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How Technology Investments Destroy and Create Manufacturing Jobs: Firm Evidence From Sweden

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ABSTRACT

This study draws on a longitudinal (2000–2020) firm-level panel data set to investigate the relationship between investments in machinery and equipment, and jobs in the Swedish manufacturing sector. It finds a positive link between such investments and job creation in firms. Adding a firm exit indicator also demonstrates that low-investing manufacturing firms are more likely to exit. Relying on a broad investment indicator, the results confirm findings in several recent European firm-level studies that use narrower indicators of technological investments and change. In the conclusion, the study attempts to span a bridge between the literature on technology, machines and jobs coming out of economics and business on the one hand, and the sociology of work on the other, to reflect on the relations between technology and jobs in firms.

1 | Introduction

The developments towards Industry 4.0 (Maresova et al. 2018; Yang and Gu 2021) are likely to intensify the use of advanced production technologies in European manufacturing. Many of these technologies carry substantial labour substitution potential (Antonazzo et al. 2024). The rapid development of new automation technologies have created widespread concerns for the future of manufacturing jobs in high-cost economies (World Economic Forum 2016; Eurofound 2018) and is often seen as an explanation to the decline of manufacturing sector employment in advanced economies. More advanced industrial robots that are informationally interlinked into production systems (Yang and Gu 2021) are expected to bring about a new wave of automation, displacing manufacturing workers and possibly also strengthening already existing tendencies of task-biased technological change (Adermon and Gustavsson 2015). This fear is not completely without reason or unwarranted. Historically, certain types of jobs have been partially or even totally replaced by new machines (Schön 2010).

Recent studies, however, show that investments in, for example, robots may expand employment rather than replace workers at the firm level (Koch et al. 2021; Acemoglu, Lelarge, et al. 2020; Aghion et al. 2020; Domini et al. 2021), offering a less dystopic view of the future of employment in industrialized economies. Several possible explanations have been suggested for the expansion of employment despite firm's investments in 'labour saving' technologies. One of the most common explanations is that of compensatory mechanisms. By investing in technologies, firms may increase productivity, broaden production repertoires, expand markets and increase market shares—thereby sustaining and even creating jobs rather than destroying them (Calvino and Virgillito 2018; Piva and Vivarelli 2018; Dosi et al. 2021). Also, as technologies grow more complex, such investments may shift the demand for workers in manufacturing increasingly towards highly educated ones. Numbers are suggestive—the share of workers in Swedish manufacturing with a university degree has increased from 17% in 2000 to 28% in 2020 (Henning et al. 2025).

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However, recent studies on the topic are limited in at least two ways.

First, studies on the impact of technology on employment have primarily been concerned with the impact of robots (Filippi et al. 2023), which is only one among many types of machines that may have an impact on employment at the firm level. Other types of potentially labour-saving technologies and machines, beyond robots, are neglected. There are many machines beyond robots that facilitate automation and may carry labour substitution potential. Furthermore, robots often require complementary investments in other types of equipment, such as conveyor systems or autonomous trucks. Overemphasizing the impact of single technologies may therefore obscure an understanding of the more general mechanisms involved in shaping jobs and employment at the firm level.

Second, much of the recent research about the link between technologies and employment has been carried out using quantitative research methods, with the associated tendency to generalize findings beyond national contexts without distinguishing between different types of national institutions. The impact of technologies on jobs are by no means deterministic, as they are dependent both on contingencies and context (Hirsch-Kreinsen 2016; Howcroft and Taylor 2023; Snell and Gekara 2023). Extensive employment protection legislation may, for example, disincentivize firms to invest in 'labour saving' technologies due to high costs of terminating jobs. Trade unions and work councils can implement different strategies to deal with technological change (Haipeter 2020; Rego 2022). In Europe, for example, social partners have signed a framework agreement to achieve a successful integration of digital technologies at the workplace, trying to prevent and minimize the risks for both workers and employers (European social partners 2020). Indeed, automation is a growing concern for labour unions (Doellgast and Wagner 2022), as some fear that it will decrease their negotiating power due to declining membership rates in the longer term (Nissim and Simon 2021). Thus, national institutions—such as the strengths and position of labour unions, collective bargaining processes and co-determination—may have important roles to play in influencing the impact of production technologies on employment (Haapanala et al. 2023; Lloyd and Payne 2023). As Filippi et al. (2023) argue, there is a need for further studies of the impact of technologies on employment in countries with very different characteristics.

Drawing upon longitudinal panel data, this article reports on an analysis of the link between investments in technologies and employment in the Swedish manufacturing sector during a 20-year period of decline of Swedish manufacturing employment. Our analysis is guided by the following research questions: Are more jobs created than those that disappear when firms invest in machines and equipment? and (2) How are investments linked to changes in the education level of workers? To answer these questions, we examine the firm-level employment effects of investments in machines and equipment in firms in the Swedish manufacturing sector between 2000 and 2020. Responding to Filippi et al's. (2023) call for further studies of the impact of technologies on employment in countries with very different characteristics, we examine the dynamics involved when manufacturing firms invest in new machines in Sweden: a high wage, internationalized economy with labour market institutions characterized by extensive employment protection and strong labour union influence (Bergström 2019).

The focus on the Swedish manufacturing sector is particularly interesting and relevant for three main reasons.

First, investments in new production technologies have been a central feature of Swedish economic development in the post-war period (Erixon 1996). The post-war 'Swedish labour-market model' (Schön 2010), where relatively high labour costs and a solidaristic wage policy, involving ambitions for equal wage for equal work across firms, independent of firm productivity, created cost pressures that encouraged employers to invest in labour-saving technologies (Schnyder 2012). Although the solidaristic wage policies, that incorporated both elements of promoting rationalization and egalitarianism, has now largely passed into the shadows of history (Lapidus 2015), the high relative costs of labour in Sweden and the need to operate with high levels of value added continues to create strong incentives for automation of manufacturing. In a high-wage sector, firms may have greater incentives to substitute labour with new automating technologies (Lloyd and Payne 2023). However, in high-wage settings, where each employee represents a substantial investment, employers may also be more inclined to treat labour as a long-term asset rather than a short-term cost, which may strengthen the incentive to combine technological investments with efforts to retain and re-skill existing workers rather than displace them.

Second, while part of the general Swedish labour market model, characterized by relatively extensive legislation regarding employment protection, co-determination and trade union rights, the Swedish manufacturing sector also exemplifies a context of strong trade union influence. In 2023, 73% of blue-collar workers and 78% of white-collar employees in manufacturing were members of a trade union (LO 2023), and 95% of all employees in manufacturing were covered by collective agreements in 2024 (Medlingsinstitutet 2025). In the Swedish manufacturing sector, dialogues between unions and employers on matters of digitalization and jobs are commonplace (Rolandsson et al. 2019). Formal rights of workers to be involved in important decision-making processes in the workplace, together with the generally pragmatic stance of Swedish labour unions towards technologies, are all likely to influence how new technologies affect the quantity and quality of jobs in the Swedish manufacturing sector. The Swedish manufacturing sector may therefore exemplify an institutional context that favours firms that deploy employment-enhancing strategies when they invest and adopt new technologies.

Third, compared to other sectors, firms in the Swedish manufacturing sector, being embedded in an open economy highly dependent on international trade, are particularly exposed to global technological competition (Howells 2002), implying that firms are not only pressured to invest in new technologies to keep up with global competition. They are also vulnerable to competitive investments made by firms in other countries. Thus, exploring the link between investment in technology and employment in the Swedish manufacturing sector may

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therefore offer an important contribution to our understanding of the link between technology and employment.

