis, what we have measured is overall retention rates for the entire observation period. For R&D firms it is 72 percent, and it exceeds the 62 percent for non-R&D firms. If the retention rates proxy the inverse of quit propensities, then it holds that $\hat{\pi}_{non-R\&D} > \hat{\pi}_{R\&D}$. Following our theoretical reasoning this difference would then provide additional support to our result that R&D firms once they have set up training facilities, they are investing more in apprenticeship training.

P4: Are R&D firms that train more responsive to cyclical fluctuations?

Figure 3 presents the dynamic business expectations fluctuations for R&D and non-R&D firms for the period 2007 to 2021. This time spell includes the 2008-2009 global financial crisis and the 2019-2020 Covid-19 pandemic. The demand for apprentices for that same period is shown in Figure 4. The average demand for apprentices by non-R&D firms is 0.33 trainees per year and 1.01 by R&D firms, roughly three times as much. The demand of R&D firms ($\overline{s.d.} = 4.57$) is also much more volatile for R&D firms than for non-R&D firms ($\overline{s.d.} = 1.38$). These graphs indicate that R&D firms' expectations and apprenticeship demand are more cyclical than those of non-R&D firms.

[INSERT FIGURES 3 AND 4 ABOUT HERE]

Poisson lagged dependent variables regressions at the firm level are conducted to account for the discrete nature of the dependent variable. The model specifies the demand for apprentices $d_{it} \sim$ P [$\exp(\mathbf{z}'_{it,t-1}\gamma)$], where $\boldsymbol{z}$ includes a firm's lagged share of unfilled skilled vacancies, and other control variables, such as the number of skilled workers, works councils, and indicator whether a firm is part of a collective bargaining agreement. We argue that "*what makes a firm special*"[11] in our context is its demand for apprentices in the previous period, rather than time-invariant unobserved heterogeneity.[12] We also tested for more than one lag of the dependent variable, but did not find statistically significant coefficients beyond the first lag.

[INSERT TABLE 4 ABOUT HERE]

Our results corroborate our initial findings based on aggregate data (Table 4). A change in a firm's difficulty to fill its vacancies is positively associated with the future demand for apprentices. The effect size is economically important too, as a 10%-point increase in the vacancy share is associated with a 16% increase in the demand for apprentices in R&D firms for both panel groups, and even slightly stronger in the full sample. For non-R&D firms, the effect size is considerably weaker (9.5% in the full sample).

[11] Angrist & Pischke (2008, p. 245) highlight the relevance of lagged dependent variables model in the context of estimating the wage returns to training and argue that "what makes a trainee special" may be his or her earnings in the pre-training period, rather than time-invariant unobserved heterogeneity as assumed in the panel fixed effects model.

[12] However, as a robustness check, we also estimated Poisson fixed effects panel regression models (see Cameron and Trivedi 2005, section 23.7.) and OLS fixed effects regressions. The results remain qualitatively similar, consistently showing that apprenticeship demand is more cyclical in R&D firms.

5. The Relevance of Apprentices in R&D Firms' Product Innovation

How relevant are our results for economic development? In terms of value added, the sample data show little difference between firms with or without R&D departments.[13] When it comes to product innovation, in this data set, firms with R&D departments are more than five times more likely to introduce new products than firms without R&D departments (21 percent vs. 4 percent) and 2.7 times more likely to improve existing products in a calendar year.

[INSERT TABLE 5 ABOUT HERE]

Notwithstanding the decline of new products brought to the market by R&D firms (see footnote 1) the results conveyed in Table 5 speak strongly in favor of all firms that train and expand their training activity through time. Accounting for time-invariant heterogeneity in a fixed effect linear probability panel regression, we find that R&D firms that train and that are characterized by increasing numbers of apprentices have a higher probability of product improvement. According to our estimates, doubling the number of apprentices in R&D training firms increases the innovation probability by 2.5%-points. This may look like a moderate effect. Bear in mind, however, that this increase goes against the consistent downward trend in new product innovation of half a percentage point per year (see footnote 1). Moreover, the retention rate of precisely these firms is higher than all other – R&D as well as non-R&D – firms. After their training many apprentices remain with the firm that expands its R&D activity, thus continuing to participate in a firm's innovation activities throughout their career.

