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ABSTRACT

The Effects of Artificial Intelligence on Jobs: Evidence from an AI Subsidy Program*

Artificial intelligence (AI) is expected to reshape labor markets, yet causal evidence remains scarce. We exploit a novel Swedish subsidy program that encouraged small and mid-sized firms to adopt AI. Using a synthetic difference-in-differences design comparing awarded and non-awarded firms, we find that AI subsidies led to a sustained increase in job postings over five years, but with no statistically detectable change in employment. This pattern reflects hiring signals concentrated in AI occupations and white-collar roles. Our findings align with task-based models of automation, in which AI adoption reconfigures work and spurs demand for new skills, but hiring frictions and the need for complementary investments delay workforce expansion.

JEL Classification: J23, J24, O33

Keywords: Artificial Intelligence, labor markets, hiring, task content, technological change

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1 Introduction

Artificial intelligence (AI) is expected to reshape labor markets across the globe (Eloundou et al., 2024; Hudson, 2024; OECD, 2023; Acemoglu et al., 2022).[1] As with previous general purpose technologies, AI adoption is likely to cause labor market disruptions, but this time changes may unfold over years rather than decades (Deming et al., 2025). AI can displace, reinstate, or complement employees in work tasks, while resulting productivity and compositional effects as well as other AI impacts, for example, on product innovation, may outweigh negative impacts on labor demand (e.g., Acemoglu and Restrepo, 2019; Bessen et al., 2022). How employment ultimately responds remains an empirical question, while popular concerns, justified or not, may have political implications (Borwein et al., 2025; Green et al., 2025).[2] Understanding these effects is key to design effective policy responses (Soroushian et al., 2025; Korinek, 2023; Frank et al., 2019). Despite many recent association-based studies on AI and work, causal estimates at the firm level are absent, leaving open concerns about self-selection of large or high-productivity firms into AI adoption.[3] This paper fills that gap by exploiting quasi-experimental variation in a Swedish AI grant program.

To our knowledge, this is the first study to directly address the challenge of self-selection when estimating the effects of AI adoption on firm outcomes, such as labor demand. We exploit a novel AI subsidy program implemented by the Swedish government innovation agency "Vinnova" between 2019–2020. The program provided financial incentives for small- and mid-sized companies investing in AI for the first time. Since there were no industry restrictions, firms from a broad range of sectors applied. To estimate causal effects, we leverage recent panel data for all applicant firms—whether awarded or rejected—and employ a synthetic difference-in-differences approach. Crucially, our data include near-universal job postings from the Swedish Public Employment Services for 2017–2024, combined with total population register data on employment

[1] AI systems can be broadly defined as algorithms and software that learn from data to perform tasks typically requiring human intelligence (Russel and Norvig, 2010; OECD, 2024).

[2] Recent surveys suggest most individuals ($\geq$ 18 in the USA, $\geq$ 16 in Sweden) expect AI to have a negative net impact on jobs (Gallup, 2024; SOM-institutet, 2025).

[3] AI adopters are larger than other firms, as shown, e.g., for the OECD (Calvino and Fontanelli, 2023), the EU (Hoffreumon et al., 2024), and for individual countries, e.g., the USA (McElheran et al., 2025), and Sweden (SCB, 2020). Recent experiments with generative AI capture effects in controlled, highly specific settings, such as particular coding tasks, and do not necessarily generalize to firms, industries or the overall economy (Humlum and Vestergaard, 2025).

behavior. Leveraging this eight-year panel, we trace vacancy responses up to five years after each firm's grant decision and track head-count outcomes for all applicant firms—awardees and non-awardees alike. Our main estimation strategy has a double robustness property due to the suitable re-weighting of both firms and time periods in a manner that accounts for pre-trends. We also combine the event-study estimates from the synthetic difference-in-differences method for different cohorts using the interaction weighted estimator proposed in Sun and Abraham (2021) to account for heterogeneous treatment effects.

We find that firms awarded AI subsidies exhibit statistically significant and sustained increases in job postings over a five-year period, with no statistically detectable change in employment. Five years post-award, treated firms were 24 percentage points (pp) more likely to post a job vacancy than non-awarded applicants. These increases in postings were larger for AI occupations and white-collar roles, with no corresponding gains in blue-collar positions. Although treated firms also saw somewhat higher hiring and lower separation rates, these differences were not statistically significant. These results are robust to alternative estimation strategies, including traditional difference-in-differences and event-study designs.

Although our quasi-experimental setting—a government subsidy program aimed at spurring AI adoption—does not ensure actual implementation, evidence of meaningful take-up is clear. Awardees increased AI-vacancy postings relative to non-awardees despite the modest maximum grant (500,000 SEK, with a partial firm match). Awardees also increased spending on external AI services, and project reports document real deployments.[4]

We contribute to the literature in several ways. First, we provide affirmative and recent causal evidence of no precise and significant effects of an AI grant on employment levels for small- and mid-sized companies. This is consistent with previous studies that document only weak associations between, for example, exposure to AI (i.e., potential AI use) and overall employment up to 2020, across macroeconomic, industry, state, and firm or establishment levels (e.g., Albanesi et al., 2025; Georgieff and Hyee, 2022; Fossen and Sorgner, 2022; Felten et al., 2019; Engberg et al.,

[4]For example, the company Monitor ERP Systems AB upgraded its planning software with a predictive analytics module that forecasted up to 40 percent of production delays, while Portalplus AB built an AI-driven bus-route scheduler that cut fuel use by 5 percent. See Appendix Table A.4 and Online Appendix D for details and impacts on external AI spending.

2024; Hampole et al., 2025; Acemoglu et al., 2022). However, by combining novel AI subsidy data with granular job advertisement data as well as high-quality register data, we are also able to demonstrate a positive causal effect on overall hiring efforts gradually over time, and in particular for white-collar jobs. This result reconciles previous findings of shifts in skills demanded related to task-based workforce AI exposure, and maintained aggregate employment levels (e.g., Acemoglu et al., 2022; Engberg et al., 2025b). A delayed effect on hiring efforts is also consistent with evidence from surveys of predominantly larger firms' self-reported use of AI, and from inferred investments in AI skills, where, after some time, firm performance may improve, e.g., in terms of sales, or employment (e.g., Aghion et al., 2025; McElheran et al., 2025; Humlum and Vestergaard, 2025; Babina et al., 2024).[5] Finally, while our primary contribution is empirical, we also provide a minimal task content framework, building on Acemoglu and Restrepo (2019), to illustrate how AI adoption, hiring frictions, and skill shortages can jointly generate the observed pattern of increased vacancies with delayed net employment gains.

Second, we add to the burgeoning experimental evidence on the short-term impact of generative AI on individuals' productivity in specific white-collar tasks. Across tasks ranging from coding a website and writing an email to designing a product or conducting legal analysis, studies often—though not always—find that productivity increases, frequently by double-digit percentages (e.g., Peng et al., 2023a,b; Dell'Acqua et al., 2023; Choi et al., 2024). While these studies provide causal evidence of the potential for AI to substitute for or complement individuals in specific cognitive tasks, their external validity in more heterogeneous settings, for more complex tasks, across occupations, and over longer time horizons remains uncertain (Soroushian, 2024; Humlum and Vestergaard, 2025).[6] In our context, AI is broadly defined based on firm-specific needs, and not necessarily limited to adoption of generative AI alone. By leveraging a quasi-experimental setting, we contribute real-world and short- to medium-term findings on the causal effects of an AI grant on small- and medium-sized enterprises, focusing on job impacts for

[5] McElheran et al. (2025) exploit survey responses on AI use for US manufacturing firms ($n = 28,500$, $\bar{x}_{emp} = 172$, where x is employment) in 2021, and other data (2012-2017) using an IV-approach; and Aghion et al. (2025) in France ($n = 868$, $\bar{x}_{emp} = 596$, $\bar{x}_{emp}^{adopters} = 896$) in 2018-2020, and other data 2014-2023, employing a standard DID approach; while Babina et al. (2024) exploit AI investment by US firms ($n = 1,052$) based on employee resumes, in 2010-2018 using long differences.

[6] For less "narrow" evidence, see, e.g., the RCT by Otis et al. (2024) on entrepreneurs in Kenya, the field experiment in Procter & Gamble by Dell'Acqua et al. (2025), and the short-term DiD-study by Teutloff et al. (2025) of labor demand on an online freelancing platform.

a category of firms that accounts for a disproportionately large share of employment and net job creation (Criscuolo et al., 2014; OECD, 2025c). Moving beyond immediate causal effects is also important, as productivity gains from technological innovations have historically required time to materialize, often involving restructuring of business practices and complementary investments (Brynjolfsson et al., 2021).

Third, we contribute to the broader literature on automation technologies and the labor market. Mokyr et al. (2015) provide a historical perspective on technological anxiety, examining whether the present differs such that there is a real risk of substantial technological dislocations. They conclude that it probably does not, although transitions may be painful for some groups or industries. More recently, studies have found mixed evidence on the impact of robots on labor, again suggesting at most moderate disruption due to advanced technologies (e.g., Acemoglu et al., 2020; Koch et al., 2021, 2023). While Deming et al. (2025) document a slow pace of structural labor market change between the 1990s and the mid-2010s, they note a rapidly changing labor market in recent years, suggesting that AI may have begun to cause substantial technological disruption. Using granular and very recent data from a highly digitalized and open economy, we find positive effects of an AI grant on workforce management in terms of hiring efforts, but no statistically significant negative effects on net employment. These results ameliorate concerns about disruptions to employment in the short-to-medium-term. Importantly, the study period spans major advances in machine learning, including the rise of large-scale models and compute use, growing AI adoption during and after the subsidy program, and the early diffusion of generative AI chatbots near the end of the period (Sevilla et al., 2022; SCB, 2024).[7]

The rest of the paper is organized as follows. Section 2 introduces the Vinnova AI subsidy program. Section 3 describes our data for the empirical analysis. Section 4 presents the empirical estimation framework. Section 5 provides the results on the effects of AI on firm hiring efforts and employment. Section 6 concludes. Additional robustness and technical details are provided in a supplementary appendix.

[7]AI use in Sweden rose nearly fivefold between 2019 and 2024, reaching 25 percent of firms with at least 10 employees and making it the second most AI-intensive country in the EU.

2 Background: The Vinnova AI Subsidy Program

The Swedish government innovation agency "Vinnova" initiated a program of AI subsidies for small and medium-sized enterprises (SMEs) in 2019. The goal of the program was to increase the practical competence, strategic ability, and experience of SMEs in AI. The subsidy call defined AI as machines mimicking intelligent human behavior, with a focus on machine learning as the most mature and accessible approach at the time. The call was targeted towards firms that wanted to implement their first AI-related project and wanted to increase their knowledge of and capacity to use AI. The process was competitive, with less than a third of applicants getting funded. Independent experts reviewed the applications, followed by a joint assessment with Vinnova. Final decisions were made by Vinnova, with no appeals possible. Decisions were based on several factors: the project's value for the organization and societal benefits, the competence, credibility, and diversity of the team, and the feasibility of the plan, budget, and approach. Successful applicants demonstrated that projects had good potential for AI use, for instance, through new products, services, or more efficient production processes. It is also worth noting that, as such, there is no explicit mention of the funding decisions being based on any of the outcomes that we focus on in this paper. The evaluation criteria laid out in the call for applications do not mention benefits to workers or employment impacts.[8] While funding could be sought for shorter demonstration projects, including processing existing data or testing AI functions using machine learning, the program was not aimed at research or developing AI methods. In short, the focus was on helping firms launch their first practical AI project, with the goal that long-term changes will follow gradually.

Most projects fit into two broad categories. The first category is to use AI to improve internal processes of the firm. The second includes projects proposing AI-based products, typically either by creating new AI-based software or implementing AI into an existing product.[9] The money received was spent on a wide range of activities. Some firms implemented their projects using external consultants, and others with a mix of internal and external resources. Some projects

[8]See Appendix F for the translated text of the call for applications for one of the funding rounds.

[9]Appendix Figure A.2-Figure A.3 show word clouds for all project descriptions, and by award-status. Appendix Table A.4 contains publicly available examples of projects, e.g., for an image-based process improvement, and for a prediction-based AI product.

mention collaborations with universities, or hiring experts for knowledge dissemination within the firm. Aside from hiring expertise, firms used the grant to buy data or equipment, to develop prototypes, or to send out surveys or arrange customer evaluations.

There were three waves of funding, with application deadlines in May 2019, January 2020, and September 2020. Decisions on whether the applications were granted were taken 2-3 months after the application deadlines, and the projects started shortly after according to timelines submitted by the applicants.[10] Firms could apply for funding in a later wave even if they (successfully or unsuccessfully) applied in an earlier wave. Eligible firms were required to have 3-249 employees and at least SEK 0.5 million in annual net revenue (first wave), 10-499 employees and SEK 5-900 million annual net revenue (second wave) and 10-249 employees and 5-500 million annual net revenue (third wave). In practice, most applicants were small firms, and the upper constraints on size and revenue were likely not binding, because very few firms with more than 100 employees applied in any of the waves.[11] Only Swedish organizations were eligible to apply, though this included foreign companies that had a branch in Sweden.[12]

The maximum award was capped at SEK 500,000 for a single project.[13] The contribution by Vinnova could constitute a maximum of 75 (50) percent of the project's total costs in the first and second (third) wave. The average award amounts were close to the maximum at approximately 470,000 SEK across the three waves.[14]

For approved applicants, a follow-up study of the projects was conducted, in which applicants described their activities and the ultimate outcomes of their projects. At the time of the evaluation, some reported having implemented their projects. Other firms mentioned promising results even if a final product had not yet been launched. Broadly speaking, most firms evaluated their projects as successful, with benefits ranging from having launched a product or process with AI to just having increased AI knowledge of employees.

[10] Figure A.1 shows the timeline of the three funding waves along with the earliest start date and latest end date for awarded projects. We use this information to align the timing of treatment with the outcome data for each firm.

[11] Therefore, we cannot exploit these thresholds for identification.

[12] In the first wave, public-sector entities (e.g., regional and municipal governments) and public enterprises could apply under the same program without size or revenue restrictions; later, they were covered by a separate scheme. We exclude all publicly owned entities and focus on private firms.

[13] This roughly corresponds to 50k US dollars, hardly funding a full-time employee for a year in Sweden.

[14] Appendix Table A.1 shows the number of project applications, awards, and award amounts in each wave. Appendix Table A.2 shows the number of firms for the projects in our sample.