We show that even in a globally interconnected, high-cost economy where investments in machines and equipment are physical embodiments of technological progress (Huggett and Ospina 2001; Shima 2010), such investments do not cause net decreases of jobs at the firm level in the manufacturing sector. We use our firm-level data to show how the loss of employees in manufacturing in general arises from a complex firm-level population dynamic, where firms' investments in machines and equipment help to explain why some manufacturing firms increase their employment stock, while others do not. It is the absence of investments in machines and equipment in lagging firms that correlates with declining employment numbers in firms, rather than large-scale automation initiatives. Furthermore, even if the number of highly educated workers in the Swedish manufacturing sector has increased by 43% since 2000, we find that investments not only are complementary to growth among very highly educated staff but creates demand for manufacturing workers in general.

The article is structured as follows. The next section reviews recent empirical evidence and conceptual issues concerning the relationship between technologies and employment in manufacturing. In the sixth section, we introduce our data set, discuss some measurement issues and account for our empirical strategy. In section seventh, we present the results of our analysis, including robustness checks. We conclude by discussing the contribution of the study and outline some issues for future studies.

2 | Technology, Machines and Employment

Already pioneering economic philosophers, such as Smith, Ricardo, Marx and Keynes raised concerns over the threats posed by machines that embody new superior technologies to the demand for manufacturing labour (Mokyr et al. 2015). Scholars from different ideological positions have repeatedly debated whether the compensatory mechanisms of economies, such as raising demand for labour in other expanding industries or downward pressure on wages, are strong enough to make economies absorb the manufacturing workers supposedly threatened by 'technological unemployment' (Freeman et al. 1982). This debate has continued and accelerated since Frey and Osborne presented a working paper in 2013 (Frey and Osborne 2017; Filippi et al. 2023), which shocked audiences with calculations suggesting that 47% of jobs in the United States are at high risk of being automated (computerized) within a foreseeable future.

The rapid development of new automation technologies have created widespread concerns for the future of manufacturing jobs in high-cost economies (World Economic Forum 2016; Eurofound 2018). More advanced industrial robots that are linked into production systems (Yang and Gu 2021) are expected to bring about a new wave of automation, displacing manufacturing workers and possibly also strengthening already existing tendencies of task-biased technological change (Adermon and Gustavsson 2015), suggesting that investment-employment complementarity effects may weaken, or outright disappear. The recent interest in the impact of technologies on employment has also initiated a formidable explosion of empirical studies exploring the link between technology investment and employment.

Much recent quantitative empirical research has been concerned with the impact of one category of machines—(industrial) robots—on the demand for labour in manufacturing (Hötte et al. 2023). Acemoglu and Restrepo (2020) identify job displacement effects on sector and regional levels from robot penetration in the US manufacturing sector. However, this finding is by no means unchallenged. Leigh et al. (2020) find a positive association between robots and employment during the post-Great Recession period in the United States, and Qin et al. (2022) arrive at similar findings in China. In Europe, Chiacchio et al. (2018) find job displacement from robots in the period 1995−2007 across demographic groups in the regions of six European countries, whereas Graetz and Michaels (2018) identify reductions in low-skill employment shares, but no reduction of total employment, resulting from the implementation of industrial robots among industries in 17 countries between 1993 and 2007. Similarly, no total employment effects resulting from robots can be identified by Dottori (2021), measuring these at the sectoral level in Italian labour markets 1990−2016, but robotization is found to impact the inflow of new workers across sectors. In their study of German labour markets, Dauth et al. (2021) identified no systematic total employment effect of industrial robot use at the individual level 1994–2014 but found job losses in manufacturing. In addition, the authors find an increased risk of individual displacement associated with robots use. In their study of manufacturing in European countries between 1993 and 2017, Klenert et al. (2023), on the other hand, record positive employment effects from robot presence in the economies, and no particular low-skill effects. With long-term data, Antón et al. (2022) bring the aggregate non-firm perspective one step further. Using periodical definitions in their study of robot use in European regional labour markets in the period 1995−2015, they find negative job effects in the early period, but positive effects in the later period.

At the firm level, Koch et al. (2021) find positive job effects from implementation of robots in a sample of Spanish manufacturing firms 1990−2016, complemented by the finding that jobs are lost in firms that do not start using robots. Acemoglu, Lelarge, et al. (2020) also find positive firm-level job effects from robot use in a large sample of French manufacturing firms in the years 2010−2015, but maybe even more importantly, negative effects for firms whose competitors adopt these new production technologies.

Investments in machines may also induce labour effects that go beyond quantitative aspects. Apart from changing net demand, technology investments are likely to shift demand towards a different type of labour in the firm (Autor 2015; Bessen 2019). Thus, investments in technology may not necessarily lead to direct displacement of labour, but changing recruitment patterns of new labour into the investing firms and sectors (Dottori 2021). As Autor et al. (2003) show, technological change may create increased demand for specific types of labour (often highly educated), whose productivity is amplified

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by new technologies. This argument is much in line with a classical capital-skill complementarity effect (Lindquist 2004).

While studies on the impact of robots on jobs at the firm level have made important contributions, they also come with some limitations (see also Aghion et al. 2023). We have no reason to question the validity of various robotization indicators, but we would welcome the use of variables regarding other complementary technology investment measures at the firm level. After all, robots could be assumed to make up only a fraction of investments in machines and equipment which may have employment effects at the firm level. In fact, many robotization studies disregard the very wide range of technologies that could influence jobs in manufacturing firms, for example, complementary investments (such as machines or material feeding systems), which may be just as important in determining the labour displacement potential as robotization itself.

A core feature of machinery and equipment used in the manufacturing sector is that they *embody* and are direct physical expressions of production technologies (Huggett and Ospina 2001; Aghion et al. 2020; Shima 2010)[1]; In the words of Barbieri et al. (2019, 207): '*innovative investment and updated scrapping are the ways how firms introduce more advanced process innovation*'.

A series of European studies do, like this study, prefer to use other measures of embodied technological change (Grazzi et al. 2016; Barbieri et al. 2019; Genz et al. 2021). These studies also focus on the implementation of technologies and the relationship of this process with jobs at the firm level. Given their measure of firms' automation costs, it is perhaps not too surprising that Bessen et al. (2025) identify job displacement effects among a large sample of Dutch firms in all private nonfinancial industries 2000–2016. In contrast, in a study of a sample of French and Italian manufacturing firms, Grazzi et al. (2016) find a positive employment effect of embodied technological change. Barbieri et al. (2019) measure embodied technological change as innovative expenditures devoted to the implementation of new machinery, equipment and software in a sample of Italian firms for the period 1998–2010 but find no significant employment effects. Genz et al. (2021) show how investments in new digital technologies have insignificant employment stability effects in manufacturing, and positive effects for service providers, in a sample of German firms and workers.

Overall, the inconsistent findings from these studies make it hard to provide any joint solid evidence that proposed labour-saving technologies, in the end, save (net) labour (Squicciarini and Staccioli 2022). It is also impossible to directly compare the findings—they originate from different definitions of production technology and machines, different samples, different time periods and from different institutional settings. However, two recent studies use indicators of embodied production technologies that are very close to the way we treat the issue, as also described below. Aghion et al. (2020) measured automation technologies by balance sheet values of industrial equipment and the usage of electro-motive power on French manufacturing plants and firms in 1994–2015 and find positive effects of automation on the number of jobs. Domini et al. (2021) find positive job effects when they investigate French manufacturing firms 2002–2015 by studying capital goods that embed automation technologies.