[13] We ran lagged dependent variable panel regressions of value added on the number of apprentices in training firms and found a positive but not statistically significant association between apprentices and value added in R&D and non-R&D firms, controlling for overall employment growth.

Our results differ from those in the rather modest literature on the innovation effects of apprenticeships in the following ways. Our paper is the first to identify the association between apprenticeships and innovation outcomes in R&D firms versus non-R&D firms. Previous studies focused on large versus small firms (Matthies *et al.* 2023) or had to rely on cross-sectional data (Rupietta and Backes-Gellner 2019). Our results confirm the importance of unobserved time-invariant heterogeneity at the firm level, because the point estimates based on random effects panel regressions are considerably higher and statistically significant for R&D as well as for non-R&D firms. Conversely, we did not find evidence at the firm level regarding the potential innovation effects of knowledge diffusion through apprenticeships in R&D firms (De la Croix et al. (2018), Backes-Gellner and Lehnert (2021)). Overall, we can conclude that cyclicality drives the input demand for apprentices, particularly for R&D firms, and that apprentices contribute significantly to product innovation in R&D firms.

6. Conclusions

The flexibility to hire and train apprentices has long been an important source of successful implementation of innovations in production technologies. In this paper, we have shown that the input flexibility of apprenticeships, specifically in German R&D firms, contributes in large part to the process of product innovation. Even though R&D firms face higher costs to set up training facilities and are therefore less likely to start up apprenticeship training than non-R&D firms, conditional on having invested set-up costs, R&D firms train more than non-R&D firms. Moreover, R&D firms are more responsive to cyclical fluctuations than non-R&D firms, which emphasizes their prime role to bolster the economy. An important finding is that R&D firms that train and that are characterized by increasing numbers of apprentices have a higher probability of product innovation. According to our estimates, doubling the number of apprentices in training firms increases the probability of improving at least one existing product by 2.5 percentage-points. This effect is not small, as this increase goes against the consistently downward trend of 0.5 percentage-points per year for product innovation by R&D firms in Germany. To conclude, apprenticeship systems form a promising vehicle for an effective solution to reinvigorate the much-debated productivity slowing down in modern economies to date.

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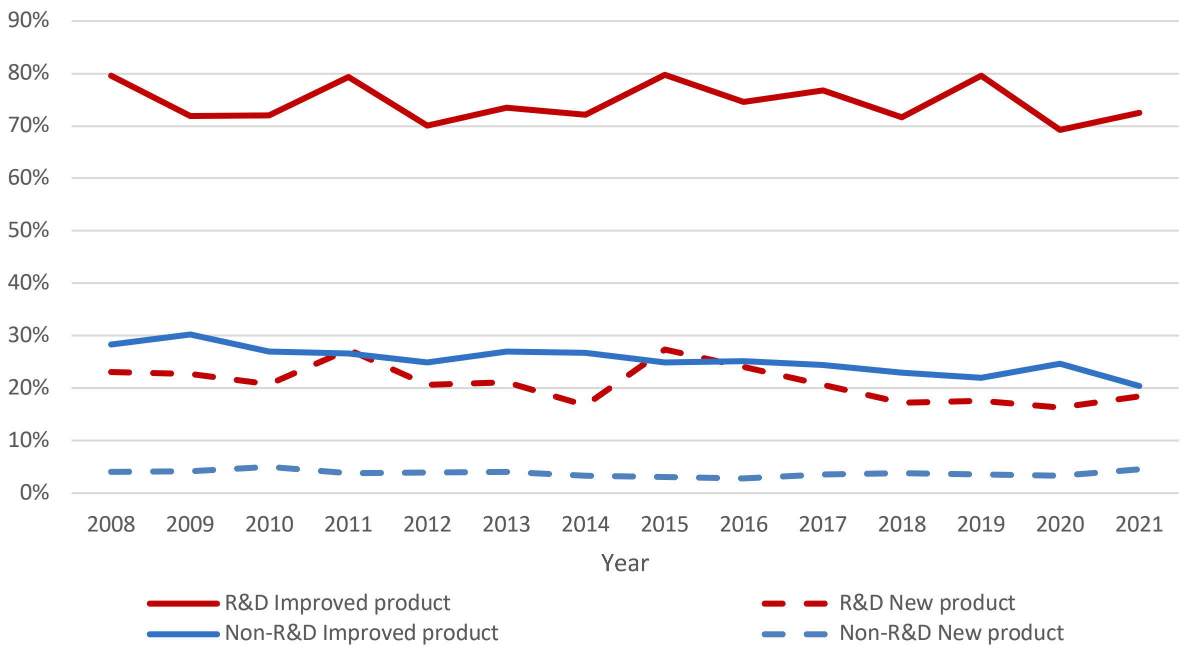
Figure 1A:

The apprenticeship market and the IFO business climate index for Germany

Figure 1B

New and improved products for R&D and non-R&D firms



<u>Figure 2</u>:
The value of the option to train under uncertainty

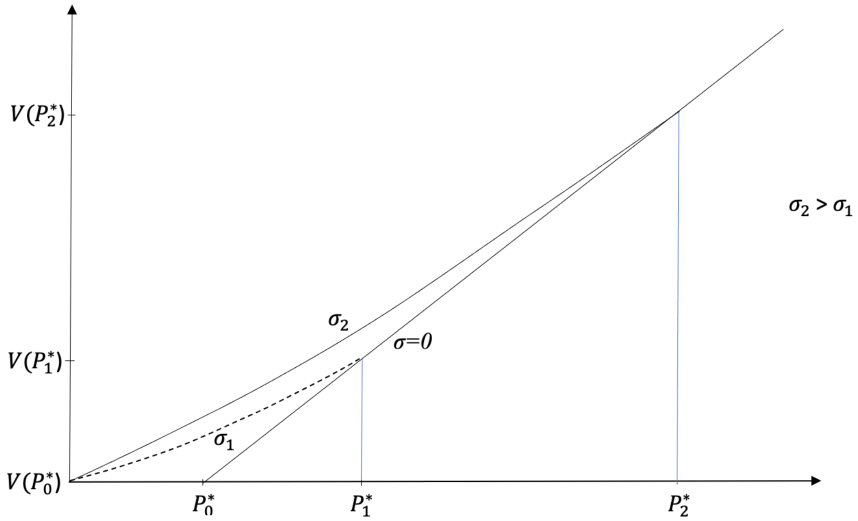
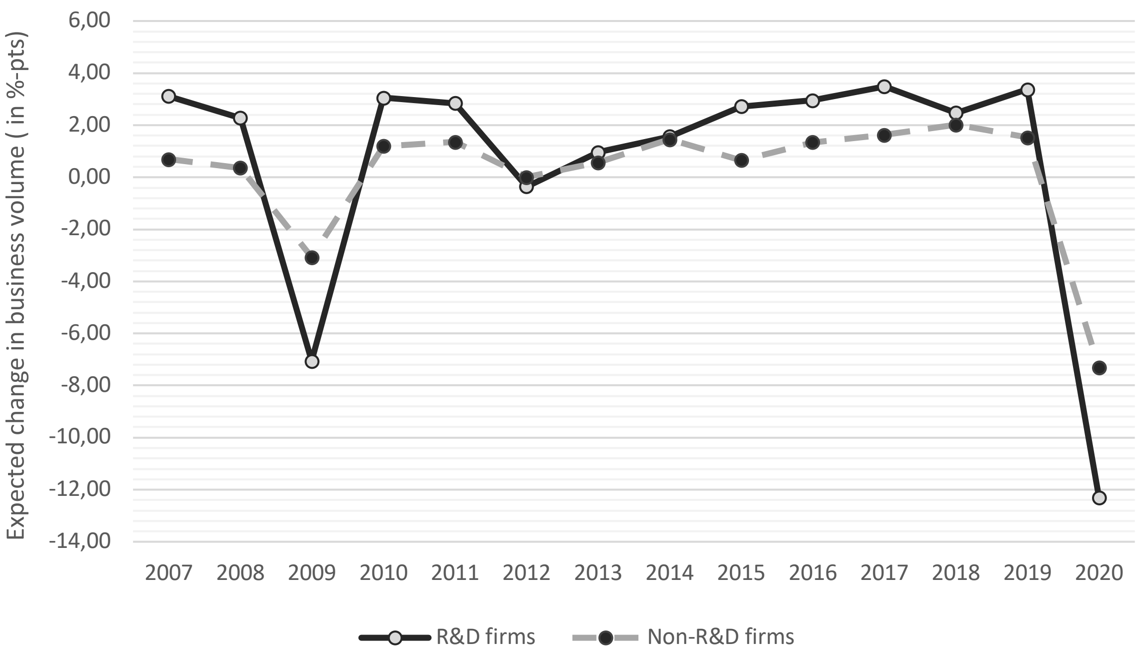
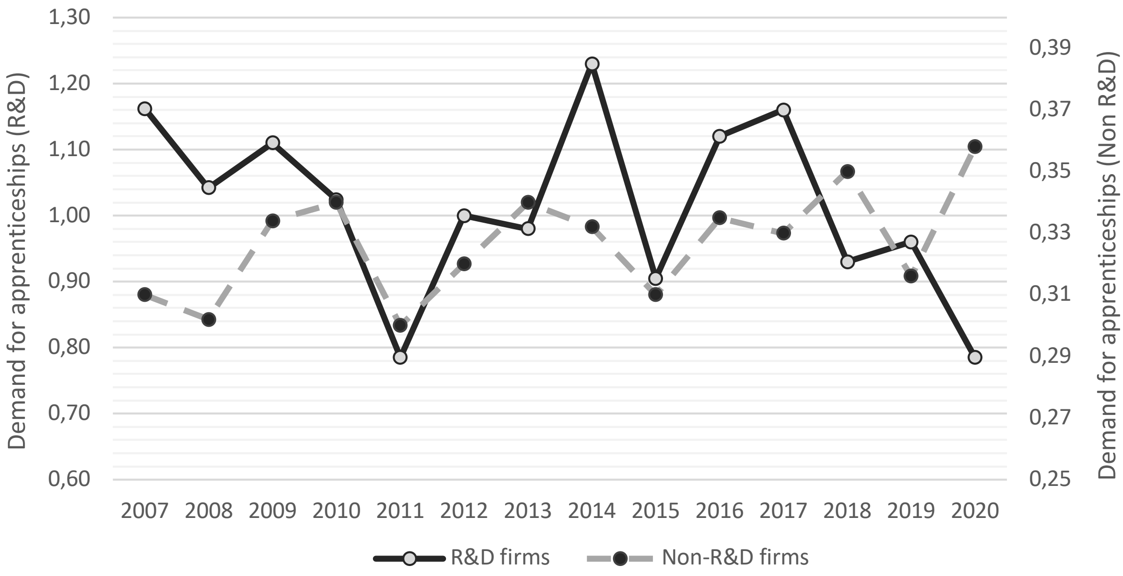


