How AI-Driven Automation Prospects Shape Firms' Training Decisions

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Abstract

This paper investigates how anticipated AI-driven automation affects firms' apprenticeship training decisions through theoretical modeling and empirical analysis conducting a vignette experiment among recruiters in more than 2800 firms in Switzerland. We find that firms significantly reduce apprenticeship positions when automation is expected to affect a larger share of tasks and occur sooner, with a 10 percentage point increase in automated tasks leading to a 1.51 percentage point reduction in apprenticeships. The impact varies by occupation type, with routine-intensive and AI-exposed occupations showing stronger responses. Firm size and sector also influence automation responses, with large firms demonstrating stronger responses to both automation share and timing and specific sectors showing heightened sensitivity to automation timing. Our research contributes to the literature on firm-based training, task-biased technological change, and generative AI's labor market impacts by revealing how automation expectations reshape firms' human capital investment strategies, potentially affecting career prospects for young labor market entrants.

1 Introduction

The launch of ChatGPT in November 2022 marked a milestone in artificial intelligence (AI), demonstrating generative AI's ability to perform previously human-exclusive tasks. While earlier AI technologies were already transforming production processes and labor demand (Acemoglu et al., 2022; Acemoglu and Restrepo, 2019), generative AI has intensified job displacement concerns, with initial evidence showing negative employment effects on exposed workers (Demirci et al., 2025; Hui et al., 2023). Unlike previous automation technologies that primarily affected low and medium-skilled workers, generative AI excels at cognitively demanding tasks like writing, designing, and programming, which typically require advanced formal education or extensive professional training (Eloundou et al., 2023). The threat of unprecedented automation of high-skilled tasks raises critical questions about firms' future training provision, which shapes both the development of the active workforce (e.g., Konings and Vanormelingen 2015; Merriam and Baumgartner 2020) and the entry of future workers into the labor market in the form of apprenticeships (Wolter and Ryan, 2011).

This paper examines how anticipated automation affects firms' apprenticeship training decisions, both through theoretical modeling and empirical analysis. Conducting a vignette experiment using hypothetical automation scenarios with recruiters from more than 2800 firms in Switzerland, we analyze how both the timeline and intensity of expected task automation influence firms' apprenticeship offerings. Based on a three-period model of apprenticeship training, we hypothesize that firms reduce apprenticeship positions more strongly when automation is expected sooner and affects a larger share of tasks. We also analyze heterogeneous effects, with our model hypothesizing stronger reductions in apprenticeships for occupations involving primarily cognitive and routine tasks and higher exposure to AI, and how responses differ by firm size and industry.

Our results show that firms significantly adjust their apprenticeship offerings in response to expected automation shocks. A 10 percentage point increase in the share of tasks automated on average leads to a 1.51 percentage point reduction in apprenticeship positions, while each additional year until automation reduces the cutback by 0.52 percentage points. The impact of automation varies substantially by occupation type. Routine-intensive occupations and those already exposed to AI demonstrate stronger responses, with higher shares of automated tasks leading to larger reductions in apprenticeship positions. Furthermore, firm characteristics strongly influence automation responses: Large firms demonstrate stronger responses to both automation share and timing, and a sectoral analysis reveals that Construction and Professional, Scientific and Technical Services show significantly stronger responses to automation timing. Interestingly, while the main effect of automation share is strong, its interaction with sector dummies is not significant, suggesting that the impact of automation intensity is relatively uniform across sectors.

The paper contributes to three main strands of literature. First, it extends research on firm-based training by providing a theoretical framework that explicitly models how automation affects training decisions through both production and investment motives, focusing specifically on apprenticeship provision rather than continuing training. Second, it contributes to the literature on routine-biased technological change by demonstrating that the routine nature of tasks is a key determinant of how automation affects training decisions, with routine-intensive occupations facing larger reductions in apprenticeship positions. Third, it adds to emerging research on generative AI's labor market impacts by showing how firms can be expected to adjust their human capital investment strategies in anticipation of further automation, revealing that these technologies reshape firms' training decisions and potentially affect career prospects for young labor market entrants.

The rest of the paper is organized as follows. Section 2 discusses the relevant literature, Section 3 portrays the Swiss apprenticeship market and Section 4 presents our theoretical model. In the empirical part of the paper, Section 5 documents our estimation strategy and Section 6 discusses the results of our experiment. Section 7 concludes.