In sum, while the literature overall points in different directions, recent empirical studies using European data tend to emphasize a positive investment-job link: more jobs are created where investments in new machines and production technologies occur. In the next section, we discuss how the link between investments in machinery and job creation may be explained.

3 | Conceptual Considerations

From a theoretical perspective, firm investments in machinery and equipment may correlate with employment changes in various ways. The most intuitive mechanism is that of complementarity. An increasing number of machines would require employers to employ more workers to operate them. Calvino and Virgillito (2018) go further and show how positive complementarity between technology and jobs may arise at the firm level through a decreasing price effect. According to this proposition, firms that adopt new production technologies are likely to reduce production costs and increase productivity, which allows them to compete with lower prices (see also Acemoglu, Lelarge, et al. 2020). Subsequently, demand for their products increases, leading to employment growth in the firm that can compensate for the initial job losses (Piva and Vivarelli 2018). In addition, a reinvestment effect could arise from the fact that new profits generated are used for new investments, which expands production capacity and further amplifies labour demand (Dosi et al. 2021).

A growing body of studies have developed alternative explanations to the positive employment effects of technological investments at the firm level (Dachs et al. 2017). Drawing upon Schumpeterian economics, we can expect that entrepreneurs coordinate investments to specialize in exploiting new untried market opportunities, and even to collect entrepreneurial rents rather than to increase productivity by reducing costs (Alvarez 2007). From such a perspective, firms are not primarily created to reduce transaction costs and not only to draw on economies of scale—they are created to generate economic value where the search for entrepreneurial rents determines if investments are made or not (Alvarez 2007). In such cases, investments in machines and equipment at the firm level are intertwined with the introduction of new products and establishing new varieties of production (Dosi et al. 2021). Yet, new products may cannibalize sales of old products, resulting in ambiguous net employment effects at the firm level (Calvino and Virgillito 2018).

However, many of these ideas give a very mechanical impression of the link between technology investments and job growth in firms. Technologies, and indeed machines and equipment at large, may be adopted for different purposes, and may not always result in the intended effects (Edwards and Ramirez 2016). Furthermore, the dynamics between firm-job growth and investments in machines in the manufacturing sector need to be interpreted in their specific economic and institutional contexts (Howcroft and Taylor 2023). Labour market institutions, such as collective agreements and trade

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unions, may influence the incidence of technology investments and the impact of such investments in the workplace.

Also, when firms are exposed to technological competition (Howells 2002) they may deploy different response strategies. Firms may, (1) accelerate investment in the old technology in response to the threat from the new, what Howells (2002) calls the sailing ship effect, (2) they may decide to switch to the new technology and (3) they may decide to exit the market, withdrawing their activities and leaving the market to other producers (Schiavone 2011). Dependent on which strategy firms use, the employment effects of technology investments may be different. Most importantly, it means that the employment effects from technology investments may occur in other firms than in the firms that do invest (Aghion et al. 2023). Consider, for example, if firm A invests in a new machine contributing to increased efficiency in the production process and employment growth, leading firm B to exit from the market due to limited ability to finance investments in similar technologies, lack of skills or other competitive disadvantages. Indeed, increasing market shares for investing firms may come at the expense of less efficient competitors (Dosi and Mohnen 2019). If qualified labour is scarce, expansion and increased productivity in investing firms serve to raise factor prices to levels where less productive firms and sectors are unable to carry costs, or where they compete with inferior products. Innovators may outcompete or erode market shares of non-innovators via such a 'business-stealing' effect, as old generations of products or production methods become obsolete (Dachs et al. 2017).

Moreover, modern manufacturing firms in high-cost economies, such as Sweden, are embedded in global production networks (Coe 2021), within which firms are exposed to cost and quality pressures from competing firms in other countries (Howells 2002). Manufacturing firms faced with global competitive pressures may decide to invest in new machines in line with the technological frontier. They may also decide to move production to locations with lower labour costs (Schmeisser 2013). They may also decide to terminate production and exit the market. In other words, the employment effects of technological investments may not only be distributed to different firms, but they may also take place in other geographical areas.

Thus, the employment outcomes of investment decisions needs to be understood in relation to the institutional context, the structures that organize conversations around technologies, jobs and competition, among unions, employer's representatives and government (Rolandsson et al. 2019). As a result, the net firm growth consequences of machines are not empirically straightforward but will vary with the strategic intentions and specificities of individual firms, their resources, business models and established practices, institutions and labour relations (Snell and Gekara 2023).

In the next section, we will explain how we study the link between technology investments and employment in the context of the Swedish manufacturing sector in the period after 2000, approaching our two research questions with a broad investment indicator.

3.1 | Data, Measurement Issues and Empirical Strategy

For our empirical enquiries, we use a firm-level data set compiled by Statistics Sweden (SCB) that covers all manufacturing firms[2] operating in Sweden 2000−2020, with annual observations on a range of different firm-level variables, including industry affiliations, employment, investments and some financial information. The selection of this particular period of analysis is pragmatic. While we would like to use as recent data possible, we would also like to rely on a richer data set than one or a very limited number of cross-sections. The time series starting in 2000 gives a desired comparability in the classification schemes and variable definitions, and rich variations in economic growth. We use year fixed effects in all relevant regressions to control for, for example, general declines in economic activity during the financial crisis or the Covid-19 pandemic.

We chose to address the relationship between investments in machines and equipment on one hand, and firm employment and turnover on the other, within a firm growth econometric framework. As a baseline, it has long been established that past firm size and age are core determinants of firm growth (Evans 1987). Our data does not record firm age, but it does give different size measures across years. We take our point of departure in the firm growth equations inspired by the strategies implemented by Coad et al. (2016), which are designed to investigate the firm growth effects of R&D investments:

$$y_{f,t} = \alpha_1 + \alpha_2\, y_{f,t-1} + \alpha_3 InvM_{f,t-1} + \alpha_4 Controls_{f,t-1} + u_f + \delta_t + \varepsilon_{f,t} \quad (1)$$

t are the years, while the term u_f refers to firm-specific fixed effects, δ_t refers to year fixed effects and $\varepsilon_{f,t}$ refers to the error term.

Our dependent variables $y_{f,t}$ are: (1) employment in a firm f at time t, (2) employment for highly educated employees in firm f at time t and (3) turnover in firm f at time t. As highly educated workers, we count those with a tertiary education. On the right-hand side, we introduce a dynamic component in the form of a lag of the dependent variable. In our panel setting using fixed effects, the results can therefore be interpreted as yearly employment and turnover growth estimations.

Our independent variable of interest is investments in machine and equipment in firm f at *t-1*: $InvM_{f,t-1}$. These are the gross investments that firms make in machines and equipment each year, as collected from firms' reporting to the Swedish Tax Agency (in 1000s SEK). This category of investments includes firm assets that are required to be (1) sizeable and (2) intended for longer-term use (more than 3 years).

In addition to the theoretical considerations above, some advantages coming with the investment indicator are that the data offers full coverage (except the excluded micro-firms), and that it is, at the moment of reporting, unbiased by any expectations that firms might have on the impact of technologies (as may be the case in sample surveys; see Kromann and Sørensen 2019).

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By using this indicator, we also capture investments that are complementary to other technologies in the plant, for example, new component feeding for robots or other machines.

