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Abstract

Recent research suggests that automation may harm workers' health by increasing the risk of job displacement and requiring constant skill adaptation. However, the relationship between automation risk and adverse health behaviors, such as alcohol consumption, remains largely overlooked, despite its potential role as a key mechanism linking automation exposure to broader health outcomes. This study investigates the relationship between high automation risk and drinking behaviors among workers in Russia. We combine individual-level data from the Russian Longitudinal Monitoring Survey (2017–2021) with occupational task content data based on the International Standard Classification of Occupations (ISCO-08). Using panel regression techniques, we show that high automation risk is positively related to all examined drinking behaviors among women, while no significant effect is found among men. Our results also indicate that, in the Russian context, dissatisfaction with growth opportunities at work is a key pathway linking high automation risk to both active drinker status and total alcohol consumption among women. Finally, high physical exposure at work tends to moderate the relationship between high automation risk and alcohol use in the female subsample. Overall, our findings demonstrate that adverse health behaviors might be a major mechanism through which automation risk affects workers' health.

JEL CODES: I10, I15, J21, J24, O33

Key words: automation risk, alcohol use, alcohol consumption, routine tasks, Russia

1. Introduction

Automation is transforming labor markets by enhancing productivity (Graetz and Michaels, 2018; Kromann et al., 2020), increasing wage inequality (Vannutelli et al., 2022; Martins-Neto et al., 2024), and driving occupational shifts that polarize employment – often at the expense of middle-skilled workers (Goos et al., 2014; Balsmeier and Woerter, 2019) – while also putting certain jobs at risk of displacement (Frey and Osborne, 2017).

Accurately measuring the extent of job displacement remains a methodological challenge, as certain occupations may become obsolete while others are expected to undergo a substantial transformation, demanding new skills and greater integration with emerging technologies. Projections are contingent upon uncertain assumptions regarding the pace and scale of technological advancement, which differ significantly across countries and industries, and are shaped by institutional capacities and economic conditions. Overall, workers in developed economies are likely to experience the risk of displacement related to automation more quickly and intensely due to their greater resources for technology adoption, whereas developing countries are generally expected to have substantial catch-up potential over time (Arntz et al., 2016).

Although automation risk is a somewhat abstract concept, it has real and noticeable effects, particularly by increasing workers' perceptions of job insecurity and affecting their health and well-being, as these outcomes are highly sensitive to the broader economic changes driven by automation (Patel et al., 2018; Abeliansky et al., 2024). Recent research generally indicates that workers exposed to high automation risk at work are more likely to experience negative health and well-being outcomes, though findings vary depending on the measurement approaches used and the country studied (Nazareno and Schiff, 2021; Liu, 2023; Gunadi and Ryu, 2021; O'Brien et al., 2022).

However, the relationship between exposure to high automation risk at work, health, and adverse health behaviors, such as alcohol consumption, remains underexplored, despite health behaviors being a plausible pathway linking automation to health outcomes. For example, the stress associated with the risk of job displacement may lead to increased alcohol intake as a coping mechanism (Colder, 2001), which can, in turn, harm both the mental and physical health of workers. Surprisingly, to the best of our knowledge, no study has yet been published that specifically aims to unravel these links.

To fill this gap, we examine the relationship between high automation risk, measured at the occupational level, and multiple drinking behaviors, including alcohol use, active drinker status, and total monthly alcohol consumption (measured in grams of pure ethanol), among workers in Russia. We combine individual-level data from the nationally representative Russian Longitudinal Monitoring Survey (RLMS-HSE), covering 2017 to 2021, with recent estimates of the proportion of routine tasks in occupations, based on the International Standard Classification of Occupations (ISCO-08), as computed by Mihaylov and Tijdens (2019). For our analysis, we employ panel regression techniques to estimate gender-specific differences in the association of interest, while also examining potential mediating and moderating factors, such as job dissatisfaction and stress at work.

Russia provides a unique and relevant context for investigating this relationship. First, it consistently ranks high in alcohol consumption and alcohol-related mortality within the WHO European Region (WHO, 2018). Therefore, in Russia, alcohol intake is expected to be a common strategy for coping with workplace-related stress, making it highly plausible that automation risk is significantly impacting drinking behaviors. Second, the specific features of Russia's economic infrastructure positions it as a promising market for robotics in the coming decade, as despite the country's relatively low adoption of these technologies to date, a substantial number of jobs in Russia are likely to be at risk of displacement due to automation in the near future. Finally, low- and middle-income countries (LMICs), including Russia, remain largely overlooked in research on the health outcomes of automation, with the exception of a study on China by Yang et al. (2022). Moreover, there is currently no research specifically addressing this issue in the Russian context.

We make several key contributions to the existing literature. First, to the best of our knowledge, this is the first study to directly link exposure to automation risk in the workplace with workers' drinking patterns. Second, our analysis utilizes an automation risk measure defined at the occupational level – an approach rarely used in prior health-related research, which predominantly relied on aggregated sectoral estimates. Third, we explore whether job insecurity, perceived labor market unviability, and dissatisfaction with growth opportunities at work mediate the relationship between high automation risk and drinking behaviors among male and female workers in Russia. Fourth, we examine how additional physical and psychosocial stressors influence the relationship between exposure to automation and workers' drinking patterns. A series of robustness and sensitivity checks confirm our baseline findings.

2. Background

2.1. Risk of automation in the workplace: a conceptual overview

Given that the risk of automation is a complex issue involving economic, technological, and social factors, its measurement is inherently challenging. Recent literature mainly captures this phenomenon through objective proxies, commonly employing one of three established methodologies.

The first objective approach, developed by Frey and Osborne (2017), utilizes data from O*NET (2010), an online database describing U.S. occupations in terms of the knowledge, skills, abilities, and tasks they entail. By integrating expert assessments with advanced algorithmic tools, the authors estimated the probability of computerization for each U.S. occupation, thereby quantifying its risk of displacement due to automation. The second objective approach is based on the concept of routine task intensity (RTI), which captures the distribution of task types within a given occupation. Under this framework, occupations with a higher concentration of routine cognitive and routine manual tasks are deemed more susceptible to automation (Autor and Dorn, 2013). The third objective measure of automation risk – commonly referred to as robot intensity, penetration, or exposure – is defined at an aggregated sectoral level, and is typically based on robotics market data regularly published by the International Federation of Robotics (IFR).