2 Literature

Digital Technology and labor demand

Over recent decades, advances in digital technology have substantially transformed labor markets in developed economies. The impact of this transformation has evolved: whereas twentieth-century innovations increased demand for skilled labor (Katz and Murphy, 1992), more recent automation technologies increasingly substitute for rather medium-skilled human labor in routine tasks (Autor et al., 2003; Goos et al., 2014). Even more recently, the emergence of generative AI represents a new frontier in automation, enabling the substitution of tasks previously restricted to high-skilled workers, with early evidence indicating negative labor market effects among exposed workers (Demirci et al., 2025; Hui et al., 2023). This latest wave has not only intensified workers' concerns about their occupations' vulnerability to automation (Cattaneo et al., 2024) but is also already shifting the career choices of labor market entrants (Goller et al., 2023).

Determinants of firm training

The factors driving firms' decision to train workers, and apprentices particularly, are manifold. Expected productivity gains drive firms' general training decisions (Colombo and Stanca, 2008), whereas apprenticeship provision specifically depends on apprentices' relative productivity and wages compared to skilled workers (Muehlemann and Wolter, 2014): Firms' incentives to train are stronger where apprentices' productivity is high relative to both their own wages and skilled workers' productivity, and where apprentices' wages are low compared to skilled workers' wages. While a high density of competing firms in the regional labor market decreases the incidence of firm-sponsored training (e.g., Brunello and Gambarotto 2007; Harhoff and Kane 1997), the effects of product market competition are ambiguous (Muehlemann and Wolter, 2014), with empirical evidence pointing to a positive effect of deregulation on training incidence (Bassanini and Brunello, 2011).

Determinants of apprenticeship provision

Research has identified two distinct motivations for firms to offer apprenticeship training: production and investment motives (Wolter and Ryan, 2011). Under the production motive, firms view apprentices primarily as substitutes for other labor inputs in current production processes, despite their initially lower productivity (Lindley, 1975). While some upfront training is necessary, firms following this motive hire apprentices based on expected net benefits from their productive work relative to their wages during their apprenticeships. In contrast, the investment motive, grounded in human capital theory (Becker, 1964), conceptualizes apprentices as future skilled workers (Stevens, 1994). Accordingly, firms accept net training costs during the time of the apprenticeships in exchange for future benefits after apprenticeships are completed, particularly in the form of secured access to skilled labor. Several labor market imperfections allow firms to recover these investments by being able to keep fully trained apprentices in their outfit: information asymmetries (Acemoglu and Pischke, 1999), worker mobility costs (Beckmann, 2002), and institutional rigidities from trade unions and work councils (Dustmann and Schönberg, 2009; Kriechel et al., 2014). Empirical evidence from cost-benefit analyses suggests that while investment motives predominantly drive German firms' demand for apprentices, significantly influenced by labor market regulations (Muehlemann et al., 2010), the majority of Swiss training firms achieve direct net benefits from apprenticeships (Muehlemann and Wolter, 2014).

Digital technology and firm training

Emerging literature examines how recent advances in digital technology affect firm-based training, with mixed findings. Heß et al. (2023) find that workers exposed to automation participate less in training, primarily because firms reduce their training support. While Brunello et al. (2023) find that advanced digital technologies reduce firm-sponsored training suggesting that the use of such technologies and employee training are substitutes, Gathmann et al. (2024) show that German firms investing in digital technologies during the pandemic reported increased training needs and provided more training to their workforce. Concerning apprenticeships, Muehlemann (2024) shows that pre-generative AI adoption in firms increases the number of apprenticeship contracts, particularly in SMEs. While these findings from the pre-generative AI era are important, it remains unclear how firms will adjust their training provision in response to automation prospects, particularly now that generative AI threatens to automate tasks previously performed exclusively by skilled workers.

