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## How do workers react to increased job loss fears? The role of training and job mobility

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Ronald Bachmann  
Roman Klauser

## How Do Workers React to Increased Job Loss Fears? The Role of Training and Job Mobility

## Imprint

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Ronald Bachmann and Roman Klauser\*

# How Do Workers React to Increased Job Loss Fears? The Role of Training and Job Mobility

## Abstract

*Labour markets are constantly subject to exogenous factors such as technological change and trade shocks. Beyond their direct effects, these factors are likely to affect workers' fears of losing their job in the foreseeable future. We therefore investigate workers' reactions to increased job loss fears, the determinants of job loss fears, and the interaction of determinants, fears, and workers' reactions. We focus on two potential reactions, training and job mobility, and three potential determinants, trade, robots and unemployment rates. Our analysis shows that increased job loss fears lead to higher job and occupational mobility, but not to higher training participation. Higher import exposure is associated with higher fears, whereas higher robot exposure slightly reduces job loss fears. Our results have important implications for firms and policymakers.*

JEL-Codes: D84, J24, J62, M53

Keywords: Job loss expectations; training; job mobility; occupational mobility

December 2024

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# 1 Introduction

Labour markets are constantly subject to exogenous factors such as technological change and trade shocks. These factors potentially change firms' demand for worker skills, and many workers' existing skills may not be adequate any more to fulfill the requirements of their job or even occupation (Autor et al. 2003; Deming and Noray 2020). This can lead to increased job loss fears (Innocenti and Golin 2022; Mueller and Spinnewijn 2023) with several important consequences. Increased job loss fears have been shown to lead to lower well-being (Clark et al. 2010), lower wages (Balleer et al. 2024), a deterioration of mental health (Reichert and Tauchmann 2017), and a reduction of durable goods consumption (Pettinicchi and Vellekoop 2019).

Given these negative consequences, workers have an incentive to engage in coping strategies, which can fall into two broad categories: First, workers can stay in the same job and occupation, and update necessary skills. This strategy has been shown to be important (Freeman et al. 2020), and to lead to long-run wage gains (Bachmann et al. 2022). Second, workers can switch their job or occupation to find a new job which fits their existing skills better (Jenkins and Morin 2018). While there is a large literature on learning on-the-job and on the beneficial effects of job mobility, there is a lack of evidence on workers' coping strategies with respect to increased job loss fears.

In this paper, we therefore investigate how employees react to an increase in the self-perceived probability of job loss, and how two fundamentally different factors, trade and technological progress, affect job loss fears. We do so using worker-level data from Germany including two measures of self-perceived job insecurity: the fear of a job loss, and the probability of losing the job within the next two years. We consider two broad coping strategies to increased job loss fears: increased training participation and a change of job or occupation. We also investigate whether workers with high job loss fears have a higher probability of becoming unemployed. To alleviate endogeneity concerns, we use an IV strategy applying several instruments, including the China shock in the context of changes to trade exposure, and a similar instrument for robot exposure.

As different shocks are likely to have different effects on fears and labour-market outcomes, we analyse two potential determinants of job loss fears. First, the trade shock we examine, the China shock, was relatively unexpected and had effects at the industry level. By contrast, our measure of technological progress, robot exposure, can be viewed as a more gradual process that affected specific occupations, i.e. effects are occupation- rather than industry-specific. As a result, the trade shock can be expected to lead to a stronger increase in fears, and less training, which generally requires more time and preparation than job or occupational mobility.

Our findings are in line with these expectations. First, in our analysis of potential determinants of individual job loss expectations, we find that higher imports significantly increase individual worries about job loss. The local unemployment rate is also weakly associated with higher job loss fears. By contrast, higher robot exposure is weakly negatively associated with job loss fears. Second, we find that worker mobility is an important coping mechanism as job loss fears are significantly correlated with both job mobility and occupational mobility. Successful transitions to another job or occupation may be an explanation for our further result that transitions to unemployment are not significantly correlated with job loss fears. Third, we do not detect any effect of job loss fears on training participation.

Our findings on job loss expectations are consistent with previous analyses of labour-market outcomes in the literature. For example, our results on job loss expectations and worker behaviour are in line with evidence that higher imports have led to some losses for affected workers in Germany (Dauth et

al. 2021a), and that higher robot exposure has generally been found to be beneficial for incumbents (Bachmann et al. 2024; Dauth et al. 2021b).

Our findings have important implications. First, the result that job and occupational mobility play an important role as a coping mechanism against a sudden shock like the China shock, whereas training does not, is important for both firms and policymakers. Given the ageing of the workforce and resulting labour shortages in many industrialised countries, job and occupational mobility as main adjustment mechanisms may not be ideal from a firm's perspective as worker mobility implies a loss of human capital for firms. Furthermore, the lack of evidence for workers increasing training participation as reaction to increased job loss fears could call for better financing of training measures, and campaigns to raise awareness for the importance of continued training for workers' careers.

Second, job loss fears are important from a policy point of view. For example, a higher occupational offshorability, and therefore higher job loss fears, has been shown to increase protectionist sentiment (Owen and Johnston 2017). A higher exposure to robots has been shown to have had a decisive influence on the 2016 US election result (Frey et al. 2018). In Spain, automation risk is perceived as a threat only by a minority of workers who prefer policies to slow down technological change (Gallego et al. 2022). It therefore seems crucial to better understand the relative importance of different factors influencing job loss expectations.

Third, we show how different shocks have led to different fears and reactions: a sudden shock to trade flows leads to more job and occupational mobility, a more gradual process like robotization does not have this effect. Against the background of the current disruption of world trade, which is likely to be exacerbated in the future, this is highly policy-relevant.

Our contributions to the literature are as follows: first, we add to the literature on how expectations shape individual-level behaviour. Building on the insight of Manski (2004) that individual job-loss fears can be elicited using expectations questions in surveys. In the context of job loss expectations, there are only few studies on the effects of job loss fears on labour-market behaviour. We add to this literature by jointly considering mobility and training decisions.

Second, we contribute to the literature on training participation. Most existing studies focus on worker heterogeneity in training with respect to occupations and skills. For example, Heß et al. (2023) show that workers exposed to automation technology participate much less in further training than less-exposed workers. Innocenti and Golin (2022) find that workers who are more afraid of automation have a higher intention to acquire further training. We add to this literature by analysing the link between exogenous factors leading to job loss fears, and actual training participation.

Third, while the existing literature has focused on specific exogenous factors, we analyse several exogenous factors, i.e. robotization, trade and unemployment fluctuations, for job loss fears and workers' coping mechanisms. This allows us to show which type of shock is likely to have a larger effect on job loss fears, and which coping mechanisms are likely to prevail.

The remainder of the paper is structured as follows. Section 2 gives a brief overview of the different data sources used in the paper. Section 3 describes the econometric analysis. Section 4 presents the results and Section 5 concludes.



## 2 Data and descriptive evidence

### 2.1 Overview

For our analysis, we use a combination of different data sources. Our primary data source is the German Socio-Economic Panel (SOEP), an annual representative household panel survey conducted since 1984 (Goebel et al. 2019). The SOEP contains individual-level and household characteristics, including socio-economic factors, information on individual labour-market histories, and on attitudes and opinions. From the yearly panel information, we can identify job and occupational mobility, as well as individual job loss fears and expectations. In addition to the annual panel information, the SOEP contains modules on specific topics rotating in and out of the survey. As we are particularly interested in training participation, a survey module consisting of three separate SOEP waves (2000, 2004, 2008) is particularly relevant. This module provides detailed information on training participation and the type of training undertaken.<sup>1</sup> Given the availability of the training module, we analyse the time period 1998 to 2007.<sup>2</sup> This time period is particularly interesting for our research question as it was characterized by substantial macro-economic developments, including the rapid rise of robotisation and changes in global trade flows induced by China's access to the WTO.

We restrict our estimation sample to working-age individuals between 20 and 60 who are in a regular employment relationship covered by social security legislation. We thus exclude interns, apprentices, self-employed individuals and members of the armed forces from the analysis. Civil servants are also excluded due to their exceptionally high job security that is not comparable to that of regularly employed workers. This results in an estimation sample of 53,711 person-year observations for the period 1998 to 2007. It should be noted that the estimation sample for the training outcomes is smaller, given that it is a subset of three years of the full estimation sample and includes 10,155 person-year observations.

We augment the individual-level data from the SOEP with information from several additional data sources that provide information on various exogenous factors at the occupational and sectoral level. Information on international trade volumes comes from the UN comtrade database and is normalised with data on home production values from the OECD Structural Analysis (STAN) database. The number of robots is provided by the International Federation of Robotics (IFR). Finally, we obtain data on the unemployment rate at the federal state level from the Federal Employment Agency (BA).

### 2.2 Expectations

The SOEP offers a range of variables for measuring individuals' expectations regarding job loss. These variables differ in availability and measurement method. Our preferred job loss fears measure is part of a question battery that assesses individuals' concerns on a number of different areas, like personal health, crime or economic development.<sup>3</sup> For employed individuals, the concerns regarding job security are elicited. Individuals can respond on a cardinal scale, indicating whether they are "*Not concerned at all*", "*Somewhat concerned*" or "*Very concerned*" about their job security. This variable has been previously used in e.g. Geishecker et al. (2012), Reichert and Tauchmann (2017) or Kohlrausch and Rasner (2014). We group respondents that are either "*Very concerned*" or "*Somewhat concerned*"

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<sup>1</sup> See Caliendo et al. (2022) and Caliendo et al. (2023) for related analyses using the training module.

<sup>2</sup> Note that the survey waves of the training module are retrospective. We therefore lag all training variables by one year to ensure consistency with the other variables.