A few studies use subjective measures of automation risk, relying on individuals’ evaluations of their job tasks, their interaction with digital systems, and the frequency of technology use in their work (e.g., Blasco et al., 2022; Giuntella et al., 2023). However, this approach remains a rare data-driven exception, highlighting the persistent lack of consistent subjective assessments of occupational tasks and working conditions in national surveys.

2.2. Previous research on health impacts of automation risk

Recent findings from sociological and health research indicate that high automation risk, proxied by the computerization probabilities of Frey and Osborne (2017), is negatively associated with general, physical, and mental health outcomes in the U.S. (Patel et al., 2018; Nazareno and Schiff, 2021; Liu, 2023). Other studies have found that it is positively linked to work-related injuries and disease prevalence in Taiwan (Cheng et al., 2020) and negatively associated with life satisfaction among middle-aged workers in the UK (Zheng et al., 2024).

Findings from studies using the robot intensity measure (defined at the sectoral level) show a positive association of robot intensity with work disability, job loss due to health issues, and all-cause mortality among older workers and young women in the U.S. (Gunadi and Ryu, 2021; O'Brien et al., 2022), as well as a modest decline in workers' mental health in Germany (Abeliansky et al., 2024). In contrast, Gihleb et al. (2022) provide evidence that higher robot adoption is associated with a decline in work-related injury rates in the U.S. and a lower likelihood of reporting disability in Germany. Additionally, in China, Yang et al. (2022) observe significant improvements in mental health outcomes among individuals exposed to high automation risk, proxied by robot intensity.

The only existing study based on the routine task intensity (RTI) measure reports a negative (positive) association of RTI with physical health and bodily pain (vitality and satisfaction with free time) in Australia (Lordan and Stringer, 2022). Finally, self-reported exposure to automation risk at work has been found to be positively associated with major depressive episodes in France (Blasco et al., 2022) and negatively associated with life satisfaction in Germany (Giuntella et al., 2023).

Overall, research linking automation risk to health and well-being outcomes remains relatively limited and has produced mixed evidence, as the effects often vary by country, demographic group, and measurement approach. Moreover, most studies focus on Western countries, with little attention given to other parts of the world. With some exceptions, the prevailing hypothesis suggests that high exposure to automation risk in the workplace tends to adversely affect individuals' health and well-being outcomes, often through increased perception of job insecurity (Patel et al., 2018; Abeliansky et al., 2024).

In this context, investigating the relationship between high automation risk at work and adverse health behaviors, particularly alcohol consumption, can offer valuable insights, as drinking may serve as a coping mechanism for workers experiencing labor market insecurity, while also negatively affecting their health (Bryden et al., 2013; Probst et al., 2017). For instance, Gihleb et al. (2022), using establishment-level data, find that higher robot intensity is associated with an increase in drug- and alcohol-related mortality in the U.S. At the same time, workers under threat of job loss may respond by improving their performance and professional image – for example, by avoiding arriving at work intoxicated, hungover, or fatigued from drinking the night before – in order to signal greater commitment and reliability to their employers (Huang et al., 2013, Shoss, 2017). Moreover, the relationship between automation risk and drinking behaviors is likely to be highly context-dependent, varying across countries due to differences in societal norms, economic conditions, and labor market regulations. Thus, the overall impact of automation risk on alcohol consumption remains unclear.

2.3. Russian context

According to World Health Organization (WHO) statistics, alcohol consumption in Russia is high, at 10.5 liters per capita in 2021 among individuals aged 15 and older, which is above the WHO European Region average of 9.1 liters and double the global average of 5.0 liters (WHO, 2024). Unlike Türkiye (2.2 liters) and Israel (3.1 liters), Russia – along with countries like Romania (17.1 liters), Latvia (14.7 liters), and Lithuania (12.2 liters) – contributes to the high prevalence of excessive drinking in Central and Eastern Europe, and to the WHO European Region having higher levels of alcohol consumption than most other global regions (Malisauskaite & Klein, 2018).

Sociological research indicates that drinking behaviors in Russia are influenced more by economic instability than by enduring cultural traditions (Cheremisina et al., 2014; Erpilov, 2015). Periods of political and economic transition characterized by declining living standards and labor market volatility have been associated with deteriorating public health and rising mortality rates, in part due to increased alcohol consumption (Herzfeld et al., 2014). Thus, Russia presents a compelling case for examining the link between drinking behaviors and exposure to automation in the workplace, an evolving trend that is expected to transform national labor markets and production systems in the coming years.

Over the past decade, the Russian labor market has undergone a prolonged period of stagnation marked by a steady decline in labor force participation, a shift to historically low unemployment rates, a sharp increase in worker turnover, and the accumulation of a substantial backlog of unfilled job vacancies. In line with historical trends, the labor market's response to the COVID-19 lockdown was predominantly characterized by adjustments in wages and working hours, rather than by elevated unemployment rates or substantial job losses (Kapeliushnikov, 2023).

Meanwhile, the rate of employment in the informal sector rose slightly from 19.7% to 20.2% between 2017 and 2021, reflecting persistent job insecurity and the lack of social protections (Kiselev et al., 2024). Finally, despite high levels of female education and workforce participation, gender segregation in the labor market remains pronounced (Klimova, 2012; Kosyakova et al., 2015). Women continue to be underrepresented in leadership positions, experience a persistent and substantial gender wage gap, and are disproportionately concentrated in sectors such as education, healthcare, and social services, while men predominate in industries such as oil, gas, and finance.

Although Russia trails European leaders (Germany, Italy, France, Spain, and the UK) in adopting industrial robots, it has significant potential to catch up in the coming years. Since July 2017, the Russian government has prioritized digitalization to drive economic growth, launching the “Digital Economy of the Russian Federation” program to foster technology adoption while reducing legal risks (Ministry of Digital Development, Communications and Mass Media, 2017). Additionally, Russia’s economy offers significant opportunities for robotics applications in metallurgy, mining, and machine building, while its northern regions serve as an ideal testing ground for partially or fully autonomous vehicles due to their harsh climatic conditions. Lastly, Russia – like China, Germany, and parts of Eastern Europe – boasts a strong tradition in mathematics and programming, which provides a robust foundation and a steady supply of skilled engineers. This legacy supports both the development and the adoption of robotics, positioning Russia as a rapidly growing market in the field (Konuikhovskaia, 2019).

