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Abstract

Artificial Intelligence (AI) is considered to be the next general-purpose technology, with the potential of performing tasks commonly requiring human capabilities. While it is commonly feared that AI replaces labor and disrupts jobs, we instead investigate the potential of AI for overcoming increasingly alarming skills shortages in firms. We exploit unique German survey data from the Mannheim Innovation Panel on both the adoption of AI and the extent to which firms experience scarcity of skills. We measure skills shortage by the number of job vacancies that could not be filled as planned by firms, distinguishing among different types of skills. To account for the potential endogeneity of skills shortage, we also implement instrumental variable estimators. Overall, we find a positive and significant effect of skills shortage on AI adoption, the breadth of AI methods, and the breadth of areas of application of AI. In addition, we find evidence that scarcity of labor with academic education relates to firms exploring and adopting AI.

JEL codes: J63, M15, O14
Keywords: Artificial Intelligence, skills shortage, CIS data

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1 Introduction

In both academic and policy debates, recent advances in Artificial Intelligence (AI) have generated enthusiasm not only for their potential to boost productivity and economic growth, but also for their supposed ability to alleviate alarming skills shortages. As Forbes columnist Schwarz (2023) notes, “the near-term threat to developed economies isn’t a lack of jobs - it’s not enough workers”, arguing that, “the latest AI tool is much less likely to steal someone’s job than to help fill roles that desperately need to be filled.” The Chartered Institute of Personnel and Development (CIPD) similarly asks whether AI can help close skills gaps, highlighting potential gains from generative AI in particular (Boys, 2023).

The widespread interest in this question reflects a broader concern among highly developed and innovation-oriented economies, where the scarcity of suitably skilled labour has become a central economic constraint (Cedefop, 2015). Skills shortages hinder firms’ productivity growth, limit innovation, and impose broader social costs (Brunello and Wruuck, 2021). Firms facing skill constraints report longer vacancy durations and increased reliance on under-qualified employees. A 2023 Eurobarometer survey found that most European SMEs regard the lack of suitable workers as a serious problem (European Commission, 2023). Previous studies consistently document the adverse consequences of such shortages: they depress productivity (Coad et al., 2016), impede technological progress (Toivanen and Väänänen, 2016), and heighten the risk of innovation failure or project abandonment, particularly among innovative firms (Horbach and Rammer, 2022).

Recent global evidence confirms that this problem remains pressing. According to McKinsey & Company’s State of AI 2025 survey, 88% of firms now report using AI in at least one business function - up from 78% a year earlier - but only about one-third have scaled AI enterprise-wide (McKinsey and Company, 2025). Similarly, Ernst and Young’s Work

Reimagined Survey 2025 finds that although 88% of employees use AI at work, but only a handful employ it in ways that fundamentally transform their workflows, largely because of persistent talent shortages (Ernst and Young, 2025).

Germany exemplifies this challenge in concrete terms. Toward the end of the 2010s, its strong economic performance and demographic ageing combined to produce acute shortages in qualified labor. By 2025, unemployment had fallen to 3.9%, one of the lowest in the European Union (Eurostat, 2025). Unemployment rates for skilled labor have been even lower, less than half of the overall rate (Röttger, Weber, and Weber, 2019), presenting a growing challenge for firms seeking to fill positions requiring high qualifications. Evidence from the 2019 German Community Innovation Survey (Rammer, 2020) further shows that finding qualified personnel ranked as the leading barrier to innovation, cited by roughly 18% of firms as a major obstacle and by 15% as a cause of delayed projects. The shortage of qualified labor thus emerged as both a productivity constraint and a bottleneck for innovation within one of Europe's most technology-intensive economies.

In this paper, we examine whether firms facing a scarcity of labor adopt AI technologies to likely mitigate that constraint. Building on the idea that technological change can respond to relative factor scarcity (Acemoglu, 2010), we test whether shortages in qualified labor stimulate AI adoption. We use firm-level data from the German part of the Community Innovation Survey (CIS), which includes detailed information on both AI usage and recruitment difficulties. Following Czarnitzki et al. (2023), we measure AI adoption in three ways: a binary indicator (yes/no), the breadth of AI methods (e.g., speech recognition, machine learning, knowledge-based systems), and the breadth of AI application areas (e.g., product and service innovation, process automation, data analysis).

To capture skills shortages, we use lagged information from the 2017 CIS wave on firms' difficulties in filling open positions. We estimate multiple regression models controlling for firm size, R&D intensity, workforce skill composition, firm age, technology acquisition, and sectoral effects. To address endogeneity of unfilled positions, we instrument skills shortages using district- and sector-level measures of local labor scarcity - specifically, the log-number of employees in bankrupt firms and the log-number of open vacancies.

Our results show that skills shortages are positively and significantly associated with AI adoption, as well as with the breadth of AI use across both methods and business areas. Moreover, we find that shortages of academically educated labor are particularly associated with AI adoption. This pattern may be consistent with the argument that AI may "restore the middle-skill set," as firms appear to use AI to compensate for the scarcity of high-skill workers by reallocating complex tasks to less-qualified employees augmented by AI tools (Autor, 2024).

The remainder of the paper is structured as follows. Section 2 reviews the related literature on skills shortages, AI technologies, and their intersection. Section 3 presents our conceptual framework, measurement strategy, and descriptive evidence. Section 4 reports the empirical results, and Section 5 concludes.

2 Skills Shortage and Artificial Intelligence

2.1 Skills shortage

Skills shortage refers to a situation in which the demand for workers in a specific occupation surpasses the supply of suitable and available workers willing to work under existing market conditions (Shah and Burke, 2005). From a neoclassical perspective, it represents a temporary imbalance in the labor market due to the slow adjustment of wages caused by high adjustment costs. Firms encounter difficulties in increasing wages for new employees without affecting the compensation of existing staff (Arrow and Capron, 1959).

Addressing skills shortage goes beyond wage adjustments and requires a focus on aligning innovation with workforce skills, since multiple factors contribute to temporary imbalances between the supply and the demand of skills. Technological advancements and demographic changes in aging societies lead to a decline in the number of young workers entering the labor market, which creates a gap in meeting the increasing demand for skills in knowledge-intensive economies. Education systems often struggle to keep up with the rapid pace and direction of technological changes, exacerbating the phenomenon of skills shortage (Toner, 2011).