3 Data on AI Grants and Firm Characteristics

We obtained program data from Vinnova for all applications across the three waves of funding. These data contain information on project start and end dates, award status, award amounts, external financing, and short descriptions of projects. Using anonymized firm identifiers for all applicants, we are able to directly match these data to population-wide administrative registers containing information on the universe of Swedish firms (*Företagsdatabasen* and *Företagens ekonomi*), and an established linked employer-employee database (*LISA*) (Ludvigsson et al., 2019). From these sources, we construct our employment outcomes (employment, hiring, and separations). The richness of these data also enables us to compare firms according to different characteristics.

We also use anonymized firm identifiers to merge firms to job vacancy data from the Swedish Public Employment Service through 2024 (Arbetsförmedlingen or AF, hereafter). Job postings data are from the AF recruitment site "Platsbanken", which is the largest recruitment site in Sweden, covering the vast majority of advertised job vacancies in Sweden.[15] From the job postings data we retrieve another outcome variable: the total number of vacancies posted by firms, which constitutes a revealed measure of gross labor demand.

The content of these job ads has also been connected to skill requirement keywords by Hellsten (2024) and Engberg et al. (2025a). This makes it possible to analyze skills requirements that are listed in the advertisement, and in particular to identify job ads that represent recruitment for AI-related positions. We use this to further classify which occupations have the highest share of AI-related job vacancies, and examine effects separately for those occupations. Briefly, our process is as follows. First, we use the universe of all private sector job advertisements on AF and calculate the share of vacancies requiring AI skills for each four-digit occupation category. We then rank occupations by this metric, and go down this list of occupations until 90 percent of all AI vacancies are accounted for.[16] We will refer to these occupations as AI-occupations and the rest of the occupations as non-AI occupations. We also classify vacancies by blue-collar and white-collar

[15]Posting job ads at AF used to be mandatory, but, since 2008, has only remained so for central government establishments. However, the regulatory change has only slightly reduced postings at AF (Cronert, 2019). Posting job ads at AF is free, and ads may be re-posted to other sites, e.g., LinkedIn.

[16]See Appendix Table A.6 for the full list of AI occupations.

occupations and examine effects separately for each.[17]

We define the year of treatment as the year when a firm first made a successful application for an AI grant from Vinnova. Awarded firms in the first application wave are treated from 2019 and firms in the second and third waves are treated from 2020, yielding two cohorts. The vacancy postings and total employment variables are available until 2024, and hiring and separation until 2023.[18] Thus, we can estimate impacts up to five years out for firms in the first wave and four years out for firms in the later waves. Further, we can examine hiring and separation impacts up to four years after treatment for firms in the first wave and three years out for firms in the second and third waves.

We start with 240 firms in our data that applied over the three waves of Vinnova funding. Most firms are private, but since the first wave of funding allowed for public sector applicants 32 of these were public entities. Since public firms were allowed as applicants only in one wave, and these firms are typically much larger (including city and municipality governments or public universities), we drop them from our analysis. We further drop 18 firms to restrict attention only to a balanced sample of firms that appeared in the data for at least three years before the first application, beginning in calendar year 2017. This gives us a sufficient pre-period to assess whether there were differential pre-trends for our treated and control firms. In sum, we track awardees and non-awardees over eight years.

Table 1 presents the descriptive statistics for the 190 firms in the final estimation sample at baseline, which corresponds to one year before an application to Vinnova. Out of the 190 applicant firms, 53 were awarded the AI subsidy by Vinnova in one of the three waves. The other 137 serve as pure controls – firms that also selected into potentially pursuing an AI adoption project. Table 1 shows that awarded firms tended to be larger than firms that were not awarded by firm employment. This is true both for the mean and median employment. We also note that roughly 40 percent of applicant firms were in the information and communication industry and over a third were in law, economics, science and technology industries. A larger share of awarded firms were

[17]We use the International Standard Classification of Occupation (ISCO-08) codes 1-4 for white collar, and 5-9 for blue-collar occupations.

[18]None of the firms disappear completely from the registers during the period we study. We keep firms even if they have zero employees.

in manufacturing (13 versus 5 percent), whereas they tended to be somewhat less concentrated in wholesale & retail (4 versus 10 percent). Our sample is also overwhelmingly urban with over half the applicants belonging to the three largest cities in Sweden (Stockholm, Gothenburg, and Malmö), while awardees were relatively less urban. The bottom panel of Table 1 provides descriptives on our outcomes. The mean number of vacancies posted the year before application was 1.7 for awarded firms and 4.3 for not awarded firms. Based on the AI-occupation classification described above, we find that for awarded (non-awarded) firms, roughly half (a quarter) of the vacancies were in AI related occupations. Since firms frequently post no vacancies in a given year, we also consider whether *any* vacancy was posted. The share of firms with at least one vacancy in the baseline year is about 23 percent for awarded firms and 29 percent for those not awarded. To conclude, awarded firms were somewhat larger, less metropolitan, and posted fewer job vacancies than non-awarded firms.[19]

4 Empirical Framework: Synthetic Difference-in-Differences

Our identification strategy relies on comparing firms that were awarded the subsidy to those that applied for funding but were not awarded. Since a firm could also apply over multiple waves, we consider a firm as "treated" the year in which it gets its first subsidy, either as a sole or joint applicant in a project.

To construct a suitable control group from among those that applied to Vinnova but did not get funded, we use a Synthetic Difference-in-Differences (SDID) approach (Arkhangelsky et al., 2021). The method effectively combines attractive features of the synthetic control and the difference-in-difference methods. Like the synthetic control method, there is reduced reliance on the parallel trends assumption. The method is invariant to additive unit-level shifts like the traditional difference-in-difference method. SDID is a re-weighting scheme that assigns more weight to units that are similar on average to the treated group in terms of pre-treatment outcomes. SDID also assigns more weight to pre-treatment time periods that are on average similar in outcomes to the treated periods. The optimally chosen unit weights, $\hat{\omega}_i^{sdid}$, and the time weights,

[19] Compared to all eligible firms in Sweden, applicants firms were generally somewhat larger, more urban, but less frequently in wholesale and retail, and they posted more AI-job ads (see Appendix Table A.3).

$\hat{\lambda}_t^{sdid}$, are used to calculate the estimand $\hat{\beta}^{sdid}$. This estimand represents the average treatment effect on the treated, as shown in Equation 1.

$$(\hat{\beta}^{sdid}, \hat{\alpha}, \hat{\mu}, \hat{\eta}) = \arg\min_{\mu,\eta,\alpha,\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \alpha - \mu_i - \eta_t - W_{it}\beta)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{1}$$

W_{it} is a binary variable that indicates that a firm i is awarded the subsidy. μ_i and η_t indicate firm and year fixed effects, respectively.[20] Note that the inclusion of firm fixed effects means that all observable and unobservable time-invariant characteristics of firms are effectively controlled for, including the baseline differences shown in Table 1. Our estimator relies on within-firm variation over time. For inference, we rely on bootstrapped standard errors, clustered at the level of the firm.

Further, to assess pre-trends and estimate impacts for each time period after the award of the subsidy, we employ an event-study design. Following the logic outlined in Clarke et al. (2024), for each time period t, we estimate:

$$\left(\bar{Y}_t^{\text{Tr}} - \bar{Y}_t^{\text{Co}}\right) - \left(\bar{Y}_{\text{Baseline}}^{\text{Tr}} - \bar{Y}_{\text{Baseline}}^{\text{Co}}\right) \tag{2}$$

where $\bar{Y}_{\text{baseline}}^{\text{Tr}}$ and $\bar{Y}_{\text{baseline}}^{\text{Co}}$ refer to the baseline means for the treated and (synthetic) control firms. Typically in event studies the baseline year is chosen as the year before the event, but since time periods are weighted optimally in SDID using time weights, the baseline quantity is instead the optimally-weighted pre-treatment aggregate:

$$\bar{Y}_{\text{baseline}}^{\text{Tr}} = \sum_{t=1}^{T_{\text{pre}}} \hat{\lambda}_t^{\text{sdid}} \bar{Y}_t^{\text{Tr}} \tag{3}$$

$$\bar{Y}_{\text{baseline}}^{\text{Co}} = \sum_{t=1}^{T_{\text{pre}}} \hat{\lambda}_t^{\text{sdid}} \bar{Y}_t^{\text{Co}} \tag{4}$$

Since we have a staggered entry design with two cohorts, we combine the event-studies that

[20] When both $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$ are equal to 1, Equation 1 reduces to the standard difference-in-differences method.

are estimated separately for each. As suggested in Clarke et al. (2024) we do this following the procedure outlined in Sun and Abraham (2021), which introduces an interaction weighted estimator to account for treatment effect heterogeneity that such designs could suffer from.[21] We also conduct robustness checks using a standard DID framework and event-studies.[22] This further speaks to the identifying assumption that treated and control firms would trend similarly after treatment, by comparing whether trends were parallel leading up to the application to Vinnova.

We next present results for vacancies, then for employment, hiring, and separations.

5 Results

5.1 Labor demand: Job vacancies

First, we examine two outcomes that capture gross labor demand: whether or not a vacancy was posted (extensive margin) and the number of vacancies posted (intensive margin). In Table 2, we present estimates corresponding to the latest available event-time as well as the ATT estimates from Equation 1. The event-study plots are shown in Figure 1.

The pre-treatment estimates in Figure 1 (a) are all close to zero, which confirms that the SDID weighting scheme was effective.[23] Consistent with a treatment effect, the estimates show an increase in the first year after award. Overall, we find that the probability of posting a vacancy rises for the treated group relative to the (synthetic) control group. While the estimates are a bit noisy, effects are significant five years after the award. Treated firms are 24 pp more likely to post a job vacancy five years after getting the award (significant at the 5 percent level). Panel (b) of Figure 1 considers the number of vacancies posted in a given year. The figure exhibits similar patterns. The estimate five years after the subsidy indicates that a treated firm posts 4.96 more vacancies than a control firm (column 1, panel B of Table 2). The baseline average number of vacancies for a control firm in the year before application was 4.3, and 1.7 for treated firms, so this

[21] See Dench et al. (2024) for a recent application of this approach to the impact of abortion bans in the United States on fertility.

[22] These results are presented in Appendix C.

[23] Note also that standard errors are much smaller leading up the treatment. This is common in SDID designs since the weights are optimized to minimize pre-treatment differences.

effect represents a substantial increase in relative terms.

We further explore impacts separately for vacancies in AI and non-AI occupations. These results are presented in Figure 2, with estimates in panel A and B of Table 2 (columns (2) and (3)). On the extensive margin, we find patterns consistent with a positive impact of the AI subsidy on the likelihood of posting a vacancy for both AI and non-AI occupations (panel (a) and (b) of Figure 2). By year 5, awardees were 19 pp more likely to post AI-role vacancies. For Non-AI vacancies while the estimate of 14.9 pp is not statistically significant, the event-study trends are consistent with a treatment effect, which increases monotonically over time. The patterns are similar for number of vacancies (Figure 2, panel (c) and (d)). The ATT estimates for these outcomes reflect these positive but imprecise effects. Overall, our results indicate a gradual but broad-based expansion in vacancies for both AI and non-AI occupations.

In addition, we investigate any heterogeneous impacts across white and blue collar occupations, with results displayed in panel (e) though (h) of Figure 2, and estimates in the last two columns of panel A and B of Table 2. Five years after the subsidy treated firms are 22.5 percent more likely to post a white-collar vacancy. Estimates for blue-collar vacancies are close to zero and not statistically significant. Along the intensive margin, Figure 2 (h) shows that vacancy postings decrease for blue collar occupations after AI subsidy, but recover (with none of the estimates being significant). For white collar occupations there is a clear and increasing upward pattern in vacancies, which also is statistically significant four and five years after the award. The estimate five years after the subsidy suggests that a treated firm posts 5.4 more white-collar job vacancies than a control firm (column 5 of panel B of Table 2).[24]

5.2 Employment, hiring, and separations

The above results indicate an increase in gross labor demand, but this would translate into a change in employment only if the firm could successfully hire additional workers. Moreover, a major concern with AI adoption is job displacement, and an increase in hiring may also be accompanied by an increase in separations. We therefore examine the net impact of the subsidy on overall firm

[24]We also explore heterogeneous impacts by geography and find that the increase in vacancies was driven by metropolitan areas as opposed to non-metropolitan areas. See Appendix Figure B.6.

employment levels, as well as hiring and separations.

Consider the event-studies in Figure 3 and the estimates in panel C of Table 2. We measure employment impacts up till five years after the subsidy, and hiring and separations outcomes up to four years after. Panel (a) of the figure shows that in the two years after the award, there appears to be no significant expansion or reduction in firms employment that can be attributed to the AI subsidy, as estimates are close to zero, while imprecisely measured.[25] In year three and four we see an uptick in employment levels, even though these estimates are not statistically significant.[26]

Panel (b) of Figure 3 shows that hiring follows an upward trend after the award, rising from year one to year three after the subsidy. While the final estimate is lower, it reflects only the first cohort of applicants and awardees. None of these estimates are statistically significant. Panel (c) shows that separations actually trended downwards after the award, mitigating concerns of an increase in labor turnover through layoffs or quits in response to the AI grant. The last panel of estimates in Table 2 shows that the ATT estimates are not significant for any of the outcomes.[27]

5.3 Discussion

Our event studies document a persistent increase in vacancy postings—especially in white-collar roles—following receipt of the AI grant, yet we find no detectable change in total employment over the ensuing five years.[28] A deliberately minimal task-content extension of Acemoglu and Restrepo (2019) helps rationalize this pattern (Online Appendix E). In our stylized framework, firms combine AI-susceptible routine tasks and human-only tasks. An AI subsidy raises the productivity of routine tasks and, via imperfect substitution, boosts the marginal value of skilled

[25]There is also a modest post-treatment decline in blue-collar and a trivial increase in white-collar employment, with the decline in blue-collar work being only weakly statistically significant in year $\tau = +1$, followed by a gradual recovery, and the one for white-collar not being statistically significant. See Figure B.2 in Online Appendix B.

[26]In Appendix Figure B.3, we examine if employment effects vary by seniority of workers based on years of experience of workers (4 years or fewer, and greater than 4 years). While Brynjolfsson et al. (2025) find that early-career workers experience a significant decline in employment associated with exposure to AI, we find no discernible employment impacts both for less and more experienced workers.

[27]Year-on-year SDID estimates for change in employment ($\Delta Emp_{it} = Emp_{it} - Emp_{i,t-1}$) remain statistically indistinguishable from zero at all horizons (see Appendix Figure B.1). Nevertheless, the ATT estimate for employment of 1.360 implies a rough cost-per-job of SEK 367 k, as the average grant size is close to the maximum (SEK 500 k). This within the range of estimates from typical technology grants (Hirvonen et al., 2025; Criscuolo et al., 2019). Note that the vacancy ATT estimate is much larger, so the cost-per-job could potentially be even lower if more vacancies translated to hiring.