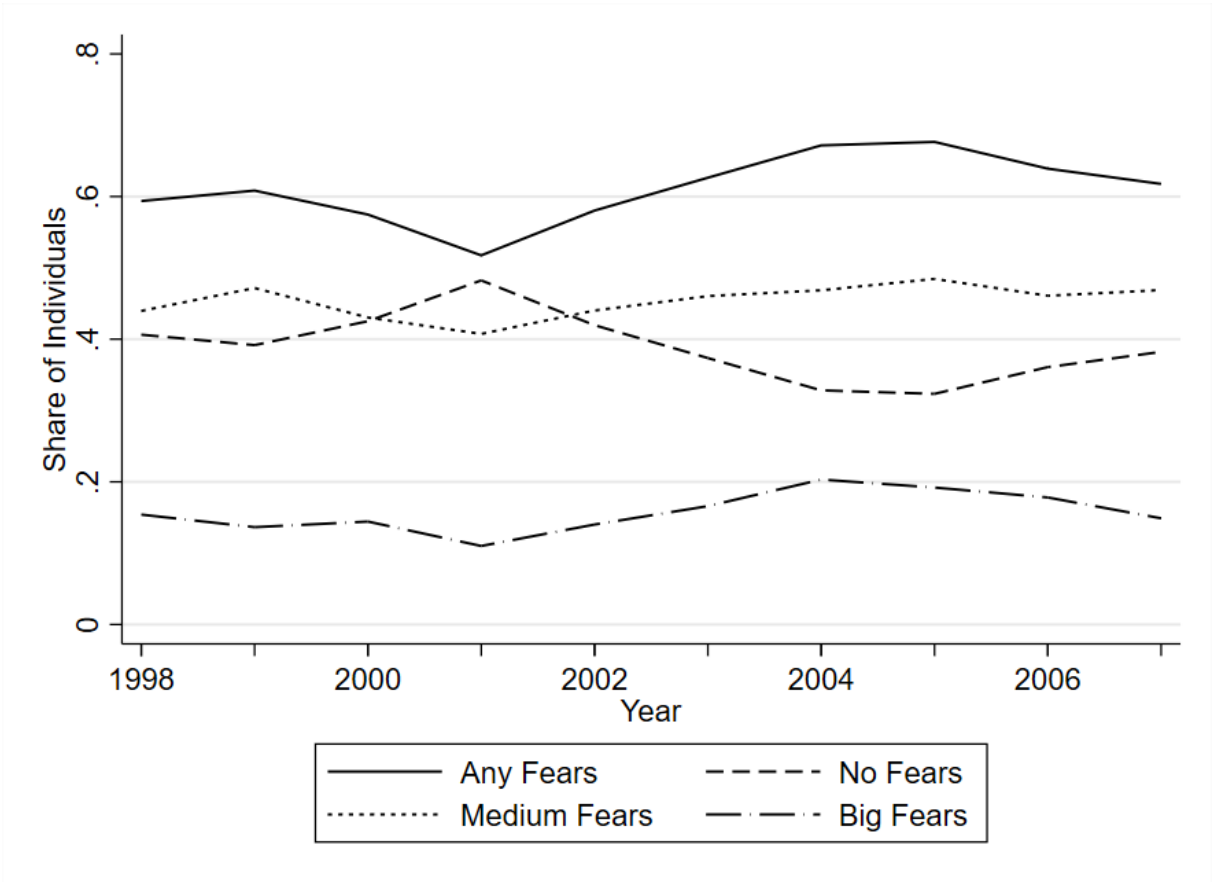
<sup>3</sup> The exact question wording is as follows: „*What is your attitude towards the following areas – are you concerned about them?*“. Some of the following areas are then: "*General economic development*", "*Your Health*", "*Crime in Germany*" or "*Your job security*".

together to create a binary indicator of individual job loss fears. In addition, the individual outcomes of “*Very Concerned*” and “*Somewhat Concerned*” are analysed separately in robustness tests. They are subsequently also referred to as “*Big Fears*” and “*Medium Fears*”.

Additionally, the SOEP also presents alternative measures for individual job loss fears, most notably a set of questions about the likelihood of certain career changes taking place in the next two years. The question reads: “*How likely is it that the following career changes will take place in your life within the next two years? - loose your job?*” Respondents can answer by ticking a box on an 11-point Likert scale that represents the probabilities from 0% “*such a change will definitely not take place*” to 100% “*such a change definitely will take place*”. These numeric measures of job loss fears have been utilized in prior research, including studies by Balleer et al. 2024, Dickerson and Green 2012, and Emmeler and Fitzenberger 2022. A key limitation of this measure is its biannual availability, which would reduce our estimation sample by half. To test the robustness of our results, we conduct all main analyses with this numeric measure.

Figure 1 illustrates the trends in the categorical job loss fears variable over time. More than half of the individuals in our sample report at least some fear of job loss, with the majority reporting as being “*Somewhat concerned*” while up to 20% indicate being “*Very concerned*”. On average, the proportion of individuals expressing fears increases over time, with a notable rise beginning in 2001, as the share of individuals with moderate or high levels of fears grows. This period coincides with significant shifts in trade dynamics and advancements in robotics (see Section 2.3).

**Figure 1:** Development of categorical job loss fears variable over time



Source: SOEP, own illustration.

A similar analysis was conducted for the numeric measure of job loss fears, with the results presented in Appendix Figure A1 and Figure A2. Appendix Figure A1 shows the distribution of responses over the

entire time period. The data reveal familiar patterns: a large share of individuals report no fear (0% probability of a job loss occurring in the next two years), some observations appear at lower percentages, and there is a notable spike at 50%. Similar distributional patterns have been documented in British and Australian data (see Stephens Jr 2004 and Dickerson and Green 2012).

To track the development of the numeric job loss fear variable over time, we group certain response categories together, following the approach of Emmler and Fitzenberger (2022).<sup>4</sup> The resulting plot is shown in Appendix Figure A2. Due to the very small sample size of individuals reporting job loss expectations of 60% or higher, the corresponding graph for this group is relatively limited. Nevertheless, we observe a notable increase in the share of individuals with very high job loss expectations, rising from approximately 5.8% in 2001 to 9.1% in 2005. This trend aligns with the patterns observed in the categorical job loss fears variable. However, due to the small sample size of individuals reporting very high job loss expectations, we refrain from using this binary classification in further analyses. Instead, we concentrate on the original categorical and numeric variables, which provide more robust insights.

Overall, all measures indicate an increase in job loss fears during the period from 1998 to 2007. Table 1 reveals significant differences between characteristics of individuals with no fears (Column 1) and those with any kinds of fears (Column 2), as nearly all T-tests on the equality of means between the two groups (Column 3) are rejected. Notably, men are more likely to report job loss fears than women. There are very large discrepancies between West and East Germany, with individuals in East Germany being nearly twice as likely to report job loss fears, a finding in line with Emmler and Fitzenberger (2022).

Education also plays a role, as individuals with lower educational attainment display higher job loss fears than individuals with higher educational attainment. Full-time workers are more likely to report job loss fears than their part-time counterparts, which may be influenced by the higher proportion of men, who are more likely to work full-time and exhibit greater fears of job loss. In comparison, workers on temporary contracts report significantly higher job loss fears.

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<sup>4</sup> The authors classify individuals into two groups: those with job loss expectations ranging from 60% to 100% and those with expectations between 0% and 50%. This creates a binary measure distinguishing between individuals with little to moderate job loss expectations and those with high levels of job loss expectations.

**Table 1:** Descriptive statistics for individuals with and without job loss fears

Characteristics	(1) Any Fears		(2) No Fears		(3)
	Mean	Std. Dev.	Mean	Std. Dev.	p-Value
Female	0.450	(0.498)	0.505	(0.500)	0.000
Age	41.145	(9.175)	41.448	(9.896)	0.000
East	0.299	(0.458)	0.151	(0.358)	0.000
Migrant	0.158	(0.365)	0.133	(0.339)	0.000
Low education	0.076	(0.265)	0.068	(0.251)	0.000
Medium education	0.630	(0.483)	0.625	(0.484)	0.178
High education	0.293	(0.455)	0.308	(0.462)	0.000
Full-time employment	0.795	(0.403)	0.725	(0.446)	0.000
Part-time employment	0.176	(0.381)	0.223	(0.416)	0.000
Marginal employment	0.029	(0.168)	0.052	(0.221)	0.000
Temporary contract	0.072	(0.258)	0.039	(0.194)	0.000
Tenure at employer	10.346	(8.979)	10.758	(9.435)	0.000
Training participation	0.245	(0.430)	0.290	(0.454)	0.000
Job change	0.164	(0.370)	0.131	(0.337)	0.000
Occupation change	0.110	(0.312)	0.086	(0.280)	0.000
Employed to unemployed	0.022	(0.148)	0.018	(0.132)	0.000
N	32,814		20,897		
Share of all observations	0.611		0.389		

Notes: Numbers in brackets represent standard deviations. Column (3) displays the p-values for a T-test on the equality of means between the groups in (1) and (2). Source: SOEP, own calculations.

### 2.3 Coping strategies

In this paper, we focus on two potential coping strategies in response to heightened job loss fears: on-the-job-training and job or occupational mobility. Both outcomes are observable in the SOEP.

For the training measure, we utilize data from a specialised training module included in the SOEP waves of 2000, 2004, and 2008. This module gathered information about individuals' participation in training over a three-year period preceding the interview. Respondents could name up to three completed training courses and provide detailed follow-up information for each individual course.

Broadly following Caliendo et al. (2022) and Caliendo et al. (2023), we consider individuals as training participants only if they reported completing a course for the year of the interview or for the preceding year. For instance, in the 2000 wave, only individuals who reported a completed training in 1999 or 2000 are classified as participants. The same criterion applies to the subsequent waves. This restriction minimizes the risk of recall bias, as training events that occurred more than a year before the interview are more likely to be inaccurately reported.