Furthermore, the cyclical variations in the demand for emerging technologies and new products can result in a temporary surge in the demand for specific qualifications, exceeding the available supply of skilled workers (Berman, Bound, and Machin, 1998).

Existing research on skills shortage has mainly focused on its detrimental effects on both firm productivity and the advancement of new technologies. High-productivity firms are particularly hindered by skills shortages, as they represent barriers to innovation (Coad et al., 2016). Additionally, skills shortages lead to innovation failures, i.e., abandonment of projects (Horbach and Rammer, 2022). Similarly, proximity to technical universities, which helps to mitigate skills shortages, is associated with a greater number of patents filed by inventors (Toivanen and Väänänen, 2016). In a complementary way, other studies emphasize the crucial role played by skills and training activities in driving innovation performance (Freel, 2005), and the importance of both technical-academic skills and relational-social skills in the innovation process (Sousa and Rocha, 2019).

2.2. AI and skills shortage

Firms may opt for certain compensating mechanisms to mitigate the harms of skills shortage. Artificial Intelligence (AI) technologies - machine-based systems that infer how to generate predictions, content, or decisions from data (OECD, 2023) - enable automation of cognitive tasks and expand firms' ability to process information, design products, and make complex decisions (Brynjolfsson et al., 2017; Baruffaldi et al., 2020).

The diffusion of AI has accelerated markedly during the 2020s, driven by advances in machine learning, data availability, and computational power. Recent evidence shows that adoption rates have more than doubled in major economies: from 7% to 13% of firms in the EU between 2021 and 2024 (Eurostat, 2025). The introduction of generative-AI (GenAI) systems - large language and multimodal models capable of content creation and reasoning - has further widened the scope of applications. Within a year of ChatGPT's release, more than half of workers in AI-exposed occupations in Denmark reported using it (Humlum and Vestergaard, 2024), while similar trends are emerging across ICT, professional services, and manufacturing sectors worldwide (McKinsey & Company, 2025).

The literature increasingly frames AI not merely as an automation tool but as a labor-augmenting technology (Acemoglu et al., 2025) that may help firms mitigate skill bottlenecks. Many organisations now view AI as a practical response to wider hiring constraints (McKinsey & Company, 2025; Ernst & Young, 2025; World Economic Forum, 2025). Experimental evidence supports this interpretation: access to generative-AI tools such as GitHub Copilot and ChatGPT increases worker productivity by 15–60%, with the largest gains among lower-skill or less-experienced employees (Noy and Zhang, 2023; Peng et al., 2023; Dell'Acqua et al., 2025; Brynjolfsson et al., 2025). At the firm level, AI adoption is associated with higher productivity and innovation outcomes, particularly among firms with strong digital infrastructure and a skilled workforce (Rammer et al., 2022; Czarnitzki et al., 2023; Babina et al., 2024; Calvino and Fontanelli, 2025).

Empirical analyses of adoption determinants identify common patterns: larger, younger, and R&D-intensive firms with a high share of graduates are significantly more likely to deploy AI, and these associations are even stronger for GenAI (McElheran et al., 2024; Calvino and Fontanelli, 2025). Digital maturity, absorptive capacity, and complementary ICT assets are critical enablers (Igna and Venturini, 2023; McElheran et al., 2024).

Despite these advances, research on the interaction between skills shortages and AI adoption remains limited. Most studies examine how AI affects employment or wages, whereas little is known about how labor-market constraints shape AI adoption incentives. From a task-based perspective (Acemoglu, 2010), scarcity of skilled labor should encourage firms to invest in technologies that substitute for or complement those missing capabilities. AI can automate routine information-processing tasks and augment the remaining workforce, enabling data-driven decision-making even when specialized expertise is scarce.

This paper aims to bridge this gap by providing firm-level evidence on how unfilled job vacancies and specific skill shortages influence the breadth and intensity of AI adoption. Using detailed German data, we distinguish between qualification levels and occupational domains of scarcity, thereby shedding light on whether firms deploy AI as a response to constrained human capital.

3 Estimating the relationship between skills shortage and AI

3.1 Conceptual model

The central question of this study is whether firms facing shortages of skilled labor are more likely to adopt AI technologies. The decision to implement AI reflects a broader optimisation problem in which firms choose among alternative production technologies given their internal resources, human capital, and market environment.

AI can substitute for or complement human labor depending on the task. When qualified workers are scarce or costly, firms may find it profitable to invest in AI systems that replicate certain cognitive or operational functions. Conversely, because AI integration also requires specific technical competencies, adoption depends on the availability of complementary digital and analytical skills within the firm. Thus, labor scarcity and skill composition may jointly shape firms' incentives to adopt AI.

Our empirical study is guided by a conceptual model which is based on three main groups of variables. AI is measured by a set of variables that denote the adoption of this technology and the breadth of its usage across different methods and areas of application. These AI-related variables are linked to skills shortage and other determinants, including innovation input measures, general firm capabilities, and market characteristics (refer to Figure 1). The details are described in the following subsections.

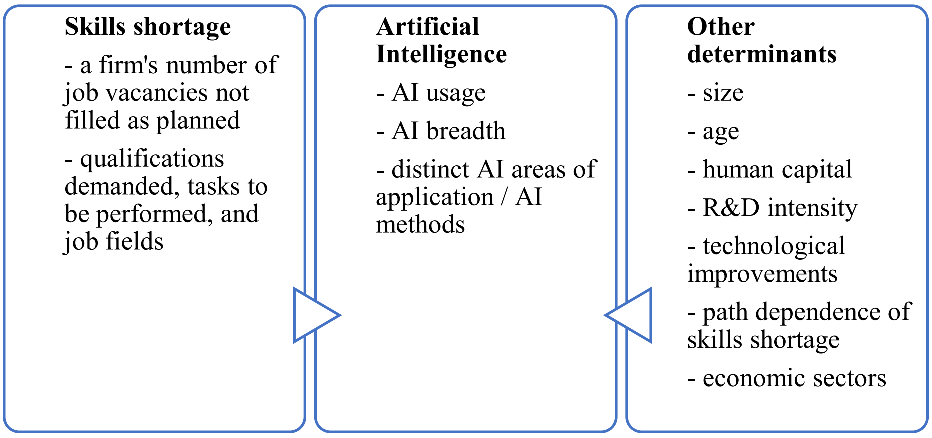


Figure 1. Variables considered to identify the role of skills shortage for AI usage in firms.