[28]We find no evidence of increased occupational switching among incumbents; see Appendix Figure B.4

labor. This induces firms to post more vacancies for both AI-specific and broader white-collar roles, consistent with U.S. survey evidence (Bonney et al., 2024). However, Sweden's labor market is characterized by severe matching frictions.[29] Recent surveys show that about half of Swedish firms report hiring difficulties, and the OECD notes that labor shortages and long-term unemployment have risen in tandem because low-skilled individuals and many immigrants lack the literacy and qualifications employers demand (Gidehag, 2024; Häkkinen and Wasén, 2025; OECD, 2025b). In this environment, vacancy posting is cheap, but conversion to hires is constrained by skill shortages; the grant therefore manifests as a surge in job ads rather than an immediate increase in head-count. This explanation is also consistent with evidence that complementary investments and task reorganization unfold slowly (Brynjolfsson et al., 2021; McElheran et al., 2025).[30]

That awardees became more likely to post AI-specific vacancies—despite modest grant size and widespread reliance on external AI services—underscores that these vacancy spikes reflect genuine AI engagement rather than mere financing. Surveys show Swedish SMEs source much of their AI capability externally (SCB, 2020, 2023), and merged Statistics Sweden survey data confirm that grant recipients increased spending on external AI services post-award (Online Appendix D). Such a pattern suggests the subsidy first catalyzed external AI adoption, with firms later internalizing skills by attempting to hire AI-competent staff.

Moreover, we find that the grants were not associated with a decline in vacancy postings in Non-AI occupations. By contrast, Acemoglu et al. (2022) show that U.S. establishments whose occupational structure makes them highly susceptible to AI technology subsequently reduce non-AI hiring relative to less-exposed establishments. This divergence likely reflects underlying labor-market conditions: U.S. job openings have exceeded the number of unemployed since about 2021, making it easier for firms in exposed sectors to automate away non-AI roles (BLS, 2025). In Sweden the vacancy-per-unemployed ratio has remained below 0.4 while there are skill shortages, so grant recipients post additional vacancies to augment existing staff but struggle to fill them

[29] There were roughly 155,000 unfilled vacancies in January 2024—up from 125,000 in January 2020—even though unemployment remained around 7–8% (OECD, 2025a).

[30] In supplementary analysis in Appendix B.2, we examine heterogeneous effects by regions with different labor market tightness as measured by filling rates (how often a posted vacancy leads to a hire). Appendix Figure B.5 shows hiring and separations impacts comparing regions characterized by high (above median) and low (below median) labor market tightness. We find that regions where the filling rate was high saw larger increases in hiring (and fewer separations) relative to regions with low filling rates. Further, we find a positive (though not statistically significant) interaction between the treatment effect on employment and the labor market tightness measure.

(OECD, 2025a). This pattern aligns with Nordic evidence that AI is used to augment non-AI roles or introducing more complex tasks (Engberg et al., 2025a; Humlum and Vestergaard, 2025), consistent with a task-reallocation view of automation.

An important threat to external validity is whether Vinnova evaluators systematically favored projects unlikely to automate, which could bias our net-employment effects upward. To investigate, we text-mined all proposals for labor-replacement language. Around half of the awarded projects mention automation, but there was no difference in their likelihood of receiving an award (Appendix Table A.5).[31] A complementary word-frequency comparison of granted versus denied applications also shows no systematic differences (Appendix Figure A.3).

6 Concluding Remarks

We provide a quasi-experimental estimate of how an AI grant shifts firm labor demand and employment. Exploiting a Swedish subsidy awarded in 2019–20 and tracking all applicant SMEs through 2024, we find that awardees are 24 pp more likely to post a vacancy after five years—predominantly in white-collar roles—yet exhibit no detectable change in net employment. A minimal task-content extension of Acemoglu and Restrepo (2019) rationalizes this pattern: AI raises the productivity of routine tasks that are imperfect substitutes for human-only tasks, increasing the marginal value of skilled labor and triggering vacancy creation. In Sweden, however, acute matching frictions—a persistently low vacancy-per-unemployed ratio and widespread recruitment difficulties—limit vacancy-to-hire conversion in the medium run, while complementary investments and task reorganization unfold gradually (Online Appendix E).

Our results differ from U.S. evidence showing that establishments with greater AI exposure (as opposed to observed adoption) reduce non-AI hiring (e.g., Acemoglu et al., 2022), yet align with European evidence of augmentation-oriented adjustments (Aghion et al., 2025; Humlum and Vestergaard, 2025). Taken together, these patterns are consistent with a task-reallocation/augmentation view in which grants stimulate AI engagement and broader

[31] As noted, most projects targeted internal processes or new product features, aligning with surveys that place customer-facing AI and product development at the forefront of Swedish firms' AI use (SCB, 2020).

white-collar hiring attempts, but Swedish skill bottlenecks and slower organizational change mute near-term head-count effects.

Our context—a high-wage flexicurity system with severe skill mismatch and universal register linkages—thus offers medium-run evidence from a setting where firms intend to augment labor but often cannot staff. We encourage comparable quasi-experimental evaluations across settings with different tightness, skills, and digital infrastructure to assess external validity and to guide the design of AI support paired with targeted skill formation.

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Figures and Tables

Table 1: Descriptive Statistics

	Shares (%)	
	Awarded	Not awarded
Firm Size (Employees)		
0-2	6	20
3-9	21	28
10-49	57	36
50-99	8	9
100-499	9	5
$\geq$500	0	1
Mean Number of Employees	34	29
Median Number of Employees	17	10
Industry		
Primary	4	1
Manufacturing	13	5
Utilities	0	0
Construction	0	0
Wholesale & retail	4	10
Transport & storage	0	1
Hotels & restaurants	2	1
Information & communication	40	39
Finance & real estate	0	4
Law/economics/science/tech	36	34
Other services	0	5
Education	0	1
Healthcare	2	0
Municipality type of HQ		
3 largest cities	51	62
Other cities	34	26
Towns	8	9
Rural areas	8	3
	Mean	
	Awarded	Not awarded
Number of Hires	9.2	8.9
Number of Separations	5.9	6.0
Number of occ. switchers	3.4	1.8
Job Ads		
Total job vacancies	1.7	4.3
AI job vacancies	0.8	1.6
White-collar job vacancies	1.0	4.0
Blue-collar job vacancies	0.8	0.3
Share with any vacancies	0.23	0.29
Share with any AI vacancies	0.21	0.18
Share with any non-AI vacancies	0.13	0.20
Share with any white-collar vacancies	0.23	0.28
Share with any blue-collar vacancies	0.06	0.07
Number of firms	53	137

NOTES— This table presents descriptive statistics for firms in the final estimation sample, separately for awarded and non-awarded firms one year before they apply for the Vinnova subsidy.

Table 2: Synthetic Difference-in-Difference Estimates

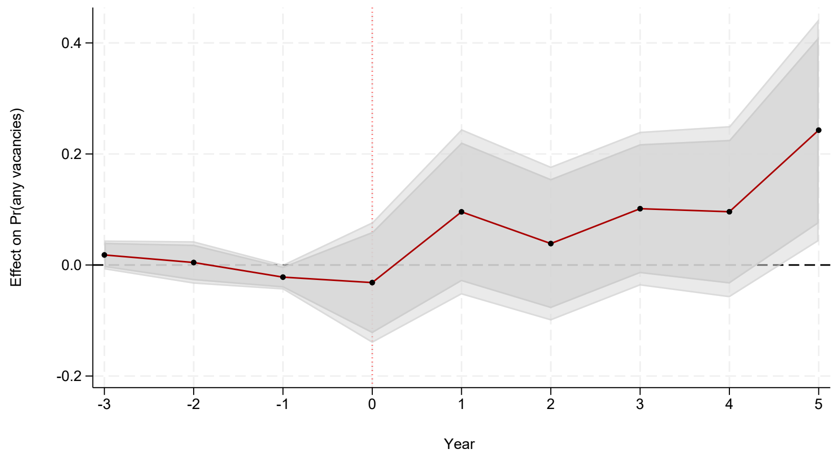
	Panel A: Any Vacancy				
	Overall	AI	Non-AI	White C.	Blue C.
Final event-time estimate	0.243**	0.189**	0.149	0.225**	-0.002
	(0.102)	(0.093)	(0.094)	(0.094)	(0.062)
ATT	0.076	0.061	0.058	0.080	-0.022
	(0.056)	(0.051)	(0.043)	(0.057)	(0.025)
	Panel B: Number of Vacancies				
	Overall	AI	Non-AI	White C.	Blue C.
Final event-time estimate	4.963**	1.166	1.839	5.402**	1.001
	(2.495)	(1.587)	(1.503)	(2.595)	(1.278)
ATT	2.037	0.701	-0.007	2.666*	-0.346
	(1.623)	(0.806)	(0.851)	(1.542)	(0.684)

	Panel C: Employment Outcomes		
	Employment	Hires	Separations
Final event-time estimate	0.995	1.019	-0.826
	(6.281)	(1.610)	(1.537)
ATT	1.360	0.363	0.234
	(3.374)	(1.298)	(0.638)
Number of firms = 190			

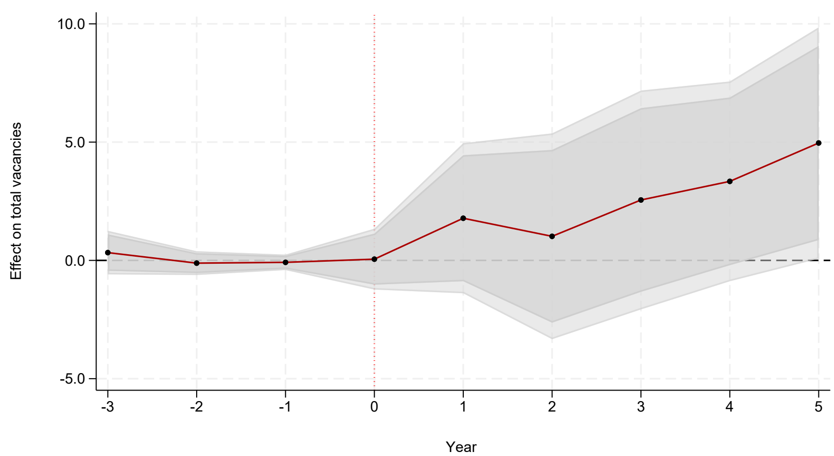
NOTES—Each column corresponds to a different dependent variable. Panel A presents estimates for any vacancy posted (extensive margin) overall, by AI/Non-AI, and White/Blue-collar occupations. Panel B shows the estimates for number of vacancies posted overall, by AI/Non-AI, and White/Blue-collar occupations. Panel C shows estimates for employment levels, hires and separations. Each panel shows the event-study estimate at $\tau = +5$ (or $\tau = +4$ for hires and separations) in the first row and the ATT estimate in the second row. The ATT estimates for vacancies and employment are based on 1,520 firm-year observations. The ATT estimates for Hires and Separations are based on 1,330 firm-year observations). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. *** p≤0.01, ** p≤0.05, * p≤0.1.

Figure 1: Synthetic DID Event-Study Plots for Vacancies

(a) Any Vacancy

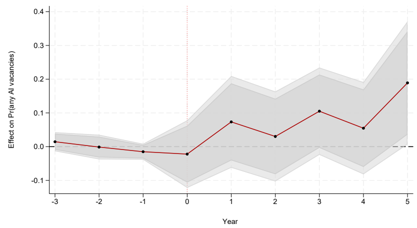


(b) Number of Vacancies

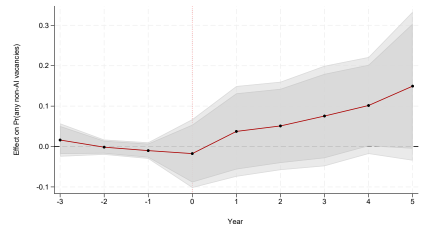


NOTES—This Figure shows the event-study estimates for vacancy outcomes using the synthetic difference-in-differences method (see Equation 2). All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

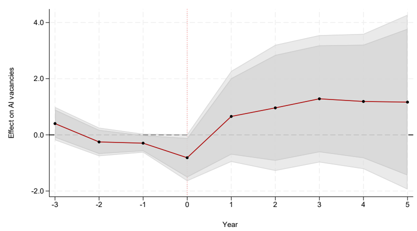
Figure 2: Synthetic DID Event-Study Plots by Occupation Types



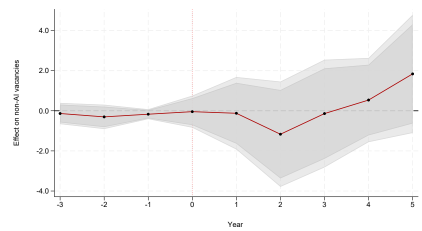
(a) Any Vacancy: AI Occupations



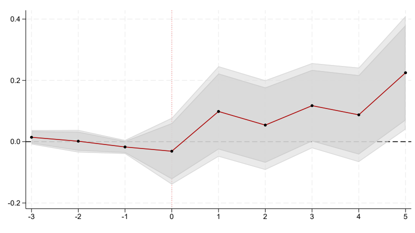
(b) Any Vacancy: Non-AI Occupations



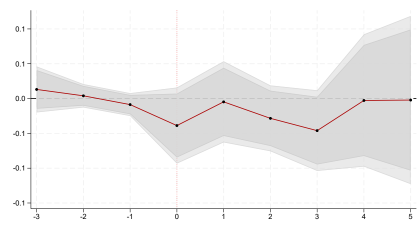
(c) Number of Vacancies: AI Occupations



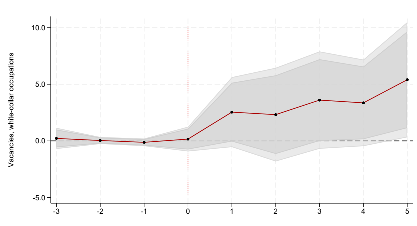
(d) Number of Vacancies: Non-AI Occupations