Moreover, Russia’s services sector has already embraced automation through the adoption of AI-driven customer service in banking, robotic inventory and self-checkout in retail, and AI-powered ride-hailing and logistics solutions. The healthcare sector benefits from the use of telemedicine and AI diagnostics, while public services are implementing smart city technologies for utilities and traffic management (Sberbank Report, 2024). These advancements reflect a growing trend of integrating automation to improve the overall efficiency and quality of services.

2.4. Research aims

This study has four key objectives. First, we investigate the relationship between high automation risk, measured at the occupational level, and drinking behaviors among workers in Russia. Given the pronounced gender differences in drinking patterns, as well as the gender-specific occupational segregation, discriminatory practices, and regulatory gaps in the Russian labor market (WHO, 2018; Kosyakova et al., 2015), we estimate separate models for male and female respondents. Second, we examine whether job insecurity, perceived labor market unviability, and dissatisfaction with growth opportunities at work serve as potential pathways linking high automation risk to drinking behaviors in Russia, building on insights from prior studies conducted in high-income countries (Patel et al., 2018; Nazareno and Schiff, 2021; Cheng et al., 2021). Third, we hypothesize that additional physical (e.g., manual handling, awkward postures, vibration exposure) and psychosocial (e.g., high job demands, limited autonomy, low social support from supervisors or colleagues) workplace stressors may act as moderating factors. These job exposures may amplify the psychological strain associated with automation-related displacement risk, thereby increasing the likelihood that workers will adopt certain coping mechanisms, such as alcohol consumption. Fourth, we conduct a series of robustness and sensitivity checks to assess the consistency of our estimates across various model specifications and sample selection criteria.

3. Data and methods

3.1. Sample

We base our analysis on three primary data sources. First, our core dataset comes from the individual data profiles collected through the Russian Longitudinal Monitoring Survey (RLMS-HSE). This nationally representative survey is conducted annually by the National Research University Higher School of Economics (Moscow, Russia), in collaboration with the Carolina Population Center at the University of North Carolina at Chapel Hill (USA). The RLMS-HSE was specifically designed to track a broad range of factors, including the social and demographic characteristics, employment histories, economic welfare, and health and well-being of Russian individuals and households. Second, our key explanatory variable, high automation risk, is derived from Mihaylov and Tijdens (2019), who provide expert estimates of the proportions of routine and non-routine tasks across occupations as categorized by the International Standard Classification of Occupations (ISCO-08). Third, we also incorporate physical and psychosocial indices from the job exposure matrices developed by Kroll (2015), all defined at the ISCO-08 level.

The three datasets are merged using the four-digit ISCO-08 occupational codes, which are available in the RLMS-HSE and harmonized across the other data sources. The resulting dataset is defined at the individual level, linking annual occupation-specific data on the proportion of routine tasks and job exposure measures to each respondent.

The scope of our analysis is confined to the 2017-2021 period for several reasons. First, our automation risk measure relies on expert evaluations reflecting the technological landscape at the time of assessment. Consequently, we begin with the 26th wave of the RLMS-HSE, corresponding to 2017, which is the year Mihaylov and Tijdens (2019) validated their original estimates using Dutch data. This year also marked the launch of Russia's government program to support digitalization. We exclude data from 2022 onward due to the ongoing military conflict between Russia and Ukraine. However, we retain the COVID-19 pandemic lockdown years, as this period was marked by an accelerated pace of automation – partly due to the widespread shift to remote work – and considerable changes in alcohol consumption patterns (Grossman et al., 2020; Garnett et al., 2021).

Our analysis focuses on currently employed individuals, excluding respondents who are on maternity leave, students, and retirees. Additionally, we exclude members of the armed forces, self-employed individuals and entrepreneurs, individuals holding multiple jobs, and individuals with disabilities, as these groups exhibit unique characteristics and are subject to distinct labor market regulations. This sample selection reduces the sample size by approximately 30%, while missing data account for an additional loss of about 10%. Our final sample consists of 8,220 regularly employed individuals with non-missing values in the variables of interest (22,181 observations spread over the 2017-2021 period).

3.2. Dependent variables: drinking behaviors

We use three indicators of drinking behaviors in our analysis. The first measure, alcohol use, is based on the question "Do you consume alcohol in general?" and is coded as 0 for abstainers, and as 1 for active and potential drinkers who do consume alcohol, but did not drink in the past month. The second measure (active drinker) is also binary: it takes the value of 0 if the respondent is either an abstainer or a potential drinker and the value of 1 if the respondent's alcohol consumption exceeded zero in the past month.

The third measure, total monthly alcohol consumption expressed in grams of pure ethanol, is a continuous variable constructed according to the following procedure. For each beverage type –

beer, braga, dry and fortified wine, samogon (homemade distilled alcoholic beverage), vodka, and other hard spirits – we multiply the reported daily consumption (in grams) by the number of days the respondent consumed that beverage in the past month. Next, we convert these amounts into pure ethanol by multiplying the beverage mass by its alcohol by volume (ABV) and the density of ethanol (0.789 g/mL). The following average ABV values are used for our calculations: 5 and 6 grams of pure ethanol per 100 grams of beer and braga, respectively; 12 and 18 grams per 100 grams of dry and fortified wine, respectively; and 40 grams per 100 grams of samogon, vodka, and other hard spirits (Lemmens, 1994). Finally, we sum the pure ethanol content across all beverages to obtain the total monthly alcohol consumption. Given that our continuous measure is right-skewed, we apply a log-transformation to normalize the distribution and mitigate potential heteroscedasticity. As a result, the association between exposure to high automation risk and total monthly alcohol consumption is analyzed exclusively within the subsample of active drinkers.

3.3 Key independent variable: high automation risk

To construct our main explanatory variable, we use the distributions of non-routine analytic, non-routine interactive, routine cognitive, routine manual, and non-routine manual tasks within four-digit ISCO-08 occupational codes, as proposed by Mihaylov and Tijdens (2019). Specifically, we first calculate the total proportion of routine tasks within each four-digit ISCO-08 occupation by summing the respective shares of routine manual and routine cognitive tasks. Occupations are then classified as being at high risk of automation if the proportion of routine tasks exceeds 70%, and as being less susceptible to technological replacement otherwise. This threshold has been widely used in earlier research on automation risk based on both task content measures and alternative approaches, and has demonstrated its reliability in studies of OECD countries (Arntz et al., 2016), the U.S. (Frey and Osborne, 2017), and Germany (Dengler et al., 2014).