3 Apprenticeship Training in Switzerland: Economic Motivations and Digital Technology Impact

After compulsory school, approximately 70% of young people in Switzerland start an apprenticeship and choose among about 200 different occupations to train in for the next three or four years. During this time, they spend 1-2 days a week in vocational school and the remaining weekdays in their training company, where they acquire general, but more importantly occupation-specific skills and earn a small wage. While for young labor market entrants the decision to do an apprenticeship is driven by the perspective of a relatively secure labor market integration after finishing it, the reasons for companies to train apprentices are mainly twofold. Apprentices can be viewed both as cheap substitutes for unskilled labor and investments in future skilled workers: While many firms accept net investments into apprenticeships in order to train and secure their future skilled workforce, a majority of training companies in Switzerland even achieve direct net benefits from training apprentices, that is, they are able to recoup their investments by the end of the training period (Muehlemann and Wolter, 2014). Beyond these strictly economic factors, heads of training firms report their personal preferences and values to play an important role in their decision to train apprentices, at least in small firms (Baumeler and Lamamra, 2024).

Table 1: Determinants of apprentice share of firm workforce

	(1)	(2)	(3)
Number of employees (FTEs)	-0.000**		0.001**
	(0.000)		(0.001)
Sales (CHF)	-0.000		-0.000*
	(0.000)		(0.000)
Product innovations in current year		-0.677**	-0.693**
		(0.270)	(0.277)
ICT specialists in firm		-0.446*	-0.449
		(0.267)	(0.280)
Use of AI		-0.853**	-0.848**
		(0.411)	(0.424)
Constant	5.859***	5.400***	5.427***
	(0.053)	(0.179)	(0.183)
Observations	22,556	3,194	2,988

Note: The table presents regression results examining how firms' apprenticeship intensity–measured as the percentage of apprentices among total employees—-correlates with various firm characteristics derived from the Swiss Innovation and Digitalization Survey 2021.

How does the firms' decision to train or not to train apprenticeships relate to their use of digital technology? The Swiss Innovation and Digitalization Survey (SIDS) biennially surveys the degree of digitalization in a representative sample of Swiss firms, also offering additional information on the surveyed firms, such as the education of their workers, number of sales—and the share of apprentices in their workforce. Regression results in Table 1 show that this share seemingly decreases with the total number of employees. Including several indicators for digital technology use into the regression, this relationship turns positive and reveals negative relationships with these indicators: Firms that introduced product innovations in the given year have a 0.70 ppt. or 13% lower share of apprentices in the firm than those without product innovations. Similarly, their share is 0.85 ppt. or 16% lower for firms that use AI compared to those that did not. While negative, the coefficient on ICT specialist employment—–commonly used to measure firms' technological intensity (Calvino et al., 2018)—does not reach statistical significance. All in all, these descriptive findings suggest a negative relationship between firms' use of digital technologies and the share of apprentices in their workforce.

4 Three-Period Apprenticeship Model with Automation, Occupational Exposure, and Firm Characteristics

The following model formalizes how automation affects firms' decisions to provide apprenticeship training. We develop a three-period framework that incorporates the investment motive for training, while accounting for the share of automated trained workers' tasks, duration until automation, occupational exposure to automation, and firm-specific characteristics. The model allows us to derive testable predictions about how automation affects training incentives across different types of firms and occupations. For firms following the production motive, we provide the corresponding analysis in Appendix A. Notably, our theoretical model predicts that the directional effects of automation share, timing, occupational exposure, and firm characteristics should be consistent regardless of whether firms follow production or investment motives, though the magnitude of these effects may differ.

4.1 Model Structure

We model a firm's decision to provide apprenticeship training as an investment problem based on the net present value (NPV) of expected benefits and costs over three periods. This approach follows the human capital investment framework established in the literature

(Becker, 1964; Stevens, 1994).

The firm's NPV is given by:

$$NPV = B_1 + \delta B_2 + \delta^2 B_3 - C \tag{1}$$

Period 1 represents the initial apprenticeship phase before any automation occurs:

$$B_1 = \alpha_1 q_t - w_a \tag{2}$$

where α_1 represents the apprentice's relative productivity compared to a trained worker (with $0 < \alpha_1 < 1$), q_t is the output of a trained worker, and w_a is the apprentice wage. The difference between the apprentice's productive contribution and their wage determines the first-period benefit.

Period 2 introduces the automation shock with variable timing:

$$B_2 = \lambda(\alpha_2 q_t - w_a) + (1-\lambda)[\alpha_2(1 - \varepsilon x \cdot \phi(s,g))q_t - w_a] \tag{3}$$

$$B_2 = \alpha_2 q_t[\lambda + (1-\lambda)(1 - \varepsilon x \cdot \phi(s,g))] - w_a \tag{4}$$

where α_2 is the improved apprentice productivity in period 2 (with $\alpha_1 < \alpha_2 < 1$), λ represents the share of period 2 before automation occurs, ε is the occupational exposure to automation, x is the share of tasks that can be automated, and $\phi(s,g)$ captures how firm size s and sector g modify the automation effect. The parameter λ allows us to model the timing of automation within the apprenticeship period.