Figure 3:
Business Expectations for R&D and Non-R&D Firms



Notes: Own calculations. Source: IAB-BP 2007-2021.

Figure 4:
Apprenticeship Input Demand for R&D and Non-R&D Firms



Notes: Own calculations. Source: IAB-BP 2007-2021.

Table 1:
Cyclical Fluctuations and the Aggregate Demand for Apprenticeships

	Model (1)	Model (2)	Model (3)	Model (4)
$\Delta \ln v/u_{st,st-1}$	0.137***	0.117***	0.120***	0.108***
	(0.00754)	(0.00720)	(0.00745)	(0.00835)
$\Delta \ln v/u_{st-1,st-2}$	0.0307***	0.0341***	0.0332***	0.0316***
	(0.00527)	(0.00535)	(0.00517)	(0.00561)
$\Delta\, GDP_{t,t-1}$		0.641***		
		(0.0694)		
$\Delta\, GDP_{t-1,t-2}$		0.306***		
		(0.0625)		
$\Delta\, State\ level\ GDP_{st,st-1}$			0.461***	
			(0.0545)	
$\Delta\, State\ level\ GDP_{st-1,st-2}$			0.302***	
			(0.0406)	
$\Delta\, BCI_{t,t-1}$				0.00518***
				(0.000429)
$\Delta\, BCI_{t-1,t-2}$				0.000965***
				(0.000237)
State and occupation trends	Yes	Yes	Yes	Yes
Number of compulsory school graduates	Yes	Yes	Yes	Yes
Observations	5511	5511	5511	5511
R-squared	0.350	0.367	0.365	0.377