As explained below, a key empirical challenge is the potential endogeneity of skills shortage. The decision to expand labor demand, and hence to experience shortages, may correlate with unobserved firm characteristics that also affect AI adoption. To address this, we estimate instrumental-variable regressions using local labor-market indicators - specifically, the log number of employees in bankrupt firms and the log number of open vacancies in the same district and sector - as instruments for firm-level labor scarcity.

3.2 Data source

We use cross-sectional data of firms from the German part of the European-wide Community Innovation Survey (CIS), which is implemented by the Leibniz Centre for European Economic Research (ZEW) in Mannheim, Germany. Differently from other CIS national innovation surveys, the German survey, known as the Mannheim Innovation Panel (MIP), is structured as an annual panel survey (Peters and Rammer, 2013). The MIP gathers information from firms in Germany that operate in sectors such as manufacturing, mining, utilities, and business-oriented services, including wholesale trade, transportation, financing and insurance, information and communication, as well as professional, scientific, technical, administrative, and support services. To ensure the data's representativeness, the MIP adheres to the methodological guidelines specified by the Statistical Office of the European Commission (Eurostat) for the CIS, encompassing sampling procedures, data processing, and quality control. The survey employs a stratified random sampling approach and employs a standardized questionnaire that can be completed through paper or online formats. The MIP achieves a response rate ranging between 25% and 35%. To assess potential bias among participating firms, an extensive non-response survey is conducted (Peters and Rammer, 2013).

After merging consecutive survey waves, we focus only on firms with complete information on all model variables, thereby reducing the final sample size to 2973 firms (we eliminate missing values, erroneous responses, and outliers).[1]

3.3 AI variables

In this study, we make use of different waves of the German Innovation Survey. In particular, the survey conducted in 2019, with the reference year 2018, included specific questions aimed

[1] When compared to the original sample, the reduced sample shows a similar distribution in terms of economic sectors (see Table 8 in the Appendix) as in the raw data.

at capturing the adoption and usage of artificial intelligence (AI) within firms. These questions allowed for the classification of firms as either AI-using or non-AI-using (refer to Figure 2).

12.4 Does your enterprise use Artificial Intelligence methods?
Artificial Intelligence (AI): A method of information processing that allows computers to autonomously solve problems.

Yes ☐ ...... No ☐ → **Please continue with Question 12.7.**

AI Method:	*Products, Services*	*Automation of processes*	*Communi-cation with-customers*	*Data analytics*	*Other areas*
Language understanding	☐	☐	☐	☐	☐
Image recognition	☐	☐	☐	☐	☐
Machine Learning	☐	☐	☐	☐	☐
Knowledge-based systems	☐	☐	☐	☐	☐
Others:	☐	☐	☐	☐	☐

12.5 Were the Artificial Intelligence methods used in your enterprise developed in-house or by others?

☐ ...... mainly developed in-house ☐ ...... mainly developed by others ☐ ...... both in-house and others

12.6 Since when is your enterprise using artificial intelligence methods?
Year of the first use of artificial intelligence in your enterprise (please provide an estimate) .... ca. ☐

Figure 2. Question on AI use in the German Innovation Survey 2019.

To measure the extent of AI implementation, a matrix-style question asked whether the firm uses AI methods at the time of the survey and the application areas in which these methods are employed. The question differentiated between five broad AI methods: language understanding, image recognition, machine learning, knowledge-based systems, and other unspecified methods. The application areas encompassed five categories: products/services, process automation, customer interaction, data analytics, and other unspecified areas. Additional questions regarded the origin of the AI technology utilized by the firms, specifically whether it was developed in-house or sourced from external entities. Furthermore, the survey sought to determine the initial year of AI adoption by each firm.

For this study, the adoption of AI is first modeled as a dummy variable (*AI*), regardless of whether the firms developed the AI applications in-house or utilized AI methods developed by external sources, and encompassing firms that adopted AI by 2017 or at any point after

2017.[2] In addition, to capture the breadth of usage of AI methods and areas of applications, we distinguish between the breadth in terms of areas of application of AI (*AIbreadth_area*) and the breadth in terms of AI methods (*AIbreadth_method*). These variables potentially range from 0 to 5. Last, we also consider the distinct methods and areas of applications (see Czarnitzki et al., 2023 and Rammer et al., 2022 for similar variables).

As shown in Table 1, our cross-sectional sample contains 2973 firms out of which 86 can be classified as AI users (around 3%), by considering only firms that introduced AI after 2017. In terms of breadth of AI methods (*AIbreadth_method*), AI-using firms employed on average around 1.8; similarly, around 1.8 areas of applications of AI characterized AI-using firms (*AIbreadth_area*). About 54% of AI-using firms used AI in products or services, 55% for the automation of processes, 44% for data analysis, and 19% for interaction with clients. In terms of methods, about 52% of AI-using firms employ image recognition, followed by machine learning (about 51%), knowledge-based systems (40%), and language understanding (31%).

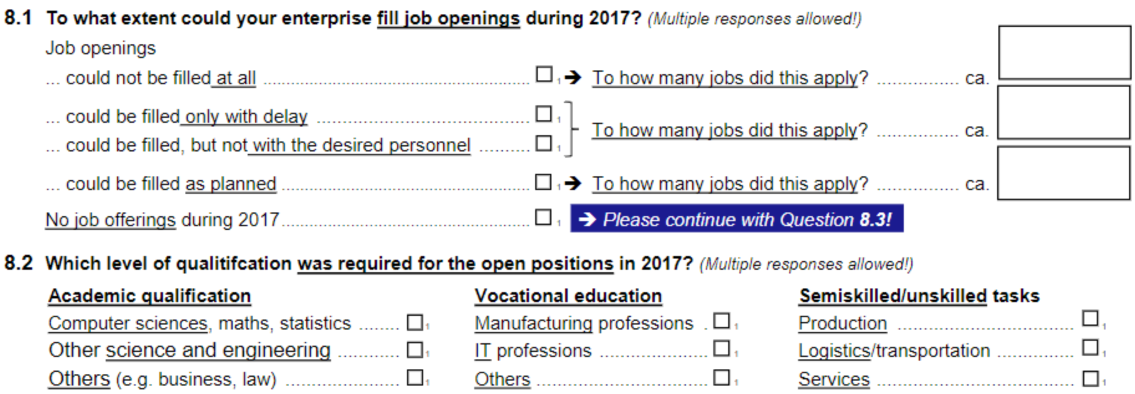
--- Insert Table 1 about here ---

3.4 Skills shortage and other independent variables

To measure skills shortage, we exploit detailed information from the 2018 wave of the MIP, with the reference year 2017, on the extent to which firms could fill job openings and on the different levels of qualifications required for the vacancies (refer to Figure 3). Following Horbach and Rammer (2022), skills shortage (*lnSkillsShort*) is operationalized as the number of vacancies that could not be filled at all, that could be filled only with delay, or that could

