Restructuring of Workforce Skills: adapting to automation technology in the wake of economic crisis

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Abstract

The financial crisis of 2007 and 2008, sometimes called the Great Recession, was a pivotal event in global economics and is considered the worst and most severe economic crisis since the Great Depression (Verick & Islam, 2010; Choudhry et al., 2012). One perspective on the effects on the labor market is the role of automation. Such a crisis can not only reshape the labor market but also accelerate trends, influencing long-term employment patterns and the nature of work. The impact of advanced automation technologies on workers has two main effects. A productivity effect occurs when technology improves workers' productivity. Conversely, the displacement effect arises when technology decreases labor demand. However, this increased efficiency can lead to the creation of new tasks for robot operators. Thus, the impact on robot operators' labor demand depends on the displacement's relative strengths and productivity effects. Nowadays, it is rather indisputable that an ongoing technology-induced polarization has significantly impacted workers in the middle tiers of wage distribution (Autor, 2019). Considering the above, our research question is: How does manufacturing firm automation affect the likelihood of different labor market outcomes of individuals employed in these firms? This paper hypothesizes that the effects of investing in automation technology on employees were not evident until there was this sizable exogenous pressure on firms. That means we assume the Great Recession was a catalyst to accelerate effects of technological change, impacting the labor market outcome of individuals. We show that in the aggregate job-worker separation is greater in firms that have previously invested in automation technology. On the level of the individual estimations show that workers are less likely to remain in the firm and more likely to be unemployed if it has invested in machinery earlier. This is true regardless of whether the individuals move to another municipality or stay in the same. Regarding the location of the firm, it seems like individuals that work in a metropolitan area are more likely to be separated from their employment.

Keywords: automation, job loss, skills, workers

JEL classification: E24, J23, J24, J31, R10

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1. Introduction

When firms invest in new technologies this will change the demand for skills in their employees. The new technology that is introduced may complement or substitute certain skills of the current workers. This may have the consequence that some current employees are discharged and that new hires replacing them possess another set of skills than those that are laid off. Of course, the net effect on the number employed workers may be positive or negative.

The effect on workers of investment in new automating technology may not be immediate. It may take some time before it permeates the operations of the firm to a degree that redundancies or new demands for complementary competencies are experienced. It may also be the case that external factors influence the timing of the effects on the workforce. For example, a decreasing demand for the output from production may force firms to downsize their operation or at least halt an ongoing expansion. This may trigger the effects of investments in automating technologies to be more acute. In many cases costs for capital equipment will be more fixed than labor costs, so downsizing will hit employees first. The type of labor that is at the highest risk are those that possess skills that are substitutes for new technology. These cutbacks will probably happen regardless of whether there is an economic downturn or not simply as an effect of technology substituting for workers.

The premise of this paper is that the downturn impacts the timing of the effect. If there is something to this, we expect that there will be an acceleration in technology induced hiring and firing in bad economic circumstances and the opposite in good times.

Another question that this paper seeks to shed light upon is the possible geographic dimension that the described process may have. Is it so that certain areas can be expected to be hit harder than others? The answer to this question is probably yes, for several reasons. The first reason is that different technologies influence different sectors and industries in distinctive ways and at various times. Technologies influencing manufacturing the most will influence more smaller towns and regions whereas technologies that affect service and knowledge intensive industries will have a relatively larger impact in bigger cities and regions.

A second reason comes from what happens to the workers that lose their job. When they get unemployed, they look for another job in the region where they reside or somewhere else. In a smaller region it may be harder to find new employment compared to a larger region with a thicker labor market and a better chance to find a job that is a good match. On the other hand, the skill-set of the individual from the smaller region may be such that it is relatively hard to find a good match in the bigger region. The potential actual choice set may comprise to try to get a similar job in a different but similar region, move to a larger region but accepting a job that is less than a perfect match, stay unemployed or enter some activity resulting in re- or upskilling. With this as a background we now go more into detail of the set-up and positioning of this research.

The financial crisis of 2007 and 2008, sometimes called the Great Recession, was a pivotal event in global economics and is considered the worst and most severe economic crisis since the Great Depression (Verick & Islam, 2010; Choudhry et al., 2012). Its profound and far-reaching impact on labor markets worldwide, leading to a sharp increase in global unemployment rates, cannot be overstated. Some industries, including finance, construction, and manufacturing, were particularly walloped (Anxo & Ericson, 2016). One perspective on the effects on the labor market is the role of automation. Such a crisis can not only reshape the labor market but also accelerate trends, influencing long-term employment patterns and the nature of work. In light of this, our research question is: How does manufacturing firm automation affect the likelihood of different labor market outcomes of individuals employed in these firms?