In our analysis, we lag the training variables by one year, because training is only observed retrospectively, so after it has already taken place. As a result, individuals are classified based on their future training participation in the same year their job loss expectations are reported. For example, individuals in 1999 are considered training participants if they report training participation in either 1999 or 2000 during the 2000 survey wave. This outcome is then linked to the 1999 job loss

expectation. This approach ensures a chronological sequence, aligning job loss expectations reported in year  $t$  with subsequent behavior occurring either within the same year ( $t$ ) or the following year ( $t+1$ ). We adopted this two-year window because the numeric expectation question explicitly refers to changes that individuals anticipate will occur to them within the next two years. Given that around 80% of all SOEP interviews happen in the first four months of a year, we assume it to be reasonable to regard the current year  $t$  as part of the “next two years” time frame.

As highlighted by Becker (1962), the distinction between general and specific human capital is a key consideration for the investment in education and training. This consideration is particularly relevant in the context of job loss fears. On the one hand, individuals concerned about job loss may proactively invest in general human capital to enhance their attractiveness on the broader labor market. On the other hand, they might rather focus on acquiring firm-specific human capital to increase their value to their current employer, which could be interpreted as an insurance motive. Distinguishing between these two strategies is therefore important for understanding the underlying dynamics of training participation in response to job loss fears.

The SOEP facilitates this distinction through follow-up questions that capture the type of training undertaken. Respondents are asked: “*To what extent could you use the newly acquired skills if you got a new job in a different company?*” The response options include: “*Completely*”, “*For the most part*”, “*Only to a limited extent*” and “*Not at all*”. Following the classification approach used by Caliendo et al. (2022) and Caliendo et al. (2023), we categorize training as *general* if the acquired skills are reported as “*Completely*” or “*For the most part*” transferable to a new employer. Conversely, training is classified as *specific* if the skills are deemed “*Only to a limited extent*” or “*Not at all*” transferable.

Employers may be reluctant to provide or finance training for employees that are likely to leave their job soon. To capture this motive, we consider how training is financed. Individuals with high job loss expectations may be more inclined to pay for their own training as a means of improving their chances on the labour market. The SOEP includes a follow-up question that helps analyze this relationship. The question asks, “*Did you receive financial support from your employer, from the Employment Office (“Arbeitsamt”), or from another source for this instruction?*” and provides several different answer options. If the training was mostly paid for by the employer, we define it as *firm-financed training*. If it was mostly paid for by the individual, the employment office, social welfare office or from another source, we consider it as *self-financed training*.<sup>5</sup>

An overview of the various types of training and their participation rates is provided in Table 2. Overall, the training participation rate is approximately 27% which is in line with findings from studies on training participation in Germany for the period we investigate (e.g. Wasmer et al. 2007, Pischke 2001). Notably, nearly two-thirds of all training is classified as general, a result that supports the notion that firms often finance general training (Acemoglu and Pischke 1998). This conclusion is further reinforced by the observation that the vast majority of training courses undertaken are funded by employers.

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<sup>5</sup> Most non-firm-financed training is paid for by the individual. Although the employment office also covers some of the costs, the other options—social welfare office and other sources—are extremely rare. Therefore, for simplicity, we classify this variable as *self-financed training*.

**Table 2:** Frequency of different training outcomes

	1999		2003		2007	
<b>Training</b>						
Non-participants	1869	(74.5)	3072	(73.7)	2492	(71.7)
Participants	641	(25.5)	1096	(26.3)	985	(28.3)
<b>Type of Training</b>						
General	422	(65.8)	700	(63.9)	631	(64.1)
Specific	219	(34.2)	396	(36.1)	354	(35.9)
Firm-financed	509	(79.4)	826	(75.4)	719	(73.0)
Self-financed	132	(20.6)	270	(24.6)	266	(27.0)
N	2510	(100)	4168	(100)	3477	(100)

Notes: Absolute number of training participants. Numbers in brackets represent percentages. For the "Type of Training", percentages are calculated relative to the total number of training participants.

The other potential coping strategy for job loss fears is job and occupational mobility. Employees may proactively seek new job opportunities before being dismissed from their current positions. Following an approach similar to that used for training, we classify individuals in year  $t$  as job changers if they transition to a new employer between year  $t$  and  $t+1$  or between  $t+1$  and  $t+2$ . This allows us to capture job changes that occur either in the same year the job loss expectation was reported in or in the year following its reporting.

A specific type of job change is an occupational change, which occurs when an individual not only transitions to a new employer but also shifts to a different occupation. To classify occupations, the SOEP uses the German Classification of Occupations 1988 (KldB 1988), which is comparable to the International Standard Classification of Occupations (ISCO). To identify occupations in the survey, interviewees are asked an open question to provide a detailed description of their occupation; using this information, and if necessary additional information from the interview, e.g. on the required education, the interviewer identifies the fitting occupational code (Tschersich and Schütz 2017). Measurement error with respect to occupations is therefore likely to be low. If a job change involves a new occupation—defined as a change in the first three digits of the KldB 1988 code—we classify it as an occupational change.

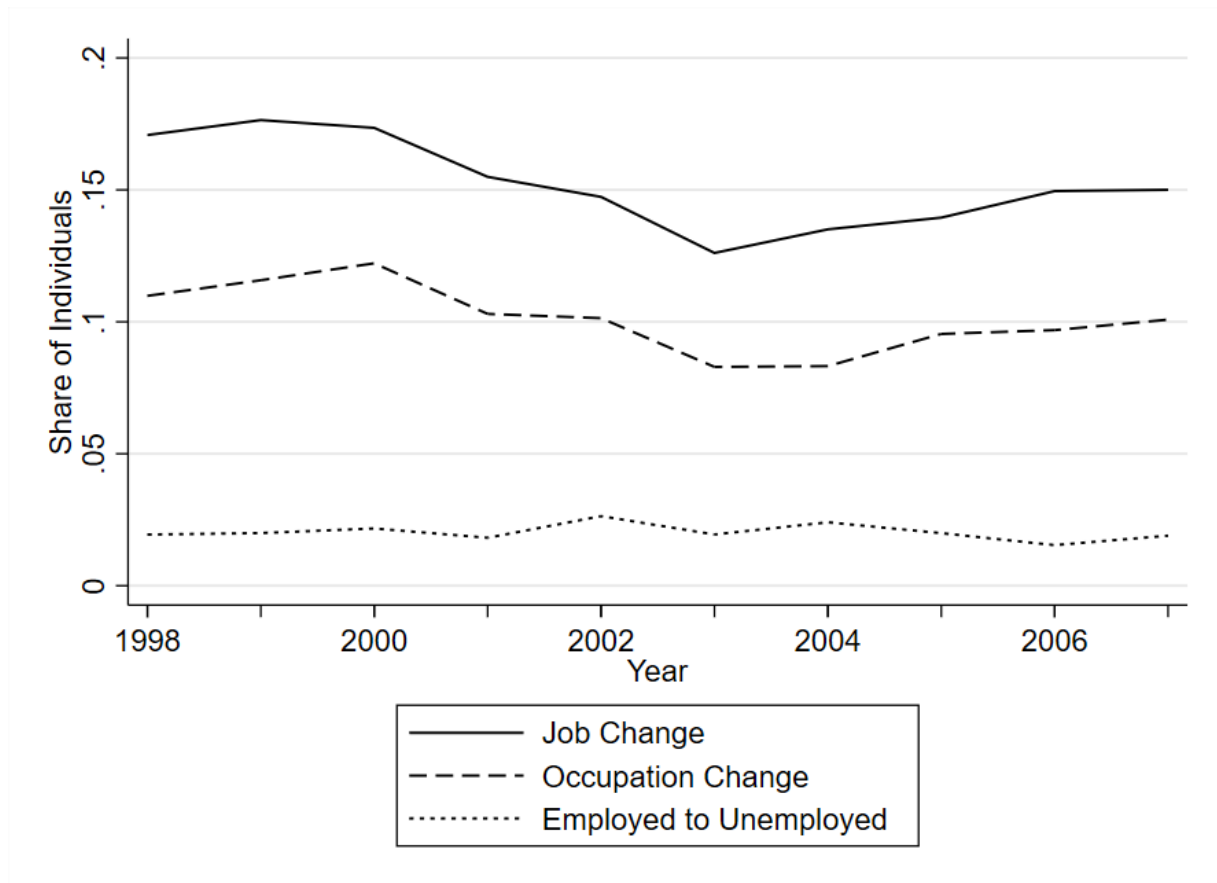
The final and most adverse form of mobility is a transition into unemployment. This outcome is defined as a binary variable taking the value of 1 if an individual is employed in year  $t$  but is unemployed in year  $t+1$ .

The development of these mobility measures over time is presented in Figure 2. The annual job change rate is approximately 15%, aligning closely with findings reported by Bachmann et al. (2020).<sup>6</sup> Occupation changes, which represent a subset of job changes, occur less frequently, with a probability of around 10%. Transitions into unemployment are the least common, averaging about 2% per year.

<sup>6</sup> While the authors report job change rates of around 8–9% and occupation change rates of approximately 4% for Germany, their analysis considers only a single year. Observing mobility over a two-year period could effectively double these numbers, bringing them in line with the rates observed in our analysis.

Over time, there is a slight decline in overall mobility, with both job and occupation change rates dropping between 2000 and 2003, followed by a gradual recovery beginning in 2004.

**Figure 2:** Mobility indicators over time



Source: SOEP, own illustration.