[2] The choice of this timeframe reflects the objective of our analysis, i.e., investigating the impact of skills shortage (measured in 2017) on AI usage. Results using different timeframes remain robust and are available upon request.

not be filled with the required personnel in 2017 (logged).[3] This variable encompasses the scarcity of skills experienced at the firm level, which may arise from the inability to fill a job vacancy, delays in the hiring process for required employees, or a mismatch between the skills required for the vacancy and the skills possessed by the newly hired individual(s). In our sample, about 37% of firms reported that they could not fill (some of) their job openings as planned.



8.1 To what extent could your enterprise fill job openings during 2017? *(Multiple responses allowed!)*

Job openings

... could not be filled at all ☐ → To how many jobs did this apply? ca. ☐

... could be filled only with delay ☐

... could be filled, but not with the desired personnel ☐ → To how many jobs did this apply? ca. ☐

... could be filled as planned ☐ → To how many jobs did this apply? ca. ☐

No job offerings during 2017 ☐ → *Please continue with Question 8.3!*

8.2 Which level of qualitifcation was required for the open positions in 2017? *(Multiple responses allowed!)*

Academic qualification	Vocational education	Semiskilled/unskilled tasks
Computer sciences, maths, statistics ☐	Manufacturing professions ☐	Production ☐
Other science and engineering ☐	IT professions ☐	Logistics/transportation ☐
Others (e.g. business, law) ☐	Others ☐	Services ☐

Figure 3. Question on skill demand in the German Innovation Survey 2018.

We use 2017 data on the type of qualifications that firms demanded and the job subfields or subsectors that required these skills to create a set of independent dummy variables. The dummy variables *Academic_qual, Vocational_qual*, and *Unskilled_tasks* represent the aggregate levels of qualifications that the firm needed for the open job position. They are equal to 1 if the firm marked at least one corresponding subfield and 0 otherwise (see question 8.2 in Figure 3). We also create seven additional dummy covariates based on the subfields for each qualification category: *STEM* (computer sciences, maths, statistics, other science and engineering), *Other_academic* (e.g., business, law), *Vocational_IT* (IT

[3] Since the variable is skewed, we use a logarithmic transformation of it. To account for firms reporting zero vacancies not filled as planned, we add 0.5 to the variable before log-transforming it, and we then deduct log (0.5) from the generated variable.

professions requiring vocational education)*, Vocational_manuf* (manufacturing professions requiring vocational education)*, Unskilled_production* (unskilled/semiskilled tasks in the production area)*, Unskilled_services* (unskilled/semiskilled tasks in the services area), and *Unskilled_logistics* (unskilled/semiskilled tasks in the logistics/transportation area). We use the data on the type of qualifications and job subfields to analyze the heterogeneous effects of skills shortage on AI adoption, as explained below.

In our analysis of the impact of skills shortage on AI adoption, we include a set of control variables to account for various factors. We control for lagged firm size (*lnEmpl*),[4] measured by the number of employees (logged), as well as the number of years since the firm started the business (logged) (*lnAge*). Firms that perform R&D may possess a larger stock of technological knowledge both from their own R&D activities and from absorbing relevant external knowledge (Cohen and Levinthal, 1990), which may lead to the decision to implement AI technologies or broaden their usage if compared to non-R&D-performers, or firms that conduct R&D only to a lower extent. We thus control for firms' absorptive capacity by including the firm-level, lagged R&D intensity (*RDint*) in our empirical model. We define lagged R&D intensity as the ratio of R&D expenditures to total sales in 2017. Additionally, we control for the lagged share of employees with a university degree (*ShareGrad*), which reflects the significance of academic knowledge embedded in the firm's human capital (Lewandowska, 2015).

Furthermore, we include the variable *Techpath* which equals to 1 if the firm has adopted, from 2016 to 2018, new or improved production technology relative to the machinery and equipment that has been used prior to the survey period (i.e., before 2016) (Czarnitzki et al., 2023). With this variable we aim to control for supplier-induced innovation

[4] To avoid double counting, we subtract the number of vacancies that were filled as planned from the total number of employees in 2017.

and technical progress embedded in acquired machinery or equipment, which may indicate that the firm is following a technological improvement path and hence may be more likely to explore AI. We also control for path dependence of skills shortage (*Pathdep*), which is constructed as the average by sector and size class of an indicator denoting the lack of suitably qualified staff in the previous period 2014–2016. Last, we include industry dummies (16 in total) to account for different propensities for AI adoption across industries.

3.5 Methods and endogeneity of skills shortage

We run OLS and Probit regressions with the dependent variable *AI* (binary indicator) and OLS regressions with the breadth variables *AIbreadth_area,* and *AIbreadth_method*.

We expand the abovementioned methods to instrumental variable (IV) regressions to address the potential endogeneity of skills shortage. Various factors can introduce bias in the assessment of the impact of skills shortage on AI due to the endogenous nature of firms' decision to demand skills. First, firms may experience a scarcity of labor as a result of AI adoption, since AI technologies require new skills for their implementation and integration in the business and innovation processes. In such cases, a firm's decision to invest in AI could be a driving factor behind skills shortage. Second, the decision to adopt AI technologies due to a shortage of skills may also alleviate the lack of skilled labor. Third, it is crucial to consider the potential presence of omitted covariates that are not accounted for in the estimated specifications, since they might be correlated with skills shortage and lead to biased estimates. For example, since more innovative firms are more likely to experience skills shortage (Horbach and Rammer, 2022), the difficulty in filling job openings could be associated with an increase in the firm’s demand for labor, which originates from a firm’s broader digitalization efforts or expansion of the technological infrastructure. To mitigate these concerns and obtain more reliable estimates, we perform IV regressions and compare the results obtained with OLS and Probit to the estimates obtained with IV 2SLS and IV Probit regressions.