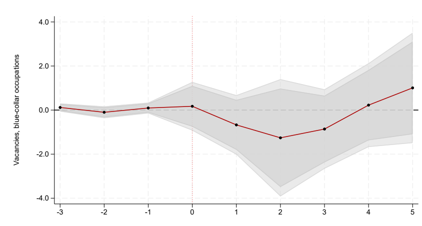
(e) Any Vacancy: White-collar



(f) Any Vacancy: Blue-collar



(g) Number of Vacancies: White-collar

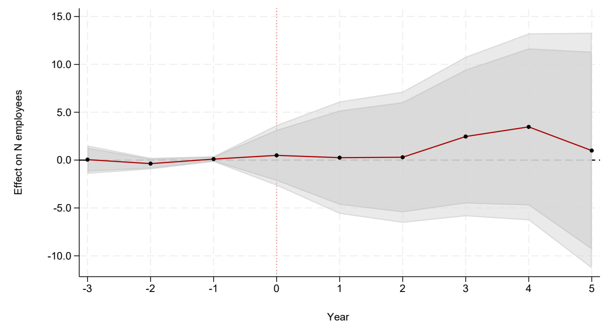


(h) Number of Vacancies: Blue-collar

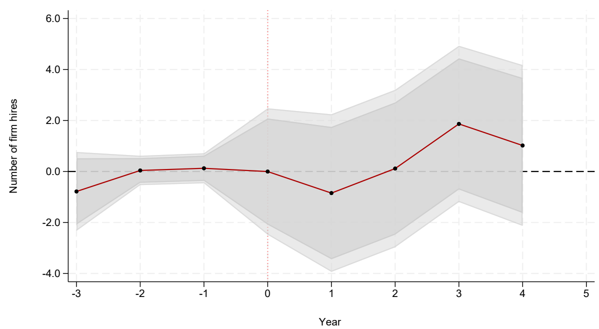
NOTES—This Figure shows the event-study estimates for vacancies in AI, Non-AI, Blue collar, and White collar occupations using the synthetic difference-in-differences method (see Equation 2). All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

Figure 3: Synthetic DID Event-Study Plots for Employment, Hires, and Separations

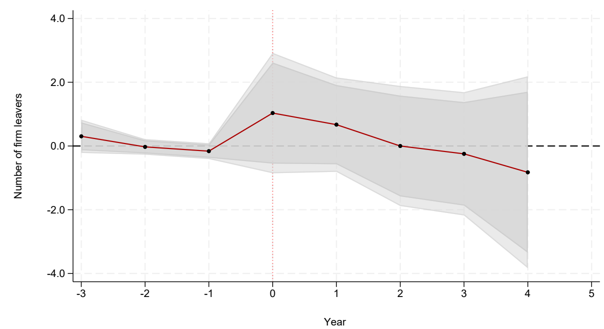
(a) Number of Employees



(b) Number of Hires



(c) Number of Employee Separations



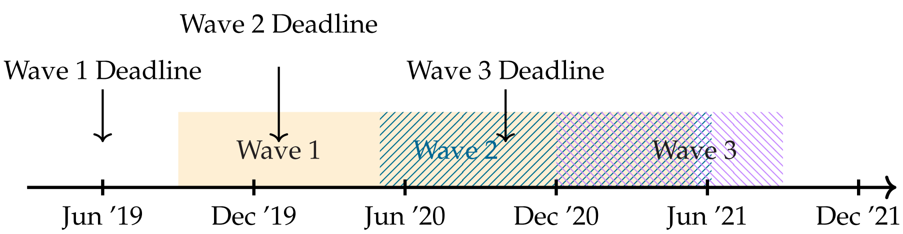
NOTES—This Figure shows the event-study estimates for employment, hiring, and separations using the synthetic difference-in-differences method (see Equation 2). All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4) . We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

Supplemental Online Appendix

A Vinnova AI Subsidy: Further Background

A.1 Descriptive Statistics

Figure A.1: Vinnova AI Project Funding Timeline



NOTES—The shaded regions in the figure represent the time spanned by the earliest start date to the latest end dates for projects in each of the three application waves. The figure also shows the application deadlines for each application wave.

Table A.1: Funding Waves

	Wave 1	Wave 2	Wave 3
Number of Projects	97	48	31
Number of firms	104	51	35
Number of projects granted	26	14	11
Mean grant size (1,000s SEK)	418	333	360

NOTES— The this table shows the number of projects, firms, and awards in each of the three application waves, along with average award amounts in each.

Table A.2: Number of Firms in Projects

Number of firms in project	Number of Firms
1	163
2	24
3	3

NOTES—The this table shows the number firms in our sample that were part of a solo project application, or joint projects (with 2 or more firms in a project).

Table A.3: Comparing all eligible firms to applicants and awardees

	Shares (%)			
	All eligible	Awarded	Not awarded	N appl.
Firm Size (Employees)				
0-2	0	6	20	31
3-9	67	21	28	50
10-49	29	57	36	80
50-99	3	8	9	16
100-499	2	9	5	12
$\geq$500	0	0	1	1
Mean Number of Employees	14	34	29	190
Median Number of Employees	6	17	10	190
Industry				
Primary	3	4	1	3
Manufacturing	10	13	5	14
Utilities	0	0	0	0
Construction	17	0	0	0
Wholesale & retail	20	4	10	16
Transport & storage	6	0	1	1
Hotels & restaurants	10	2	1	2
Information & communication	5	40	39	74
Finance & real estate	3	0	4	4
Law/economics/science/tech	11	36	34	66
Other services	9	0	5	7
Education	3	0	1	2
Healthcare	4	2	0	1
Municipality type of HQ				
3 largest cities	41	51	62	112
Other cities	26	34	26	54
Towns	14	8	9	16
Rural areas	19	8	3	8
	Mean			
	All eligible	Awarded	Not awarded	N appl.
Revenue (million SEK)	29.4	66.6	61.1	190
Job Ads				
Total job vacancies	4.4	1.7	4.3	190
AI job vacancies	0.4	0.8	1.4	190
Share with any vacancies	0.17	0.23	0.29	190
Share with any AI vacancies	0.03	0.21	0.18	190

NOTES—This table presents descriptive statistics for firms in the final estimation sample, separately for awarded and non-awarded firms one year before they apply for the Vinnova subsidy. In addition, the first column of ”All eligible” firms shows similar descriptives for the universe of all private sector firms in Sweden that were technically eligible to apply for Vinnova based on size requirements.

A.2 Text Analysis of Project Descriptions and Examples of Reports

We have studied the free text of project descriptions and reports to describe and analyze the content and reported outcome of all projects, employing keyword matching, word frequencies, and manual reviews of the texts. The relatively few projects makes a more manual review of the projects accessible and reliable. The number of projects may not provide enough data for many unsupervised machine learning methods.

Many of the project descriptions and reports contain sensitive information on firm strategy and operations. To ensure that this kind of information remains confidential, we rigorously check any descriptions or numbers that we report about the projects in the paper. Due to the relatively low number of total projects, we therefore only report patterns that are true for a large number of projects. As a general rule, we report information that is present in at least 10 firms, or being of a nature that cannot be considered confidential.

Below, we present an illustrative overview of awarded projects, indications on the importance of automation in project applications, and visualizations of the main content of projects, overall and by award-status.

In Table A.4, we provide an illustrative overview with two example project summaries, and summaries of the results in two other projects.

Table A.4: Examples of awarded Vinnova projects

Illustrative Example: Optimization of plant cultivation
An agriculture firm describes a project consisting of using image recognition to optimize cultivation of plants. The firm used the services of a consulting company specialized in machine learning to create a model that monitors and predicts the expected size and yield of plants. The firm describes successfully implementing the product into their firm, and is committed to future implementation of AI based solutions. The direct benefit of the project was reduced waste of input-material.

Illustrative Example: Sustainable product recommendations
A technology firm proposes a product aimed at e-commerce firms that creates more sustainable customer recommendations, with the aim of reducing product returns. The firm developed the product using data from one of their customers. The product was then tested in the intended e-commerce environment. The firm benefited from increased worker competencies in AI methods, and is continuing the development of their customer recommendation product.

Project Report: Monitor ERP System AB (Smarter ERP System)
The company updated its enterprise resource planning (ERP) platform with predictive analytics to enhance planning precision and quality. Using historical order data for model training, their classification algorithms were able to predict up to 40 percent of production delays in out-of-sample tests.

Project Report: Portal+ AB (AI for Bus Traffic Planning)
"The project delivered a model to optimize fuel consumption during transportation within the BPL system. The new scheduling approach has achieved a 5 percent reduction in fuel use." This is equivalent to annual savings of approximately 210,000 liters of diesel and 546,900 kg of CO_2 across the 200 buses in the pilot.

NOTES—This table displays examples of awarded Vinnova projects. In the first two examples are abridged texts and translated versions of the self reported project descriptions and evaluations. In the last two examples are summaries or translated excerpts of results from project reports. Full texts (in Swedish) available at: https://www.vinnova.se/e/ai-kompetens-kapacitet-och-formaga/.

In Table A.5, we report the share of project descriptions mentioning automation. Fewer than a third of awardees reference automation-related terms, well short of a majority.

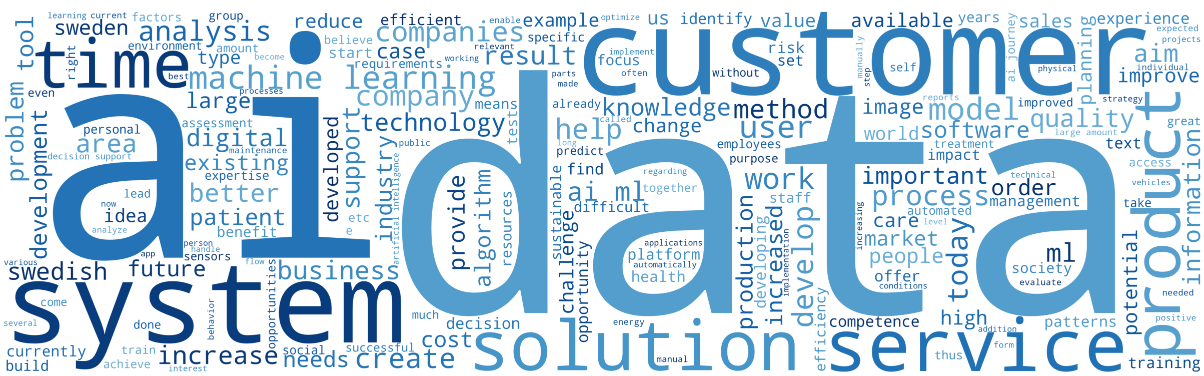
Table A.5: Task replacement in project descriptions

Mentions automation?	Share granted
Yes	27.0%
No	27.1%

NOTES—This table displays the share of project descriptions that mention at least one word that may indicate the displacement of workers. The words used are the stemmed Swedish versions of “automation”, “autonomous”, “work task”, “optimization” and “efficiency” (“automat”, “autonom”, “arbetsuppgift”, “effektiviser”). 41% of applications mention at least one of these words.

In Figure A.2 and Figure A.3, we visualize the main content of project applications, overall and by award-status, respectively.

Figure A.2: Vinnova application text frequent words

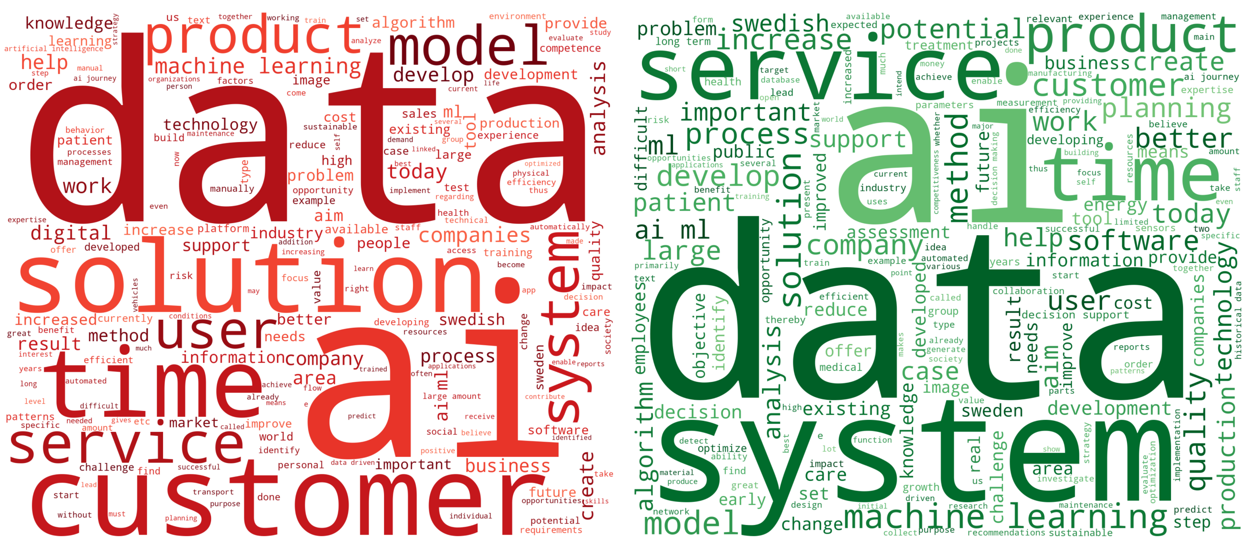


NOTES—This figure displays the most frequent words of project descriptions. Stop words are removed. For data confidentiality, words that appear in fewer than 10 project descriptions are also removed.

Figure A.3: Vinnova application text frequent words, by granted and denied status

Denied

Granted



NOTES—This figure displays the most frequent words of project descriptions. Stop words are removed. For data confidentiality, words that appear in fewer than 10 project descriptions are also removed.