In the context of studying the impact of new technologies on jobs, our investment indicator as an independent variable also comes with some drawbacks. In the data, investments in machines are not distinguished from those in equipment, and there is no encompassing list of what these could actually be; but they are defined as physical assets that are not buildings, land, financial assets and items in stock.[3] We could think of both machines and different kinds of tools in this context. Nevertheless, investments in machines are often found to be the largest investment category where the exact categories can be deciphered (e.g., Shima 2010).

The main drawback, though, we believe, is that the investment indicator includes investments particularly targeted at automation, as well as those that are not (Kromann and Sørensen 2019). We assume that firms, when they invest, are likely to do so in machines and equipment that embody the same or a superior level of process technology as what they presently have (Grazzi et al. 2016). Indeed, since Sweden is a country with comparably high labour costs, we find it reasonable to assume that any machinery and equipment investment that manufacturing firms make must embody at least the same or higher technology levels and must promise positive or at least neutral labour productivity effects, compared to the already present capital stock. In those cases when firms just replace machines and equipment with the same level of technology (which we think is, on average, unlikely), we should expect neutral effects on labour demand.

Inspired by the specifications of Coad et al. (2016) and Grazzi et al. (2016), we include a range of control variables ($Controls_{f,t-1}$). To make sure that the growth results are not driven by expansions in firm's scale of production, we rely on the fact that our data set includes a variable covering firms' investments in buildings and premises. Assuming that firms engaging in expansion also often need to enlarge their physical premises with buildings and/or land, we use this data on investment in buildings and premises as a control variable. While the empirical distinction between pure expansion and investing in new embodied technologies is subtle—many expanding firms combine the two strategies—such controls should allow us to distinguish some pure expansion effects from effects driven by investments in new technologies for other purposes.

Our estimation strategy comes at two major technical perils: the risk of econometric endogeneity in a firm's decision to invest and expand employment and the risk of creating biases in the introduction of the dynamic component (y_{t-1}). Our strategy to handle these falls into three avenues. First, we estimate traditional panel data fixed effects models based on Equation (1). The firm fixed effects, as well as controlling for labour productivity, should allow us to account for the fact that some firms are generally better or more efficient than others in the longer term. However, with the introduction of a dynamic component, these also risk being biased. Therefore, we investigate the effect size of the dynamic component to assess its importance. Second, based on this, we experiment with Arellano-Bond dynamic panel data model specifications to investigate if they can assist us in adjusting for any biases in the traditional fixed effects models. Third, independently of the dynamic panel data specifications, we also follow an empirical strategy inspired by Domini et al. (2021), who in turn draw on, among others, Guadalupe et al. (2012). This builds on the idea of mediating biases from endogeneity by finding a way to calculate the latent propensity of firms to both invest and grow. This procedure should allow us to come very close to isolating the effects of investments in machines and equipment on employment, while still maintaining a high degree of transparency. The details of the procedure are explained in Appendix 1. In the empirical section, we report on the outcomes of all these experiments.

Another challenge when studying the effects of technological investments is the time windows of investments and their effects. Some studies define investment thresholds to avoid routine investments or to capture investment spikes (Shima 2010; Grazzi et al. 2016). We do not follow this strategy. Some investments may have a spiky character, but some are also routine or everyday investments that may have important employment effects, even in the shorter term. Our analysis focuses on short-term effects (1 year, *t-1* to *t*). The shorter the time range, the more likely we are to keep the indicators clean of various other confounders.

For our exit variable, we measure the short-term year-to-year likelihood of firm exit as an alternative to relying on time series analysis. We prefer this estimation method, because we are focussing on short-term investment impacts, and not long-term firm survival. To define the firm exit variable, we track each firm across time by its official business registration number. The business registration number is usually relatively stable, but a firm may exit our data for various reasons, including bankruptcy, acquisition and voluntary dissolution (Lamberg and Peltoniemi 2020). Since we are mainly interested in exits that are not the result of acquisition or dissolution of successful firms, we only count exits for those firms that disappear from our panel data set, and record losses in the year before the exit. By taking an interest in only 1-year relationships, we rely on the estimation of a binary exit variable. In these regressions, we also control for firm size and profits in the previous year.

In Appendix 2, we provide descriptive information and correlations between our variables.

4 | Results

In 2000, there were about 5300 firms in our database. They employed 427,000 workers, of whom 17% had a degree from tertiary education. During the period studied in this article (2000−2020), the number of manufacturing firms in our data decreased by about 860 firms. Employment among these firms fell by about 15%, while the number of highly educated employees increased by 46%. During the same period, average firm labour productivity increased by about 17% (in 2000 price levels). Except for a significant drop during the years following the financial crisis of 2007−2010, aggregate annual gross

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investments in machines and equipment increased by almost 25% between 2000 and 2019, with a drop in 2020—the first year dominated by the Covid pandemic. In our database, most observed manufacturing firms (84%) invest in machines and equipment in a given year (measured as year/firm combinations). Relatively few firms make very small investments, whereas a few firms carry out very large investments in machines and equipment, thereby extending the right tail of the investment distribution.

In Table 1, we first turn to the results on the link between investments in machines and equipment on one hand, and firm employment on the other. Firms that invest in machines and equipment grow. The fixed effects panel estimation records a significant positive association between investments and employment (model 1). The size of the coefficient is very modest, however, investment volumes must be manifolded to transform into traceable estimated employment changes. This being said, the differences in the sizes of yearly investments are substantial in our data.[4] Nevertheless, even if the estimated coefficient is small, it does *not* signal a negative relationship between investments in machines and tools, and jobs.

Even though our tests do not show signs of the presence of endogeneity,[5] we still would like to explicitly test if the already 'good firms' are more likely to invest. Therefore, in model 2, we run a linear regression with firm- and year fixed effects, and weight observations according to the procedure described in the methods section. In Appendix 1, we show that the weighting has the intended effects and breaks any positive link between investments and the previous positive performance of the firm.

For model 2, the results uphold the positive and significant association between investments in machines and equipment on one hand and firm employment growth on the other. The size of the coefficient is also very close to model 1: the link between investment and future firm employment remains positive but modest.

In model 3, we focus on whether investments in equipment and machines are linked to changes in the number of highly educated employees in the firms. The model yields a significant positive association between investments in machines and equipment and an increase in the number of highly educated employees, with a slightly higher effect than in model 1. In evaluating endogeneity, we run similar tests to the ones we did for models 1−2. The direction and significance is retained as we weight observations (model 4). Investments in machines and equipment are not only linked to general employment growth, but also to slight employment increases among highly educated employees.

Our conceptual discussion above highlights that the increased competitiveness of investing firms may give them a more advantageous position in the context of technological competition. We test this in two ways: by estimating turnover, and by assessing the impact of investments on firm exit. The impact of investments in machines and equipment on the short-term economic growth of the business (turnover change) is positive and significant, but again modest (Table 2, model 6).

Table 2 shows that there is a negative association between investments and firm exit. In sum, firms that do not invest in

TABLE 1 | Regression outcomes.