The impact of advanced automation technologies on workers has two main effects. A productivity effect occurs when technology improves workers' productivity. Conversely, the displacement effect arises when technology decreases labor demand. A compelling example of how automation technologies can boost labor productivity is using artificial intelligence (AI) to optimize industrial robot movements. AI can reduce programming time from 90 minutes, the average time for a skilled human operator, to just 2 seconds (ABB, 2023) – a significant productivity gain. However, this increased efficiency can lead to the creation of new tasks for robot operators. Thus, the impact on robot operators' labor demand depends on the displacement's relative strengths and productivity effects. Nowadays, it is rather indisputable that an ongoing technology-induced polarization has significantly impacted workers in the middle tiers of wage distribution (Autor, 2019).

From a societal perspective, Total Factor Productivity (TFP) is crucial for economic growth (Krugman, 1997), with technological advancement playing a vital role in this process. Swedish labor productivity grew rapidly in the late 1990s and early 2000s (Oh et al., 2012), but since the onset of the financial crisis, productivity growth in Sweden has slowed down. This pattern is observed in many OECD countries. Notably, in Sweden, the slowdown in TFP appears to be driven by a decrease in technological change (Matsson et al., 2020). A noteworthy difference between Sweden's pre- and post-crisis productivity growth is that, before the financial crisis, productivity was primarily driven by the entry of new firms. In contrast, post-crisis growth has been primarily driven by incumbent firms in the manufacturing sector, a phenomenon known as the within-firm effect, gradually pushing labor into more productive firms (Anxo & Ericson, 2016).

This makes it likely to believe that the financial crisis in 2007 and 2008 offset an important shift in the Swedish labor market.

This paper propose the hypothesis that the effects of investing in automation technology on employees were not evident until there was this sizable exogenous pressure on the firms. That means that we assume that the Great Recession was a catalyst to accelerate effects of the technological change, having an impact on the labor market outcome of individuals, following arguments by for example Hershbein & Kahn (2018). One advantage of this design is that the shock is sudden and external to firms and employees (Bezemer, 2009), contradictory to e.g., investment programs that may have a much slower and more gradual effect on employees.

The paper proceeds as follows. In section 2, we present related literature focusing on the labor market effects of automation, specifically productivity and displacement effects, and how these are affected in economic recessions. In Section 3, we describe our data and descriptive statistics on what characterizes firms and employees in this analytical context, and the empirical strategy where we also define the role of an exogenous shock in our modeling framework. In Section 4, we present and analyze the results and conclude in Section 5.

2. Labor market effects of automation

2.1 Long-term trends

Automation has the potential to increase productivity and significantly contribute to economic growth. However, it also poses challenges regarding job displacement and the need for workers to adapt to new roles and acquire new skills.

To understand this controversy of effects on labor market outcomes, it is essential to grasp the long-term trends shaping them. Extensive documentation shows a polarized effect on the labor market for over four decades in many countries worldwide (Acemoglu & Autor, 2011; Bachmann et al., 2019; Green & Sand, 2015). In short, job opportunities and wages are becoming concentrated at the high and low ends of the skill spectrum, squeezing out those in the middle (Autor, 2020). This trend has garnered the attention of both researchers and policymakers, as it widens the employment growth and income gap between high- and low-skilled workers. A dominant factor driving this polarization is, in fact, automation. Technological advancements have historically replaced workers performing routine tasks, with automation significantly accelerating this trend. As technology costs decrease, the demand for workers in routine, middle-skill jobs has fallen, leading to a decline in these positions. In contrast, non-routine tasks, at both the high and low ends of the skill spectrum, are more resilient to automation, thus maintaining or increasing their demand (Goos & Manning, 2007; Autor et al., 2003; Autor & Dorn, 2013).

This polarization is ongoing, but despite these long-term trends, labor is still not obsolete, not even in manufacturing. The general explanation is that machinery substitutes *and* complements labor (Autor, 2015; Graetz & Michales, 2018). This leads to a productivity effect and a reinstatement effect, which is derived from the fact that when new technology is introduced, it shifts the task content of production, resulting in a broader range of tasks (rather than occupations) for labor to handle (Acemoglu & Restrepo, 2019; Arntz et al., 2016).