A.3 Classifying AI Occupations

Table A.6: AI occupations

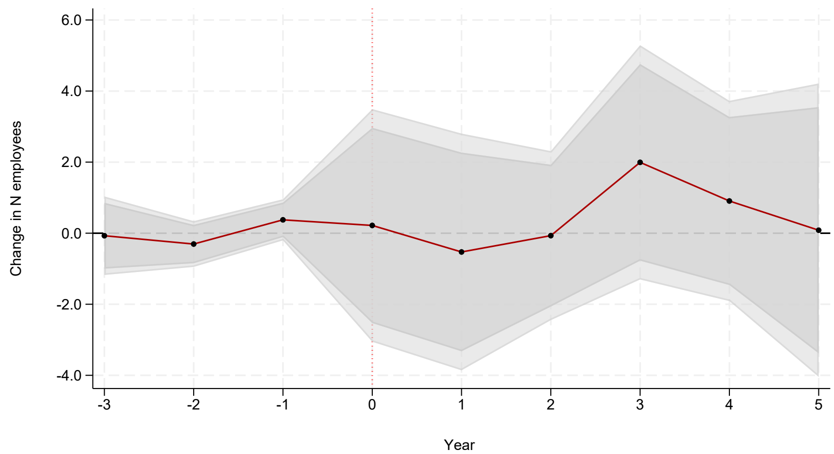
2314 PhD Students	3321 Insurance sellers and insurance advisers
2121 Mathematicians and actuaries	2611 Lawyers
8199 Process control technicians not elsewhere classified	8142 Machine operators, plastic products
2171 Product designers, industrial	2432 Public relations professionals
2311 Professors	2614 Business and company lawyers
2513 Games and digital media developers	2641 Authors and related writers
2519 ICT-specialist professionals not elsewhere classified	2621 Museum curators and related professionals
2512 Software- and system developers	3514 Computer network and systems technicians
7412 Electrical mechanics and fitters	2654 Film, stage and related directors and producers
3211 Medical imaging and therapeutic equipment technicians	2612 Judges
2511 System analysts and ICT-architects	2623 Archaeologists and related professionals
3431 Photographers	8132 Machine operators, chemical and photographic products
2122 Statisticians	134 Unspecified architectural and engineering managers
2313 Research assistants	2615 Management and organisation lawyers
2516 Security specialists (ICT)	7223 Machine-tool operators
3113 Electronics engineering technicians	2173 Game and digital media designers
131 Unspecified information and communications managers	2414 Traders and fund administrators
2514 System testers and test managers	2619 Legal professionals not elsewhere classified
2642 Journalists and related professionals	2413 Financial and investment advisers
2131 Cell and molecular biologists and related professionals	3351 Customs and coast guard officers
2172 Graphic designers	7321 Pre-press technicians
2133 Pharmacologists and related professionals	7531 Tailors and related workers
2149 Engineering professionals not elsewhere classified	4114 Market and sales assistants
2132 Plant and animal biologists	3432 Interior designers and decorators, scenographers
2163 Architects, town and traffic planners	3521 Broadcasting and audio-visual technicians
1111 Legislators	8141 Machine operators, rubber products
125 Unspecified sales and marketing managers	149 Unspecified education managers not elsewhere classified
2515 System administrators	2643 Translators, interpreters and other linguists
3515 Webmasters and web administrators	2146 Engineering professionals in mining-, metallurgy technology
2111 Physicists and astronomers	8189 Machine operators not elsewhere classified, stationary plant and
2622 Librarians and archivists	1120 Directors and chief executives
2143 Engineering professionals in electronics and telecommunications	2415 Economists and macro analyst
2651 Visual artists and related artists	7420 Electronics repairers and telecom electricians
2144 Engineering professionals in mechanical technology	3439 Artistic and cultural associate professionals not elsewhere classified
133 Unspecified research and development managers	7233 Agricultural and industrial machinery mechanics and repairers
2113 Chemists	2223 Anaesthesia nurses
3511 ICT operations technicians	132 Unspecified supply, logistics and transport managers
3513 System administrators	3339 Business services agents not elsewhere classified
2231 Nurses - operation	2145 Engineering professionals in chemical technology
3151 Ships' engineers	4410 Library and filing clerks
2421 Management and organisation analysts	3341 Office supervisors
124 Unspecified communication and public relations managers	2320 Vocational education teachers
3114 Mechanical engineering technicians	3116 Mining and metallurgical technicians
2312 University and higher education lecturers	4116 School assistants
2431 Advertising and marketing professionals	2669 Social work professions not elsewhere classified
2179 Fashion designers and related professionals	

NOTES—This table lists all four digit occupations that we classify as "AI occupations". We first rank each four digit occupation based on the share of job advertisements that use AI keywords (see data section for details). The occupations listed here account for 90 percent of all AI vacancies.

B Supplementary Results

B.1 Change in Employment, White/Blue Collar Employment, Junior/Senior Positions, and Occupational Switching

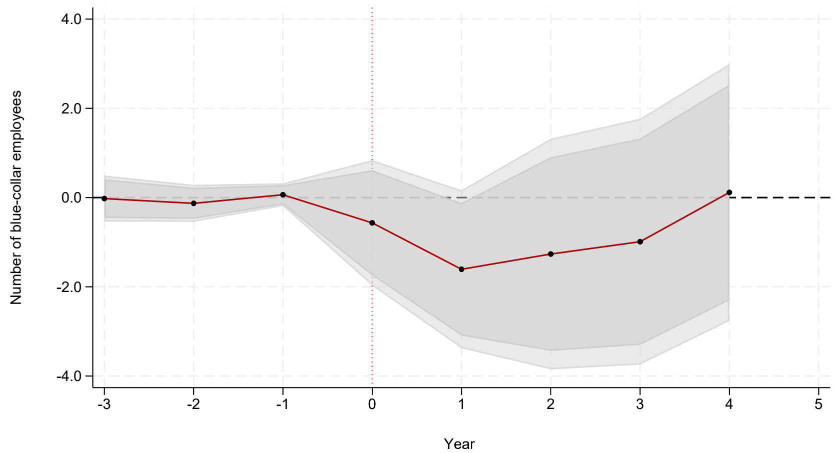
Figure B.1: SDID Event-Study Plots for Change in Employment



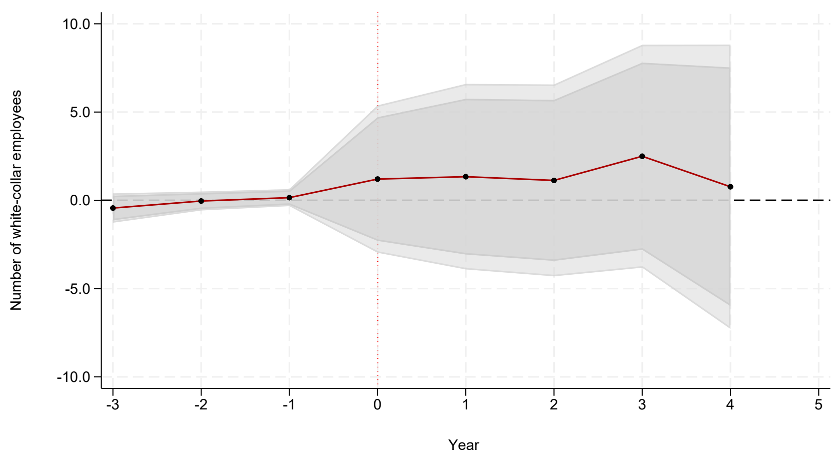
NOTES—This Figure shows the event-study estimates for change in employment using the synthetic difference-in-differences method (see Equation 2). All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

Figure B.2: Synthetic DID Event-Study Plots for White and Blue Collar Employment

(a) Blue-Collar Employment



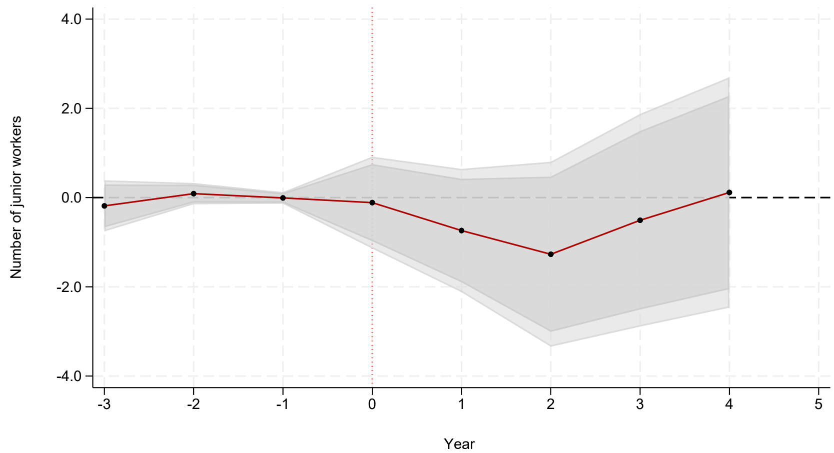
(b) White-Collar Employment



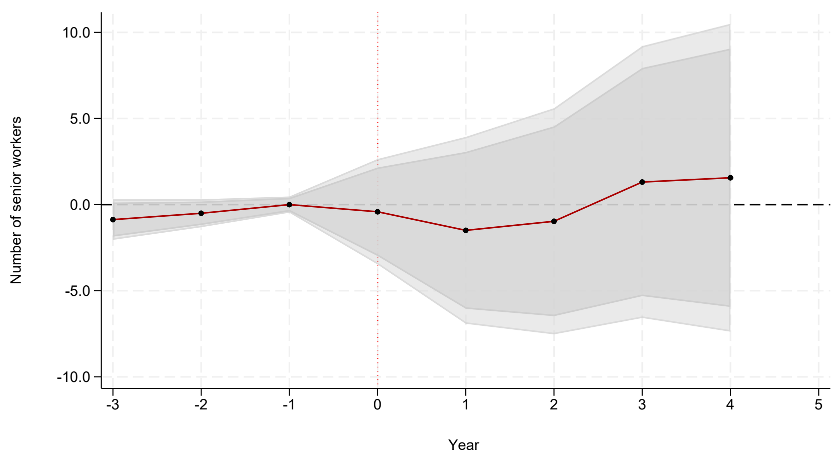
NOTES—This Figure shows the event-study estimates for blue-collar and white-collar employment using the synthetic difference-in-differences method (see Equation 2). All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

Figure B.3: Synthetic DID Event-Study Plots for Employment in Junior and Senior Positions

(a) Employment in Junior Positions

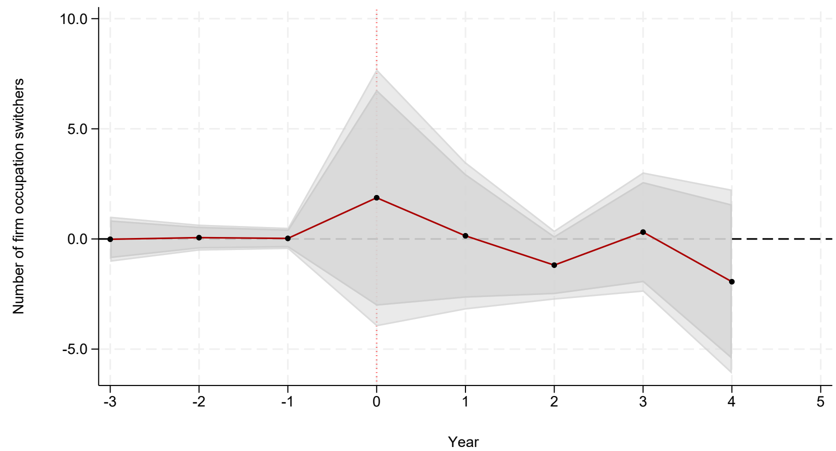


(b) Employment in Senior Positions



NOTES—This Figure shows the event-study estimates for employment in junior (4 years experience or less) and senior positions (greater than 4 years of experience) using the synthetic difference-in-differences method (see Equation 2). All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

Figure B.4: SDID Event-Study Plots for Occupation Switching



NOTES— This Figure shows the event-study estimates for the share of workers in a given firm that switched their occupations, using the synthetic difference-in-differences method (see Equation 2). All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

B.2 Heterogeneity by firm location

Filling rate is a measure of how often a posted vacancy leads to a hire, thereby capturing one dimension of labor market tightness. Since the measure is based on vacancies posted through AF, a simple ratio of hires to posted vacancies may also reflect how intensively firms use AF as a recruitment channel, in addition to underlying tightness. We therefore construct an alternative measure by matching vacancies to the hires that filled them using shared characteristics, following the methodology of Hellsten (2024). Vacancies are matched to relevant hires within a five-month rolling window. A relevant hire is defined as a hire in the same firm, municipality, and 3- or 4-digit ISCO occupational code as the vacancy. Hires that match multiple vacancies are weighted so that their total weight across matched vacancies sums to one.

The raw measure is calculated at the vacancy level, with the filling rate representing the extent to which a vacancy (listing) was filled, as a single listing may correspond to multiple vacancies. The mean filling rate is then computed at the FA-15 region level.[i] In order to capture tightness of relevant workers, we take two steps: first, we exclude all public-sector vacancies. Second, we weight each filling-rate value by the industry distribution of the grant-applicant firms so that, for example, 38% of the filling-rate value of a location is based on the filling rate of firms in the Information & Communication sector; see Table A.3.

Because this measure conditions on relevant hires, it is less sensitive to variation in firms' use of AF as a recruitment channel and better captures tightness for workers in the occupations and industries most relevant to our setting.

[i] A Swedish equivalent of commuting zones.

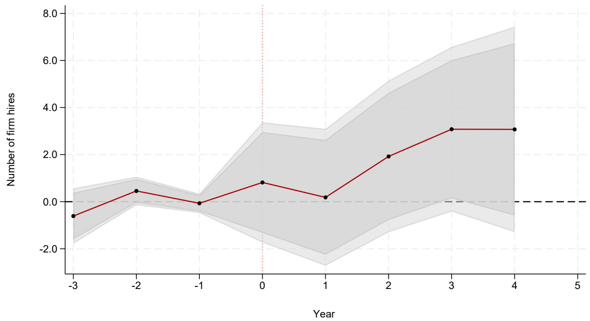
We study heterogeneity in effects on vacancies and hiring across local labor markets, defined as commuting zones. Local filling rate is measured as the average for each commuting zone over 2017–2023.[ii] Firms are assigned to commuting zones based on the location of their headquarters in period $t = -1$.

When we split commuting zones into those with above- and below-median filling rates, we use the median in our sample (rather than for the Swedish economy as a whole). The Stockholm commuting zone contains 80 of the 190 firms in our sample and lies close to the median; we assign it to the above-median group to obtain roughly equal numbers of firms in each category. The above-median group thus consists of Stockholm, Gothenburg (Sweden's second largest commuting zone), and two smaller commuting zones. The below-median group consists of Malmö (the third largest commuting zone) and 22 smaller commuting zones.

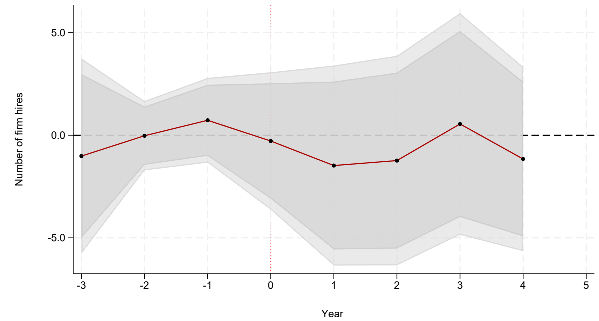
When we analyse heterogeneity between metropolitan and non-metropolitan areas, the metropolitan category consists of the Stockholm, Gothenburg, and Malmö commuting zones, while the non-metropolitan category consists of the remaining 24 smaller commuting zones.

[ii] Filling-rate data for 2024 are unavailable.