Model	**1**	**2**	**3**	**4**	**5**
	Firm employment (ln)				**Firm turnover (ln)**
	All	**All**	**High edu**	**High edu**	
Estimation type	**FE**	**Linear regression, PS weighted**	**FE**	**Linear regression, PS weighted**	**FE**
y (t−1)	0.791***	0.783***	0.658***	0.653***	0.7***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Investments in machines and equipment (ln, t−1)	0.002***	0.002***	0.003***	0.003***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls					
Investments in buildings and premises (ln, t−1)	0.001***	0.001***	0.001***	0.001**	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Labour productivity (ln, t−1)	0.08***	0.077***	0.061***	0.06***	0.23***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Number of firms (groups)	7054	7054	6399	6399	7054
Number of observations	92,674	92,674	75,336	75,336	92,677
R^2	0.62	0.98	0.5	0.96	0.71

Note: We allow firms to exit during the period and display missing data. Models 1, 3 and 5 are fixed effects panel regressions and use bootstrapped standard errors. Fixed effects selected after the Hausman test. Models 2 and 4 are weighted linear regression and with robust standard errors. All models include firm and year fixed effects. For variable definitions and construction of the sample and weights, please refer to the data section. R^2 for panel specifications is for within-variation. Source: Own elaboration on data from Statistics Sweden. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

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TABLE 2 | Regression outcomes, logit specifications.

Effects of investments on exit	
Model **Estimation type**	**6** **Logit**
Investments in machines and equipment (ln)	−0.108***
	(0.009)
Controls	
Investments in buildings and premises (ln)	−0.021
	(0.012)
Size (ln)	−0.149**
	(0.043)
Labour productivity (ln)	−1.173***
	(0.057)
Profit previous year	0.000
	(0.000)
Number of observations	87,481
Log likelihood	−3634.476

Note: The model uses fixed effects according to Table 1. Source: Own elaboration on data from Statistics Sweden. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

machines and equipment are more likely to exit the next year. For those who do invest, however, this is likely to impact their business positively. It should, though, be noted that the frequency of firm exits is low—it happens in less than 1% of the year-firm combinations. Nevertheless, about 30,000 manufacturing jobs are lost in the firms that we categorize as exiting, which is more than 50% of the total job loss in the manufacturing sector during the studied period. Exits take place for many reasons, but firms that invest less have a higher exit risk.

5 | Robustness

In this section explicates some of the methodological decisions we have made and explain how they may affect our results.

First, in all of our estimations, we use gross investments in machines and equipment rather than net investments. Even though we think that gross investment is the most relevant variable to use in this case, the choice is not empirically important. Using net investments only does not change the results for investments in terms of direction and significance in any of the estimated models.

Second, we investigated how the coefficient for investments in machines and equipment changed when dividing our firm population into the industry groups used to calculate the weights p (see Appendix 1). These are the same industry groups as those used by Domini et al. (2021). In Figures 1–3, we plot the estimated coefficients for investments in machines and equipment according to the specifications in Equation 1 (panel, fixed effects with controls) for firms in the different industry groups. Figure 1 (on employment change) shows that the investment coefficients are positive and significant for all industry groups. However, they vary significantly in size, with higher coefficients for lighter industries than for heavier ones. Figure 2, for high-education employment change, also indicates that the picture is somewhat differentiated across industries. Food and other manufacturing even record nonsignificant impacts on higher-education employment change, whereas the link is decisively positive for more knowledge-intensive activities such as pharmaceuticals and chemicals. For turnover change (Figure 3), we again find overall positive relationships, but not all of them are significant.

Third, we explore differences in the links between investments and firm employment across time. Figures 4–6 show the estimated coefficients of investments in machines and equipment according to the specifications in Equation 1 (linear regressions with controls) for each bi-annual period (2000−2001, 2001−2002, etc.). Coefficients for employment change (Figure 4) are mostly positive and significant. The confidence intervals signal a wider spread in years of business cycle downturns, such as during the financial crisis (2008/2009). We observe much the same patterns for high-education employment change and turnover change.

6 | Discussion

This paper set out to create a better understanding of the link between investments in technology and firm employment. Drawing upon firm-level longitudinal panel data from investments in machinery and equipment, and employment in the Swedish manufacturing industry, we find a positive link between investment in machines and job creation in firms. Technology investments create an increasing demand for a broad set of manufacturing workers, and not only highly educated ones. We also find that low-investing manufacturing firms are more likely to exit.

While our analysis shows that firms investing more in new technologies also tend to employ more workers, this finding is not unique. There are several recent studies in the European context that find a positive association between technology investments and employment creation at the firm level (Koch et al. 2021; Acemoglu, Lelarge, et al. 2020; Aghion et al. 2020; Domini et al. 2021). Our contribution to this literature is threefold.

First, in contrast to several other studies, we have used a broader indicator of technology investments: investments in machines and equipment. Interestingly, while the employment effects are small, we also find significant effects when using this broad indicator. This has important implications, both for theory and in practice. It implies that the employment-enhancing effects of technology investments are not limited to specific technologies, such as robots. Investments in other, perhaps complementary technologies or machines, may well contribute to job creation at the firm level. In practice, this means that policies to support or curb the employment effects of technology investments should not be limited to specific technologies, such as robots. Thus, to better understand the link between investments in technology and employment, the question is not whether specific technologies have an impact on employment.

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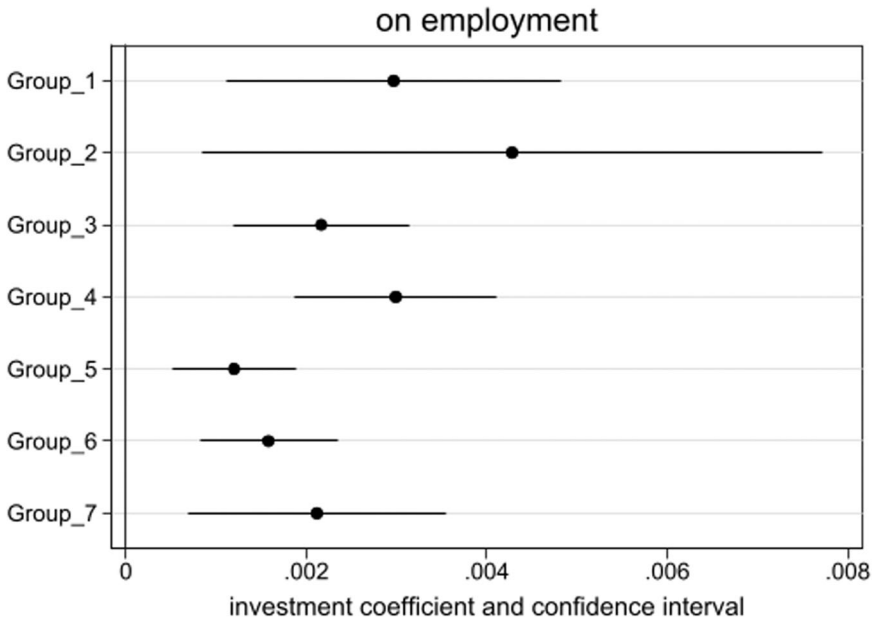

FIGURE 1 | Estimated regression coefficients of the variable investments in machines and equipment according to Equation 1 (employment change), but for industry groups. Panel estimations (fixed effects) with controls. Points represent the point estimate, and lines represent the 95% confidence intervals. The industry groups are: SNI 10–12 (food and drink), group 2 SNI 13–15 (textiles), group 3 SNI 16–18 (wood and paper), group 4 SNI 19–23 (pharmaceuticals and chemicals), group 5 SNI 24–25 (steel and metal goods), group 6 SNI 26–30 (electronics and vehicles), group 7 SNI 31–33 (other manufacturing). *Source:* Own elaboration on data from Statistics Sweden.