3.4 Other variables: controls, moderators, and mediators

We include a standard set of socioeconomic control variables in our models, consistent with existing literature on work-related determinants of health and well-being. These include age, age squared, marital status, the presence of children under age 18, educational attainment, the natural log of monthly individual income (in thousands of rubles, adjusted for inflation), self-reported nationality, self-reported health status, type of settlement, and federal district. Additionally, we control for company size, industry sector, and the period of the COVID-19 lockdown.

As previous research has shown that the relationship between highly automatable jobs and workers' health is often mediated by perceived job insecurity and reduced job satisfaction (Patel et al., 2018; Abeliansky et al., 2024), we hypothesize that similar mechanisms may link high automation risk in the workplace to individuals' drinking behaviors. To test this, we use self-reported measures from the RLMS-HSE on job insecurity, labor market unviability, and dissatisfaction with growth opportunities at work (all originally measured on a five-point scale), and convert them into binary indicators. The job insecurity variable is coded as 1 if the respondent is concerned or very concerned about potential job loss in the future, and as 0 otherwise. Labor market unviability is coded as 1 if the respondent feels uncertain or very uncertain about finding a new equivalent job if laid off, and as 0 otherwise. The dissatisfaction variable equals 1 if the respondent is dissatisfied or very dissatisfied with growth opportunities at work, and equals 0 otherwise.

Additionally, we examine whether the relationship between high automation risk and drinking behaviors is moderated by high physical and psychosocial job exposures. To assess this, we use the exposure indices developed by Kroll (2015), which range from 1 (lowest) to 10 (highest), and convert them into binary variables, assigning a value of 1 to occupations ranked in the seventh or higher category of the original scale (representing the top 25% of the distribution), and a value of 0 otherwise.

Finally, we examine whether the association between high automation risk and workers' drinking behaviors changes once internal monitoring, proxied by a dummy indicator for occupations subject to mandatory or recommended pre-shift alcohol testing, is incorporated into our models. To do this, we identify four-digit ISCO-08 occupations in Russia for which such testing procedures are required or advised (The Labor Code of the Russian Federation, Articles 213, 220, 330). A detailed overview of all variables used in our study, along with their descriptive statistics, is presented in Tables S1 and S2 of the supplementary materials.

3.5. Estimation strategy

Given the longitudinal structure of our final dataset, we estimate random effects (RE) logistic regression models for the binary outcome variables and a RE linear regression model for the log-transformed total monthly alcohol consumption. We employ RE models rather than fixed effects (FE) specifications due to the limited within variation observed in our main explanatory variable.

Specifically, the task content estimates for ISCO-08 occupations provided by Mihaylov and Tijdens (2019) are time-invariant, meaning that any within variation in our main explanatory variable arises solely from respondents' occupational changes. However, such cases are rare in our sample, with only 6% of men and 7% of women experiencing a change in their automation risk status throughout the period we observe. Thus, employing FE specifications to address unobserved heterogeneity would eliminate nearly all variation in our main explanatory variable.

Nevertheless, we estimate correlated random effects probit models (fixed effects approximation, also known as the Mundlak correction) for the binary outcome variables and a FE linear model for our log-transformed continuous outcome as a robustness check (Mundlak, 1978). Additionally, we perform a decomposition on the extensive (first hurdle: decision to consume alcohol versus to remain an abstainer) and intensive (second hurdle: decision on the level of consumption once the first hurdle is crossed) margins by estimating the double-hurdle model (Cragg, 1971). To ensure model convergence, we adopt a pooled specification, assuming that the conditional mean of the latent variable follows an exponential form (Engel and Moffatt, 2014). As a final robustness check, we estimate dynamic models incorporating a one-year lag and an initial state of related dependent variables in our models (test for path dependence).

To decompose the total effect of high automation risk on drinking behaviors, reported in our baseline specifications, into direct effect (attributable to automation risk itself) and indirect effect (operating through job insecurity, perceived labor market unviability, and dissatisfaction with growth opportunities at work) components, we apply the Karlson-Holm-Breen (KHB) method. This approach allows for the inclusion of multiple mediators, while disentangling the individual contribution of each. We employ linear probability models for binary outcomes and a linear regression model for the continuous dependent variable, as these specifications allow for the estimation of standard errors for indirect effects, which is not feasible when using average partial effects in non-linear settings (Kohler et al., 2011).

Finally, we conduct a series of sensitivity checks that involve excluding individuals residing in Moscow and St. Petersburg, which are highly urbanized areas with elevated automation exposure and greater access to alcohol-serving venues, as well as respondents whose religion prohibits alcohol use and those engaged in unofficial employment, and omitting the year 2017, when automation had not yet been integrated into the core political or economic agenda. Additionally, we control for pre-shift alcohol testing to verify whether our results remain consistent under these alternative specifications. Our baseline findings, along with further robustness and sensitivity checks, are discussed in Sections 4.1-4.5 and summarized in Table S8 of the supplementary materials.

4. Results

4.1. Descriptive analysis

Gender-specific descriptive statistics for the full sample and the subsample of active drinkers are presented in Tables S1 and S2 of the supplementary materials. As shown in Table S1, 77% of men and 71% of women in the sample report general alcohol use, while 57% of men and 43% of women have consumed alcohol in the past month. These figures are consistent with WHO estimates on alcohol abstinence and intake rates in Russia for 2017-2019 (WHO, 2025). Among active drinkers, average monthly alcohol intake amounts to 354.6 grams of pure ethanol for men and 136.8 grams for women. Finally, the share of individuals in highly automatable occupations is 14.2% among men and 14.8% among women, closely aligned with estimates for OECD countries (Arntz et al., 2016).

Table S3 in the supplementary materials indicates that the proportion of abstainers (active drinkers) is lower (higher) among both male and female respondents exposed to high automation risk at work than among those employed in less automation-prone occupations. As shown in Table S4, among active drinkers, women in the high-risk group report consuming more alcohol on average in the past month than women in the low-risk group (157.0 vs. 132.8 grams of pure ethanol, respectively). The opposite pattern is observed among men, with 335.7 and 358.0 grams of pure ethanol being consumed in the high- and low-risk groups, respectively; however, this difference is not statistically significant.