A large Dutch micro-data study by Bessen et al. (2023) reveals that automation within firms significantly increases the risk of job separation for incumbent workers. However, the impact varies widely among individuals. In a study of 16 European countries, including Sweden, Bachmann et al. (2024) found that the overall effect of robot exposure on job separations between 2000 and 2017 was relatively small. Yet, the results varied significantly across countries, indicating that labor costs play a crucial role in understanding the impact of robot exposure. Labor is more likely to be substituted by other factors of production when labor costs are relatively high. This variation in effects is influenced by factors such as geography, type of economic activity, business culture, and individual factors like educational levels, gender, and age (Clifton et al., 2020; Acemoglu & Restrepo, 2020).

2.2 Fast changes

These long-term trends are occasionally disturbed by other events, such as economic recessions or more disruptive financial crises. In such time periods, one might expect certain categories of employees or segments of the labor market to be hit harder than others. The literature is relatively unanimous that young people are significantly affected. They are not as knowledgeable or experienced, meaning they have larger difficulties finding a job but are also more sensitive to economic peaks and troughs than the older part of the population (see e.g., Verick, 2009). There is also evidence that men are more vulnerable than women, generally explained by the fact that they are employed in sectors such as construction and manufacturing, which tend to be sectors sensitive to business cycles (Hoynes et al., 2012).

There are various alternatives to downsizing during a crisis, and the likelihood of these responses can vary over time (Datta et al., 2010; Dencker, 2012; Ferreira & Saridakis, 2017). Possible strategies include reducing or eliminating overtime, using temporary staffing, freezing investments and expenditures, and encouraging early retirement (Strandholm et al., 2013; Svalund, 2013). A survey conducted in several European countries, including Sweden, found that early retirement was the most common response during the Great Recession of 2007-2008 (Van Dalen & Henkens, 2013). This approach was often preferred over downsizing, likely due to factors such as employment protection and generational fairness. Additionally, different types of organizations respond differently to crises. For instance, Baù et al. (2024) found that family firms have higher employee retention rates than other firms during such periods.

It is also crucial to emphasize that the Swedish labor market is relatively rigid but has some negotiated flexibility (Anxo, 2011). This creates some firm maneuvers, but the firms cannot arbitrarily adjust employment levels, even with the introduction of automation, such as welding robots. This rigidity implies that institutional factors might impede some theoretically plausible labor market outcomes from automation (Acemoglu et al., 2023; Acemoglu & Restrepo, 2022; Graetz, 2020). In countries with highly coordinated collective bargaining systems, such as Germany or Sweden, increased automation rates can have zero or even negative effects on unemployment (Leibrecht et al., 2023). In the wake of the crisis, and line with Sweden's "flexicurity" model, the government implemented interventions to mitigate the economic downturn. However, measures to stimulate labor demand were pre-planned and cannot be considered a direct response to the crisis, which means that all parties in the labor market already had this information (Anxo, 2011).

3. Data and Empirical Strategy

In this section we outline the data and our research design used to examine the firm-level automation impacts on individual-level outcomes. We focus on manufacturing workers and utilize an individual-level panel spanning from 2000 to 2010. The manufacturing sector is particularly relevant for several reasons, one of which is its significant contribution to the economy. Approximately 20% of Swedish value added is generated by manufacturing, which also represents the dominant share of Swedish exports. Additionally, the financial crisis significantly impacted the manufacturing sector, but it has also been extensively exposed to automation over a prolonged period (Anxo & Ericson, 2016).

Our comprehensive data include detailed information on individuals, such as their wages, education, occupations, firms (and workplaces), and industries.[2] In addition to these data on individuals, we also access information on firm size, location, and type of investments. The latter investment variable is key in this study since it enables us to extract the firm's investment in machinery, which we use as a proxy for automation technology adoption.

[2] Data are provided via *Longitudinal integrated database for health insurance and labour market studies* (LISA) and firms via *Firm Register and Individual Data Bases* (FRIDA) by Statistics Sweden.

3.1 Machine investments and automation

We use firms' machinery and equipment investments to measure automation technologies. This investment category includes various machines, such as industrial robots and computers, and machinery leasing.

Another way to proxy the degree of automation is to use robot investments more precisely, which we have difficulties accurately capturing in our data. We know about international imports of robots in these firms but not the investments specifically related to these. With some major robot productions within Sweden (ABB and Yaskawa), robot purchases are likely not exclusively discovered using trade data. Also, the increase in the number of industrial robots does not fully resemble the explosive use of technologies in general (Benmelech & Zator, 2022).