Period 3 represents the post-apprenticeship phase when the worker is fully trained:

$$B_3 = (1-\mu)[(1 - \varepsilon x \cdot \phi(s,g))q_t - w_t] \tag{5}$$

where μ is the probability that the trained worker leaves the firm, and w_t is the trained worker wage. The term $(1 - \varepsilon x \cdot \phi(s,g))q_t$ captures how automation reduces the productivity of trained workers by eliminating a portion of their tasks.

Combining the three periods, the complete net present value of apprenticeship training is:

$$\begin{aligned} NPV = (\alpha_1 q_t - w_a) + \delta[\alpha_2 q_t(\lambda + (1-\lambda)(1 - \varepsilon x \cdot \phi(s,g))) - w_a] + \\ \delta^2(1-\mu)[(1 - \varepsilon x \cdot \phi(s,g))q_t - w_t] - C \end{aligned} \tag{6}$$

This equation captures the full investment calculation that firms face. The first term represents the net benefit from the apprentice's work in period 1. The second term, discounted by factor δ, represents the period 2 benefit, which is affected by automation according to the share of automated tasks (x) and its timing (λ), as well as occupation (ε) and firm characteristics $\phi(s,g)$. The third term, discounted by δ^2, captures the expected future return from retaining the trained worker, accounting for both the probability of retention $(1-\mu)$ and the automation-adjusted output. Finally, C represents the fixed training costs incurred by the firm. This formulation allows us to analyze how automation affects both the production value of apprentices during training and their future value as skilled workers.

4.2 Training Viability Condition

The firm will provide apprenticeship training only when the expected benefits exceed the costs:

$$\begin{aligned} (\alpha_1 q_t - w_a) + \delta[\alpha_2 q_t(\lambda + (1-\lambda)(1 - \varepsilon x \cdot \phi(s,g))) - w_a] + \\ \delta^2(1-\mu)[(1 - \varepsilon x \cdot \phi(s,g))q_t - w_t] > C \end{aligned} \tag{7}$$

This inequality establishes a critical threshold for training provision. The left side captures all benefits: the apprentice's productive contribution in periods 1 and 2 (adjusted for automation effects), plus the expected returns from employing the fully trained worker in period 3. For training to be viable, these cumulative benefits must exceed the fixed training costs C. This condition allows us to identify how automation parameters (x, λ, and ε) shift the training threshold. As automation increases, the benefits from both apprentice productivity during training and post-training employment diminish, potentially pushing some firms below the viability threshold and causing them to cease offering apprenticeships.

4.3 Comparative Statics

Our model provides testable predictions about how automation affects training incentives:

Effect of automation share (x) on training:

$$\frac{\partial NPV}{\partial x} = -\delta\alpha_2 q_t(1-\lambda)\varepsilon\phi(s,g) - \delta^2(1-\mu)q_t\varepsilon\phi(s,g) < 0 \tag{8}$$

This derivative indicates that increasing the share of automated tasks reduces training incentives through two channels: by diminishing apprentice productivity in period 2 and by reducing the value of trained workers in period 3. The negative effect is stronger for occupations with higher exposure (ε) and in firms where the automation impact factor $\phi(s,g)$ is larger.

Effect of automation timing (λ) on training:

$$\frac{\partial NPV}{\partial \lambda} = \delta\alpha_2 q_t \varepsilon x \cdot \phi(s,g) > 0 \tag{9}$$

Later automation timing (higher λ) increases training incentives by preserving apprentice productivity for a longer portion of period 2. This positive effect is proportional to the automation exposure (ε) and share of tasks automated (x), suggesting that timing becomes more critical as automation intensity increases.

Second-order effect of automation share (x) and exposure (ε):

$$\frac{\partial^2 NPV}{\partial x \partial \varepsilon} = -\delta \alpha_2 q_t (1-\lambda)\phi(s,g) - \delta^2 \phi(s,g) q_t (1-\mu) < 0 \tag{10}$$

This cross-derivative shows that the negative effect of automation is amplified in occupations with higher exposure. Empirically, we would expect to observe larger reductions in apprenticeship provision for highly exposed occupations as automation increases.