Tables S5 and S6 in the supplementary materials list the most common occupations among men and women in the high- and low-risk groups, along with gender-, risk group-, and occupation-specific averages of the outcome variables for both the full sample and the subsample of active drinkers, respectively. Taken together, the descriptive findings reveal a mixed relationship between automation risk and our binary outcomes, pointing to the presence of heterogeneity across occupations within each gender group. In contrast, among active drinkers, the occupation-specific averages of total alcohol consumption in the male (female) high-risk group consistently fall below (exceed) both the gender-specific and risk group averages across all listed four-digit ISCO-08 codes (see Table S6 in the supplementary materials). Given that among active drinkers, 61.9% of men working in highly automatable occupations are concentrated in the secondary sector of the economy – compared to only 27.9% of women – our descriptive findings may suggest either that industrial jobs with high exposure to automation risk are subject to stricter internal controls and alcohol-preventive policies, or that a selection mechanism is at play in certain male-dominated occupations.

4.2. Baseline results

Table 1 summarizes gender-specific marginal effects from the logistic regression models and estimated coefficients from the linear models for high automation risk. Results are presented for bivariate models, multivariate models with socioeconomic controls (SEC), and our preferred specification of multivariate models that include both socioeconomic and work-related controls (WRC). As expected, moving from the bivariate model to the final specification with both SEC and WRC results in a certain change in the magnitude – and, in some cases, in the statistical significance – of the estimated association between high automation risk and drinking behaviors in both gender groups. Nevertheless, the direction of the effect remains consistent across all model specifications.

Table 1 – Average marginal effects (AME) and estimated coefficients on high automation risk

	Alcohol use		Active drinker		Alcohol consumption (ln)	
	Men	Women	Men	Women	Men	Women
	AME (SE)	AME (SE)	AME (SE)	AME (SE)	Coef. (SE)	Coef. (SE)
Bivariate model	0.011	0.047***	0.031*	0.045***	-0.034	0.137***
	(0.012)	(0.013)	(0.016)	(0.014)	(0.043)	(0.041)
Multivariate model with SEC	0.013	0.043***	0.023	0.038***	-0.063	0.106**
	(0.012)	(0.013)	(0.016)	(0.014)	(0.042)	(0.041)
Baseline: Multivariate model with SEC and WRC	0.008	0.040***	0.016	0.034**	-0.071	0.090**
	(0.013)	(0.013)	(0.016)	(0.014)	(0.043)	(0.041)
Number of observations	10,907	11,274	10,907	11,274	6,245	4,873
Number of individuals	4,020	4,200	4,020	4,200	2,800	2,409

*Note: *p-value<0.10, **p-value<0.05, ***p-value<0.01*

Robust standard errors are clustered at an individual level.

In the baseline specification, the reference individual is of average age, is married or cohabiting, has young children, holds a postsecondary degree or less, earns an average income, identifies as Russian, reports relatively good health, lives in a city within the Central federal district, works at a small- or medium-sized company in the trade and consumer services sector, and is employed in an occupation with a low risk of automation prior to the COVID-19 pandemic.

Our baseline results indicate that compared to women in less automation-prone jobs, women exposed to high automation risk at work are 4.0 percentage points more likely to report alcohol use and are 3.4 percentage points more likely to be active drinkers. Among active drinkers, high automation risk is associated with a 9.0% increase in total monthly consumption of pure ethanol (in grams) in the female subsample. Given that the average monthly consumption of pure ethanol among women in the low-risk group is 132.8 grams, transitioning to a high-risk occupation is associated with a relatively modest increase of about 12.0 grams (just over one standard drink per month) for women in this group. No statistically significant associations between high automation risk and any of the drinking behaviors considered are found among male respondents.

4.3. Mediation analysis: job insecurity, labor market unviability, and dissatisfaction with growth opportunities at work

Table 2 presents the results of the mediation analysis. Using the KHB method, we decompose the total effect (as estimated in our baseline models) into a direct component (attributable to high automation risk itself) and an indirect component (attributable to selected mediators). When the indirect effect estimates are statistically significant, we calculate the contribution of each mediator.

As shown in Table 2, the selected work-related mediators do not function as transmission mechanisms between high automation risk and drinking behaviors in the male subsample, as the estimated indirect effects are consistently statistically insignificant. In contrast, among women, job insecurity, self-reported labor market unviability, and dissatisfaction with growth opportunities at work collectively appear to mediate the relationship between exposure to high automation risk and both active drinker status and total alcohol consumption.

Once potential transmission channels are incorporated into our models, the direct effect of high automation risk on the likelihood of becoming an active drinker and on total alcohol consumption in the female subsample slightly declines to 3.1 percentage points and 8.2%, respectively. Thus, the indirect effects account for approximately 9% of the estimated total effect in both models.

Table 2 – Summary of estimates: mediation analysis (KHB method)

	Alcohol use		Active drinker		Alcohol consumption (ln)	
	Men	Women	Men	Women	Men	Women
	AME (SE)	AME (SE)	AME (SE)	AME (SE)	Coef. (SE)	Coef. (SE)
Total effect (TE)	0.008	0.040***	0.016	0.034**	-0.070	0.090**
	(0.014)	(0.013)	(0.016)	(0.014)	(0.043)	(0.041)
Direct effect (DE)	0.008	0.040***	0.016	0.031**	-0.072*	0.082**
	(0.014)	(0.013)	(0.016)	(0.014)	(0.043)	(0.041)
Indirect effect (IE)	0.000	0.000	0.000	0.003***	0.002	0.008**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Decomposition of IE:						
Job insecurity				0.000		0.000
				(0.000)		(0.001)
Labor market unviability				0.000		0.000
				(0.000)		(0.001)
Dissatisfaction with growth				0.003***		0.008***
				(0.001)		(0.003)
Number of observations	10,907	11,274	10,907	11,274	6,245	4,873
Number of individuals	4,020	4,200	4,020	4,200	2,800	2,409

*Note: *p-value<0.10, **p-value<0.05, ***p-value<0.01*

All models include controls for age, squared age, marital status, presence of children under age 18, educational attainment, income, nationality, health status, type of settlement, federal district, company size, industrial sector, and the years of the COVID-19 pandemic lockdown.

Robust standard errors are clustered at an individual level.

Furthermore, our findings indicate that the contributions of job insecurity and low self-reported labor market viability as channels linking high automation risk to women's drinking behaviors appear quite limited. This is, however, not particularly surprising given that approximately 20% of the workforce was engaged in informal employment in Russia between 2017 and 2021 (Kiselev et al., 2024). In contrast, dissatisfaction with growth opportunities at work emerges as the key factor linking high automation risk and increased drinking behaviors among women, implying that highly automatable (routine-intensive) jobs are perceived more as lacking professional and career development than as posing an immediate threat of job loss. Moreover, this evidence suggests a gradual shift in Russian society from a traditional (patriarchal) model toward a more egalitarian one in which men and women share roles more equally and women increasingly participate in employment and income-earning.