In total, we examine eight different binary outcomes. Five of these relate to training: overall training participation, participation in general training, participation in specific training, participation in firm-financed training, and participation in self-financed training. The remaining three outcomes relate to job mobility: job changes, occupation changes, and transitions into unemployment. In our analysis, we link these outcomes to job loss fears.

Doing so shows that individuals with job loss fears are less likely to participate in training and are more likely to change employers compared to those without fears (Table 1). Additionally, individuals with job loss fears are at greater risk of transitioning into unemployment than those who do not express any concerns about their job security.

### 2.3 Exogenous Factors

We are also interested in potential determinants of individual job loss expectations. For that purpose, we merge several different data sources to the SOEP to analyse the impact that exogenous factors might have on individual job loss fears.

First, we aim to investigate the impact of increased international trade on individual job loss expectations. A vast literature has analysed the effect of the so called “China shock” on labor markets (see Autor et al. 2016 for an overview). China's accession to the World Trade Organization (WTO) at

the end of 2001 brought important tariff reductions and regulatory changes, enabling a substantial expansion of Chinese exports on a global scale. This surge in international competition had significant effects on domestic production and thus also on employment. Although Dauth et al. 2014 found only mild adverse effects of rising imports from China on German employment, there might still be large effects on the job loss expectations and fears of individuals working in exposed industries.

To analyse these potential effects of the China Shock on job loss fears, we use data on international trade flows from the UN comtrade (United Nations International Trade Statistics) database. UN comtrade provides annual information on imports and exports, categorized by product category for over 170 countries (a detailed description of the database can be found in Autor et al. (2013)). We focus on German imports of Chinese goods, as well as US imports of Chinese goods. Imports and exports are classified under 4-digit SITC (Standard International Trade Classification) Revision 3 codes, which are available at different levels of aggregation. We match these SITC to NACE (Nomenclature of Economic Activities) industry codes using a correspondence table by the UN.

The total import value per industry is normalised using data on domestic production from the OECD Structural Analysis (STAN) database. STAN captures the total value of all goods and services produced in a certain ISIC Rev. 4 (International Standard Industrial Classification of All Economic Activities) industry in a given country and year (on overview of variables, methods and sources is given in Horvát and Webb (2020)). Given that the NACE classification is derived from ISIC, we can easily crosswalk the ISIC codes to NACE codes using a correspondence by the European Commission (Eurostat 2008). We divide the total value of Chinese imports by the total domestic production value of this industry in a given year. The resulting share is our normalised trade exposure measure expressed as the percentage of Chinese imports relative to domestic production.

Figure A3 in the Appendix illustrates the development of the import share for the manufacturing sector over the analysis period. Beginning in 2002, there is a noticeable spike in trade exposure, with the share more than doubling within a few years. It increased from approximately 2.8% prior to 2002 to nearly 7% in 2007. As the manufacturing sector was the most impacted industry, this sharp increase likely triggered significant adjustment mechanisms, potentially influencing workers' job loss expectations during this period.

Apart from the developments in trade, the early 2000s also saw significant advancements in robotisation. As a global leader in the development and deployment of industrial robots, Germany has been at the forefront of this technological shift. While the evidence on the overall employment effects of robots is mixed (see Acemoglu and Restrepo 2020, Bachmann et al. 2024, Graetz and Michaels 2018), the rise of automation has sparked widespread discussions about the risks of job displacement and the replacement of workers by machines. Although studies such as Dauth et al. (2021b) suggest that these fears may not have fully materialised in Germany, automation could still influence individual job loss fears and expectations. For this reason, we analyse robotisation as another exogenous factor potentially shaping job loss expectations.

To measure individual exposure to robots, we use data on robot stock and new installations from the International Federation of Robotics (IFR). The IFR (International Federation of Robotics 2019) compiles information from nearly all global industrial robot suppliers, detailing current stock levels and new robot deliveries by industry. To normalise this data, we divide the current stock of robots by the number of workers in a specific industry for a baseline year (in our case 1995). This yields a measure of robot exposure, expressed as the number of robots per 1,000 workers in each industry.

The evolution of this robot exposure measure for the manufacturing sector is depicted in Figure A4 in the Appendix. The number of robots per 1,000 workers steadily increased, growing from around 5 to



nearly 9. These trends broadly align with findings from Dauth et al. 2021b, who report slightly lower but comparable figures.

Both the trade and robot exposure measures are calculated at the industry level. As the SOEP includes industry indicators for the jobs held by individuals, we can merge the exposure measures with the SOEP data at the industry-year level enabling us to link exogenous shocks from trade and robotisation to individual job loss expectations.

Finally, we include a general measure for the status of the labor market in some of our analysis by using the unemployment rate at the federal state level, provided by the Federal Employment Agency (BA). This unemployment rate helps capture regional idiosyncratic trends. The data from the BA is merged with the SOEP using the federal state-year indicators, which are readily available in the survey.

### 3 Econometric analysis

We examine how individual fears of job loss influence behavior and identify potential determinants of these fears. To do so, we conduct various estimations on different components of the causal chain. First, we establish a link between exogenous factors and expectations. Next, we analyse the relationship between expectations and behavioral outcomes. Finally, we estimate a comprehensive model that integrates all elements: exogenous factors, individual expectations, and behavioral outcomes.

#### 3.1 Determinants of job loss expectations

The descriptive analysis revealed significant shifts in trade and robotisation for the period analysed. Our objective is to estimate the impact of these factors on job loss fears. However, directly running linear regressions on the job loss fears dummies may lead to issues of endogeneity. Changes in trade and robot adoption do not occur in isolation; they may be correlated with occupation and industry characteristics accompanied by anticipatory effects, such as discussions in the workplace or preparatory measures, which could influence job loss fears even before the actual changes take place.

To address these endogeneity concerns, we employ instrumental variable (IV) approaches. For trade, we follow Aghelmaleki et al. (2022) and instrument German industry trade exposure using the trade exposure of equivalent industries in the United States. The U.S. trade exposure measures are constructed similarly to the German ones, utilizing data from UN comtrade and the OECD STAN database.

For robot adoption, we use a comparable approach, but instead of U.S. robot adoption as an instrument for Germany, we rely on a multi-national measure. This measure is constructed by considering robot adoption trends in other Western countries, as well as South Korea and Japan, which are global leaders in robot adoption. This international robot measure serves as the instrument for German robot adoption. An exemplary estimation equation for these models is presented below.

$$Exposure_{jt}^{ger} = \delta_0 + \delta_1 Exposure_{jt}^{int} + X'_{it} \mathbf{d} + \epsilon_{it} \quad (1)$$

$$\mathbb{1}(Fears_{it}) = \gamma_0 + \gamma_1 \widehat{Exposure}_{jt}^{ger} + X'_{it} \mathbf{c} + \epsilon_{it} \quad (2)$$

Our outcome of interest is  $Fears_{it}$ , an indicator of job loss fears for individual  $i$  in year  $t$ . It is either the dummy for having any concerns, or not or one of the individual outcomes of medium fears or big fears. Given the binary nature of our outcome variables, we estimate linear probability models in all our regressions. Additionally, we use a numeric version of the job loss fears variable (the job loss

expectations on a scale of 0 to 10), which allows the outcome to take continuous values rather than binary ones.

In the IV approach, the prediction from the first stage (1) serves as the main regressor in the second stage (2). For example, in the case of trade, the first stage regresses German trade exposure in industry  $j$  in year  $t$  on U.S. industry trade exposure in the same year and industry, along with a vector of additional individual and occupational controls  $X_{it}'$  ( $\mathbf{d}$  and  $\mathbf{c}$  are the vectors of the coefficients). The predicted values of German industry trade exposure  $\widehat{Exposure}_{jt}^{ger}$  are then used in the second stage regression, where job loss fears is the dependent variable.

The exclusion restriction for the IV approach requires that U.S. industry trade exposure must not directly influence German individual job loss fears, except through its role as an instrument. We consider this restriction valid because the only link between U.S. trade exposure and German job loss fears lies in overarching global trade trends, which our analysis seeks to measure. The coefficient  $\widehat{\gamma}_1$  from the second stage then captures the effect of an increase in trade exposure on the likelihood of experiencing job loss fears.

For robot adoption, the first stage regresses German robot adoption on international robot adoption, alongside additional controls. As with trade, the exclusion restriction requires that German job loss fears are not directly influenced by international robot adoption, except through the global trend in robotization. If this restriction holds, the second stage estimate  $\widehat{\gamma}_1$  reveals the effect of increased robot adoption within an industry on the likelihood of experiencing job loss fears.

Finally, we also examine how the overall state of the labor market influences job loss fears. To do this, we regress the job loss fears indicators on the federal-level unemployment rate. For this analysis, we do not employ any instruments; instead, we rely on straightforward OLS estimation.

### 3.2 The effect of job loss expectations on labour-market mobility and training

Next, we focus on the relationship between job loss fears and various coping mechanisms. In this analysis, we regress the behavioral outcomes on the job loss fears indicator and a number of control variables using ordinary least squares (OLS) regressions. The estimation model is structured as follows:

$$\mathbb{1}(y_{it}) = \alpha_0 + \alpha_1 Fears_{it} + X'_{it}\mathbf{a} + \theta_i + \varepsilon_{it} \quad (3)$$

The outcome  $y_{it}$  represents one of our eight binary indicators for various forms of training participation or mobility.  $Fears_{it}$  denotes the individual's job loss fears, and  $X_{it}$  includes individual-level and occupational controls. To account for unobservable time-invariant individual-level characteristics, we include individual fixed effects  $\theta_i$ . The coefficient  $\widehat{\alpha}_1$  represents the probability of participating in a specific type of training or experiencing job mobility in the following years for individuals who have job loss fears compared to those who do not have job loss fears.