The risk of using our measure of machine investments is that it does not pinpoint the specific technologies adopted, potentially including technologies that are not directly related to automation. However, this more generous view of firm-level technology adoption implies that we capture all types of automation rather than a single one. Furthermore, machinery and equipment investments are positively associated with a decreasing labor share and an increasing labor productivity at the firm-level; these associated relationships offer suggestive evidence that machine investments signify automation (Restrepo, 2023).

3.2 Timeline of events

By using the financial crises in 2007 and 2008 as a sudden exogenous event for firms and individuals alike, we carefully construct our sample of individuals following the timeline featured in Figure 1. At the time, the shock was an unexpected event affecting most parts of the economy, and its unanticipated nature makes it a useful tool for causal inference.

The timeline consists of three consecutive periods. A hiring period from 2000 to 2002 when workers join the firm or are already employed. The investment period from 2003 to 2006 containing investments spikes (defined in the next section), 2007 as a cutoff point, and a lay off period from 2008 to 2010.

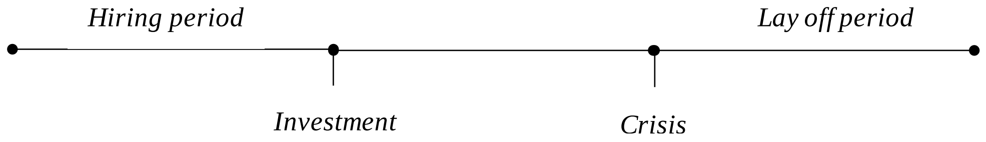

Figure 1. Research design timeline of events

We choose to focus on employees working in the firms during the hiring period, determine whether the firms have investments spikes or not in the investment period, and determine individual outcomes during the lay off period. The outcomes will constitute an unordered categorial dependent variable for which we will run multinomial logistic regressions, using machine investment spikes as the main explanatory variable.

The research design aims to minimize selection effects by tracking employees who joined or were employed in the firm during before the machinery investment. From the firm's perspective, these investments were made well before the economic crisis.

From the perspective of the firms under study, the investment in automation technology occurs significantly ahead of the upcoming economic shock. This sequential division is crucial as it allows us to isolate the effects of the automation event, enabling a richer analysis of the impact of automation on the potential job loss of individual workers. This research design enhances the reliability and validity of our findings by carefully managing the timing of both the selection of workers, and the automation investment relative to the economic downturn.

3.3 Main explanatory variable – machine investment spike

For the exercise described in the aforementioned section, we disregard start-ups during the period 2000–2010 and furthermore focus on manufacturing firms that were not discontinued during the crisis. The main interest lies in the impact of automation, rather than firm entries or exits, on individual-level outcomes.

We then divide our sample of manufacturing firms into two groups: automating and non-automating. This classification is based on a threshold for firms' investments in machinery and equipment per worker prior to 2007. We use investment per worker to weight the investments by firm size.

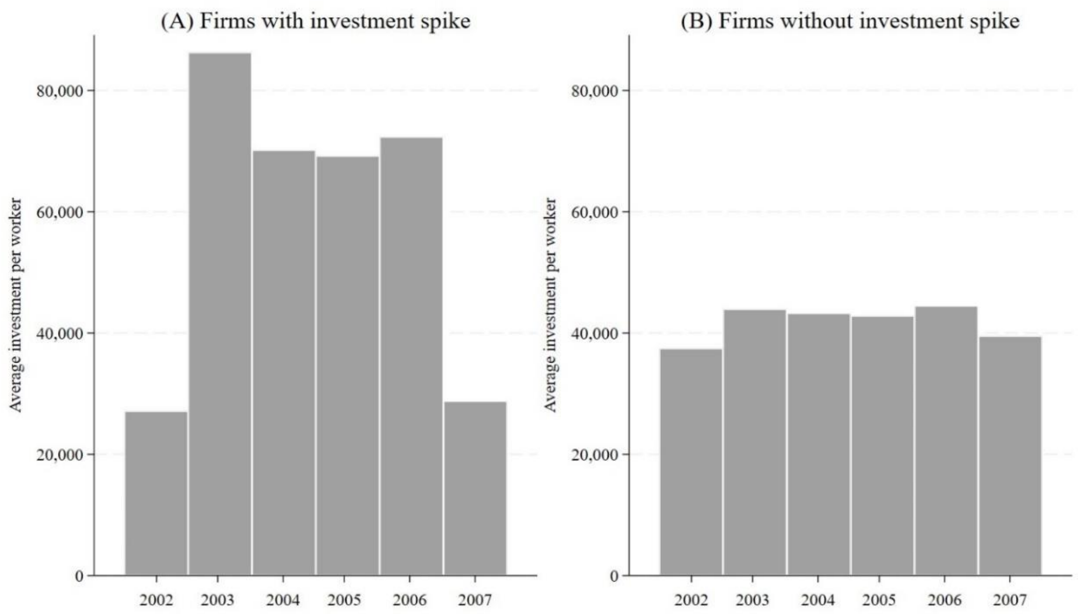

Figure 2. Investment in machinery and equipment spikes

Note: Investments measured in SEK.