4.4. Moderation analysis: job exposure indices

As shown in Table 3, among men, high physical (OPI) and psychosocial (OSI) exposure indices do not moderate the relationship between high automation risk and any of the drinking behaviors examined, as the coefficients on interaction terms are not statistically significant. However, high physical (psychosocial) stress at work is associated with a 7.0% (1.9 percentage point) increase in total alcohol consumption (probability of reporting alcohol use) in the male subsample. In contrast, among female respondents, the estimated simple slopes indicate that women in highly automatable occupations are 4.5 percentage points more likely to report alcohol use when their jobs involve high levels of physical exposure, as the interaction term coefficient is statistically significant. In addition, the inclusion of job exposure variables in our models slightly alters the magnitude, and, in some cases, the statistical significance, of the main effect estimates, which may suggest the presence of mild mediation.

Table 3 – Summary of estimates: moderation analysis

	Alcohol use		Active drinker		Alcohol consumption (ln)	
	Men	Women	Men	Women	Men	Women
	AME (SE)	AME (SE)	AME (SE)	AME (SE)	Coef. (SE)	Coef. (SE)
High risk: Baseline model	0.008 (0.014)	0.040*** (0.013)	0.016 (0.016)	0.034** (0.014)	-0.070 (0.043)	0.090** (0.041)
High risk	0.000 (0.015)	0.039*** (0.013)	0.004 (0.018)	0.036** (0.015)	-0.215** (0.106)	0.121** (0.047)
High OPI	0.012 (0.010)	-0.006 (0.012)	0.002 (0.013)	-0.007 (0.014)	0.070* (0.037)	0.062 (0.046)
High risk X High OPI	0.014 (0.014)	0.045** (0.021)	0.028 (0.018)	0.013 (0.023)	0.156 (0.116)	-0.105 (0.089)
High risk	0.005 (0.013)	0.039*** (0.012)	0.012 (0.016)	0.035** (0.015)	-0.091 (0.071)	0.076 (0.054)
High OSI	0.019** (0.009)	0.003 (0.010)	0.002 (0.011)	0.005 (0.011)	-0.009 (0.034)	0.007 (0.037)
High risk X High OSI	0.006 (0.015)	0.031 (0.019)	0.025 (0.020)	0.010 (0.021)	0.033 (0.089)	0.029 (0.080)

*Note: *p-value<0.10, **p-value<0.05, ***p-value<0.01*

All models include controls for age, squared age, marital status, presence of children under age 18, educational attainment, income, nationality, health status, type of settlement, federal district, company size, industrial sector, and the years of the COVID-19 pandemic lockdown.

Robust standard errors are clustered at an individual level.

4.5. Further robustness checks

Table S8 in the supplementary materials summarizes the estimates from alternative model specifications, along with results from several sensitivity checks. Our findings from the correlated random effects probit models (used as fixed effects approximations for binary outcomes) and fixed effects linear regression for the continuous outcome are largely consistent with our baseline results across both gender groups. The only notable exceptions are the models for alcohol use and active drinker status among men, where the direction of the effect changes once the issue of unobserved heterogeneity is accounted for; however, the estimates remain statistically insignificant. Nevertheless, we interpret these findings with caution considering the quasi-time-invariant nature of our main explanatory variable.

The decomposition along extensive and intensive margins using Cragg's double hurdle models (CDH) is also consistent with our main findings on alcohol use and total alcohol consumption in terms of the direction and statistical significance of the effects, although the coefficient estimates are not directly comparable. Specifically, the estimated average marginal effects from the CDH model indicate that transitioning from a low-risk to a high-risk occupation in terms of automation exposure is associated with a decrease in total monthly alcohol consumption of 8.8 grams of pure ethanol for men (not statistically significant) and an increase of 10.7 grams for women.

Furthermore, our findings from the dynamic models, which partially address the issue of reverse causality (i.e., whether automation risk influences workers' drinking patterns or whether individuals with certain drinking behaviors self-select into occupations with varying levels of risk), also closely align with our baseline results. The estimated effects generally maintain the same direction, magnitude, and statistical significance across most drinking outcomes, with the exception of total alcohol consumption in both gender groups. In addition, all models indicate the presence of state dependence, as the coefficients on the one-year lag or the initial value of the corresponding dependent variables are statistically significant.

As a sensitivity check, we exclude respondents who reside in Moscow and St. Petersburg, whose religion prohibits alcohol consumption, or who are employed unofficially, and observations from 2017, when the government announced digitalization as a strategic priority, though without substantial policy implementation. These exclusions lead to a slight change in the magnitude, and, in some cases, the significance, of the estimated effects due to the reduced sample size affecting the statistical power of our analysis. Nevertheless, the estimates remain relatively consistent with our baseline findings.

Finally, prompted by the puzzling negative association between high automation risk and total alcohol consumption in the male subsample (observed across baseline models and alternative specifications), we hypothesize that this effect may be driven by internal monitoring practices, which are particularly prevalent in male-dominated industrial occupations, and may reduce or discourage alcohol consumption among men. To test this, we control for occupations subject to pre-shift alcohol testing, as defined by Russian labor law. However, once incorporated into our models, this variable shows no significant association with drinking behaviors, and does not alter the relationship between high automation risk and our outcome variables in the male subsample. In contrast, among women, pre-shift alcohol testing is associated with a 7.7 and 5.8 percentage point reduction in the likelihood of reporting alcohol use and active drinker status, respectively, while having no impact on the association between automation risk and drinking behaviors.

Overall, our findings indicate that high automation risk at the occupational level is positively related to drinking behaviors among women in the Russian context, suggesting that female workers are a key target group for policy interventions.

5. Discussion

5.1 Main findings

This study investigates the relationship between exposure to high automation risk in the workplace and drinking behaviors among workers in Russia between 2017 and 2021, highlighting potential mediation and moderation factors. Our findings indicate that employment in highly automatable occupations is positively related to all examined drinking outcomes among women. In contrast, no statistically significant associations are observed among men.

More specifically, among women, high automation risk is associated with a 4.0 and 3.4 percentage point increase in the likelihood of reporting alcohol use and being an active drinker, respectively, compared to low automation risk. Among active female drinkers, high automation risk is linked to a 9.0% increase in monthly pure ethanol consumption, which is equivalent to an increase of around 12 grams (about one drink) based on the average consumption level in the low-risk group.

