Automation and regional employment spillovers

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Introduction and motivation

The effects of automation on employment have in the past decades received great scrutiny in the wake of the increased adoption of industrial robots and artificial intelligence technologies. The effects on employment work mainly through two effects: a displacement effect where automation technologies substitute capital for labor and a productivity effect where labor demand increases. Which effect outweighs the other determines the outcome of employment (Acemoglu & Restrepo, 2019). The outcomes differ, however, depending upon the level of analysis and the type of automation technology (Filippi et al., 2023). For instance, the impact of industrial robots on employment in US local labor markets has been found to be both negative (Acemoglu & Restrepo, 2020) and positive (Sequeira et al., 2021). In contrast, in European regions the outcome has been found to be positive (Klenert et al., 2022). This highlights the importance of considering geography when examining the impact of automation (Wernberg, 2019; Leigh et al., 2020). The choice of automation technology considered is also important since different choices yield different outcomes (Mondolo, 2021). Despite this, few studies have considered the regional dimension of automation, in particular at a subnational level (Boschma, 2023). Various regions within a country exhibit distinct perspectives shaped by their labor forces and industry composition (Wernberg, 2019), Certain areas may be more vulnerable to a displacement effect (Crowley et al., 2021), potentially leading to adverse consequences on local employment in the aftermath of increased automation. The purpose of this paper is to examine the impact of automation on employment in regions at the subnational level.

The purpose of this paper is to examine the impact of automation on employment in regions at a regional level. I consider Sweden and use its municipalities as the spatial unit of choice. The questions are how automation affects a regions' employment growth in the automating manufacturing firms, the non-automating manufacturing firms, and the remaining firms. By analyzing the overarching regional employment growth, the aim is to investigate the specific firms within a region where the impacts of automation, encompassing displacement and productivity effects, become apparent. And more precisely, do these variations vary across different regions?

Contributions in relation to earlier research

Previous research that considers a regional dimension of automation tends to focus on particular automation technologies (such as industrial robots, e.g., Acemoglu & Restrepo, 2020; Klenert et al., 2022) or on total employment effects in an industry or region (Aghion et al., 2023).

Firstly, focusing on a particular automation technology when assessing the impacts of automation risks leaving out valuable information (Mondolo, 2021). Robot-adopting firms tend to be larger and only account for a small subset of the firm population (Acemoglu et al., 2023). But smaller firms also adopt automation technologies, albeit do not rely as much on robotics. In a survey conducted with approximately 300 manufacturing subcontractors, half of the respondents indicated that they have automated roughly 30 per cent of their production processes, while nearly a fifth reported automating around 70 per cent (Sinf, 2023). Studies that rely on for instance the International Federation of Robotics data or import data on industrial robots (Acemoglu & Restrepo, 2020; Humlum, 2021) thus only capture part of the automation in the population of firms they consider.

Secondly, focusing on aggregate employment growth (industry or region) tells one part of the story, but it obscures the changes occurring in the said industry or region. An increase in the number of automating firms may have a positive productive effect on employment in those particular firms (Cortes et al., 2023), but this might also translate into negative displacement effects on employment in non-automating firms via a business-stealing effect (Aghion et al., 2022). Aggregate effects are of interest since they bring suggestive evidence on the net impact of automation technologies on employment. Such as for an example, evidence the country level is inconclusive but tend to point to that automation via robots brings about a net increase in employment (Filippi et al., 2023). But it has also been shown that there is great heterogeneity among subnational regions in terms of susceptibility to the displacement effect of automation (OECD, 2018). An overall positive effect on employment may thus hide the negative impacts on employment in certain regions within the country. Examining the effects of automation from a geographical perspective can shed some light on whether the productivity and displacement effects are more prevalent in the proximate area.

I build upon earlier research and contribute to the literature on the impacts of automation on labor market outcomes in two ways: I use an automation measure that captures a wider range of automation technologies, rather than for instance only industrial robots, and provide a microlevel analysis disentangling their impacts on regional employment growth, by examining the employment outcomes in different sets of firms.