A firm with an annual investment per worker during the years 2003 to 2006 that exceeds twice as much of its mean per capita investments during the period 2002-2007 is labeled as having an automation investment spike. Of course, firms may or may not automate regardless of sudden spikes in machinery and equipment investments, but using a threshold to sort firms into automating versus non-automating for the sake of analysis is a common approach (e.g., Acemoglu et al., 2023a; Bessen et al., 2023). We proceed to match automating firms with non-automating firms one-to-one on their number of workers, using coarsened exact matching (Blackwell et al., 2010). The result is a sample consisting of 1129 automating firms (firms with an investment spike prior to 2007) and 1129 non-automating counterparts (Figure A1. In Appendix A depicts the density of number of workers in the firms). Figure 2. depicts the annual average machine investments per worker for both the treatment and the control group.

Unlike earlier studies, we do not treat sudden spikes in automation investments as shocks on employees. Instead, we are interested in how automating firms respond to shocks, such as economic crises, compared to their non-automating counterparts, and the effect of this response on the employees. For each worker in the sample, the machine investment spike variable takes the value 1 if working at a firm that had an investment spike during the period 2003-2006 and 0 otherwise.

Table 1. Dependent variable outcomes

	Outcome 1	Outcome 2	Outcome 3	Outcome 4
Unemployment	No	No	Yes	Yes
Move	No	Yes	No	Yes

Note: Outcome 1 is the benchmark.

3.4 Dependent variable

The aim is to examine individual labor market outcomes conditioned on firm-level automation in the wake of an economic downturn. For this endeavor, we utilize an unordered categorical variable with four possible outcomes presented in Table 1 as the dependent variable in our analysis. The outcomes encompass unemployment and/or the individual moving to another municipality for work. All outcomes are measured during the years 2008 to 2010. An individual's outcome is defined as unemployment if the individual experienced unemployment during the period (number of registered unemployment days greater than zero). An individual's outcome is defined as move if the individual has changed both living municipality and workplace municipality. Combining the prospect of unemployment with the possible necessity to move for job opportunities allows us to capture both a worker displacement effect and the potential geographical consequences.

3.5 Control variables

We complement the analysis with a set of control variables. First, we include demographic and household control variables: gender (male: 1, female: 0), age, foreign-born (yes: 1, no: 0), partnership (married or registered partner: 1, otherwise 0), children living in household (yes: 1, no 0), higher education (education exceed upper secondary: 1, otherwise 0). Second, we consider work-related control variables, *log*-transformed annual wage earnings and the occupational skill level according to the *International Standard Classification of Occupation* ISCO-88: the lowest level 1 featuring elementary occupations), level 2 containing assemblers, clerks, and machine operators, level 3 containing technicians and associate professionals, and the highest level 4 containing managers and professionals. Finally, we include establishment size, whether firm size is small (10-49 workers), mid (50-249 workers), or large (250 and above workers), and a categorial variable classifying municipalities as either metropolitan, urban, dense rural, or sparse rural according to population density and labor flows across municipality borders. This classification rests on the definitions by *The Agricultural Agency* (2005).

3.6 Regression model

The multinomial logit model is given in the following equation:

$$\Pr\,(Y_i = k) = \frac{\exp\,(\beta_k X_i)}{1 + \sum_{j=1}^{K-1} \exp\,(\beta_j X_i)} \qquad (1)$$

Where k is one of the four outcomes of the dependent variable. We observe an individual i with an outcome k measured during the years 2008–2010. The matrix X_i contains the control variables, all measured for the cutoff year 2007. The main explanatory variable is the machine investment spike dummy, taking the value 1 if the firm where individual i works experienced an investment spike in machinery and equipment during 2003–2006. To further explore how geography and skills affect outcome k, we introduce occupational skill-level dummies, and interactions between the investment spike variable and dummies for municipality categorizations (metropolitan, urban, dense rural, sparse rural).