As a first instrument for skills shortage, we use the log-number of employees working in bankrupt firms in 2017 (*lnEmpl_local_bankrupt*) per German district. This instrument is constructed using data on firm bankruptcies from the Creditreform database and spatial data on firms' locations in different German districts. A higher number of employees working in financially distressed firms in the same local market indicates a larger pool of potential employees seeking new job opportunities within the same district. Consequently, it is more likely that firms will be more able to fill their job vacancies, resulting in a negative effect on skills shortage. We argue that the instrument is valid because there is no direct link between a firm's decision to use AI and the number of employees working in bankrupt firms in the same district.

As a second instrument, we use the average number of open vacancies (in logs) in the same district and NACE five-digit sector of the focal firm (*lnAverage_vacancies*). The information regarding firms' location in German districts is obtained from the Creditreform database. This variable captures the intensity of the competition for skills at the district-sector level. For higher values of this variable, it is more difficult for firms in the same district and sector to fill their open job vacancies; thus, this variable is expected to positively influence skills shortage (i.e., the number of vacancies not filled as planned). This variable should not independently affect the use of AI (in the subsequent period), as we control for the focal firm's skills shortage.

3.6 Descriptive statistics

On average, we observe that firms experiencing skills shortage are more prone to adopt AI (refer to Table 2). Around 4.2% of firms reporting not being able to fill their vacancies as planned used AI technologies, while the proportion of AI users among firms without skills shortage amounts to only 2.1%. In addition, their usage of AI is broader, both in terms of methods and areas of application, than firms not experiencing skills shortage. The score for *AIbreadth_area* amounts to 0.083 and 0.035 for firms with skills shortage and without it, respectively. A similar pattern is observed when we consider the breadth of breadth of AI methods.

On average, around 5 job vacancies could not be filled as planned among firms with skills shortage. In terms of demand for qualifications and skills, among firms reporting skills shortage most open job vacancies pertained to tasks that did not require an academic qualification (*Vocational_qual* and *Unskilled_tasks*); more specifically, these vacancies were mostly related to skills for manufacturing professions and production tasks.

Furthermore, firms experiencing skills shortage have, on average, a lower share of graduates than firms that could fill all their job vacancies. The variable indicating the adoption of new or improved technologies in the period 2016-2018 exhibits a higher average value for firms experiencing scarcity of labor. As expected, the indicator for past skills shortage has a higher average value among firms that could not fill some of their job vacancies as planned, in line with the path dependency of the phenomenon.

--- Insert Table 2 about here ---

4 Estimation results

Table 3 shows the estimates obtained in the baseline model in which the outcome variable is the binary indicator for AI usage. For the variable *lnSkillsShort* in the OLS model, we observe a positive coefficient of 0.011, indicating that if the number of vacancies that are not filled as planned increases by 10%, the probability of adopting AI is estimated to increase by around 0.11 percentage points. In the IV 2SLS model, the coefficient is 0.023 with a similar interpretation, and it is statistically significant at the 1% level. A similar result is obtained with the Probit and IV Probit models: an increase in skills shortage is associated with a higher probability of using AI technologies. The coefficient in both models is statistically significant at the 1% level.

--- Insert Table 3 about here ---

Table 9 in the Appendix shows the first-stage regression of the IV 2SLS estimation. The instrumental variable indicating the number of employees working in bankrupt firms in the same district of the focal firm has a negative sign, in line with our expectations, and exhibits statistical significance at the 5% level. A higher supply shock in the local labor market facilitates firms that need to fill their job vacancies, resulting in a negative effect on skills shortage. The second instrumental variable, namely the average number of open vacancies in the same district and sector of the focal firm, has a positive sign and exhibits significance at the 1% level. Due to the intense competition for skills at the district-sector level, it is more difficult for firms in the same district and sector to fill their open job vacancies. The Kleibergen-Paap Wald F statistic is above the conventional levels (221.78), and the instruments pass the test of overidentifying restrictions (chi-sq = 1.07; p = 0.30).

We find that the expected probability of adopting AI for a firm with average employment and no unfilled positions is about 2.4%. The average marginal effect of hiring five new employees only amounts to 0.2%. Instead, the average marginal effect of having five positions that could not be filled is about ten times larger, namely 2.2%. We, therefore, conclude that skill shortage is an economically significant reason for firms to explore AI technology.

In Table 4, we look at the impact of skills shortage on the breadth of AI methods/areas of application. We observe a positive and significant effect of skills shortage on *AIbreadth_area* and *AIbreadth_method*, which is robust to different specifications (OLS and

IV 2SLS). For instance, if we consider the 2SLS estimated coefficient in column (2), we find that a 10% increase in skills shortage is associated with an average increase in the breadth of AI methods of 0.004.

--- Insert Table 4 about here ---

In Table 5, we examine the effects of skill shortages on AI adoption by differentiating between academic, vocational, and unskilled or semiskilled tasks. We thus add an interaction term between the variable *lnSkillsShort* and the three dummy variables of aggregated qualifications. This analysis aims to investigate how the lack of specific skills influences a firm's decision to invest in AI technologies or expand its use of AI methods and areas of application. First, we find that the interaction coefficient between skills shortage and academic qualification *(Academic_qual # lnSkillsShort*) is highly significant in all models. On the other hand, the coefficient of unskilled labor is only (weakly) significant in two out of three models. Second, the interaction term between skills shortage and academic qualification has a larger coefficient than the interaction terms between skills shortage and vocational qualification/unskilled tasks in all models. This implies that unfilled positions that require a university degree have a stronger positive impact on AI usage and the measures of AI breadth (areas of application and methods) than positions related to non-academic jobs. This result aligns with recent conjectures that AI can potentially reduce the relative scarcity of skilled workers and, in turn, shrink the productivity gap between workers in the middle and upper parts of the skill distribution (Autor, 2024).

--- Insert Table 5 about here ---

In Table 6, we use the information about subfields of jobs and types of tasks required in the job openings. Among skills that require academic qualifications, skills related to computer science, math, engineering, and statistics (under the label *STEM*) have a larger positive impact on the decision of firms to use AI technologies and on AI methods/areas of application than other types of academic qualifications that are related to, for example, business and law. Interestingly, vocational IT and manufacturing skills are associated with a negative effect, which could be because these skills are often more specialized and less transferable than general skills (Shiohira, 2021). Finally, the positive impact of skills shortage for semi-skilled and unskilled tasks that was observed in Table 5 is mostly driven by a scarcity of labor dedicated to production tasks. Shortage of skills for unskilled production tasks may also create higher incentives for firms to use AI technologies to automate or optimize routine and repetitive processes.