Overall, our findings suggest that, in the Russian context, drinking behaviors may act as a pathway linking automation risk to health outcomes among female workers. However, the magnitude of the effects we observe is relatively moderate, and is several times smaller than the estimates of the relationship between unemployment, unexpected job loss, or job insecurity and drinking behaviors for other countries (Probst et al., 2017 for Europe; Park et al., 2022 for South Korea). Moreover, our findings do not fully align with those of Gihleb et al. (2022), who report a positive association between high automation risk and alcohol-related mortality in the U.S. As alcohol-related mortality is largely driven by excessive alcohol consumption among men, both globally and in Russia (WHO, 2018), the absence of statistically significant effects in our male subsample prevents us from drawing similar conclusions in the Russian context.

Furthermore, unlike in Western countries (Patel et al., 2018; Abeliansky et al., 2024), we find no evidence that job insecurity links high automation risk to drinking behaviors of workers in Russia. This is perhaps unsurprising, given that around 63% of respondents in our sample are already concerned about future job loss, and approximately 20% of total employment in the country is concentrated in the shadow sector. In addition, the finding that dissatisfaction with growth opportunities at work mediates the relationship between automation risk and both active drinker status and alcohol consumption in the female subsample suggests that skills utilization, professional fulfillment, and career development appear to be of growing importance to Russian women. This shift has been occurring alongside the persistence of traditional expectations of motherhood, signaling a significant societal move toward more egalitarian values.

Finally, our analysis demonstrates that high job exposures (physical and psychosocial) are significant determinants of drinking behaviors among men in Russia. Notably, high physical exposures moderate the relationship between high automation risk and alcohol use among female workers, underscoring the presence of gender-specific occupational and sectoral segregation in the labor market.

Although previous research shows that high automation risk negatively affects the health of both men and women (Abeliansky et al., 2024), in the Russian context, drinking behaviors are unlikely to serve as a plausible transmission mechanism for this relationship among male workers. The lack of a significant association between automation risk and drinking patterns among men may reflect a ceiling effect, suggesting that general alcohol use and overall alcohol consumption levels are already sufficiently high to limit observable variation. However, the negative association between high automation risk and total alcohol consumption observed among men – though sensitive to model specification and sample selection – remains puzzling. One possible explanation is the presence of internal workplace control mechanisms, such as pre-shift alcohol testing, which may act as a deterrent to drinking.

Once pre-shift alcohol testing is included in the models, we find no statistically significant association between this variable and drinking behaviors among men, and it does not alter the relationship between automation risk and the considered outcomes in the male subsample. In contrast, among female workers, pre-shift alcohol testing is negatively associated with the likelihood of reporting alcohol use and being an active drinker. These gender differences might be explained by the fact that pre-shift alcohol testing seems to be unevenly applied across the sample and limited to specific sectors and occupations (about 90% of occupations subject to pre-shift testing are concentrated in the male subsample). Furthermore, our findings could imply that pre-shift testing is either infrequent, inconsistently enforced, or insufficiently effective in altering male drinking behaviors. As pre-shift testing primarily addresses alcohol use immediately before work, it may not capture broader patterns of drinking outside work hours, which are more relevant to overall consumption. In addition, workers aware of pre-shift testing might adjust their drinking patterns (e.g., drink less before work but not reduce overall consumption), such that the test does not affect the total alcohol intake measured in the study.

Overall, our findings highlight the need for more accurate data on alcohol consumption and more precise measures of workplace control mechanisms. They also suggest the presence of gender-specific occupational self-selection patterns in the Russian context, thereby providing a foundation for more targeted future research.

5.2 Methodological considerations

Our analysis faces several challenges. First, the estimates for total alcohol consumption, measured in grams of pure ethanol, may be affected by reporting bias. This variable relies on respondents' self-assessments of the frequency and quantity of various alcoholic beverages consumed, which introduces the risk of misreporting or recall errors (Gmel and Rehm, 2004; Boniface et al., 2014). Additionally, our analysis also considers homemade beverages, which are predominantly produced and consumed in rural areas and may contain a higher concentration of pure ethanol than the average ABV reported for commercially produced beverages (Rehm et al., 2014). This may lead to underreporting of our continuous outcome that particularly affects the rural populations in our sample. Second, the limited within variation in our key explanatory variable, high automation risk, restricts our capacity to fully control for unobserved heterogeneity via fixed effects models. Finally, our estimates may be affected by misclassification, as workers in high-risk jobs might be unaware of automation threats, while those in low-risk roles could still perceive potential disruption. This issue tends to bias results toward zero. Nevertheless, both our study and previous research building on objective automation risk proxies still demonstrate significant effects on health-related outcomes.

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Conflict of interests

We have no conflict of interests to declare.

Data availability

The RLMS-HSE data cannot be publicly shared due to contractual agreements with the data provider. Other sources of data are openly available.

We also provide estimation codes for STATA (version 18), which are available at: https://osf.io/wz6kc/?view_only=be51de1dddf743eca06336ea04e88d6a.

References

Abeliansky, A. L., Beulmann, M., & Prettner, K. (2024). Are they coming for us? Industrial robots and the mental health of workers. Research Policy, 53(3), 104956. https://doi.org/10.1016/j.respol.2024.104956.

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis (OECD Social, Employment and Migration Working Papers, No. 189). OECD Publishing. https://doi.org/10.1787/5jlz9h56dvq7-en.

Autor, D., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the U.S. labor market. American Economic Review, 103(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553.

Balsmeier, B., & Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. Research Policy, 48(8), 103765. https://doi.org/10.1016/j.respol.2019.03.010.

Blasco, S., Rochut, J., & Rouland, B. (2022). Displaced or depressed? The effect of working in automatable jobs on mental health (IZA Discussion Paper No. 15434). IZA Institute of Labor Economics. https://www.iza.org/en/publications/dp/15434.

Boniface, S., Kneale, J., & Shelton, N. (2014). Drinking pattern is more strongly associated with under-reporting of alcohol consumption than socio-demographic factors: Evidence from a mixed-methods study. BMC Public Health, 14, 1297. https://doi.org/10.1186/1471-2458-14-1297.

Bryden, A., Roberts, B., McKee, M., & Petticrew, M. (2013). Unemployment and substance use: A systematic review of studies from North America and Europe. Drug and Alcohol Dependence, 134, 122–131. https://doi.org/10.1016/j.drugalcdep.2013.01.031.