3.7 Reducing selection bias

Due to the cross-sectional framework, we cannot include worker fixed effects to capture unobserved individual characteristics, thus our estimates risk being biased by selection bias. To reduce this bias, we propose three remedies. First, as described in our timeline framework we examine incumbent workers prior to potential machine investment spikes, following Bessen et al. (2023). Second, we apply a coarsened exact matching procedure, according to Blackwell et al. (2010), to our sample of workers, attempting to improve covariate balance. The matching results in weights that we apply to our regressions, with a final sample size of 73,871 workers. Appendix A Section A2 presents the coarsened exact matching output. Third, we follow the approach outlined by Abowd, Kramarz and Margolis (1999) and include so called AKM fixed effects, referred to as AKM-ability in analysis. We retrieve this variable by regressing a worker's wage on individual characteristics (demographics, firm-level characteristics and firm-level fixed effects) and retrieve the estimated individual intercept and use it as a covariate in our main regressions. Although this wage-earning ability cannot fully replace individual fixed effects, it acts as a proxy reducing potential selection bias.

4. Results

In this section we present our results, beginning with a descriptive analysis of the data and proceeding with the multinomial logistic regression output.

4.1 Descriptive analysis

Figure 3 depicts graphs showing the average employment growth from 2003 to 2011 for our sample's firms by experiencing an investment spike or not. It is clear that employment growth on average has been higher in the firms investing more in machinery and equipment compared to their counterparts not having significant investment spikes prior to the crisis. During the economic downturn, however, it appears that automating firms experienced an on average lower employment growth. This firm-level evidence offers a fitting steppingstone for the upcoming individual level analysis, since it offers suggestive evidence that workers in firms with investment spikes are more likely to suffer from job loss.

Table 2 presents the mean statistic for the control variables by dependent variable outcome. A majority of the workers fall in outcome 1, which implies no unemployment or a move. This is not a surprise, since we choose to examine incumbent workers prior to the investment spike and hence workers that have been employed for quite some time. Bessen et al. (2023) also find that incumbent workers are safer to automation displacement, much due to labor market regulations, compared to newly hired employees. Almost 10 % of the sample end up in outcome 3, entailing unemployment but no move. Looking closer at the mean statistic for each covariate, we observe that workers with an on average lower occupational skill level and education appear to be more susceptible to unemployment.

Regarding the main explanatory variable, machine spike, we note that the average prevalence of machine investment spikes is higher for outcomes 3 and 4 encompassing unemployment.

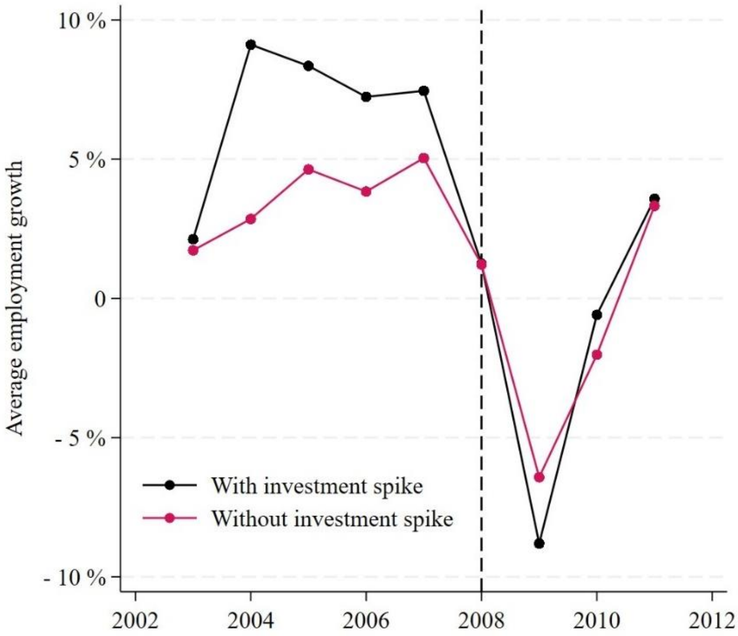

Figure 3. Average employment growth in firms with and without machine spike prior to 2007

Table 2. Variable means by dependent variable outcomes

	Outcome 1	Outcome 2	Outcome 3	Outcome 4
	No move	Move	Unemployment	Unemployment and move
Mean:				
Machine spike	0.41	0.39	0.49	0.46
Male	0.86	0.82	0.83	0.84
Age	42	32	36	34
Foreign-born	0.07	0.05	0.12	0.12
Higher education	0.19	0.33	0.08	0.18
Partner	0.65	0.41	0.51	0.37
Children	0.49	0.27	0.39	0.25
log Wage	8.02	7.83	7.81	7.79
Occupational skill	2.34	2.47	2.04	2.19
Establishment size	956	959	1196	1289
Frequency	65,041	1,314	6,169	1,398

Notes: Outcome 1 is the benchmark. Total number of observations is 73,922.