--- *Insert Table 6 about here* ---

These results provide some evidence of the fact that firms also adopt AI when they cannot find suitable employees for the completion of tasks for which they rely on highly skilled personnel. We consider this finding of particular interest since it provides support to a more nuanced view of the determinants of the diffusion of AI. While a generally accepted view in the economic literature is that AI technologies are implemented to automate routinized tasks through machines (Acemoglu, 2025), we find some evidence that the potential of AI is broader and also enables firms to mitigate the harms of scarcity of highly qualified labor (Autor, 2024).

We further explore if skills shortage is specifically associated with one or more areas of application of AI and one or more AI methodologies. Based on the categorization of AI areas and AI methodologies in the survey question, we group areas of applications in two categories, i.e., (1) products/services and automation of processes, on the one hand, and (2) interaction with clients, data analytics, or other areas, on the other hand. Similarly, we distinguish between two classes of AI methods: (1) language understanding, image recognition, machine learning, and, on the other hand, (2) knowledge-based systems and other methods. Since we suppose that the decision to introduce AI in each category of application areas/methodologies is not independently determined, we estimate a bivariate probit regression for areas of application and methodologies of AI. The bivariate probit is a natural extension of the probit model which, similar to seemingly unrelated regression models, allows for two equations with correlated disturbances (Greene, 2003). As shown in Table 7, skills shortage seems to be positively associated with both categories of areas of application, namely automation of processes, products/processes, and interaction with clients/data analytics. Conversely, when it comes to methodologies, our results suggest that the positive association between skills shortage and AI does not entail knowledge-based systems methodologies but involves machine learning, image recognition, and language understanding.[5]

--- Insert Table 7 about here ---

5 Conclusions

This study seeks to better understand the relationship between labor scarcity and the adoption of Artificial Intelligence (AI) as a potential solution for firms with unfilled job vacancies. Contrary to the prevailing concern that AI may lead to a reduction in labor demand, our study takes a different perspective by examining the adoption of AI methods as a response to the difficulty of finding suitable employees who meet firms' human capital demands. Our study sheds light on the potential effects of AI technologies in helping firms overcome skills shortages.

Through the analysis of data from a representative and large-scale survey, we explore the implications of skills shortages on AI adoption. Our findings indicate a positive and

[5] Based on the Wald test of rho equal to 0 in Table 7, we can reject the null hypothesis of independent equations for both specifications.

significant relationship between skills shortage and AI adoption, encompassing both the breadth of AI methods and the areas of application.

Furthermore, our study distinguishes between shortages of skills of different types of qualifications (academic, vocational, and unskilled) to discern their respective influences on AI adoption. We find indications that the scarcity of labor with academic education, and in particular of skills associated with STEM fields, positively influences the adoption of AI technologies, methods, and applications. This finding emphasizes that firms adopt AI not only for process automation and robotization but also to accomplish tasks traditionally requiring highly skilled personnel.

Moreover, our analysis shows that the positive association between skills shortage and AI adoption entails various areas of application of AI, including the automation of processes, products/processes, interaction with clients, and data analytics. Conversely, in terms of AI methodologies, our results suggest that the positive association between skills shortage and AI involves machine learning, image recognition, and language understanding but not the usage of knowledge-based systems methods.

It is worth noting that our study has certain limitations. The analysis is based on cross-sectional data from the German part of the Community Innovation Survey, and hence, caution should be exercised when generalizing the findings to other contexts. Future research could employ longitudinal data and expand the analysis to encompass a broader range of countries and industries.

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Tables

Table 1: AI methods and areas of application in AI-using firms.

	AI-using firms (86 obs.)			
	Mean	St. Dev.	Min	Max
Breadth variables				
AIbreadth_area	1.826	0.984	1	4
AIbreadth_method	1.791	0.883	1	5
Areas of application				
Products, services	0.535	0.502	0	1
Automation of processes	0.547	0.501	0	1
Interaction with clients	0.186	0.391	0	1
Data analysis	0.442	0.500	0	1
Other areas	0.116	0.322	0	1
AI methods				
Language understanding	0.314	0.467	0	1
Image recognition	0.523	0.502	0	1
Machine learning	0.512	0.503	0	1
Knowledge-based system	0.407	0.494	0	1
Other methods	0.035	0.185	0	1

Sources: German CIS, 2019 survey wave.

Table 2: Descriptive statistics.

		Firms with skills shortage (1095 obs.)				Firms without skills shortage (1878 obs.)			
Variable	Source	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
AI variables									
AI	MIP19	0.042	0.201	0	1	0.021	0.144	0	1
AIbreadth_area	MIP19	0.083	0.448	0	4	0.035	0.273	0	4
AIbreadth_method	MIP19	0.077	0.405	0	5	0.037	0.286	0	4
Skills variables									
SkillsShort	MIP18	4.996	10.859	1	150	0	0	0	0
Academic_qual[a]	MIP18	0.448	0.497	0	1	0.188	0.391	0	1
Vocational_qual[a]	MIP18	0.718	0.450	0	1	0.301	0.459	0	1
Unskilled_tasks[a]	MIP18	0.519	0.500	0	1	0.210	0.408	0	1
STEM[a]	MIP18	0.361	0.480	0	1	0.140	0.347	0	1
Other_academic[a]	MIP18	0.151	0.359	0	1	0.068	0.252	0	1
Vocational_IT[a]	MIP18	0.129	0.335	0	1	0.045	0.208	0	1
Vocational_manuf[a]	MIP18	0.366	0.482	0	1	0.147	0.354	0	1
Unskilled_production[a]	MIP18	0.249	0.432	0	1	0.109	0.312	0	1
Unskilled_services[a]	MIP18	0.210	0.408	0	1	0.077	0.267	0	1
Unskilled_logistics[a]	MIP18	0.191	0.393	0	1	0.068	0.252	0	1
Control variables									
lnEmpl	MIP18	3.656	1.442	0	10.270	2.941	1.417	0	10.987
lnAge	MIP18	3.063	0.800	0	6.809	3.120	0.784	0	5.268
RDint	MIP18	0.016	0.063	0	0.780	0.021	0.085	0	0.997
ShareGrad	MIP18	0.209	0.256	0	1	0.251	0.292	0	1
Techpath	MIP19	0.622	0.485	0	1	0.515	0.500	0	1
Pathdep	MIP18	0.681	0.102	0	1	0.662	0.092	0	1
Instrumental variable									
lnEmpl_local_bankrupt	Creditreform	5.847	1.344	1.099	8.730	5.900	1.366	2.197	8.730
lnAverage_vacancies	MIP18	1.573	0.892	0.288	5.993	0.655	0.861	0	6.399

Sources: German CIS. (a) The variables denoting the type of qualification demanded are available for 2929 observations (1070 firms with skills shortage and 1859 firms without skills shortage).