Second-order effect of automation timing (λ) and exposure (ε):

$$\frac{\partial^2 NPV}{\partial \lambda \partial \varepsilon} = \delta \alpha_2 q_t x \cdot \phi(s,g) > 0 \tag{11}$$

This positive cross-derivative indicates that later automation timing is particularly beneficial for occupations with high exposure to automation. In empirical settings, we would expect the timing of automation adoption to have stronger effects on training decisions for highly exposed occupations.

5 Estimation Strategy

Our theoretical model predicts that automation reduces firms' incentives to provide apprenticeship training by lowering the NPV of such investments. This reduction in training incentives should manifest empirically as a decrease in apprenticeship provision. Specifically, we expect that firms faced with a higher share of automated tasks (higher x) and earlier automation (lower λ) will reduce their apprenticeship offerings more substantially, with these effects moderated by occupational exposure (ε) and firm characteristics (ϕ).

To empirically investigate firms' training decisions in response to different automation scenarios, we conducted a vignette experiment among recruiters in 2840 firms in Switzerland that provide apprenticeships. More specifically, our experiment was incorporated into the so-called *Nahtstellenbarometer*, a bi-annual survey among a representative sample of firms conducted on behalf of the Swiss State Secretariat for Education, Research and Innovation. The survey containing our experiment was conducted in April 2024 and realized a response rate of 63%. In our vignette experiment, we present firms with three randomly selected hypothetical scenarios in which they receive the result of a hypothetical internal analysis about future task automation. Each scenario specifies that in λ years (2, 4, or 6), x% (20, 40, or 60) of tasks in their trained occupation will be automated due to advances in AI and robots. We then ask how this would affect their decision about the number of apprentices they will start training in the upcoming training year.

To test our model's predictions, we estimate the following equation relating automation to the reduction in apprentices trained:

$$\begin{aligned} r_{fi} = \beta_0 + \beta_1 \lambda_i + \beta_2 x_i + \beta_3(\lambda_i \times \varepsilon_j) + \beta_4(x_i \times \varepsilon_j) + \\ \beta_5(\lambda_i \times \phi(s,g)) + \beta_6(x_i \times \phi(s,g)) + \sigma_f + u_{fi} \end{aligned} \tag{12}$$

Where r_{fi} represents the reduction in apprentices reported by firm f in scenario i. The variables λ_i and x_i capture the automation timing and share that characterize scenario i. The occupational exposure ε_j refers to the exposure of occupation j to automation, while $\phi(s,g)$ represents the firm-specific automation modification factor based on size s and sector g. Based on our theoretical model, we expect $\beta_2 > 0$ (higher automation share increases apprenticeship reduction) and $\beta_1 < 0$ (later automation timing decreases apprenticeship reduction). The interaction coefficients β_4 and β_3 test our predictions regarding occupational exposure: $\beta_4 > 0$ would confirm that automation's negative effect is amplified in highly exposed occupations, while $\beta_3 < 0$ would indicate that later automation timing is particularly beneficial for highly exposed occupations. Similarly, β_5 and β_6 capture how firm characteristics modify these relationships. Firm fixed effects σ_f control for unobserved firm-specific factors that might affect training decisions.

To examine how occupational exposure influences firms' apprenticeship training decisions under different automation scenarios, we employ multiple exposure measures. First, drawing on research on task-biased technological change (e.g., Acemoglu and Autor, 2011), we classify training occupations as either routine or non-routine and as either manual or cognitive, using task measures from Mihaylov and Tijdens (2019) and the classification framework proposed by Gschwendt (2022).[1] Second, we match AI exposure measures developed by Felten et al. (2021) to training occupations to assess how exposure to AI technologies affects firms' training decisions.[2]

6 Results

6.1 Occupational Exposure

Table 2 presents compelling evidence that both automation intensity and timing significantly affect firms' apprenticeship decisions, with important variations across occupational characteristics. The baseline results in column 1 show that a 10 percentage point increase in the share of tasks automated leads to a 1.51 percentage point reduction in apprenticeship positions on average. Similarly, each additional year until automation implementation reduces the cutback by 0.52 percentage points on average. Both effects are highly significant at the 1% level, indicating that firms strongly adjust their training decisions based on both the intensity and timing of automation threats.