### 3.3 Determinants, Fears and Outcomes

Finally, we bring all elements together by adding the potential determinants of job loss fears to the analysis of the impact of job loss fears on the different behavioral responses. To achieve this, we re-estimate equation (3) using a two-stage least squares (2SLS) approach. In the first stage, we predict the exposure rate using the previously described instruments. Additionally, we conduct a second first-stage regression, where we model the interaction between job loss fears and German exposure rates as a function of the interaction between job loss fears and the instrumented exposure rates while controlling for the previously used set of controls. In the second stage, we estimate the effect of job

loss fears on the coping mechanism, incorporating both the predicted exposure rates and the predicted interaction terms from all first stages. The resulting estimation equation for the second stage is:

$$1(y_{it}) = \beta_0 + \beta_1 Fears_{it} + \beta_2 \widehat{Exposure}_{jt} + \beta_3 (Fears_{it} \times \widehat{Exposure}_{jt}) + X'_{it} \mathbf{b} + \theta_i + \varepsilon_{it} \quad (4)$$

Equation (4) analyses the effect of job loss fears on the coping mechanism ( $\widehat{\beta}_1$ ) while also controlling for the exposure rate within industry  $j$  to trade or robots ( $\widehat{\beta}_2$ ). The interaction term  $\widehat{\beta}_3$  captures differential behavioral responses between worried individuals in highly exposed industries and those in less exposed industries. This regression still controls for various time-varying individual-level characteristics, occupational characteristics ( $X'_{it}$ ), and individual fixed effects ( $\theta_i$ ).

In all the regressions on the behavioral outcomes, we cluster the standard errors at the individual level to account for individuals appearing in the sample multiple times. This approach ensures that the standard errors are robust to potential correlations in the error terms within the same individual across different observations.

## 4 Results

In this section, we present the results from our regression analyses. In Section 4.1, we examine three potential determinants of job loss fears: trade, robots, and unemployment. In Section 4.2, we analyse the coping mechanisms related to increased job loss fears: training, job and occupational mobility, and transitions to unemployment. In Section 4.3, we present a unified analyses of determinants, fears and coping strategies.

### 4.1 Exogenous Factors and Job Loss Fears

To analyse the role of imports for job loss fears, we use the China shock as exogenous variation and apply the instrumental variables strategy described in Section 3.1, using imports from China to the US as an instrument for imports from China to Germany. From the first stage of this regression in Table 3, it becomes clear that there is a significant correlation between imports to the US and imports to Germany with a sufficiently high F-statistic to provide a strong instrument.

The second stage of the regressions shows that higher exposure to imports from China increases the likelihood of having job loss fears. In particular, a 0.01-percentage point increase in trade exposure increases the probability of having fears by 0.43 percentage points. Given the mean and standard deviation of trade exposure for the whole sample, an increase of 1 standard deviation in trade exposure increases the likelihood of having job loss fears by nearly 1 percentage point. Controlling for individual fixed effects turns the coefficient of interest insignificant. Looking at different sub-groups and their job loss expectations in Appendix Table A1 shows that this reversal is mostly driven by individuals with no job loss fears to begin with. Estimations on alternative measures for job loss fears reveal similar patterns (Appendix Table A2). We can therefore conclude that import exposure is a relevant determinant of job loss fears.

**Table 3:** Trade exposure and job loss fears

	(1) Job Loss Fears	(2) Job Loss Fears	(3) Job Loss Fears	(4) Job Loss Fears
<b>Second Stage</b>				
GER imports	1.146*** (0.246)	1.004*** (0.204)	0.429*** (0.088)	-0.045 (0.146)
<b>First Stage</b>				
US imports	0.403*** (0.032)	0.404*** (0.032)	0.400*** (0.034)	0.353*** (0.025)
F-Statistic	163.46	161.53	138.14	206.16
Individual Controls		X	X	X
Occupation Controls			X	X
Individual FE				X
<i>N</i>	53,711	53,711	53,711	53,711
Centered <i>R</i> <sup>2</sup>	0.002	0.018	0.016	0.004

Notes: Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at one-digit industry x year level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Turning to robots as a potential determinant of job loss fears, we apply the same IV methodology, using worldwide robot exposure as an instrument for robot exposure in Germany. Again, the first-stage results of the IV regression show that worldwide robot adoption is highly correlated with German robot adoption, yielding a strong instrument (Table 4).

The second-stage regression results yield some indication that robot exposure increases job loss fears (columns 1 and 2 of Table 4). However, including occupation fixed effects into the regression turns the coefficient very small and only significant at the 10%-level (Column 3). Furthermore, the sign of the coefficient turns negative. We can therefore conclude that robots are only weakly associated with job loss fears. The effect of robots on job loss fears is therefore very small, and if anything, it is negative, i.e. robot exposure may even reduce job loss fears rather than increasing them. Our alternative job loss measures yield similar (negative) findings for robots (see Appendix Table A3).

Regarding the economic significance of the coefficient in column 3, the exact value of the coefficient is -0.00031, and the mean number of robots per 1,000 workers in the estimation sample is 4, with a standard deviation of 15. These number imply that increasing the robot exposure per 1,000 workers by one standard deviation would decrease the likelihood of having job loss fears by around

0.5 percentage points. Therefore, the economic significance is not negligible. However, given the low statistical significance, this result should not be overinterpreted.

**Table 4:** Robot exposure and job loss fears

	(1) Job Loss Fears	(2) Job Loss Fears	(3) Job Loss Fears	(4) Job Loss Fears
<b>Second Stage</b>				
GER robots	0.001*** (0.000)	0.001*** (0.000)	-0.000* (0.000)	0.001 (0.000)
<b>First Stage</b>				
International robots	2.640*** (0.042)	2.649*** (0.043)	2.728*** (0.046)	2.561*** (0.054)
F-Statistic	3946.64	3882.67	3536.46	2333.57
Individual Controls		X	X	X
Occupation Controls			X	X
Individual FE				X
<i>N</i>	53,711	53,711	53,711	53,711
Centered <i>R</i> <sup>2</sup>	0.001	0.016	0.016	0.004

Notes: Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at one-digit industry x year level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Finally, we analyse the link between the unemployment as an indicator of the general condition of the labour market and job loss fears using a simple OLS framework. It becomes apparent that there is only a weak link between the aggregate unemployment rate and job loss fears (Table 5). The only statistical significance arises for the specification with individual fixed effects (Column 4 of Table 5). Among the alternative job loss fear measures, only the continuous job loss expectation measure features a significant coefficient that provides some indication towards a positive relation between the unemployment rate and job loss fears (Appendix Table A4).

**Table 5:** Unemployment rate and job loss fears

	(1) Job Loss Fears	(2) Job Loss Fears	(3) Job Loss Fears	(4) Job Loss Fears
Unemployment Rate	0.009 (0.007)	0.008 (0.007)	0.008 (0.007)	0.007* (0.004)
Individual Controls		X	X	X
Occupation Controls			X	X
Individual FE				X
<i>N</i>	53,711	53,711	53,711	53,711
<i>R</i> <sup>2</sup>	0.040	0.056	0.086	0.561

Notes: Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at one-digit industry x year level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

#### 4.2 Job Loss Fears and Coping Mechanisms

In the second step of our econometric analysis, we investigate the role of job loss fears for the different coping mechanisms, training, job and occupational mobility, and exits into unemployment. For training participation, we do not find any significant relation with individual job loss fears, i.e. individuals with higher job loss fears do not have a higher likelihood of training participation than individuals with lower job loss fears (Table 6, Column 1). This result holds for all types of training (Table 6, Columns 2-5).

Job mobility and occupational mobility, by contrast, are significantly correlated with job loss fears (Table 6, Columns 6 and 7). Individuals that report job loss fears are 2.5 percentage points more likely to change their employer than individuals that do not report job loss fears. The corresponding figure for occupational mobility is 1.6 percentage points which means that a large share of workers with higher job loss fears who change job also change their occupation. Given the average job change rate of 15% for the entire sample this is a quite sizable effect. By contrast, we do not find a significant correlation between our indicator variable of job loss fears and transitions into unemployment. Therefore, job and occupational mobility turn out to be the main coping mechanisms for individuals with higher job loss fears.

Our results are robust to using a differentiation into low, medium and large job loss fears as alternative measure of job loss fears (see Appendix Table A6 and Table A7): Workers with medium and large job loss fears do not feature higher training activities than workers with low job loss fears, but they are more likely to engage in job mobility. This differentiated analysis also shows that the level of job loss fears is relevant for workers' reactions as the coefficients are larger for workers with big fears for workers with medium fears. Furthermore, while individuals with medium fears are less likely to transition into unemployment, the probability for individuals with big fears is higher.

The numeric job loss fear indicator, measured on a scale of 0 to 10, supports the previous findings (Appendix Table A5). We observe mostly no effect of job loss expectations on training participation. However, just as before positive coefficients are found for the mobility outcomes. A 1-point increase on the scale raises the probability of experiencing a job change by 1.7 percentage points. The probability of an occupation change increases by 1.4 percentage points. The effect size is slightly smaller compared to the binary indicator in Table 6, though the transition from not being concerned to having any fears may represent a larger change than a single step on the numeric scale. In terms of magnitude, this change is comparable to moving from no fears to somewhat concerned (Table A6). The results for transitions into unemployment are also positive for the job loss expectation variable. Higher perceived likelihood of job loss is associated with an increased probability of actual transitions into unemployment, although the effect is less pronounced than the difference observed between individuals with big fears and those with no fears (see Appendix Table A7).