Table 3: Regression coefficients table: the impact of skills shortage on AI use.

	(1) OLS AI (0/1)	(2) IV 2SLS AI (0/1)	(3) Probit AI (0/1)	(4) IV Probit AI (0/1)
lnSkillsShort	0.0106**	0.0233***	0.1323***	0.2560***
	(0.0041)	(0.0076)	(0.0444)	(0.0836)
lnEmpl	0.0133***	0.0099***	0.1723***	0.1336***
	(0.0034)	(0.0034)	(0.0353)	(0.0416)
RDint	0.2168***	0.2217***	1.7929***	1.8121***
	(0.0777)	(0.0772)	(0.4059)	(0.4010)
ShareGrad	-0.0077	-0.0066	-0.1476	-0.1369
	(0.0151)	(0.0152)	(0.2283)	(0.2271)
lnAge	-0.0002	0.0013	-0.0102	0.0033
	(0.0043)	(0.0044)	(0.0660)	(0.0651)
Techpath	0.0127**	0.0122**	0.3022**	0.2917**
	(0.0057)	(0.0057)	(0.1215)	(0.1208)
Pathdep	0.0420	0.0368	0.4857	0.3856
	(0.0653)	(0.0641)	(0.5647)	(0.5400)
Constant	-0.0777*	-0.0769*	-3.6621***	-3.5708***
	(0.0471)	(0.0465)	(0.5280)	(0.5024)
16 sector dummies	Yes	Yes	Yes	Yes
N	2973	2973	2973	2973
R-sq.	0.05	0.05		
Pseudo R-sq.			0.17	
Kleibergen-Paap Wald rk F statistic		221.78 (p = 0.00)		
Test of overidentifying restrictions (chi-sq.)		1.07 (p = 0.30)		

Note: Robust standard errors in parentheses. * *p < 0.10, ** p < 0.05, *** p < 0.01*

Table 4: Regression coefficients table: the impact of skills shortage on the breadth of AI methods/areas of application.

	(1) OLS *AIbreadth_method*	(2) IV 2SLS *AIbreadth_method*	(3) OLS *AIbreadth_area*	(4) IV 2SLS *AIbreadth_area*
lnSkillsShort	0.0211**	0.0399**	0.0231**	0.0456***
	(0.0085)	(0.0178)	(0.0094)	(0.0175)
lnEmpl	0.0239***	0.0190**	0.0311***	0.0252***
	(0.0072)	(0.0087)	(0.0081)	(0.0086)
RDint	0.4396**	0.4467**	0.4115**	0.4201**
	(0.1796)	(0.1789)	(0.1685)	(0.1671)
ShareGrad	-0.0300	-0.0284	0.0039	0.0058
	(0.0315)	(0.0314)	(0.0288)	(0.0289)
lnAge	-0.0098	-0.0075	-0.0040	-0.0013
	(0.0092)	(0.0092)	(0.0089)	(0.0092)
Techpath	0.0193*	0.0185	0.0198*	0.0188
	(0.0114)	(0.0114)	(0.0117)	(0.0117)
Pathdep	0.0916	0.0839	0.0861	0.0769
	(0.1296)	(0.1269)	(0.1589)	(0.1560)
Constant	-0.1141	-0.1129	-0.1597	-0.1583
	(0.0923)	(0.0911)	(0.1080)	(0.1067)
16 sector dummies	Yes	Yes	Yes	Yes
N	2973	2973	2973	2973
R-sq.	0.05	0.05	0.05	0.05
Kleibergen-Paap Wald rk F statistic		221.78 (p = 0.00)		221.78 (p = 0.00)
Test of overidentifying restrictions (chi-sq.)		1.03 (p = 0.31)		1.57 (p = 0.21)

Note: Robust standard errors in parentheses. * *p < 0.10, ** p < 0.05, *** p < 0.01*

Table 5: Regression coefficients table: the impact of skills shortage on AI use and the breadth of AI use based on the type of qualification demanded or the type of tasks to be performed.

	(1) Probit *AI (0/1)*	(2) OLS *AIbreadth_area*	(3) OLS *AIbreadth_method*
lnSkillsShort	-0.0725	-0.0354*	-0.0244
	(0.1037)	(0.0197)	(0.0201)
Academic_qual	-0.0238	-0.0344	-0.0284
	(0.1654)	(0.0238)	(0.0260)
Academic_qual # lnSkillsShort	0.3407***	0.0838***	0.0737***
	(0.1005)	(0.0226)	(0.0215)
Vocational_qual	0.2848*	0.0303	0.0085
	(0.1572)	(0.0187)	(0.0164)
Vocational_qual # lnSkillsShort	-0.1943*	-0.0096	-0.0059
	(0.1033)	(0.0170)	(0.0169)
Unskilled_tasks	-0.2525	-0.0429**	-0.0152
	(0.1711)	(0.0196)	(0.0182)
Unskilled_tasks # lnSkillsShort	0.1775*	0.0475**	0.0294
	(0.0983)	(0.0221)	(0.0204)
lnEmpl	0.1436***	0.0276***	0.0207**
	(0.0405)	(0.0086)	(0.0080)
RDint	1.8032***	0.3831**	0.4303**
	(0.4078)	(0.1677)	(0.1800)
ShareGrad	-0.2909	-0.0094	-0.0477
	(0.2535)	(0.0286)	(0.0344)
lnAge	-0.0037	-0.0039	-0.0091
	(0.0660)	(0.0087)	(0.0091)
Techpath	0.3061**	0.0209*	0.0213*
	(0.1231)	(0.0116)	(0.0115)
Pathdep	0.4455	0.0550	0.0626
	(0.5787)	(0.1537)	(0.1256)
Constant	-3.5293***	-0.1114	-0.0716
	(0.5589)	(0.1036)	(0.0893)
16 sector dummies	Yes	Yes	Yes
N	2929	2929	2929
R-sq.		0.07	0.06
Pseudo R-sq.	0.19		

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regression coefficients table: the impact of skills shortage on AI use and the breadth of AI use based on the type of qualification demanded or the type of tasks to be performed.