When examining occupational exposure to automation, routine-intensive occupations

[1] To match these measures provided for ISCO-08 occupations to Swiss apprenticeships, we leverage the Swiss Standard Classification of Occupations CH-ISCO-19.

[2] To assign these AI exposure measures provided only for O*NET-SOC occupations to 4-digit ISCO-08 occupations we use the crosswalk provided by Hardy et al. (2018).

Table 2: Tasks

	(1)	(2)	(3)	(4)	(5)
% of tasks automated * 10	1.506***	1.230***	1.610***	1.580***	1.222***
	(0.130)	(0.149)	(0.187)	(0.146)	(0.219)
Time to automation	-0.521***	-0.394***	-0.583***	-0.607***	-0.379*
	(0.122)	(0.140)	(0.177)	(0.135)	(0.214)
Routine tasks * % of tasks automated * 10		0.915***			0.806*
		(0.319)			(0.414)
Routine tasks * Time to automation		-0.513*			-0.183
		(0.297)			(0.403)
Manual tasks * % of tasks automated * 10			-0.253		0.164
			(0.268)		(0.378)
Manual tasks * Time to automation			0.089		-0.465
			(0.249)		(0.344)
Exposure to AI * % of tasks automated * 10				0.327**	0.122
				(0.160)	(0.275)
Exposure to AI * Time to automation				-0.251*	-0.371
				(0.145)	(0.254)
Firm FE	✓	✓	✓	✓	✓
R-squared	0.863	0.862	0.861	0.861	0.862
N	8531	8066	8066	8066	8066
Mean of Dep. Var.	11.927	11.709	11.709	11.709	11.709

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: The dependent variable is the reduction of apprenticeship positions offered. Standard errors are clustered on the firm level. Differences in N stem from the unavailability of task and AI exposure measures for some occupations.

demonstrate particularly strong sensitivity to automation. Column 2 shows that these occupations face an additional 0.92 percentage point reduction in apprenticeships per 10 percentage point increase in automated tasks (significant at 1%). This aligns with empirical findings on the impact of earlier automation technologies on routine work, making firms faced with increasing automation more hesitant to invest in training for these occupations. The interaction between routine tasks and automation timing is also significant at the 10% level, suggesting that later automation does provide some relief for routine-intensive occupations. Notably, while the main coefficients for both timing and intensity of automation do decrease in values, they remain significant and economically relevant. Interestingly, manual task intensity does not significantly moderate the effects of automation share or timing, as column 3 shows. This suggests that, in contrast to earlier waves of automation, the physical nature of tasks does not determine how firms respond to upcoming automation shocks in their training decisions.

Column 4 reveals that occupations exposed to AI show higher sensitivity to automation shocks, with an additional 0.33 percentage point reduction in apprenticeships offered per 10 percentage point increase in automated tasks. Similarly, these occupations also respond more strongly to timing, with each additional year until automation reducing the cutback by an extra 0.25 percentage points. This pattern suggests that firms consider automation scenarios more credible for occupations that are more likely to be affected by AI technologies based on the study by Felten et al. (2021).

The comprehensive model in column 5 confirms the robustness of the routine task effect, which remains significant even when controlling for other occupational characteristics. However, the manual and AI exposure interactions lose significance in this full model, suggesting some overlap between task intensity and AI exposure measures. The correlations between the routine dummy and AI exposure (0.6701) and between the manual dummy and AI exposure (-0.7172) are indeed substantial, indicating strong relationships between these occupational characteristics.

6.2 Firm Characteristics

Table 3 reveals substantial heterogeneity in how firms of different sizes and sectors respond to automation threats. Firm size emerges as a critical factor moderating automation responses. Column 2 shows that while small firms (<10 employees) don't differ significantly from medium-sized firms, large firms (>99 employees) demonstrate substantially stronger responses to both automation share and timing. Large firms reduce apprenticeships by an additional 1.03 percentage points per 10 percentage point increase in automated tasks compared to medium-sized firms. They also show heightened sensitivity to timing, with each additional year until automation reducing the cutback by an extra 0.75 percentage points. This suggests that larger firms may be more responsive to technological changes due to more formalized training and, thus, more flexible schemes.