**Table 6:** Individual job loss fears and coping mechanisms

	(1) Training Overall	(2) General Training	(3) Specific Training	(4) Firm-financed Training	(5) Self-financed Training	(6) Job Change	(7) Occupation Change	(8) Employed to UE
Job Loss Fears	0.004 (0.016)	-0.010 (0.015)	0.014 (0.012)	-0.009 (0.015)	0.013 (0.011)	0.025*** (0.005)	0.016*** (0.004)	-0.002 (0.003)
Individual Controls	X	X	X	X	X	X	X	X
Occupation Controls	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X
<i>N</i>	10,155	10,155	10,155	10,155	10,155	53,711	53,711	64,413
<i>R</i> <sup>2</sup>	0.661	0.613	0.580	0.635	0.563	0.547	0.505	0.361

Notes: Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at individual level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



### 4.3 Factors, Fears and Coping Mechanisms

We now combine the analyses on the determining factors of job loss fears (Section 4.1) and on job loss fears and coping mechanisms (Section 4.2). This allows us to analyse the role of the interaction of exogenous factors and of job loss fears for coping mechanisms in one unified regression framework. We perform the analysis in this section using the dummy variable for job loss fears, and perform separate regressions for trade and robot exposure.

The results for trade confirm the separate analyses from Sections 4.1. and 4.2 (Table 7). Neither trade exposure by itself nor job loss fears are significantly correlated with training participation. This holds for training overall, and for all types of training: general and specific training, as well as firm-financed and self-financed training.

By contrast, job loss fears are strongly positively correlated with job and occupational mobility, i.e. workers with job loss fears are more likely to change job and occupation than workers without job loss fears. Furthermore, the interaction term between trade exposure and job loss fears is positive and significant, indicating that individuals with fears in highly exposed industries are even more likely to change job or occupation. This interaction term is also positive and significant for the outcome “transition to unemployment”. Given that there are no other significant coefficients for this outcome variable, these results suggest that individuals who have job loss fears and who work in industries exposed to trade are most likely to transition into unemployment.

The results for robot exposure in Table 8 are also mostly in line with the previous findings. As for training, most correlations are insignificant, with one notable exception: the interaction between robot exposure and firm-financed training, which yields a positive and significant coefficient. This may indicate that firms retrain their workers when introducing robots, helping them retain their jobs and reducing job mobility.

Similarly to the results in Section 4.2, we find a significant correlation between job loss fears and job and occupational mobility. However, unlike trade exposure, robot exposure does not appear to amplify the size of the effects of job loss fears on job and occupational mobility, as all coefficients related to robots are insignificant. This suggests that robots do not directly influence job loss fears or mobility, confirming the previous results.

Finally, the results for the unemployment rate do not yield significant correlations, neither for direct effects of the unemployment rate on coping mechanisms, nor for the interaction of job loss fears with the unemployment rate (Table A8 in the Appendix). The only exception is the result that a higher unemployment rate is correlated with a higher transition rate to unemployment.

**Table 7:** Individual job loss fears, trade exposure and coping mechanisms

	(1) Training Overall	(2) General Training	(3) Specific Training	(4) Firm-financed Training	(5) Self-financed Training	(6) Job Change	(7) Occupation Change	(8) Employed to UE
Job Loss Fears	0.006 (0.017)	-0.009 (0.015)	0.015 (0.012)	-0.006 (0.016)	0.012 (0.011)	0.023*** (0.005)	0.013*** (0.004)	-0.003 (0.003)
Trade Exposure	0.551 (0.458)	0.163 (0.382)	0.388 (0.355)	0.798* (0.485)	-0.247 (0.300)	-0.218 (0.235)	-0.020 (0.278)	-0.050 (0.204)
Fears x Trade	-0.396 (0.654)	-0.016 (0.570)	-0.380 (0.428)	-0.683 (0.549)	0.286 (0.482)	0.472** (0.215)	0.695** (0.270)	0.393** (0.199)
F Statistic	252.78	252.78	252.78	252.78	252.78	230.26	230.26	252.76
F Statistic (Interaction)	140.32	140.32	140.32	140.32	140.32	216.55	216.55	253.12
Individual Controls	X	X	X	X	X	X	X	X
Occupation Controls	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X
<i>N</i>	10,155	10,155	10,155	10,155	10,155	53,711	53,711	63,307
<i>Centered R</i> <sup>2</sup>	0.005	0.002	0.003	0.005	0.003	0.067	0.046	0.006

Notes: The table displays the estimation results from the second stage of a 2SLS IV regression. First stage coefficients are omitted. Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at individual level in parentheses. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01.

**Table 8:** Individual job loss fears, robot exposure and coping mechanisms

	(1) Training Overall	(2) General Training	(3) Specific Training	(4) Firm-financed Training	(5) Self-financed Training	(6) Job Change	(7) Occupation Change	(8) Employed to UE
Job Loss Fears	-0.003 (0.017)	-0.014 (0.016)	0.011 (0.012)	-0.018 (0.016)	0.015 (0.011)	0.025*** (0.005)	0.017*** (0.004)	-0.002 (0.003)
Robot Exposure	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.000)	0.000 (0.001)	-0.001 (0.000)	-0.001* (0.000)	0.000 (0.000)
Fears x Robots	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002** (0.001)	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
F Statistic	2628.28	2628.28	2628.28	2628.28	2628.28	8276.86	8276.86	8913.82
F Statistic (Interaction)	4268.20	4268.20	4268.20	4268.20	4268.20	18,088.36	18,088.36	18,612.94
Individual Controls	X	X	X	X	X	X	X	X
Occupation Controls	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X
<i>N</i>	10,155	10,155	10,155	10,155	10,155	53,711	53,711	64,413
<i>Centered R</i> <sup>2</sup>	0.005	0.003	0.003	0.006	0.003	0.067	0.046	0.006

Notes: The table displays the estimation results from the second stage of a 2SLS IV regression. First stage coefficients are omitted. Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at individual level in parentheses. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01.

## 5 Conclusion

Labour markets are constantly subject to exogenous shocks. Beyond their direct effects, such shocks have the potential to affect the perceived stability of existing jobs, leading to job loss fears. In this paper, we have therefore analysed three questions: First, how do changes to trade and to technology as well as changes in the unemployment rate affect workers' job loss fears? Second, which coping strategies do workers use, i.e. do they increase training participation or do they change job or occupation as their job loss fears increase? Third, do job loss fears mediate exogenous shocks when exogenous shocks, job loss fears and coping strategies are analysed together?

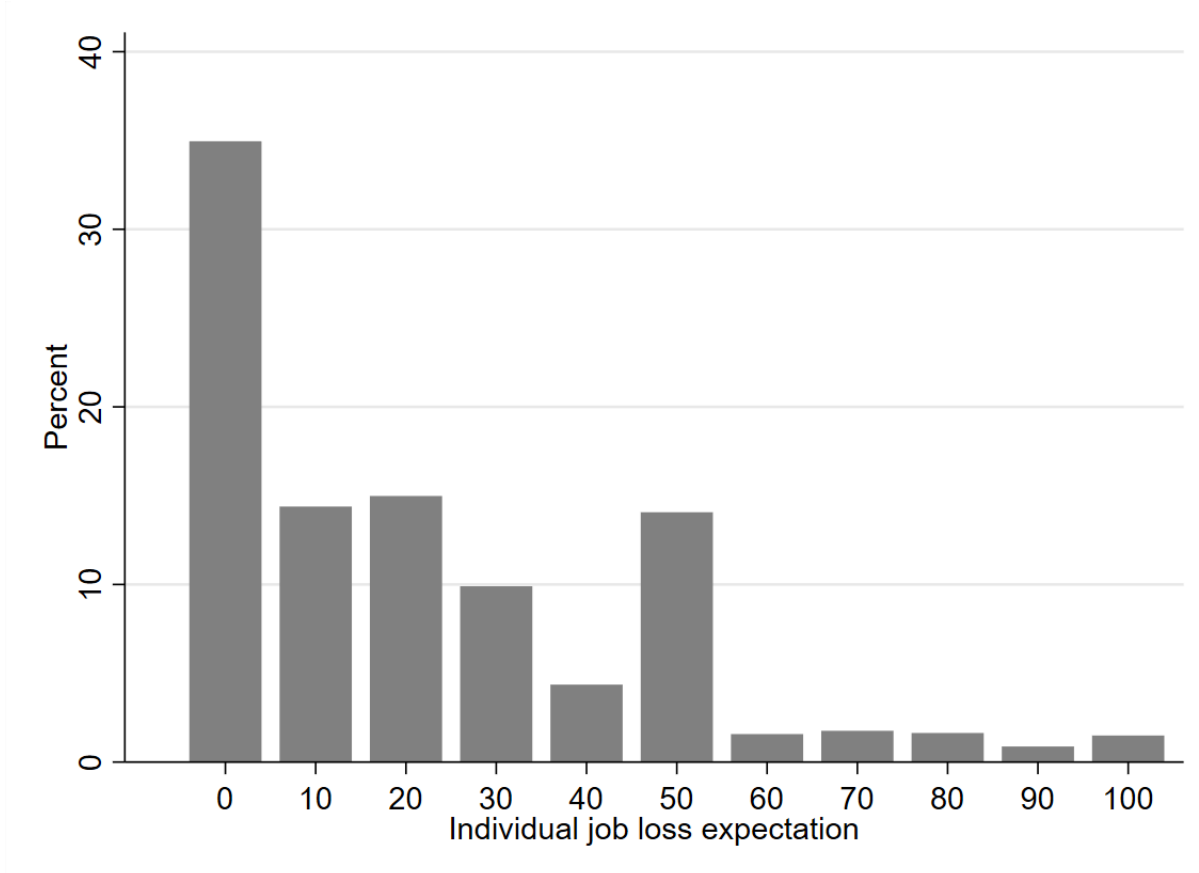
Our analysis yields the following results. First, higher imports significantly increase job loss fears. The local unemployment rate is also weakly associated with higher job loss fears. By contrast, higher robot exposure is weakly negatively associated with job loss fears. Second, job loss fears are significantly correlated with both job mobility and occupational mobility. Successful transitions to another job or occupation may be an explanation for our further result that transitions to unemployment are not significantly correlated with job loss fears. By contrast, we do not detect any effects of job loss fears on training participation, regardless of the type of training (overall, general vs. specific, firm-financed and self-financed). Third, we find that job loss fears are more pronounced for workers in industries highly exposed to the trade shock. This is not the case for workers who are highly exposed to robots.