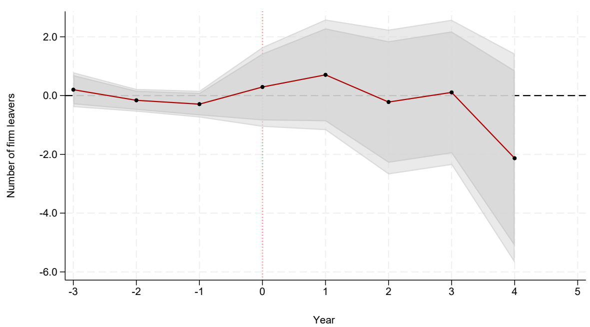
Figure B.5: Synthetic DID Event-Study Plots for Hires and Separations by Labor Market Tightness



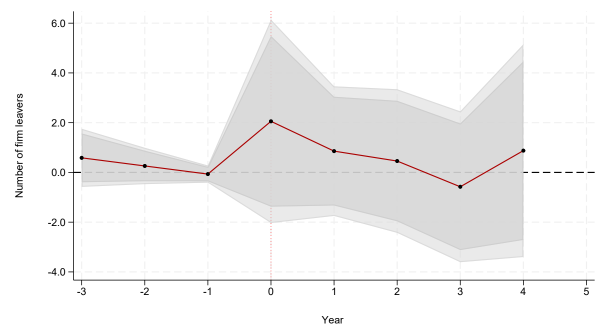
(a) Number of Hires: High Filling Rate



(b) Number of Hires: Low Filling Rate



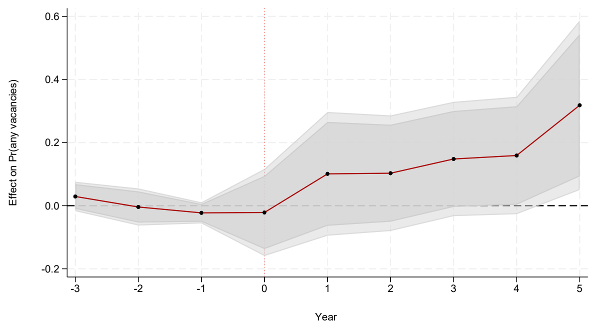
(c) Number of Separations: High Filling Rate



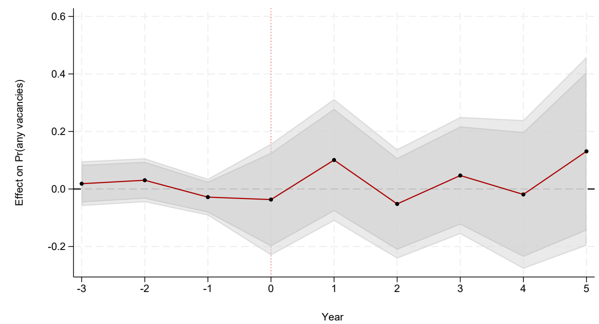
(d) Number of Separations: Low Filling Rate

NOTES—This Figure shows the event-study estimates for hiring and separations using the synthetic difference-in-differences method (see Equation 2), comparing locations with high versus low vacancy filling rates. All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

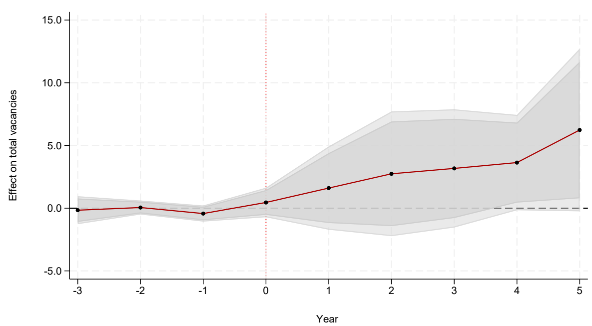
Figure B.6: Synthetic DID Event-Study Plots for Vacancies by Metro and Non-metro areas



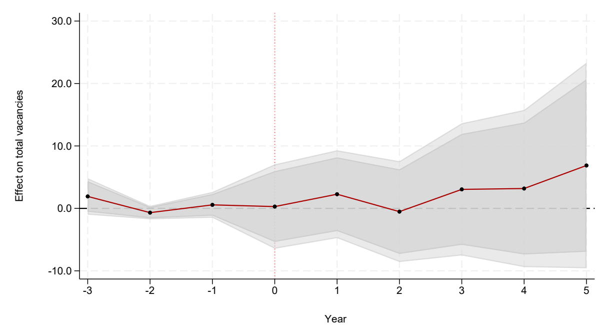
(a) Any Vacancy: Metro Areas



(b) Any Vacancy: Non-metro Areas



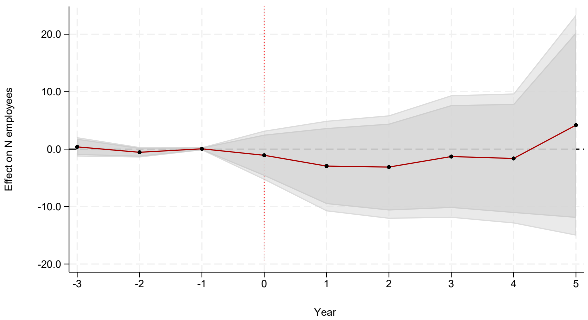
(c) Number of Vacancies: Metro Areas



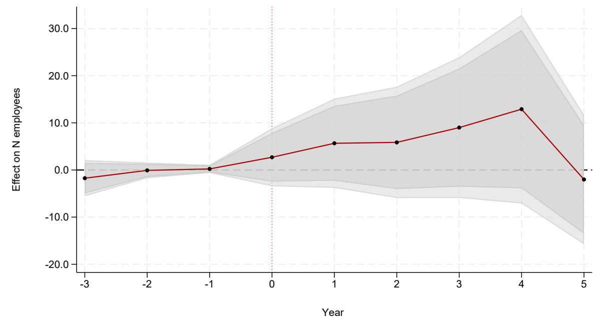
(d) Number of Vacancies: Non-metro Areas

NOTES—This Figure shows the event-study estimates for vacancy outcomes using the synthetic difference-in-differences method (see Equation 2), comparing metropolitan versus non-metropolitan areas. All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

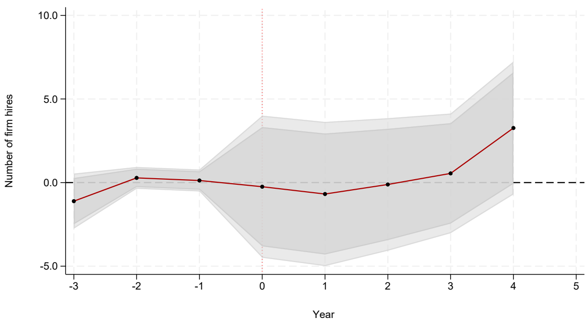
Figure B.7: Synthetic DID Event-Study Plots by Metro and Non-metro areas



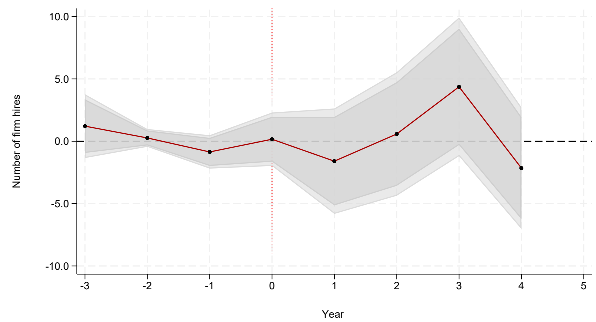
(a) Number of Employees: Metro Areas



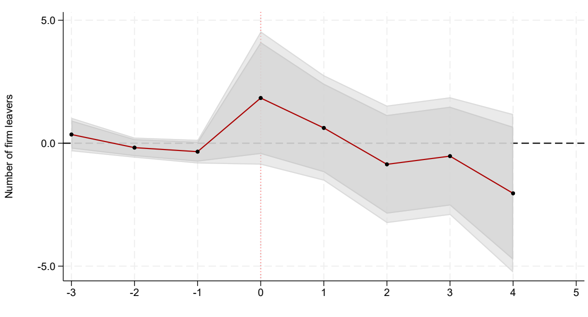
(b) Number of Employees: Non-metro Areas



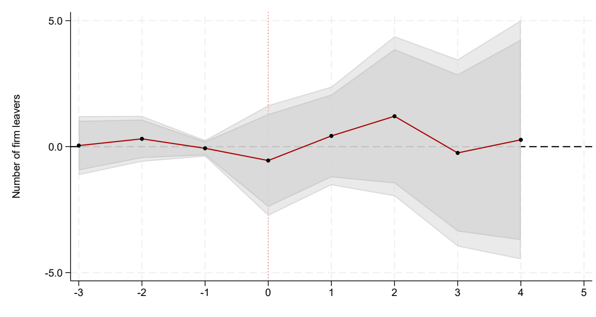
(c) Number of Hires: Metro Areas



(d) Number of Hires: Non-metro Areas



(e) Number of Separations: Metro Areas



(f) Number of Separations: Non-metro Areas

NOTES—This Figure shows the event-study estimates for employment, hiring, and separations using the synthetic difference-in-differences method (see Equation 2), comparing metropolitan versus non-metropolitan areas. All estimates are relative to a baseline pre-treatment aggregate (see Equation 3 and Equation 4). We combine estimates from two cohorts of applicants using Sun and Abraham (2021). Standard errors are bootstrapped, clustered at the level of the firm, and based on 1,000 replications. The shaded regions represent 90% (dark gray) and 95% (light gray) confidence intervals.

C Robustness: Difference-in-Difference Event-Studies

As a robustness check, we present the standard DID event-studies for all outcomes by estimating Equation 5:

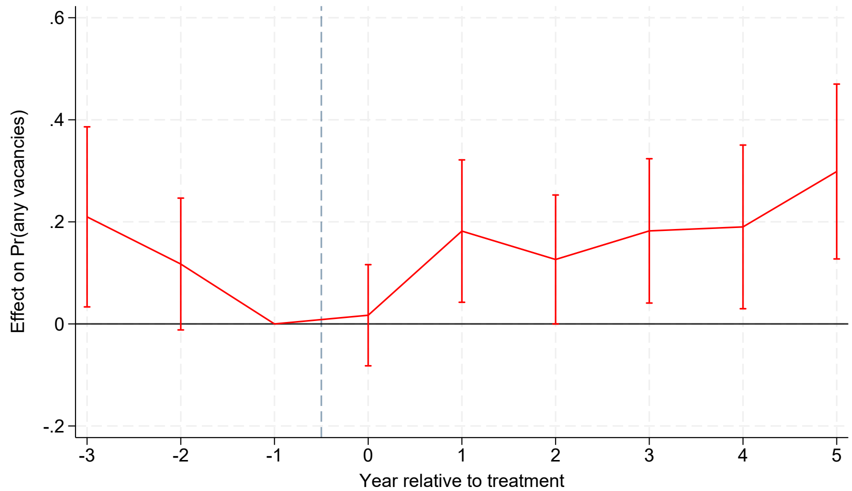
$$Y_{it} = \alpha + \sum_{\tau \in \{-m,...,0,...,n\}} \beta_\tau \cdot D_{i,t-\tau} + \mu_i + \eta_t + \varepsilon_{it} \quad (5)$$

where τ represents event time which starts m years before the award to n years after. $D_{i,t-\tau}$ is an indicator variable for event time τ, which means the award took place τ periods before this observation's calendar time. The coefficients of interest β_τ provide the dynamic effects of the award for $\tau \geq 0$, and provide a falsification check for parallel pre-trends for $\tau < 0$. A key difference relative to the SDID procedure is that all firms and time-periods get equal weights. Estimates are relative to event-year $\tau = -1$, which serves as the omitted year, and standard errors are clustered at the level of the project.

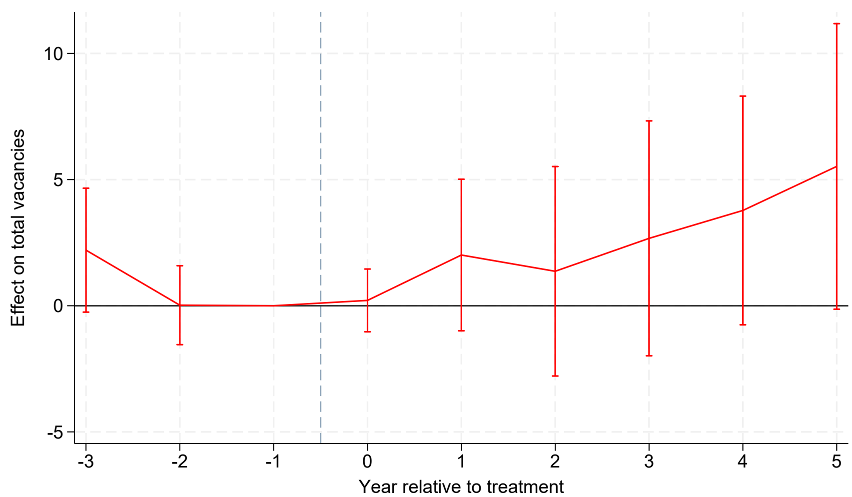
Figures C.1 through C.2 present the standard event study results using estimating Equation 5. These correspond exactly to the three SDID event study figures in the main results. Our qualitative findings are robust to the methodology used. For most outcomes, the estimates in each of the pre-periods are statistically indistinguishable from zero. Note that in this methodology, there is no re-weighting of firms or time-periods in a way that accounts for pre-trends. As such, this result further validates our empirical approach of comparing firms that were awarded to those that applied but were not awarded the subsidy. If anything, the pre-trends for the vacancy variables in Figure C.1 indicate that treated firms were actually on a declining trend before the subsidy award relative to control firms, and that the award reversed this trend. The top panel of Figure C.1 also indicates a more immediate positive impact on any vacancy posted, as significant effects emerge one year after the award. Estimates five years after the subsidy are somewhat higher in magnitude than our main results. Figure C.3 confirms the finding of no significant effects on employment. Figure C.2 also confirms the positive effects for any vacancy posted in both AI and non-AI occupations five years after the subsidy.

Figure C.1: DID Event-Study Plots for Vacancies

(a) Any Vacancy



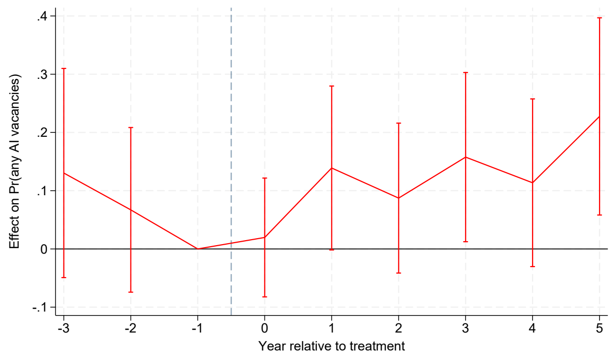
(b) Total Vacancies



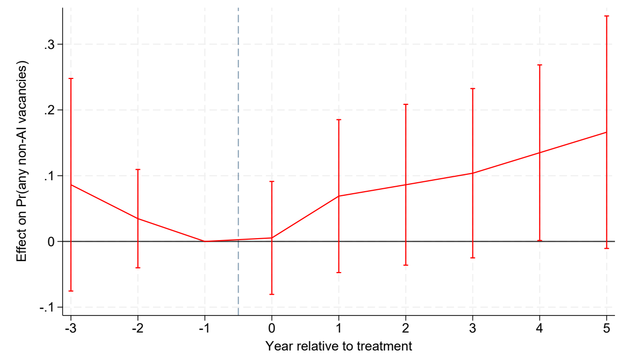
NOTES—This figure shows the event-study estimates for vacancy outcomes, with 95 percent confidence intervals (see Equation 5). Standard errors are clustered at the level of the project. All estimates are relative to one year before application ($\tau = -1$).