4.2 Regression output

In this section the average marginal effects for the multinomial regression model with and without interactions are presented in Table 3. In column 1, the machine spike dummy is statistically significant and negatively associated with outcome 1, no move, entailing that workers in an automating firm are on average 2.7 percentage points less likely to remain employed at the same workplace. Machine spike is statistically insignificant in column 3, indicating that machine investments have no bearing on workers' choice to move to other job opportunities. In both columns 5 and 7 the machine spike variable is statistically significant and positively associated with outcomes 3 and 4, encompassing unemployment and/or move. This result suggests that individuals in automating firms are more susceptible to job displacement in the wake of an economic downturn, and that some may be forced to move to another municipality on hunt for a job.

By introducing regional heterogeneity via interactions in the even numbered columns, we aim to examine whether the density of local economic activity in tandem with machine investments exacerbates or improves the risk of job displacement. The benchmark is metropolitan municipalities and the positive coefficient in column 6 suggests that workers in metropolitan municipalities are on average more likely to experience job loss. The magnitude of the coefficient decreases as the municipality becomes sparser. The opposite pattern is detected in column 2, where workers in metropolitan and urban municipalities are on average less likely to remain employed compared to their counterparts in rural municipalities. A possible explanation for these findings might be that workers with an outcome of 3 or 4 on average work at a larger establishment with more employees (Table 2) and these establishments tend to be located in the more population dense regions of the country.

Occupational skill level appears to matter for outcomes 1 to 3, but not for workers that are displaced and move. A higher occupational skill level increases on average the probability of no firm separation and decreases the risk for unemployment. This finding aligns with earlier literature in that workers blue-collar workers in manufacturing are more susceptible to the displacement effect of automation.

Table 3. Average marginal effects from multinomial logit regressions

	Outcome 1		Outcome 2		Outcome 3		Outcome 4	
	No move		Move		Unemployment		Unemployment and move	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Machine spike	-0.027***	-0.063***	-0.002	-0.002	0.025***	0.058***	0.039***	0.007***
	(0.003)	(0.008)	(0.001)	(0.002)	(0.003)	(0.008)	(0.001)	(0.002)
Machine spike × urban		0.039***		-0.002		-0.035***		-0.003
		(0.011)		(0.003)		(0.009)		(0.004)
Machine spike × dense rural		0.045***		0.001		-0.041***		-0.004
		(0.009)		(0.002)		(0.008)		(0.003)
Machine spike × sparse rural		0.046***		-0.001		-0.046***		0.001
		(0.017)		(0.004)		(0.015)		(0.008)
Occupational skill level 2	-0.009	-0.008	-0.002	-0.002	0.012	0.011	-0.001	-0.001
	(0.008)	(0.008)	(0.004)	(0.004)	(0.007)	(0.007)	(0.003)	(0.003)
Occupational skill level 3	0.059***	0.061***	0.009**	0.009***	-0.071***	-0.071***	0.002	0.002
	(0.012)	(0.012)	(0.005)	(0.005)	(0.011)	(0.011)	(0.004)	(0.004)
Occupational skill level 4	0.081***	0.079***	0.012***	0.013***	-0.095***	-0.095***	0.002	0.003
	(0.013)	(0.013)	(0.004)	(0.004)	(0.011)	(0.011)	(0.004)	(0.0049
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AKM-ability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,871	73,871	73,871	73,871	73,871	73,871	73,871	73,871

Notes: *** indicates significance at the 1 % level, ** at the 5 % level, * at the 10 % level. Robust standard errors in parentheses. The benchmark occupational skill level is 1. The benchmark municipality category in columns 2, 4 and 6 is metropolitan.

5. Conclusion

In this paper we have sought to disentangle the influence of investments in automation technology in manufacturing firms on individual labor market outcomes for workers in these firms. We hypothesize that effects will be more visible during economic downturns when the pressure to cut costs is higher.

To test this hypothesis, we use the great recession of 2008-2009. The research design rests on following individuals over a relatively long period. The start of this period occurs well before any investment spike is observed. Then we observe that some (but not all) firms invest in automation technology. After that, during the great recession, we investigate if labor market outcomes differ for individuals employed at firms that made such investments to those that did not.