Notes: Dependent variable: Δ log demand for apprentices in occupation o, and state s in year t. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. *** Significant at the 1%-level; ** significant at the 5%-level; * significant at the 10%-level. Data sources: Vocational training statistics of the statistical offices of the federal and state governments, ifo Business Climate Index.

Table 2A: Descriptive Statistics of Firm-Level Data

Variable	Mean	SD	Min	Max	N
Full sample					
Apprentice demand (for new training positions)	0.360	1.695	0	766	101,945
Total number of apprentices	0.693	3.911	0	2014	101,945
Skilled worker vacancy share (in %)	3.312	11.77	0	100	101,945
Share of apprentices in relation to all employees	0.033	0.0331	0	1	101,945
Number of employees (total)	18.021	85.657	1	62601	101,945
Number of skilled workers	10.421	52.434	0	42556	101,945
Training firm	0.239		0	1	101,945
R&D firm	0.046		0	1	101,945
Training firm and R&D firm	0.016		0	1	101,945
Works council	0.091		0	1	101,945
Collective bargaining agreement	0.385		0	1	101,945
Benchmark collective bargaining agreement	0.290		0	1	101,945
SMEs (< 250 employees)	0.978		0	1	101,945
Product innovation (completely new product)	0.045		0	1	101,613
Product innovation (improved product)	0.277		0	1	101,602
Panel cases 2007					
Apprentice demand (for new training positions)	0.325	1.835	0	766	58,942
Total number of apprentices	0.664	4.573	0	2014	58,942
Skilled worker vacancy share (in %)	2.021	8.064	0	100	58,942
Share of apprentices in relation to all employees	0.030	0.078	0	1	58,942
Number of employees (total)	17.444	120.872	1	61211	58,942
Number of skilled workers	10.064	72.493	0	42556	58,942
Training firm	0.223		0	1	58,942
R&D firm	0.045		0	1	58,942
Training firm and R&D firm	0.014		0	1	58,942
Works council	0.091		0	1	58,942
Collective bargaining agreement	0.397		0	1	58,942
Benchmark collective bargaining agreement	0.284		0	1	58,942
SMEs (< 250 employees)	0.978		0	1	58,942
Product innovation (completely new product)	0.044		0	1	58,764
Product innovation (improved product)	0.280		0	1	58,752
Panel cases 2012					
Apprentice demand (for new training positions)	0.357	2.0667	0	766	50,644
Total number of apprentices	0.658	4.604	0	2014	50,644
Skilled worker vacancy share (in %)	3.904	11.77	0	100	50,644
Share of apprentices in relation to all employees	0.279	0.0711	0	1	50,644
Number of employees (total)	17.731	108.394	1	62601	50,644
Number of skilled workers	10.331	69.336	0	42556	50,644
Training firm	0.211		0	1	50,644
R&D firm	0.044		0	1	50,644
Training firm and R&D firm	0.014		0	1	50,644
Works council	0.084		0	1	50,644
Collective bargaining agreement	0.295		0	1	50,644
Benchmark collective bargaining agreement	0.281		0	1	50,644
SMEs (< 250 employees)	0.978		0	1	50,644
Product innovation (completely new product)	0.039		0	1	50,511
Product innovation (improved product)	0.263		0	1	50,502

Notes: Own calculations, using survey weights. Standard deviations in parentheses. Source: IAB-BP 2007-2021.