We can therefore draw two general conclusions. First, exogenous shocks have the potential to significantly increase job loss fears. However, this depends on the nature of the shock: the trade shock analysed, which occurred suddenly and had effects at the industry level, led to a strong increase in job loss fears. The robot shock, which was more gradual in nature and rather occupation-specific, did not lead to an increase in job loss fears.

Second, job mobility and occupational mobility seem to be the most important coping mechanisms, independently of the nature of the shock. By contrast, training of any type does not seem to play an important role in this context. Only for the robot shock, we could find some weak indication that it led to an increase in training participation. Note that it is not clear *ex ante* whether job and occupational mobility or training (without mobility) are better coping strategies against the background of structural change and labour shortages. However, the apparent lack of a response of training to exogenous shocks calls for more research in this field. Likewise, the importance of mobility as the prime coping mechanism means that more research should be done on the transferability of human capital across jobs and occupations.

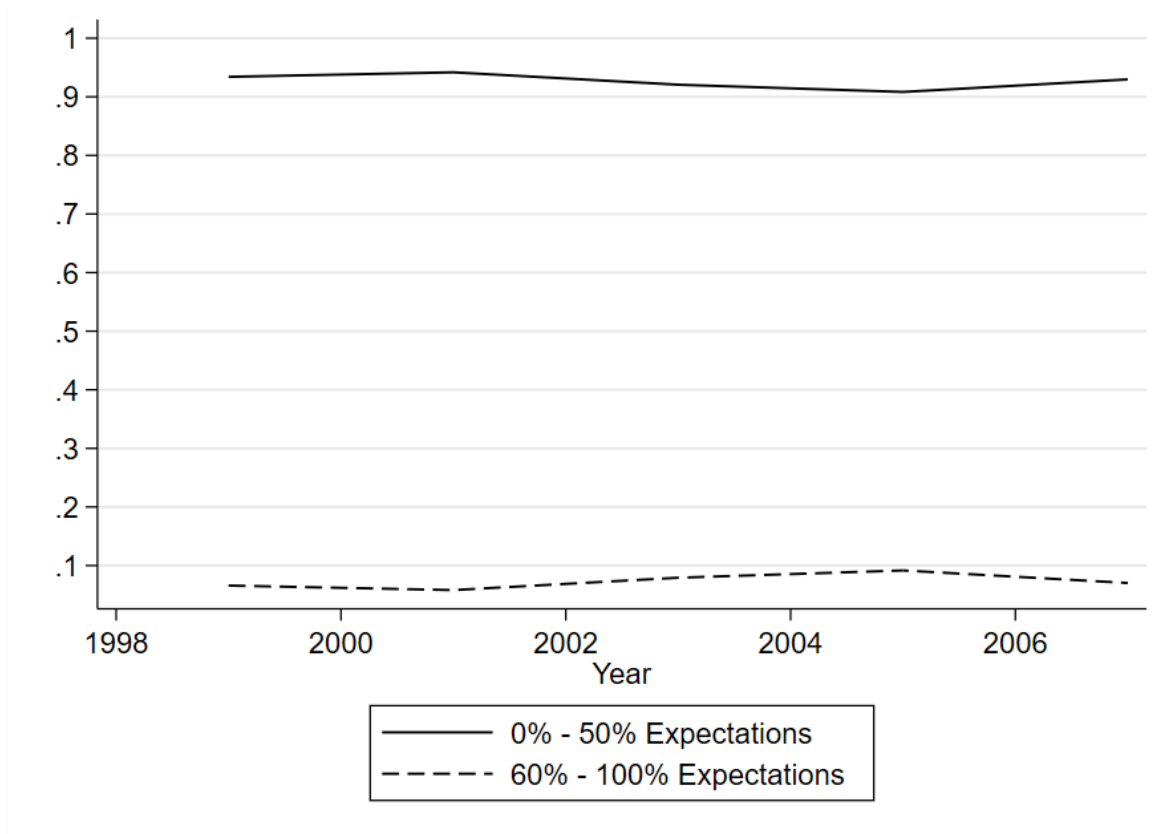
## Appendix

**Figure A1:** Histogram of individual job loss expectations



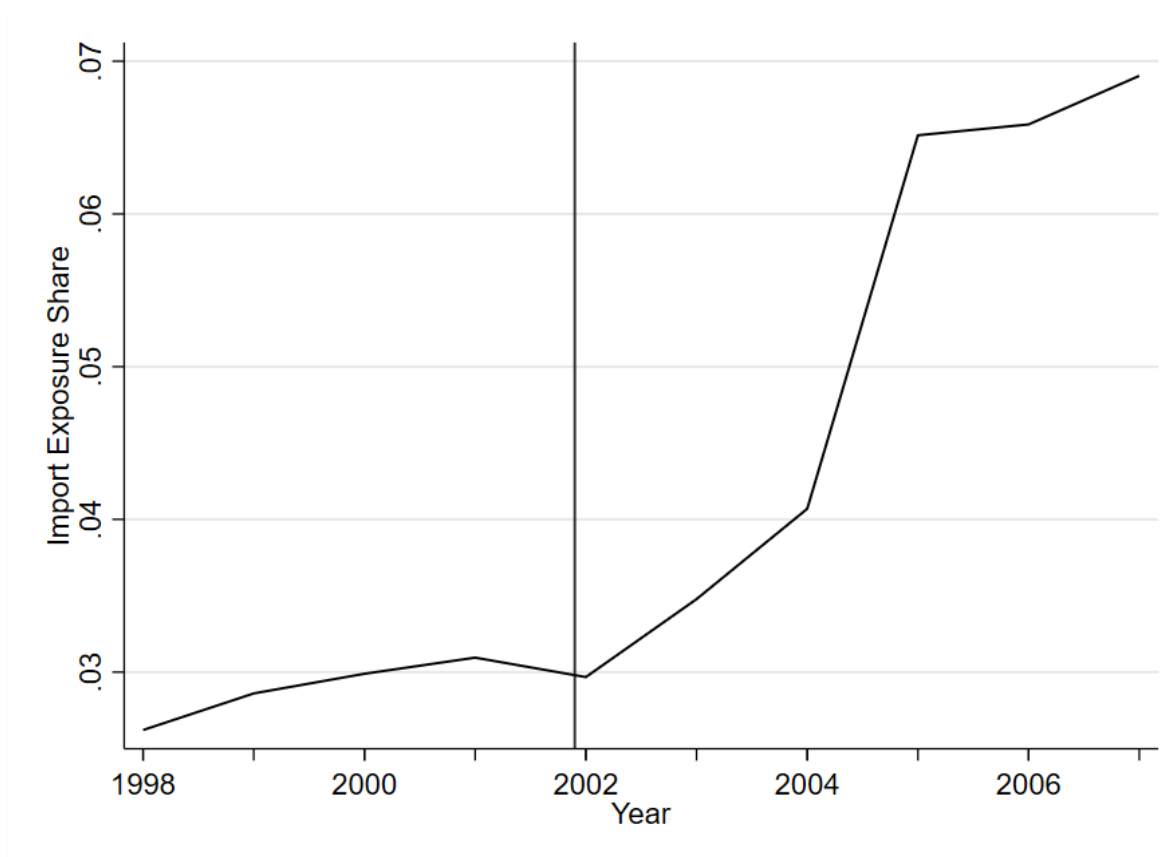
Source: SOEP, own illustration.

**Figure A2:** Development of numeric job loss fear variable over time (divided in two groups)



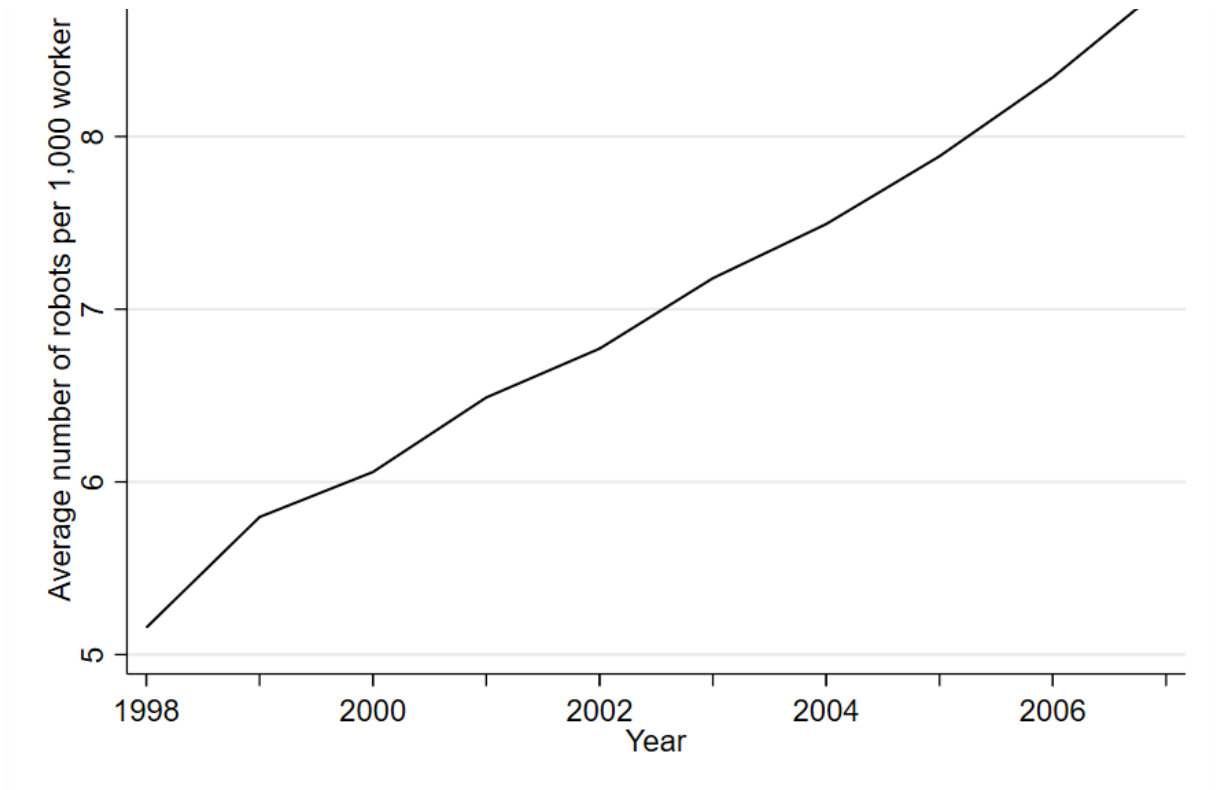
Source: SOEP, own illustration.