	(1) Probit *AI (0/1)*	(2) OLS *AIbreadth_area*	(3) OLS *AIbreadth_method*
lnSkillsShort	-0.0928	-0.0388**	-0.0312**
	(0.0784)	(0.0166)	(0.0154)
STEM	-0.0935	-0.0403	-0.0315
	(0.1867)	(0.0285)	(0.0298)
STEM # lnSkillsShort	0.2880***	0.0887***	0.0679***
	(0.1015)	(0.0258)	(0.0248)
Other_academic	-0.1178	-0.0323	-0.0424
	(0.2326)	(0.0324)	(0.0331)
Other_academic # lnSkillsShort	0.2119**	0.0424	0.0551*
	(0.1050)	(0.0306)	(0.0288)
Vocational_IT	0.7372***	0.1672**	0.0935
	(0.2281)	(0.0814)	(0.0639)
Vocational_IT # lnSkillsShort	-0.1904*	-0.0178	0.0049
	(0.1081)	(0.0454)	(0.0397)
Vocational_manuf	0.2088	0.0282	0.0296
	(0.1915)	(0.0224)	(0.0219)
Vocational_manuf # lnSkillsShort	-0.2358**	-0.0352*	-0.0247
	(0.1058)	(0.0194)	(0.0172)
Unskilled_production	-0.2508	-0.0636***	-0.0318
	(0.2371)	(0.0215)	(0.0247)
Unskilled_production # lnSkillsShort	0.2384**	0.0603***	0.0371*
	(0.1208)	(0.0230)	(0.0205)
Unskilled_services	-0.0691	-0.0148	0.0199
	(0.2221)	(0.0298)	(0.0362)
Unskilled_services # lnSkillsShort	0.0678	0.0438	0.0207
	(0.1033)	(0.0284)	(0.0276)
Unskilled_logistics	-0.1625	-0.0382*	-0.0314
	(0.2814)	(0.0221)	(0.0248)
Unskilled_logistics # lnSkillsShort	0.1254	0.0349	0.0315
	(0.1120)	(0.0230)	(0.0229)
lnEmpl	0.1132***	0.0226***	0.0167**
	(0.0436)	(0.0085)	(0.0084)
RDint	1.7688***	0.3778**	0.4213**
	(0.4070)	(0.1665)	(0.1804)
ShareGrad	-0.2950	-0.0172	-0.0479
	(0.2473)	(0.0271)	(0.0342)
lnAge	0.0110	-0.0013	-0.0074
	(0.0689)	(0.0084)	(0.0088)
Techpath	0.3108**	0.0228*	0.0213*
	(0.1231)	(0.0117)	(0.0115)
Pathdep	0.0492	0.0039	0.0097
	(0.6040)	(0.1421)	(0.1152)
Constant	-3.1871***	-0.0622	-0.0292
	(0.5929)	(0.0943)	(0.0824)
N	2929	2929	2929
R-sq.		0.09	0.08
Pseudo R-sq.	0.22		

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regression coefficients table: the impact of skills shortage on areas of applications of AI and methodologies of AI.

	(1) Bivariate Probit		(2) Bivariate Probit	
	Products, services, automation of processes (0/1)	*Interaction with clients, data analytics, others (0/1)*	*Language understanding, image recognition, machine learning (0/1)*	*Knowledge-based system, others (0/1)*
lnSkillsShort	0.1559***	0.1168**	0.1603***	0.0261
	(0.0448)	(0.0547)	(0.0461)	(0.0576)
lnEmpl	0.1891***	0.1680***	0.1630***	0.1735***
	(0.0379)	(0.0379)	(0.0365)	(0.0494)
RDint	1.8743***	1.6672***	1.6060***	2.0162***
	(0.4122)	(0.4611)	(0.4221)	(0.4819)
ShareGrad	-0.0229	-0.1969	-0.1415	-0.2784
	(0.2389)	(0.2520)	(0.2334)	(0.3077)
lnAge	-0.0056	-0.0309	-0.0439	0.0416
	(0.0704)	(0.0717)	(0.0714)	(0.0820)
Techpath	0.4303***	0.0676	0.3368***	0.1692
	(0.1328)	(0.1332)	(0.1236)	(0.1557)
Pathdep	0.4394	0.8071	0.5443	0.3699
	(0.5857)	(0.7274)	(0.6056)	(0.7427)
Constant	-3.9866***	-3.7963***	-3.6316***	-3.9430***
	(0.5415)	(0.6375)	(0.5535)	(0.6667)
16 sector dummies	Yes		Yes	
N	2973		2973	
Rho	0.9428***		0.8954***	
	(0.0189)		(0.0340)	
Log Pseudolikelihood	-389.12		-387.89	
Wald Chi	4887.05		8789.82	

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table 8: Economic sectors (N=2973).

Economic sectors	%
Consumer goods	9.49
Other materials	10.33
Chemicals and pharmaceuticals	2.93
Metals and metal products	7.37
Electronics and electrical equipment	6.26
Machinery and equipment	7.16
Vehicles	1.61
Utilities, waste management, mining	9.62
Wholesale trade	4.10
Transport and logistics services	7.37
Media services	2.19
Software, IT services	4.78
Financial services	2.62
Legal, accounting, consulting, advertising serv.	8.85
Engineering and R&D services	9.38
Other producer services	5.95
	100

Sources: German CIS reference year 2018.

Table 9: First-stage IV 2SLS regression.

	First-Stage IV 2SLS *lnSkillsShort*
lnEmpl_local_bankrupt	-0.0232**
	(0.0116)
lnAverage_vacancies	0.5967***
	(0.0285)
lnEmpl	0.0533***
	(0.0178)
RDint	-0.5819***
	(0.1955)
ShareGrad	-0.1778***
	(0.0678)
lnAge	-0.0991***
	(0.0219)
Techpath	-0.0361
	(0.0307)
Pathdep	0.2047
	(0.4168)
Constant	0.3085
	(0.2919)
16 industry dummies	Yes
R-squared	0.39
Kleibergen-Paap Wald rk F statistic	219.78 (p = 0.00)
N	2973

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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