Figure C.2: DID Event-Study Plots, AI and Non-AI Occupations

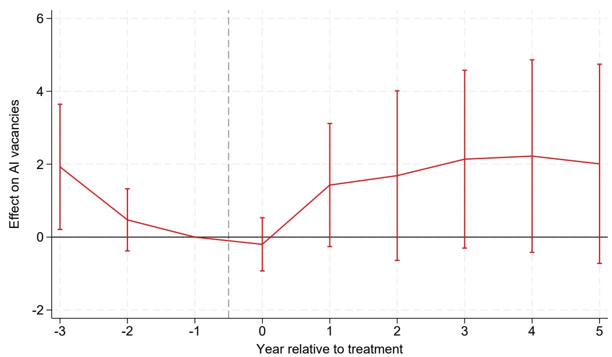
(a) Any Vacancy: AI Occupation



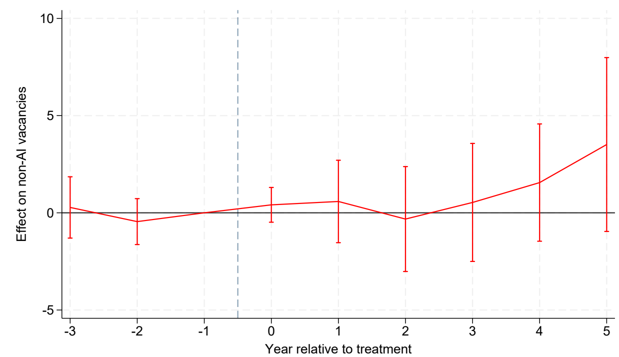
(b) Any Vacancy: Non-AI Occupations



(c) Total Vacancy: AI Occupations



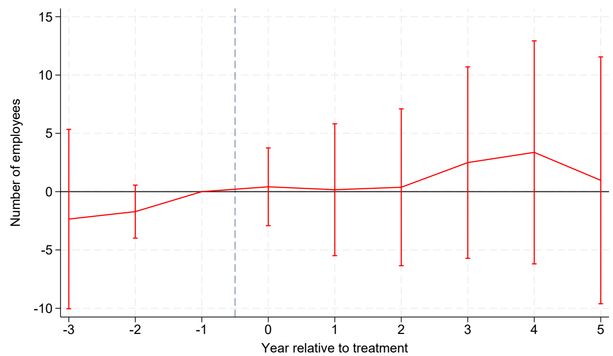
(d) Total Vacancy: Non-AI Occupations



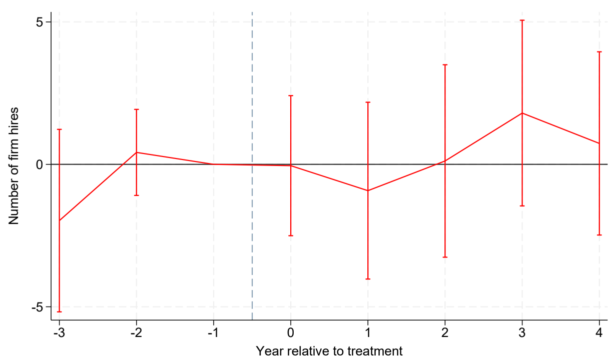
NOTES—This figure shows the event-study estimates for vacancy outcomes, separately for AI and Non-AI occupations, with 95 percent confidence intervals (see Equation 5). Standard errors are clustered at the level of the project. All estimates are relative to one year before application ($\tau = -1$).

Figure C.3: DID Event-Study Plots for Employment, Hires, and Separations

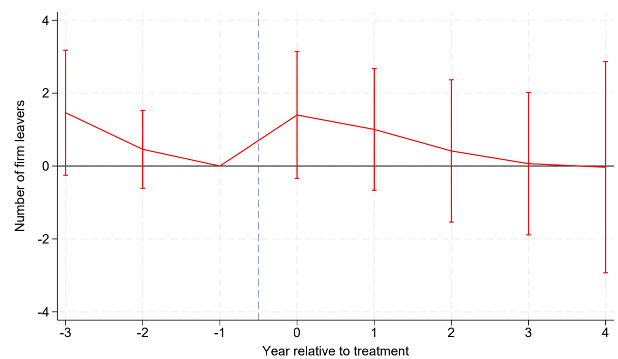
(a) Number of Employees



(b) Number of Hires



(c) Number of Employee Separations



NOTES—This figure shows the event-study estimates for employment, hiring, and separations, with 95 percent confidence intervals (see Equation 5). Standard errors are clustered at the level of the project. All estimates are relative to one year before application ($\tau = -1$).

D Validating AI use

To validate whether receiving the AI grant actually led to the adoption of AI, we leverage data on reported AI expenditure from the Statistics Sweden survey 'ICT usage in enterprises' (SCB, 2020, 2023). The survey covers all firms with ≥ 200 employees, and a stratified sample of smaller firms. In total, it includes 9,082 distinct responding firms across the 2019 and 2021 surveys. Participation in the survey is mandatory, with a response rate exceeding 80%. The overlapping sample of firms in the survey, and firms applying to the grant consist of 44 firms. This naturally limits how much evidence can be inferred from these firms. However, we use this data to gain some insight into the verified use of AI among the firms awarded the grant. Since our primary interest lies in AI adoption, we focus on the extensive margin—that is, whether firms reported any AI-related expenditure. To provide additional context on how AI is utilized, we also consider the extensive margin for the use of externally sourced AI services.

We implement a simple difference-in-differences model with two periods. As the grants were awarded between 2019 and 2021, we treat the 2019 survey wave as the pre-treatment period and the 2021 wave as the post-treatment period. We estimate the following probit regression:

$$\Pr(Y_{it} = 1) = \Phi\left(\beta_0 + \beta_1 \cdot \text{post}_t + \beta_2 \cdot \text{treated}_i + \beta_3 \cdot (\text{post}_t \times \text{treated}_i)\right) \tag{6}$$

where *post* denotes observations in 2021, *treated* denotes firms that were awarded the grant.

Table D.1: AI use in awarded firms

	Unbalanced sample		Balanced sample	
P(AI expenditure)	All	External	All	External
	(1)	(2)	(3)	(4)
Post awarded	0.230	4.630***	-0.033	4.739***
	(0.640)	(0.606)	(0.755)	(0.735)
Awarded	0.493	-4.242***	0.674	-4.446***
	(0.473)	(0.397)	(0.540)	(0.438)
Post	0.024	0.345	0.244	-0.000
	(0.431)	(0.506)	(0.549)	(0.615)
Obs.	68	68	48	48

NOTES—This table displays the result of four probit regressions. In columns (1) and (3), the outcome variable is a dummy variable indicating Any reported AI expenditure. In columns (2) and (4), the outcome variable is indicating any External AI expenditure. The first two columns includes firms that only took part in one of the two survey years, whereas the last two columns exclude these. The main explanatory variable Post awarded denotes treated (awarded grant) firms in 2021. *** p$\leq$0.01, ** p$\leq$0.05, * p$\leq$0.1.

We find that receiving the grant is not significantly associated with overall reported AI use. However, there is a significant and positive relationship with external AI expenditure.

E Stylised Task-Based Framework

To interpret our finding—persistent increases in AI-related vacancies without clear net job gains—we outline a minimal task-based framework. Firms combine a routine task bundle, increasingly performed with subsidized AI, and a human-only task requiring skilled labor. Imperfect substitution, skill shortages, and the need for complementary investments together produce the observed rise in vacancies with flat employment. See Acemoglu and Restrepo (2019) for a formal model of automation and task reallocation, and and Autor et al. (2003) for an empirical framework linking technology to routine and non-routine task demand.

E.1 Setup

We model a representative firm combining two task bundles: a routine task T_R (prone to AI-automation) performed with AI capital A, and a human-only task T_H performed exclusively by labor L_H. Output is:

$$Y \;=\; \Big[(1-\alpha)\,(A\,T_R)^{\rho} \;+\; \alpha\,\big(\lambda(T,R)\,T_H\big)^{\rho}\Big]^{1/\rho}, \quad \rho = 1-\frac{1}{\sigma},\ \sigma<\infty,$$

where $\alpha \in (0,1)$ is the share of human tasks, $\lambda(T,R) \in (0,1]$ is effectiveness from training T and reorganization R, and where an AI grant raises A, boosting the routine bundle's productivity.

E.2 Vacancies and Employment

Firms post V vacancies at cost c_V, filled at rate $\theta(S) \in (0,1)$, with:

$$\theta'(S) < 0, \quad S = \text{share of firms reporting skill shortages.}$$

Employment evolves by $\Delta L_H \;=\; \theta(S)\,V \;-\; \delta\,L_H$, with separation rate $\delta > 0$.

E.3 Predictions and Discussion

The AI subsidy raises A, which increases Y and the marginal product of human-only tasks T_H via the CES structure. This induces firms to post more vacancies V to supply L_H. However, skill shortages limit the conversion of these vacancies into hires: with $\theta(S)$ decreasing in S, a high share of firms reporting recruitment difficulties caps the flow of new employment, keeping ΔL_H close to zero despite elevated vacancy posting. Over time, as complementary investments T and R accumulate and $\lambda(T,R)$ rises, employment gradually adjusts.

This framework captures our empirical pattern of persistent increases in AI-complementary vacancies without clear net employment changes. It nests within the task-content model of Acemoglu and Restrepo (2019), where imperfect substitution ($\sigma < \infty$) and new human-only tasks sustain labor demand in the face of automation. Our extension emphasizes two frictions: skill shortages limiting hires from posted vacancies, and the need for complementary investments for headcount to adjust. Related work includes Autor et al. (2003) on task decomposition and Zeira (1998) on task-level automation and growth.

F Vinnova Call for Applications

In the following pages, we include the full announcement for the most recent application round, translated into English. Among other details, this document describes the goals of this program, eligibility, evaluation criterion, and application procedures. The calls for the first two application rounds was similar. These documents are publicly available.

Start your AI journey! Company

Companies with 10 to 249 employees can apply for a first innovation project in artificial intelligence

A call within Vinnova's investment in artificial intelligence

Contents

Audit history

Date	Amendment
2020-08-10	Clarification in chapter 4.1 on how to calculate the number of employees and net sales.

1 The Offering in brief

This offer is aimed at companies with 10 to 249 employees[1] according to the latest annual report that have a good potential to use artificial intelligence (AI), and who therefore need to increase their knowledge and ability in the area.
The companies are offered funding to carry out their first AI project, based on machine learning, in order to increase both practical competence and strategic capability in AI.

We finance projects with a maximum of SEK 500,000. The grant can amount to a maximum of 50 per cent of the project's total costs.

The following dates apply to the call:
For current information see www.vinnova.se.

Opening date: Last day c	2020-06-09
application: Last decisio	2020-09-30 at 14:00
date:	2020-11-20
Project start at th earliest:	2020-12-01
Project start at the latest:	2020-12-20
Project completion at th latest:	2021-08-31

Contact persons for the call:

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Vilgot Claesson, Programme Director Tel: 08-473 30 56
vilgot.claesson@vinnova.se

[1] To be eligible to apply, the company must also be a limited liability company and have a minimum of SEK 10 million and a maximum of SEK 500 million in turnover. If the company owns or is owned by other companies, these circumstances may also be included, see more information in section 4.1. The company must have an establishment in Sweden. The intended project must be conducted at the Swedish site and the costs of the project must be borne by the site.

Administrative matters:
Jenny Johansson Tel: 08-473 30 13
jenny.johansson@vinnova.se

Vinnova's IT support:
Technical questions about the Stakeholder Portal Tel: 08-473 32 99
helpdesk@vinnova.se

Current information about the call and a link to Vinnova's Stakeholder Portal can be found on www.vinnova.se.

2 What do we want to achieve with the funding?

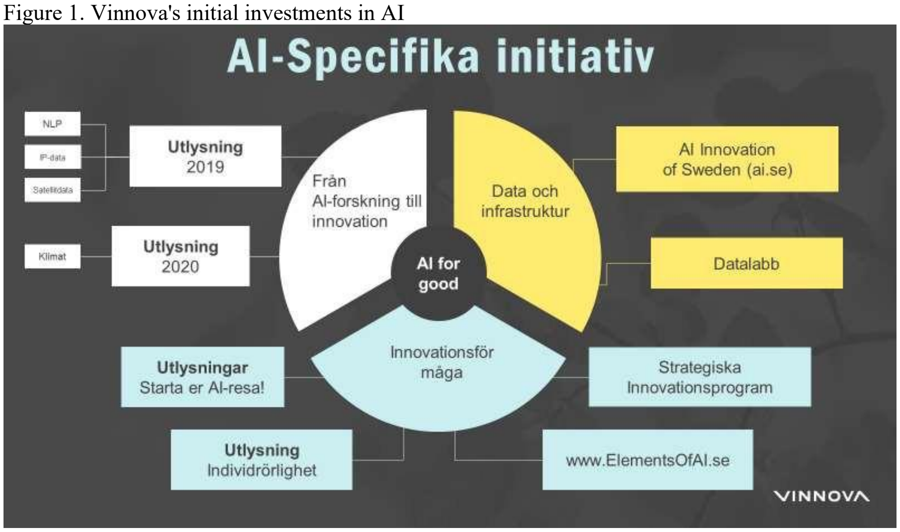
2.1 Background and rationale

Vinnova's vision is to strengthen Sweden as a research and innovation country. Artificial intelligence is already important and will become even more important for Sweden's future innovation and competitiveness in all private and public sectors and industries. AI is therefore a prioritized development area for Vinnova with the aim of strengthening Swedish competitiveness and creating positive societal effects. However, investments in AI cannot be made in isolation but are also dependent on closely related areas such as the development of digital infrastructure and cybersecurity.