Sectoral analysis in column 3 also reveals interesting patterns. While most sectors don't show significantly different responses to automation share, Construction shows a marginally significantly lower sensitivity with 0.79 percentage points less reduction per 10 percentage point increase in automated tasks. Regarding timing effects, Professional, Scientific and Technical services show significantly stronger responses, with each additional year until automation reducing the cutback by an extra 0.73 percentage points. This suggests that knowledge-intensive sectors may be particularly sensitive to the timing of automation.

The comprehensive model in column 4 largely confirms these findings. The large firm effects remain significant for both automation share and timing. The sectoral timing effect for Professional services remains marginally significant, while the Construction effect on automation share becomes non-significant. Overall, these results indicate that firm size is a more consistent predictor of automation response than sector, with large firms showing particularly strong adjustments to both automation intensity and timing. This aligns with the theoretical model's prediction that firm characteristics significantly moderate how automation affects training incentives.

7 Conclusions

Our study examines how the expectations of automation shocks affect firms' apprenticeship training decisions through both theoretical modeling and empirical analysis. The findings reveal important insights into the mechanisms through which automation impacts training incentives and how these effects vary across occupations and firm characteristics.

Our theoretical model predicts that automation reduces firms' incentives to provide apprenticeship training by lowering the net present value of such investments through two

Table 3: Firm Characteristics

	(1)	(2)	(3)	(4)
% of tasks automated * 10	1.506***	1.377***	1.768***	1.581***
	(0.130)	(0.215)	(0.267)	(0.324)
Time to automation	-0.521***	-0.165	-0.322	0.068
	(0.122)	(0.193)	(0.231)	(0.279)
<10 employees * % of tasks automated * 10		-0.116		-0.109
		(0.285)		(0.288)
<10 employees * Time to automation		-0.396		-0.372
		(0.263)		(0.265)
>99 employees * % of tasks automated * 10		1.027***		0.943**
		(0.384)		(0.401)
>99 employees * Time to automation		-0.747**		-0.845**
		(0.351)		(0.360)
Manufacturing * % of tasks automated * 10			0.329	0.292
			(0.467)	(0.462)
Manufacturing * Time to automation			-0.308	-0.276
			(0.456)	(0.454)
Construction * % of tasks automated * 10			-0.787*	-0.599
			(0.450)	(0.457)
Construction * Time to automation			-0.382	-0.507
			(0.391)	(0.393)
Trade & Repair * % of tasks automated * 10			-0.512	-0.341
			(0.411)	(0.417)
Trade & Repair * Time to automation			-0.204	-0.271
			(0.397)	(0.401)
Professional, Scientific & Technical * % of tasks automated * 10			-0.329	-0.162
			(0.437)	(0.445)
Professional, Scientific & Technical * Time to automation			-0.730*	-0.796*
			(0.428)	(0.432)
Health and Social Work * % of tasks automated * 10			-0.429	-0.441
			(0.380)	(0.381)
Health and Social Work * Time to automation			0.062	0.099
			(0.331)	(0.332)
Firm FE	✓	✓	✓	✓
R-squared	0.863	0.864	0.864	0.864
N	8531	8531	8531	8531
Mean of Dep. Var.	11.927	11.927	11.927	11.927

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is the reduction of apprenticeship positions offered. Standard errors are clustered on the firm level. Results show differences to a medium-sized firm (10 – 99 employees) in none of the listed major sectors.

channels: diminishing apprentice productivity during training and reducing the future value of trained workers. The model predicts these negative effects are moderated by the timing and intensity of automation (λ and x) and firm characteristics, and are stronger for occupations with higher exposure to automation (ε).

Our empirical findings strongly support these theoretical predictions. Firms significantly adjust their apprenticeship offerings in response to automation threats, with a 10 percentage point increase in the share of tasks automated leading to a 1.51 percentage point reduction in apprenticeship positions, while each additional year until automation reduces the cutback by 0.52 percentage points. The empirical analysis confirms the predicted heterogeneous effects, with routine-intensive occupations and those particularly exposed to AI demonstrating stronger negative responses to automation, and large firms showing substantially stronger responses to both automation share and timing compared to medium-sized firms. Interestingly, while we find some sectoral heterogeneity regarding the response to automation timing, the impact of automation intensity is relatively uniform across sectors.