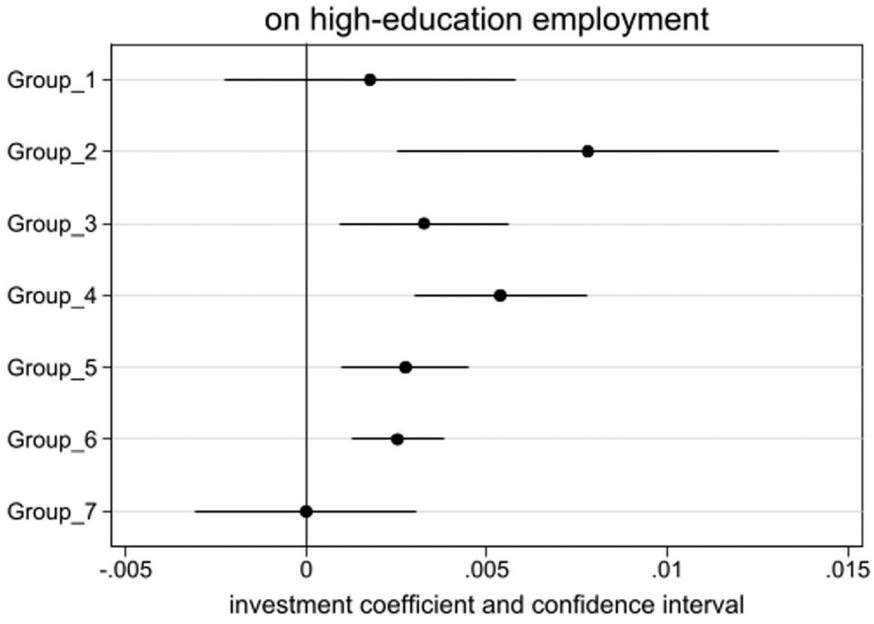

FIGURE 2 | Estimated regression coefficients of the variable investments in machines and equipment according to Equation 1 (higher education employment change), but for industry groups. Panel estimations (fixed effects) with controls. Points represent the point estimate, and lines represent the 95% confidence intervals. The industry groups are: SNI 10–12 (food and drink), group 2 SNI 13–15 (textiles), group 3 SNI 16–18 (wood and paper), group 4 SNI 19–23 (pharmaceuticals and chemicals), group 5 SNI 24–25 (steel and metal goods), group 6 SNI 26–30 (electronics and vehicles), group 7 SNI 31–33 (other manufacturing). Source: Own elaboration on data from Statistics Sweden.

It is more relevant to understand the general mechanisms in which technologies are associated with changes in employment at the firm level, and how such changes are linked to changes at the sectoral level.

Second, our study shows that significant employment effects of technology investments at the firm level can also be found in Sweden, an economy with relatively high labour costs and a rather particular institutional framework, where it may be expected that firms would have a greater incentive to invest in technologies to substitute labour. Given the consistency of European firm-level results, one could perhaps argue that the findings suggest that the national institutional context has very little to do with the employment impact of technological investments.

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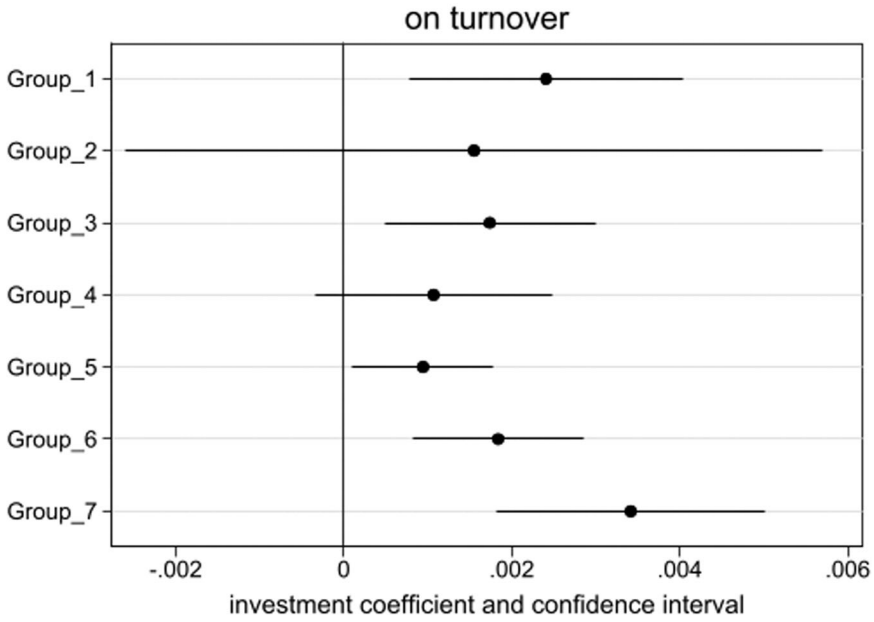

FIGURE 3 | Estimated regression coefficients of the variable investments in machines and equipment according to Equation 3 (turnover), but for industry groups. Panel estimations (fixed effects) with controls. Points represent the point estimate, and lines represent the 95% confidence intervals. The industry groups are: SNI 10–12 (food and drink), group 2 SNI 13–15 (textiles), group 3 SNI 16–18 (wood and paper), group 4 SNI 19–23 (pharmaceuticals and chemicals), group 5 SNI 24–25 (steel and metal goods), group 6 SNI 26–30 (electronics and vehicles), group 7 SNI 31–33 (other manufacturing). *Source:* Own elaboration on data from Statistics Sweden.

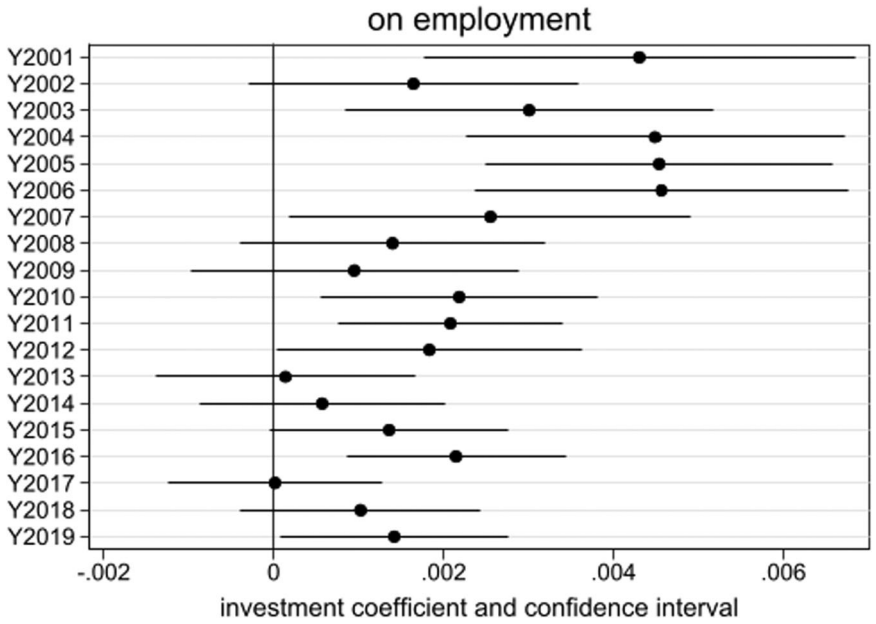

FIGURE 4 | Estimated regression coefficients of the variable investments in machines and equipment according to Equation 1 (employment change), but for individual years. Points represent the point estimate, and lines represent the 95% confidence intervals. *Source:* Own elaboration on data from Statistics Sweden.