The focus of Vinnova's investments in AI is primarily based on the agency's analysis and report on AI2. The report shows that access to data will be crucial for AI development. It also shows that the limited AI expertise of companies and public organisations is hampering development in Sweden. To realise the great potential of AI, Vinnova has initiated several complementary initiatives (see Figure 1).

[2] Artificial intelligence in Swedish business and society, Vinnova report VR 2018:08. https://www.vinnova.se/publikationer/artificiell-intelligens-i-svenskt-naringsliv-och-samhalle/

Figure 1. Vinnova's initial investments in AI



2.2 Artificial intelligence

There is no clear and universally accepted definition of artificial intelligence. In this call, we use AI as the ability of a machine to mimic intelligent human behavior. The ability to learn is something that is behind the great successes that have taken place in the field in recent years, and machine learning (ML) has been central to the large increase in AI applications. As ML is the most developed and often most accessible area to start with, the call is therefore focused on projects within ML.

2.3 Purpose of this call

The main purpose of this initiative is to stimulate Swedish companies in all sectors to get started with and benefit from AI faster. The granted projects will increase the companies' knowledge, skills and capacity in AI while their experiences and insights can be shared with the outside world for increased effect.

In this call, it is therefore possible to receive support for a shorter project based on ML to build knowledge and competence about and internally demonstrate the potential of AI. Although the most important aspect of the call is the development of skills and knowledge, we want the projects to have a long-term potential to lead to a concrete benefit for the organisation, for example in the form of streamlining, insights or improvement/development of products, services and processes.

2.4 A sustainable approach to AI

AI has the potential to significantly change the business of many companies. But it usually does not happen through a single project or an initial change to a product or service. For many, it is about long-term change work with new approaches, for example on how data is collected and used, how the organization works or perhaps even how they view the offers and business models they work with.

To achieve full success with AI in industries where the potential is great, it needs to become a prioritized and ultimately an integrated part of the business. This is a task that cannot be carried out by, for example, a single IT department without a mandate to achieve good collaboration with other departments ~~regarding the collection and management of data.~~ The management needs to support the long-term work, invest in skills development and possibly recruitment, train the different parts of the organization and set realistic interim goals. The team appointed to drive the development must be given the conditions to be able to carry out projects that, step by step, build momentum in the AI initiative. An AI strategy that sees the potential needs to be developed gradually, while it is important not to aim too high in the beginning. It is better to let the first projects be pilot projects, the successful implementation of which may be more important than the size of their ambition. It is this type of journey that we wish to see begin through this call.

3 Gender equality, ethics and Agenda 2030

In order to strengthen and broaden the positive societal effects that can come from innovation, Vinnova has integrated a number of perspectives into its work.

Gender equality is an important dimension in Vinnova's initiatives from two main perspectives. The first perspective is that both women and men take part in the grant on an equal footing, participate in and have influence over the project. The second perspective is that approved projects need to analyze and take a position on whether there are gender equality aspects (sex and/or gender) that are relevant to consider within the problem area of the intended solution and utilization. This may concern questions about possible distortions in data, what consequences the solution will have for different groups or in the choices for the development of algorithms. In this way, we can increase women's participation in and strengthen a process that is of strategic importance to Sweden, while at the same time making innovation work more inclusive and constructive in cases where there is an opportunity to integrate gender equality aspects.[3]

[3] Read more about what our work for gender equal innovation means for those who apply for a grant from us: https:// www.vinnova.se/m/jamstalld-innovation/

Furthermore, AI projects may contain biased results in data, such as lack of representation in data (bias towards a group) but also lack of data (underrepresentation among certain groups). Therefore, it is important to keep ethics, diversity, and gender equality aspects in mind when implementing an AI project. Otherwise, AI risks perpetuating or reinforcing bias. If, for example, the data on which the algorithm is trained consists to a large extent of a group of male individuals, the solution may work less well for the underrepresented group of female individuals.

The 2030 Agenda is a framework for sustainable development that was adopted by the UN member states in 2015. By 2030, the countries will have eradicated poverty and hunger, realised human rights for all, achieved gender equality and created lasting protection for our planet and our natural resources. The 2030 Agenda is a powerful framework that can be used to identify problems and challenges, which in turn can be addressed by a new or already planned/implemented innovation. We want to be able to see an awareness of Agenda 2030 and how the projects fit into these goals. [4]

4 Who is the call aimed at?

The call is aimed at companies (see definition below) that have an idea of how AI based on ML can improve part of their business. The organisation must have made an analysis of its strategic opportunities with AI, see our information on "A sustainable strategy for AI" in section 2.4.

The call is aimed at companies that want to do their **first** practical AI project. Data for processing must be available even before the start of the project.
Vinnova assesses that most applicants will need to engage an external "AI/ML expert", i.e. a project partner such as a consultant, an institute or a university. This is both to be able to carry out the project and to raise the competence in the company's own organization. AI experts can contribute with everything from acting as a sounding board to having a responsibility for the development and processing of data together with their own organization's development managers.
A university, college, or institute can participate as an "AI/ML expert" but cannot be the party that starts their AI journey.

NOTE! The call is thus not aimed at companies that are already working with AI. On the other hand, companies that have the role of "AI/ML expert" and help the main applicant to carry out their first practical AI project should of course have worked with this before.

[4] Read more about Agenda 2030 here: https:// www.globalamalen.se/om-globala-malen/

Grants are only awarded to Swedish limited liability companies. Swedish limited liability companies also mean foreign companies that have a branch or place of business in Sweden. For grant recipient organisations, the costs of the project must be attributable to the Swedish establishment.

4.1 The size of companies that can apply

The applicant company (coordinator) must meet the following requirements according to its most recent annual report , which must be attached to the application:

- The applicant company is registered with the Swedish Companies Registration Office no later than 2017-06-01
- Applicant companies must have at least 10 employees and at least SEK 5 million in net sales.
- Applicant companies must have a maximum of 249 employees and a maximum of SEK 500 million in net sales. This calculation shall be made in accordance with the EU definition of SMEs[5]. If the company owns, or is owned by, at least 25% of other companies, these circumstances need to be taken into account before the company can be considered to meet these requirements for maximum number of employees and maximum net sales.

Other companies and organisations can participate in the project as project partners if they are legal entities.

5 What do we finance?

5.1 Activities for which funding can be applied for

It is possible to apply for funding for a shorter project to evaluate, build knowledge about and internally demonstrate the potential of AI. The project may include, for example, processing existing data, or testing AI functions using Machine Learning (ML). The results from the project should have the potential to contribute to sustainable growth; for example, new and/or improved products and services, better decision support or more resource-efficient production processes. You will also be asked to write a brief report after the project has been completed so that your experiences can benefit the outside world.

However, this call is **not aimed** at projects that:

- are in a very early phase, which aims, for example, to start measuring or looking for data

[5] https:// www.vinnova.se/globalassets/huvudsajt/sok-finansiering/regler-och-villkor/dokument/eu-definition-smf.pdf

- mainly want to develop new methods in AI (focus will be a first practical AI project)
- includes marketing and sales, regular business development (e.g. launch of existing offering in a new market)
- Includes ongoing operation
- Includes investments in equipment/tools
- contains certification or equivalent (e.g. CE marking)
- includes educational initiatives or courses.

5.2 Eligible costs

Our funding is through grants. Grants to organisations carrying out economic activities are subject to State aid rules.[6] The rules govern, among other things, the types of costs and the proportion of them that may be covered by grants. In this call, grants are awarded in accordance with Vinnova's Ordinance SFS 2015:2087 on state aid for research and development and innovation.

In most cases, the rules mean that the company or organisation receives a grant for only part of its eligible costs, or with a limited amount. For this call, grants are expected to be awarded with the support base "Experimental development"[8]. For more information, see the next section.

The following costs are eligible:

- Personnel costs.
- Depreciation cost of instruments, equipment and buildings to the extent that they are used for the implementation of the project.
- Costs for consultancy services and licences to the extent that they arise during the project period and as a direct consequence of the implementation of the project.
- Other direct costs, such as consumables, inputs and travel expenses.
- Indirect costs (overhead) to the extent that the company has them for the project. Surcharges for indirect costs must correspond to actual costs incurred by the company and may amount to a maximum of 30 per cent of the eligible personnel costs.

For a cost to be eligible, it must:

[6] Read more about State aid on our website: https:// www.vinnova.se/sok-finansiering/regler-for-funding /State-aid/. There you will also find our general terms and conditions for grants and a guide to the conditions for eligible costs: https:// www.vinnova.se/sok-finansiering/regler-for-funding /general-conditions/

[7] https:// www.vinnova.se/globalassets/dokument/forordningen-for-statligt-stod-till-forskning-och-utveckling-samt-innovation-2015.pdf

[8] Commission Regulation (EU) No 651/2014, Chapter 1, Article 2, paragraphs 85 and 86.

- Be real and auditable
- be borne by applicant companies
- have arisen during the project period
- be determined in accordance with the company's standard accounting principles and generally accepted accounting principles

The accounting of the project costs must be separate from the company's other transactions. In the document "Guide to Vinnova's terms and conditions on eligible costs" you can see in depth which costs are considered eligible and the principles for how these costs should be calculated.

6 Amount of grant and basis for support

In this call, a maximum of SEK 500,000 can be granted per project. The grant can amount to a maximum of 50 per cent of the project's total costs.

This call uses the Experimental Development Funding Basis under Article 25 of Commission Regulation (EU) No 651/20149.

[9] Read more here: https:// www.vinnova.se/globalassets/huvudsajt/sok-finansiering/regler-och Terms/Documents/gber-inkl-andringen-2017.pdf

7 Prerequisites for us to assess the application

We will only assess applications that meet the following formal requirements:

- According to the latest annual report, the company meets the definition of employees and turnover according to section 4.1
- The application, including the mandatory appendices, meets the requirements under chapter 10 "How to apply"
- All project parties are legal entities
- Organisations applying for grants have a place of business in Sweden (the project activities are carried out at the Swedish site and the costs of the project are borne by the site)
- The amount applied for amounts to a maximum of SEK 500,000 and corresponds to a maximum of 50 per cent of the project's total eligible costs
- The activities for which the company is seeking funding have not begun
- The application must be received by Vinnova no later than 2020-09-30 at 14:00
- Projects may be planned to run until 2021-05-31
- The application is written in English or Swedish.

Once the application period has expired, supplementation of the application can only be made at our request.

8 Assessment of applications received

8.1 What do we assess?

The application is assessed in competition with other applications received and the assessment is based on the electronic application sent to Vinnova via the Stakeholder Portal. Read more about the assessment process on Vinnova's website, https://www.vinnova.se/sok-finansiering/sa-har-gar-det-till/.

The following criteria are important in the assessment. In addition to an individual assessment of each project, Vinnova, in its assessment of which projects are granted, also strives to achieve a certain spread of the approved projects' areas of activity and application. Vinnova takes a positive view of projects with a higher degree of co-financing, i.e. that our contribution represents less than 50% of the project's total costs, but this is not a formal requirement.

Potential

- The long-term potential of the need owner to benefit from AI in their business and products/services
- The potential of the project to raise the competence and ability of the needs owner in a way that is in line with their goals and strategy for AI

- The potential of the project to contribute to the benefit of the need owner and its customers, suppliers, etc
- The project's potential to contribute with positive Swedish societal impacts, such as sustainable growth and increased gender equality

Actors
- The ability and credibility of the project partners to implement the project
- That the company has access to the expertise, partners and networks needed to develop the solution, especially in terms of ML
- That participating organizations have the financial prerequisites to carry out the project
- That the applicant organization starting its AI journey has limited experience with AI
- How well the team (key people) is composed in terms of gender distribution, as well as the distribution of power and influence between women and men

Feasibility
- That the need owner can account for how the learning from the project will take place, for example how knowledge transfer from the AI/ML expert to the need owner is ensured
- That the budget, plan and approach for the implementation of the project are credible and relevant in relation to the project's objectives, for example that personnel costs and other costs are reasonable
- Relevance and long-term perspective in the choice of intended ML methods
- That data for processing is available before the start of the project.
- The project's anchoring in the organization and its AI strategy
- How well ethics and gender equality aspects have been taken into account and integrated into the project plan

8.2 How do we assess?

In view of the principle of equal treatment, only those applications that meet the requirements under section 7 are assessed. Applications received that meet the requirements under section 7 will be assessed according to the above assessment criteria in competition with each other. The applications will be assessed by Vinnova's specially appointed assessors. Applicants may be invited to an interview. Vinnova then makes a decision on funding and announces the decision to all applicants.

9 Decisions and conditions

9.1 About our decisions

The amount of grants granted to each party in the project is stated in the decision. Grants will be awarded with the support of "Experimental Development". The basis for support is stated in the decision and also governs which costs are eligible.

Our decision to grant or reject an application cannot be appealed.

9.2 Conditions for grants awarded

For granted grants, our general terms and conditions for grants apply.[10] The terms and conditions contain, among other things, rules on project agreements, conditions for payment, follow-up, reporting and utilisation of results.

The following special conditions also apply to all those who are awarded a grant under this call:

- The project must be represented by at least one project party at the programme seminars and conferences organised by Vinnova within the programme during the project period. The cost of such participation is eligible.
- In connection with the final report, applicants must submit a brief public description of the project and its implementation so that Vinnova can openly share important experiences and lessons learned that can benefit others.

Supplementary special conditions may be decided for individual projects.

If you do not comply with our terms and conditions, you may be liable to repay. This also applies if you have been granted a grant incorrectly or with too high an amount.

10 How to apply

To apply for a grant, you fill out a web-based form on Vinnova's Stakeholder Portal, which can be accessed via www.vinnova.se. There you can also upload the following mandatory attachments11:

- Project description, maximum nine A4 pages, designed according to the template available on the call's website.

[10] Current terms and conditions can be found on our website, along with help to understand and comply with the terms: https:// www.vinnova.se/sok-finansiering/regler-for-finansiering/allmanna-villkor/
[11] Templates for the appendices can be found on the call's website

- Curriculum vitae (CV), maximum three A4 pages, designed according to the template available on the call's website.
- A copy of the most recently registered annual report.

No other appendices may be included.

Keep in mind that it takes time to make an application. You can start filling in information, save and continue at a later time. When the application is complete, mark it as ready. You can unlock the application and make changes at any time, right up to the application deadline.

Mark the application as ready well in advance of the call closes.

When the call has closed and the application has been registered with Vinnova, a confirmation will be sent out by e-mail to you who are responsible for the user account, the project manager and the signatory/head of department. It may take a few hours for you to receive the email.

Once the application period has expired, supplementation of the application can only be made at our request.

11 Who can read the application?

Applications submitted to us become public documents, but we do not disclose information about an individual's business or operating conditions, inventions and research results if it can be assumed that an individual will suffer harm if the information is disclosed.