Data and method

I use geocoded employer-employee matched data provided by Statistics Sweden. The data contains firm-, establishment-, and individual-level information, and I use it to construct a balanced panel encompassing 288 municipalities, the spatial unit of choice, for the time period 1997 to 2021. The overall approach of my empirical analysis is to compute the municipality automation rate, use it as the independent variable of interest, and examine its impact on the employment growth in automating firms, non-automating firms, and overall employment growth in the municipality, in a fixed effects framework. I define the automation rate as the number of automating establishments over the total number of establishments in municipality i in year t. This approach borrows from the ecological approach for computing firm start-up rates (Audretsch & Fritsch, 1994). I limit the pool of firms considered for automating or non-automating to firms in manufacturing. Although this narrows down the number of firms I study, manufacturing is the sector whose workers have been hit the hardest by automation in the period I study (Hötte et al., 2023).

To measure automation, I use firms' machinery and equipment investments (machine for short). Machine investments cover a broader range of machines, including industrial robots, leasing of machinery, and computers, which allows for more automation technologies to be covered in the analysis. An immediate downside of this broader measure, as compared to focusing on a particular automation technology, is that I cannot single out the technology that is adopted, nor can I affirm that the machinery and equipment correspond to automation technologies. I include a wider range of technologies at the expense of also including technologies that do not yield automation.

To be certain that such machine investments on the whole translate into automation technologies, I separately regress firms' labor share and labor productivity on machine investments and retrieve an associated negative relationship between labor share and machine investments and an associated positive relationship between labor productivity and machine investments. These associated relationships confirm that machine investments capture automation technologies (Acemoglu et al., 2023; Restrepo, 2023). Hence, I can use machine investments to single out automating firms from non-automating firms. A firm is defined as automating in year *t* and onwards if its cumulative machine investments exceed the mean investments in its 2-digit industry[1] for the study period in *t*. Since this definition is arbitrary, I consider other cut-off values for the sake of robustness. The main results remain the same with these different values.

Preliminary results

My preliminary results indicate that automation rate has an associated positive relationship with employment growth in automating firms, which indicates a productivity effect, an associated negative relationship with non-automating firms, which indicates a displacement effect, and an associated positive relationship with overall employment growth. These findings differ when comparing municipalities with low population density to those with a relatively high population density. The displacement effect on non-automating firms is stronger in population sparse regions, while the effect on overall employment growth is stronger in population dense regions. The findings are tentative but offer suggestive evidence of the point raised that geography needs to be considered when examining the automation impacts on labor market outcomes.

However, endogeneity issues are inherent in my automation rate variable. Automating part of a production process is an active choice made by the firm (Schoenberger, 1989), and there is great heterogeneity in the extent to which firms adopt automation technologies (Dinlersoz & Wolf, 2023). Acemoglu et al. (2023) find that it is mostly large and older firms that invest in advanced automation technologies such as robotics or artificial intelligence. They further argue that the effect of such investments on employment can be interpreted in mainly two ways: either employment casually increases as a result of increased investments in advanced automation technologies, or it boils down

[1] NACE Rev. 1 classification.

to selection, where firms that already were productive with increasing employment invest in automation. The authors favor the second explanation and argue that inherent endogeneity needs to be dealt with. It should, however, be pointed out that the selection argument made by Acemoglu et al. (2023) mainly adheres to larger firms, since those are the ones observed to invest the most in robotics and artificial intelligence, and thus leaves out the perspective of smaller firms that utilize other automation technologies.

Since my study includes a wider range of automation technologies, and thus both small and large automating firms, I need to address the inherent endogeneity in my automation rate variable. In an attempt to circumvent the endogeneity, I consider a shift-share instrumental variable design as outlined by Goldsmith-Pinkman et al. (2020), where I decompose the automation rate. This is work in progress.

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