However, it is also possible that in the European context, the national institutional context plays a role in favouring investments that enhance employment rather than labour-substituting effects. In the Swedish context, for example, the relatively extensive employment protection legislation and strong trade union negotiating power may contribute to favour firms that deploy investment strategies that enhance employment. Our study, however, is not able to determine which explanation is more plausible. By showing that employment-enhancing effects of technology investment also exist in the Swedish national context, we advance our understanding of the link between technology and employment at the firm level. It does not suggest, however, that the mechanisms involved may be generalized to any national institutional context. Future studies may explore the role of trade unions and labour market institutions in shaping firm investments in technologies in different national contexts.

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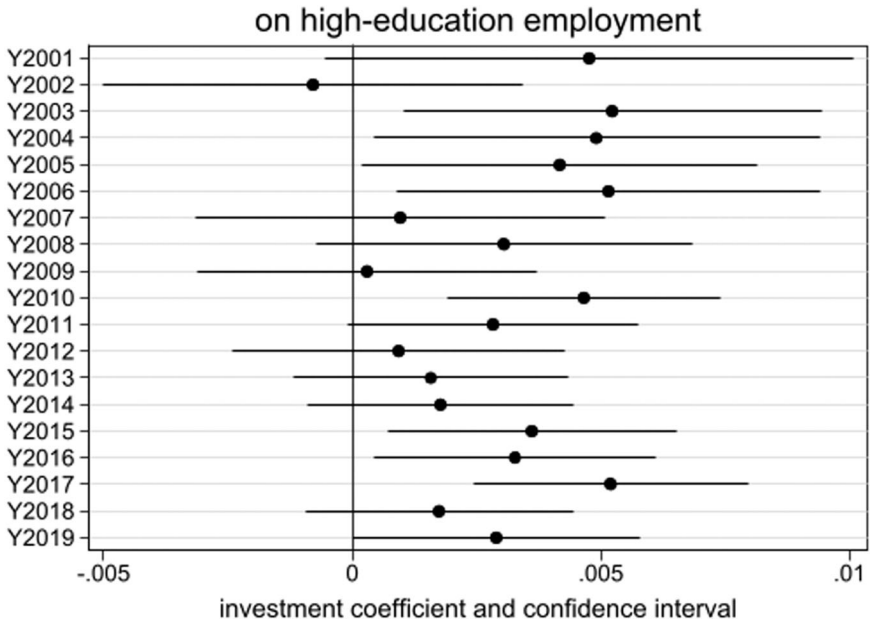

FIGURE 5 | Estimated regression coefficients of the variable investments in machines and equipment according to Equation 1 (higher education employment change), but for individual years. Points represent the point estimate, and lines represent the 95% confidence intervals. *Source:* Own elaboration on data from Statistics Sweden.

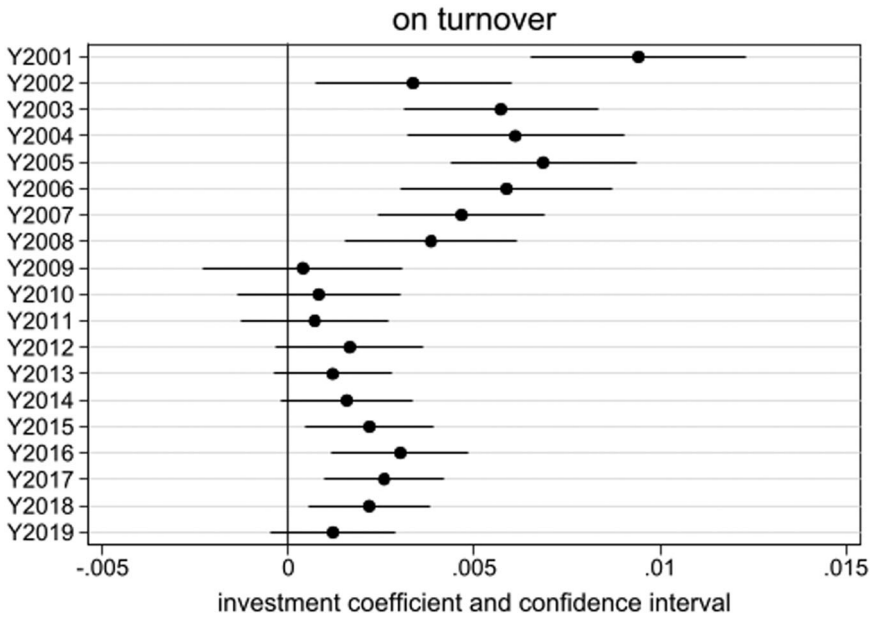

FIGURE 6 | Estimated regression coefficients of the variable investments in machines and equipment according to Equation 1 (turnover), but for individual years. Points represent the point estimate, and lines represent the 95% confidence intervals. *Source:* Own elaboration on data from Statistics Sweden.

Third, we explore the sector-level dynamics and the role of technological competition. By adding a firm exit indicator, we are not only able to explore the impact of technology investment on employment in the investing firms. We are also able to capture the impact on employment in those firms that do not invest in machinery and equipment or invest little. As shown, low-investing manufacturing firms are more likely to exit. Our general findings hold even when we consider that these might be weaker firms from the start.

Exploring the employment impact in non-investing firms is important to understand the broader implications of technology investments at the sector level. At the sector level, the number of jobs in manufacturing are decreasing during the studied period, but this does not necessarily mean that workers are replaced by new machines. Notably, the decline of manufacturing employment at the sector level should not be confused with a direct effect of implementation of new technologies at the firm level. To the extent that technology investments play a

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role in explaining the decline of employment, it is rather through competitive pressures (domestic or international) that make non-investing firms decide to exit the market. Thus, even if the job loss at the firm level is not driven by the implementation of 'labour-saving technologies', technology may still have a role to play for the developments at the sector level. Expanding firms may invest in more efficient production technologies or offer more technologically advanced products in the market, contributing to increasing sales and expansion of market shares. Faced with such competitive pressures, firms have no other choice than to close down operations, to invest in the new technology or to invest in the established technology (Howells 2002). Thus, job loss in firms that exit may be seen as a result of technological competitive pressures, driven by technological investments in other firms.

7 | Conclusions

Responding to Filippi et al.'s (2023) call for further studies of the impact of technologies on employment in countries with very different characteristics, we have examined the dynamics involved when manufacturing firms invest in new machines in Sweden: a high wage economy with strong labour union influence (Bergström 2019).

Investment in technologies does not seem to serve the function to replace human labour in firms; on the contrary, firms that invested most in new technologies benefited most in terms of employment growth, and firms that invested less were more likely to exit the market. This firm-sector ambiguity (decreasing manufacturing employment and expansion of certain investing firms) may be seen as derived from the ongoing competitive and selection process occurring in the market (Staccioli and Virgillito 2021). Firms that invest in new technologies might well increase their labour demand because of market expansion, higher sales and increasing market shares. However, at the sector level, there may be an overall decrease in employment if expanding firms are able to increase their market shares at the expense of their competitors (Dosi and Mohnen 2019). We find that firms that do not invest have a greater risk of leaving the market, with the associated increasing risk of job loss for their employees. Any attempt to analyse the impact of new technologies on employment and labour markets in general needs to take these structural dynamics into account. Furthermore, the interplay between sectoral dynamics, labour market institutions and technological investments at the firm level should be recognized when considering the impact of technology on employment in advanced economies.