Table 2B: Descriptive Statistics of Firm-Level Data

Year	Pr(Product innovation) in R&D firms		# apprenticeships in R&D firms	N
	New product	Improved product		
2007	0.212	0.837	6.786 (16.042)	836
2008	0.228	0.768	7.214 (16.465)	611
2009	0.251	0.802	6.866 (19.264)	743
2010	0.288	0.854	6.773 (15.092)	541
2011	0.123	0.667	6.343 (14.827)	657
2012	0.138	0.683	6.122 (17.193)	515
2013	0.151	0.757	6.288 (15.900)	705
2014	0.241	0.792	8.294 (29.104)	515
2015	0.188	0.751	6.871 (23.312)	656
2016	0.127	0.752	7.168 (23.007)	488
2017	0.137	0.771	7.147 (27.360)	565
2018	0.161	0.863	7.067 (14.163)	377
2019	0.209	0.789	7.884 (15.528)	394
2020	0.311	0.776	5.778 (11.654)	240

Notes: Own calculations, using survey weights. Standard deviations in parentheses.
Source: IAB-BP 2007-2021.

Table 3A:
Input Demand of Apprentices of R&D and non-R&D Firms

(Is possible)

Demand	All firms	Panel cases 2007	Panel cases 2012
R&D firm	0.079**	0.0717	0.0967*
	(0.037)	(0.0541)	(0.0502)
# Obs.	44387	22583	26251

Notes: Poisson lagged dependent variables regressions. Control variables: log skilled workers, works council, collective bargaining agreement and year dummy variables. Standard errors in parentheses. *** Significant at the 1%-level; ** significant at the 5%-level; * significant at the 10%-level. Source: IAB-BP 2007-2021.

Table 3B:
Input Demand of Apprentices Conditional on Being a Training Firm

(Currently training)

Demand	All firms	Panel cases 2007	Panel cases 2012
R&D firm	0.0610	0.0520	0.0829
	(0.0376)	(0.0554)	(0.0507)
# Obs.	27137	13502	15343

Notes: Poisson lagged dependent variables regressions. Control variables: log skilled workers, works council, collective bargaining agreement and year dummy variables. Standard errors in parentheses. *** Significant at the 1%-level; ** significant at the 5%-level; * significant at the 10%-level. Source: IAB-BP 2007-2021.

Table 4:
Business Cycle Effects on Firms' Apprentices Input Demand

Demand	All firms	R&D	Non-R&D
Full sample			
Vacancy share	0.0139***	0.0181***	0.0095***
	(0.0020)	(0.0047)	(0.0022)
Observations	45299	6365	38934
Panel cases 2007-2017			
Vacancy share	0.0110***	0.0161***	0.0034***
	(0.0037)	(0.0056)	(0.0040)
# Obs.	24981	3434	21547
Panel cases 2012-2021			
Vacancy share	0.0154***	0.0161***	0.0133***
	(0.0025)	(0.0056)	(0.002)
# Obs.	24267	3268	20999

Notes: Poisson lagged dependent variables regressions. Control variables: log skilled workers, works council, collective bargaining agreement and year dummy variables. Standard errors in parentheses. *** Significant at the 1%-level; ** significant at the 5%-level; * significant at the 10%-level. Source: IAB-BP 2007-2021

Table 5:
Product Innovation and Apprentices in R&D and non-R&D Firms

	R&D firms				Non-R&D firms			
	New product		Improved Product		New product		Improved Product	
	RE	FE	RE	FE	RE	FE	RE	FE
log apprentices	0.013**	-0.021	0.039***	0.029**	0.012***	-0.002	0.053***	0.006
	(0.006)	(0.017)	(0.006)	(0.013)	(0.002)	(0.004)	(0.004)	(0.007)
Observations	5449	5449	5449	5449	25178	25178	25178	25178
R-squared	0.01	0.01	0.03	0.02	0.001	0.001	0.034	0.01

Notes: Linear probability panel random effects (RE) and fixed effects (FE) regression model with binary indicators for *Product Innovation* (New product, improved product) as dependent variables. Control variables: Year dummies. Robust standard errors in parentheses. *** Significant at the 1%-level; ** significant at the 5%-level; * significant at the 10%-level. Source: IAB-BP 2007-2021.