**Figure A3:** Import share in relation to the domestic industry production for the manufacturing sector



Notes: Total value of imports in a given industry divided by the industries' domestic production. The vertical line marks China's entry to the WTO. The included industries are those present in the SOEP estimation sample for the analysis period. Source: UN comtrade & OECD STAN, SOEP; own calculation.

**Figure A4:** Average number of robots per 1,000 workers in the manufacturing sector



Notes: Stock of robots in a given industry divided by the number of persons employed in that industry in 1995. Normalised to 1,000 workers. The included industries are those present in the SOEP estimation sample for the analysis period. Source: IFR, SOEP; own calculations.



**Table A1:** 2SLS regressions on different sub-groups of the categorical job loss variable

	(1) Job Loss Expectations	(2) Job Loss Expectations	(3) Job Loss Expectations
<b>Second Stage</b>			
GER imports	-4.065*** (1.228)	1.537 (1.723)	4.272 (8.174)
F-Statistic	71.848	87.199	243.315
Individuals Controls	X	X	X
Occupation Controls	X	X	X
Individual FE	X	X	X
Subgroup of individuals with	No Fears	Medium Fears	Big Fears
<i>N</i>	7461	8925	2250
Centered $R^2$	0.007	0.016	0.027

Note: Separate regressions on the numeric job loss expectation variable as the dependent variable for the sub-groups of the categorical job loss fear variable. Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at one-digit industry x year level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A2:** Trade Exposure and different job loss fears measures

	(1) Job Loss Expectations	(2) Medium Fears	(3) Big Fears
<b>Second Stage</b>			
GER imports	2.944*** (1.089)	0.338*** (0.094)	0.850*** (0.172)
F-Statistic	69.45	125.99	153.84
Individuals Controls	X	X	X
Occupation Controls	X	X	X
Individual FE			
<i>N</i>	26,077	45,212	29,396
Centered <i>R</i> <sup>2</sup>	0.056	0.012	0.039

Notes: Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Column 1 presents regression results using the continuous 0–10 expectation measure as the dependent variable. Column 2 examines a binary outcome, contrasting individuals who are "somewhat concerned" with those who are not concerned at all (reference group). Column 3 displays the group that are very concerned compared to the reference group of "not concerned at all". First stage coefficients are omitted from the table. Robust standard errors clustered at one-digit industry x year level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A3:** Robot exposure and different job loss fears measures

	(1) Job Loss Expectations	(2) Medium Fears	(3) Big Fears
<b>Second Stage</b>			
GER Robots	-0.004*** (0.001)	-0.000** (0.000)	-0.000 (0.000)
F-Statistic	1830.07	3126.79	3513.85
Individuals Controls	X	X	X
Occupation Controls	X	X	X
Individual FE			
<i>N</i>	26,077	45,212	29,396
Centered <i>R</i> <sup>2</sup>	0.056	0.012	0.038

Notes: Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Column 1 presents regression results using the continuous 0–10 expectation measure as the dependent variable. Column 2 examines a binary outcome, contrasting individuals who are "somewhat concerned" with those who are not concerned at all (reference group). Column 3 displays the group that are very concerned compared to the reference group of "not concerned at all". First stage coefficients are omitted from the table. Robust standard errors clustered at one-digit industry x year level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A4:** Unemployment rate and different job loss fears measures

	(1) Job Loss Expectations	(2) Medium Fears	(3) Big Fears
UE Rate	0.069** (0.026)	0.007 (0.007)	0.011 (0.008)
Individuals Controls	X	X	X
Occupation Controls	X	X	X
Individual FE			
<i>N</i>	26,077	45,212	29,396
<i>R</i> <sup>2</sup>	0.106	0.069	0.153

Notes: Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Column 1 presents regression results using the continuous 0–10 expectation measure as the dependent variable. Column 2 examines a binary outcome, contrasting individuals who are "somewhat concerned" with those who are not concerned at all (reference group). Column 3 displays the group that are very concerned compared to the reference group of "not concerned at all". Robust standard errors clustered at one-digit industry x year level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A5:** Job loss expectations and coping mechanisms

	(1) Training Overall	(2) Training General	(3) Training Specific	(4) Training Firm-financed	(5) Training Self-financed	(6) Job Change	(7) Occupation Change	(8) Employed to UE
Job Loss Expectations	-0.002 (0.003)	-0.003 (0.003)	0.001 (0.002)	0.002 (0.003)	-0.005** (0.002)	0.017*** (0.002)	0.014*** (0.002)	0.006*** (0.001)
Individuals Controls	X	X	X	X	X	X	X	X
Occupation Controls	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X
<i>N</i>	10,079	10,079	10,079	10,079	10,079	23,504	23,504	28,027
<i>R</i> <sup>2</sup>	0.662	0.613	0.579	0.636	0.563	0.533	0.503	0.466

Notes: Regression results for the continuous 0–10 expectation measure as the job loss variable. Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at individual level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A6:** Medium Fears and coping mechanisms

	(1) Training Overall	(2) Training General	(3) Training Specific	(4) Training Firm-financed	(5) Training Self-financed	(6) Job Change	(7) Occupation Change	(8) Employed to UE
Medium Fears	0.009 (0.017)	-0.009 (0.016)	0.017 (0.012)	0.001 (0.016)	0.007 (0.012)	0.015*** (0.005)	0.009** (0.004)	-0.009*** (0.003)
Individuals Controls	X	X	X	X	X	X	X	X
Occupation Controls	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X
<i>N</i>	7,987	7,987	7,987	7,987	7,987	44,589	44,589	53,063
<i>R</i> <sup>2</sup>	0.666	0.618	0.582	0.642	0.551	0.551	0.512	0.367

Notes: Regression results for the binary indicator of being “somewhat concerned” (reference group: individuals that are “not concerned at all”). Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at individual level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A7:** Big fears and coping mechanisms

	(1) Training Overall	(2) Training General	(3) Training Specific	(4) Training Firm-financed	(5) Training Self-financed	(6) Job Change	(7) Occupation Change	(8) Employed to UE
Big Fears	-0.011 (0.045)	-0.013 (0.036)	0.002 (0.035)	-0.045 (0.041)	0.034 (0.025)	0.082*** (0.010)	0.056*** (0.009)	0.028*** (0.008)
Individuals Controls	X	X	X	X	X	X	X	X
Occupation Controls	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X
<i>N</i>	3,705	3,705	3,705	3,705	3,705	27,576	27,576	33,370
<i>R</i> <sup>2</sup>	0.689	0.648	0.615	0.669	0.580	0.605	0.560	0.413

Notes: Regression results for the binary indicator of being “very concerned” (reference group: individuals that are “not concerned at all”). Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at individual level in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A8:** Individual job loss fears, unemployment rate and coping mechanisms

	(1) Training Overall	(2) Training General	(3) Training Specific	(4) Training Firm-financed	(5) Training Self-financed	(6) Job Change	(7) Occupation Change	(8) Emp to UE
Job Loss Fears	-0.008 (0.041)	-0.003 (0.040)	-0.005 (0.032)	-0.025 (0.040)	0.017 (0.032)	0.020 (0.012)	0.013 (0.011)	-0.008 (0.008)
UE Rate	-0.002 (0.008)	-0.004 (0.008)	0.002 (0.007)	-0.011 (0.008)	0.009 (0.006)	0.006 (0.004)	0.005 (0.003)	0.007*** (0.003)
Fears x UE Rate	0.001 (0.003)	-0.001 (0.003)	0.002 (0.003)	0.001 (0.003)	-0.000 (0.003)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)
Individual Controls	X	X	X	X	X	X	X	X
Occupation Controls	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X
<i>N</i>	10,155	10,155	10,155	10,155	10,155	53,711	53,711	64,413
<i>Centered R<sup>2</sup></i>	0.661	0.613	0.580	0.635	0.564	0.547	0.505	0.361

Notes: Individual controls include gender, age groups, migration status, East Germany indicator and educational groups. Occupation controls include part time, temporary contract, marginal employment, tenure at employer, firm size, one-digit ISCO88 occupational fixed effects and one-digit NACE industry fixed effects. All regressions include year and federal state fixed effects. Robust standard errors clustered at individual level in parentheses. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01.



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