Indeed, the impacts of technologies on employment are likely to differ between countries depending on country-specific characteristics, for example, labour market regulations, the legal systems, fiscal policies and collective bargaining institutions (Filippi et al. 2023; Haapanala et al. 2023). Although we have attempted to make use of robust quantitative techniques, we certainly do not rule out that our findings are limited to the Swedish or at least Nordic context and the period of industrial capitalist development that we investigate. The Swedish manufacturing industry is highly dependent on international trade and embedded in global value chains, implying that the employment impact of technological investments may take place both in Sweden and in other countries.

In this study, we have strived to apply robust quantitative methods to study the relations between investments, technologies and jobs, while at the same time attempted to explain and situate the results in a particular institutional and 'non-deterministic' setting. When contextualizing our finding in light of the broader literature, we have found the *social shaping of technology approach* (SST) useful (Howcroft and Taylor 2023), as it both attempts to create a theoretial balance between the social/institutional and technological realms in the study of technologies and work, and provides an interpretative setting for diversity in the econometric evidence coming out of the recent literature.

Future studies should explore the impact of technologies in other countries, considering not only the institutional setting, but also the type of technologies implemented and how workers are directly and indirectly affected by technological investments in the longer term. We hope that this study could stimulate more empirical quantitative research from different countries, but with an interpretation of results relying rather on an SST- or critical-realist approach (Snell and Gekara 2023), than conventional labour economics only. Qualitative plant-level studies may reach even further in studying the balance between technological and social factors influencing job outcomes from automation initiatives, as well as how different types of institutions shape job consequences within plants, firms and industries (Rolandsson et al. 2019; Lloyd and Payne 2023).

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The firm microdata used in this study is confidential. Researcher access can be granted access following application to Statistics Sweden and through Statistics Sweden's servers.

Endnotes

[1]We use 'embody' in the meaning of the Cambridge Dictionary: 'to have and show particular qualities or ideas; represent' (https://dictionary.cambridge.org/dictionary/english/embody).

[2]We identify manufacturing firms by their main industry affiliations, and we use the earliest firm industry affiliation that appears in our data set. Because of the simplified investment reporting procedures that apply to very small firms, we exclude firms with five employees or below.

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[3]We refer to the definitions of the Swedish Tax Agency: https://www4.skatteverket.se/rattsligvagledning/edition/2024.4/339113.html#:~:text=Reglerna%20om%20inventarier%20%C3%A4r%20till%C3%A4mpliga%20p%C3%A5%20maskiner%20och%20andra%20inventarier

[4]Moving from the mean to the third quartile involves almost a fivefold increase in investments, and moving from the mean to the 90th percentile involves an 18-fold increase in real investments.

[5]The effect size of the dynamic component (y−1) is far from 1, and experiments with dynamic panel data models (Arellano−Bond estimator) do not result in model diagnostics that confirm the relevance of such a model. This suggests that the FE in model (1) is already giving a good empirical estimation.

[6]Group 1 SNI 10−12 (food and drink), group 2 SNI 13−15 (textiles), group 3 SNI 16−18 (wood and paper), group 4 SNI 19−23 (pharmaceuticals and chemicals), group 5 SNI 24−25 (steel and metal goods), group 6 SNI 26−30 (electronics and vehicles), group 7 SNI 31−33 (other manufacturing).

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Appendix 1

Weighting

We initially think of investments as a treatment to the firm (in a similar way to a drug treatment to humans) and define a binary treatment variable $Invest_{f,t}$. Inspired by Grazzi et al. (2016), we calculate an investment indicator based on the relation between investments in machines and equipment on one hand, and net turnover of the firm on the other, for each year: $RelInv_{f,t} = Investment_{f,t}/Turnover_{f,t}$. Those firms that belong to the upper 75% of investors are considered as treated: $Invest_{f,t} = 1$. The rest obtain 0. Using this as a response variable, we estimate a firm-specific score p to obtain the investment treatment based on firm employment change in the previous year, for each industry group separately. We replicate the industry groups in Domini et al. (2021).[6] The term p is estimated by probit regression using previous firm performance as an independent variable (employment change in the previous year). Following on this, we weight an OLS-regression including firm fixed effects, with treated firms weighted $1/p$ and nontreated firms $1/(1-p)$. This procedure adjusts for an underlying latent potential both to invest and to change the use of labour. It also removes, as shown below, the significant link between past firm performance and investments in machinery and equipment.

In Table A1, we show the outcomes of a linear regression according to $InvM_{f,t}=f(\Delta Emp_{f,t-1}, InvB_{f,t}, Emp_{f,t}, LP_{f,t}\ TO_{f,t},)$, where $\Delta Emp_{f,t-1}$ is the firm employment change in the previous period (year combination), $InvB_{f,t}$ is investments in buildings and premises in firm f in year t,

$$Emp_{f,t}$$

is firm size in year t, $LP_{f,t}$ is labour productivity in firm f year t, $TO_{f,t}$ is firm turnover in year t and $InvM_{f,t}$ is investments and machines and equipment firm f in year t. Model A1 is unweighted. There is a positive and significant link between previous firm performance (employment change) and investments in machines and equipment. In model A2, we use firm-specific weights according to the procedure explained in the methods section. In this estimation, there is no significant correlation between previous firm performance (employment change) and investments in machines and equipment. The procedure removes the circular link between previous performance and investment, while largely retaining directions and significance of other independent variables. We therefore employ these firm-specific weights in models 2 and 4.

TABLE A1 | Regression outcomes, comparison between unweighted (model A1) and weighted (model A2) specifications.

Model	A1	A2
	Previous performance on investments in machines and equipment	
Estimation type	Linear regression	Linear regression, weighted
Previous employment growth	21.958***	−0.133
	(0.06)	(0.09)
Controls		
Investments in buildings and premises (ln)	0.12***	0.108***
	(0.00)	(0.00)
Size (ln)	0.131***	0.186***
	(0.03)	(0.03)
Labour productivity (ln)	0.653***	0.865***
	(0.03)	(0.04)
Turnover (ln)	0.49***	0.252***
	(0.03)	(0.03)
Number of observations	94,906	94,906
R^2	0.11	0.11

Note: Procedure to derive firm-specific weights is described in the methods section. Source: Own elaboration on data from Statistics Sweden. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

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Appendix 2

Descriptives

Tables B1 and B2

TABLE B1 | Descriptives: mean, standard deviation, min and max of the variables.

	Mean	Standard deviation	Min	Max
Employment (size) (ln)	3.3	1.13	1.61	10.1
Employment highly educated (ln)	1.57	1.34	0	9.22
Turnover (ln)	10.57	1.45	8.01	18.79
Exit	0.01	0.09	0	1
Investments in machines and equipment (ln)	1.78	3.7	−6.91	11.27
Investments in buildings and premises (ln)	−4.92	3.92	−6.91	7.98
Labour productivity (ln)	6.27	0.47	−1.1	10.51
Previous employment growth	0.00	0.18	−3.81	3.67
Profit previous year	14,440	416,958	−4,715,285	60,300,000

Note: Changes are calculated in log differences. Units of original variables: employment and size variables are in persons. Pecuniary-based variables are in 1000s Swedish kronor. Exit is binary. Source: Own elaboration on data from Statistics Sweden.

TABLE B2 | Correlations between the independent variables.

	1	2	3	4	5
(1) Investments in machines and equipment (ln)					
(2) Investments in buildings and premises (ln)	0.18				
(3) Size (ln)	0.27	0.22			
(4) Labour productivity (ln)	0.17	0.06	0.20		
(5) Previous employment growth	0.10	0.05	0.07	−0.08	
(6) Profit of the previous year	0.03	0.05	0.12	0.1	−0.01

Source: Own elaboration on data from Statistics Sweden.

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