Our findings contribute to several strands of literature. First, we extend the literature on firm-based training by providing a theoretical framework that explicitly models how automation affects training decisions through both production and investment motives. While previous research has examined how digital technologies affect continuing training (Heß et al., 2023; Brunello et al., 2023), our study is the first to systematically analyze how anticipated automation affects apprenticeship provision specifically. Second, we contribute to the literature on routine-biased technological change by showing that the routine nature of tasks is a key determinant of how automation affects training decisions aligning with and extending previous work on how automation affects labor demand across different task types (Autor et al., 2003; Goos et al., 2014). Moreover, our findings might indicate a continuation of ”de-routinization” trends in the Swiss labor force as observed by Gschwendt (2022). Third, we add to the emerging literature on generative AI's labor market impacts by revealing how firms can be expected to adjust their human capital investment strategies in anticipation of further automation. While recent studies have documented negative employment effects of generative AI (Demirci et al., 2025; Hui et al., 2023), our research shows that these technologies also reshape firms' training decisions, potentially affecting the career prospects of young labor market entrants.

Regarding policy implications, our results highlight the importance of aligning education and training systems with changing skill demands. As automation shifts occupational task content, apprenticeship curricula need to evolve accordingly, with greater emphasis on non-routine cognitive skills and human-machine complementarity. This adaptation is essential to ensure that apprenticeships continue to provide relevant skills for labor market entrants in an increasingly automated economy.

While our study provides valuable insights, several limitations should be acknowledged. Our empirical analysis relies on stated responses to hypothetical scenarios rather than observed behavior, which may not perfectly predict actual training decisions. Future research could complement our approach with longitudinal studies tracking actual apprenticeship provision as automation technologies diffuse. Additionally, our theoretical model, while capturing key mechanisms, necessarily simplifies the complex decision-making processes within firms. Notably, our study operates under the strong assumption that current and emerging automation technologies will displace substantial portions of trained workers' tasks, which may not fully materialize as predicted. Furthermore, we do not examine the compensatory dynamics of task creation—specifically whether automated tasks might be replaced by modified or entirely new responsibilities that could potentially mitigate displacement effects. Future work could extend this framework to incorporate additional factors such as labor market institutions, competitive dynamics, or uncertainty about technological developments.

Finally, our study focuses primarily on the quantity of apprenticeship positions rather than their quality or content. An important direction for future research is to examine how automation affects the curriculum, duration, and skill focus of apprenticeship programs, and how these changes influence apprentices' labor market outcomes. Despite these limitations, our study makes a significant contribution to understanding how automation shapes firms' training decisions and provides a foundation for developing evidence-based policies to support apprenticeship systems in an era of rapid technological change.

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A Production Motive

For firms following the production motive (considering only periods 1 and 2):

$$NPV_{prod} = (\alpha_1 q_t - w_a) + \delta[\alpha_2 q_t(\lambda + (1-\lambda)(1 - \varepsilon x \cdot \phi(s,g))) - w_a] - C_t \tag{13}$$

Training remains viable under the production motive when:

$$(\alpha_1 q_s - w_a) + \delta[\alpha_2 q_t(\lambda + (1-\lambda)(1 - \varepsilon x \cdot \phi(s,g))) - w_a] > C_t \tag{14}$$

A.1 Comparative Statics under Production Motive

Effect of automation share (x) on production-motivated training:

$$\frac{\partial NPV_{prod}}{\partial x} = -\delta\alpha_2 q_t(1-\lambda)\varepsilon\phi(s,g) < 0 \tag{15}$$

Effect of automation timing (λ) on production-motivated training:

$$\frac{\partial NPV_{prod}}{\partial \lambda} = \delta\alpha_2 q_t[1 - (1 - \varepsilon x \cdot \phi(s,g))] = \delta\alpha_2 q_s \varepsilon x \cdot \phi(s,g) > 0 \tag{16}$$

Second-order effect of automation share (x) and exposure (ε):

$$\frac{\partial^2 NPV_{prod}}{\partial x \partial \varepsilon} = -\delta\alpha_2 q_t(1-\lambda)\phi(s,g) < 0 \tag{17}$$

Second-order effect of automation timing (λ) and exposure (ε):

$$\frac{\partial^2 NPV_{prod}}{\partial \lambda \partial \varepsilon} = \delta\alpha_2 q_t x \cdot \phi(s,g) > 0 \tag{18}$$