The usefulness of this design rests on a couple of assumptions. First, we assume that when we start observing individuals it is sufficiently well before the investments so that employees cannot anticipate which employers will invest in automation technology, and which will not. The second assumption is that the main thrust of effects of these investments on hiring and firing to optimize the employee's skill-structure happen in economic downturns. If these assumptions are met then individuals contemplating to start working for a particular firm will have few leads on what investments that will made down the line, furthermore they won't know when the effects kick in. In this case one can argue that the effects that we measure can be interpreted as casual ones.

The question we investigate also has geographic dimensions both in terms of where the investments and their effects happen and the possible reaction of moving by individuals that lost their jobs.

Estimating a multinomial logit model, we find individual level effects on four probabilities. These are if individuals: (1) stay employed and do not move, (2) stay employed and move, (3) are unemployed and do not move, and (4) are unemployed and move.

Looking at descriptive evidence we can see that firms that do invest heavily in machinery are growing faster in employment before the economic downturn compared to those that don't invest. The reverse is true during the recession years. This implies that, in the aggregate, job-worker separation is greater in firms that invest in automation technology.

On the level of the individual estimations show that workers are less likely to remain in the firm if it has invested in machinery earlier. Also, for workers in firms that previously invested in such machinery there is a higher risk of unemployment. This is true regardless of whether the individuals move to another municipality or stay in the same. Furthermore, the is no discernable influence on moving even if the worker finds a job elsewhere. So, results seem to show that the act of moving is independent from whether one's firm invests in automation machinery or not.

Regarding the location of the firm, it seems like individuals that work in a metropolitan area are more likely to be separated from their employment. Individuals in smaller and less dense areas are less likely to become unemployed compared to those residing in metro-regions. The relationship between the location of the firm and one's job and the likelihood of moving is non-existent. Getting separated from employment due to automation investment does not seem to increase movement of individuals either up or down the regional hierarchy.

Individuals with relatively high occupational skill levels are less likely to lose their job due to investments in automation technology. They are also less likely to move.

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Appendix A

A1. Matching output for firms

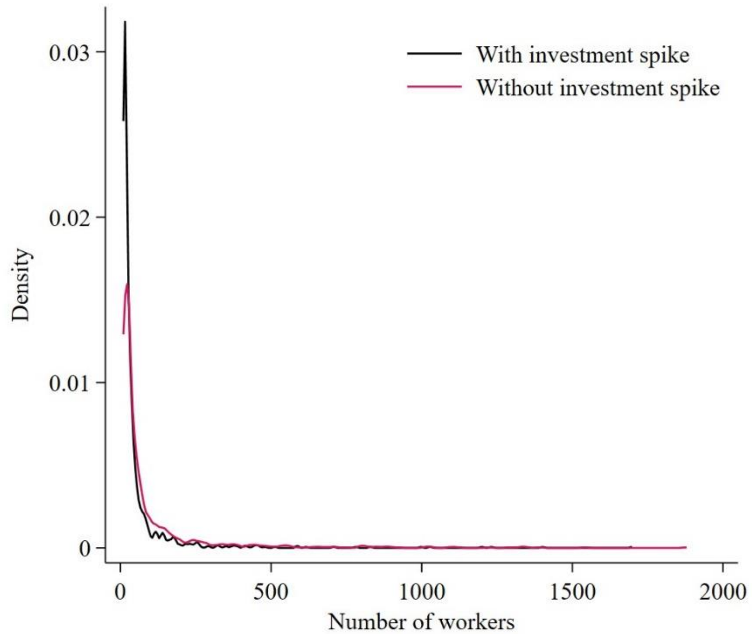

Figure A1. Densities of number of workers in firms in 2007 with and without investment spike

A2. Matching output for workers

Table A1. Matching output for workers

Variable	L1 distance	Difference in means
Male	5.7e-15	-9.9e-15
Age	0.01668	0.00015
Foreign-born	3.3e-15	1.3e-16
Higher education	3.7e-15	4.3e-14
4-digit occupation[a]	3.6e-15	2.2e-10
2-digit industry[b]	1.6e-15	7.1e-13
Municipality[c]	7.2e-15	-5.3e-15

Notes: [a]classified accord to the *Swedish Standard Classification of Occupations* (SSYK-2012). [b]classified according to the *Swedish Standard Industrial Classification* (SNI-2002) which resembles NACE rev. 1 with minor adjustments. [c]metropolitan, urban, dense rural, or sparse rural. Multivariate L1 distance: 0.34.