Cheng, W., Pien, L., & Cheng, Y. (2021). Occupation-level automation probability is associated with psychosocial work conditions and workers' health: A multilevel study. American Journal of Industrial Medicine, 64(2), 108–117. https://doi.org/10.1002/ajim.23182.

Cheremisina, N. V., Ivliyev, M. I., & Talalayev, D. D. (2014). Alcoholism: Global problem of modern Russia. Economics and Business, 9(10), 163–167.

Colder, C. R. (2001). Life stress, physiological and subjective indexes of negative emotionality, and coping reasons for drinking: Is there evidence for a self-medication model of alcohol use? Psychology of Addictive Behaviors, 15(3), 237–245. https://doi.org/10.1037/0893-164X.15.3.237.

Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. Econometrica, 39(5), 829–844. https://doi.org/10.2307/1909582.

Dengler, K., Matthes, B., & Paulus, W. (2014). Occupational tasks in the German labour market: An alternative measurement on the basis of an expert database (FDZ-Methodenreport). Institute for Employment Research (IAB).

Engel, C., & Moffat, P. G. (2014). dhreg, xtdhreg, and bootdhreg: Commands to implement double-hurdle regression. The Stata Journal, 14(4), 778–797. https://doi.org/10.1177/1536867X1401400403.

Erpilov, A. A. (2015). Alcoholism as a social problem of Russian society. Theory and Practice of Service: Economics, Social Sector, Technologies, 4(26), 31–34.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019.

Garnett, C., Jackson, S., Oldham, M., Brown, J., Steptoe, A., & Fancourt, D. (2021). Factors associated with drinking behaviour during COVID-19 social distancing and lockdown among adults in the UK. Drug and Alcohol Dependence, 219, 108461. https://doi.org/10.1016/j.drugalcdep.2020.108461.

Gihleb, R., Giuntella, O., Stella, L., & Wang, T. (2022). Industrial robots, workers' safety, and health. Labour Economics, 78, 102205. https://doi.org/10.1016/j.labeco.2022.102205.

Giuntella, O., Koenig, J., & Stella, L. (2023). Artificial intelligence and workers' well-being (IZA Discussion Paper No. 16485). IZA Institute of Labor Economics. https://www.iza.org/publications/dp/16485.

Gmel, G., & Rehm, J. (2004). Measuring alcohol consumption. Contemporary Drug Problems, 31(3), 467–540. https://doi.org/10.1177/009145090403100304.

Graetz, G., & Michaels, G. (2018). Robots at work. The Review of Economics and Statistics, 100(5), 753–768. https://doi.org/10.1162/rest_a_00754.

Grossman, E. R., Benjamin-Neelon, S. E., & Sonnenschein, S. (2020). Alcohol consumption during the COVID-19 pandemic: A cross-sectional survey of US adults. International Journal of Environmental Research and Public Health, 17(24), 9189. https://doi.org/10.3390/ijerph17249189.

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review, 104(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509.

Gunadi, C., & Ryu, H. (2021). Does the rise of robotic technology make people healthier? Health Economics, 30(9), 2047–2062. https://doi.org/10.1002/hec.4330.

Herzfeld, T., Huffman, S., & Rizov, M. (2014). The dynamics of food, alcohol and cigarette consumption in Russia during transition. Economics and Human Biology, 13, 128–143. https://doi.org/10.1016/j.ehb.2013.11.004.

Huang, G., Zhao, H., Niu, X., Ashford, S. J., Lee, C., Huang, C., & Emily, G. (2013). Reducing job insecurity and increasing performance ratings: Does impression management matter? Journal of Applied Psychology, 98(5), 852–862. https://doi.org/10.1037/a0033067.

Kapeliushnikov, R. I. (2023). The Russian labor market: Long-term trends and short-term fluctuations. Russian Journal of Economics, 9(3), 245–270. https://doi.org/10.1016/j.ruje.2023.07.002.

Kiselev, S. V., Seitov, S. K., Samsonov, V. A., & Filimonov, I. V. (2024). Employment in informal sector of Russia: Unemployment and other socio-economic factors. Population and Economics, 8(3), 197–219.

Klimova, A. (2012). Gender differences in determinants of occupational choice in Russia. International Journal of Social Economics, 39(9), 648–670. https://doi.org/10.1108/03068291211246049.

Koen, J., Low, J. T. H., & Van Vianen, A. (2020). Job preservation efforts: When does job insecurity prompt performance? Career Development International, 25(3), 287–305. https://doi.org/10.1108/CDI-07-2019-0152.

Kohler, U., Karlson, K. B., & Holm, A. (2011). Comparing coefficients of nested nonlinear probability models. The Stata Journal, 11(3), 420–438. https://doi.org/10.1177/1536867X1101100304.

Konuikhovskaia, A. (2019). IFR forum: Five trends in Russian robotics. International Federation of Robotics. https://ifr.org/post/five-trends-in-russian-robotics (accessed March 2025)

Kosyakova, Y., Kurakin, D., & Blossfeld, H. P. (2015). Horizontal and vertical gender segregation in Russia: Changes upon labour market entry before and after the collapse of the Soviet regime. European Sociological Review, 31(5), 573–590. https://doi.org/10.1093/esr/jcv049.

Kroll, L. E. (2011). Job Exposure Matrices (JEM) for ISCO and KldB (Version 1.0) [Data set]. GESIS – Leibniz Institute for the Social Sciences. https://doi.org/10.4232/1.10717.

Kromann, L., Malchow-Møller, N., Skaksen, J. R., & Sørensen, A. (2020). Automation and productivity: A cross-country, cross-industry comparison. Industrial and Corporate Change, 29(2), 265–287. https://doi.org/10.1093/icc/dtz033.

Lemmens, P. H. (1994). The alcohol content of self-report and 'standard' drinks. Addiction, 89(5), 593–601. https://doi.org/10.1111/j.1360-0443.1994.tb03362.x.

Liu, L. (2023). Job quality and automation: Do more automatable occupations have less job satisfaction and health? Journal of Industrial Relations, 65(1), 72–87. https://doi.org/10.1177/00221856221143988.

Lordan, G., & Stringer, E.-J. (2022). People versus machines: The impact of being in an automatable job on Australian workers' mental health and life satisfaction. Economics and Human Biology, 46, 101144. https://doi.org/10.1016/j.ehb.2022.101144.

Malisauskaite, G., & Klein, A. (2018). Drinking under communism: Why do alcohol consumption habits in Eastern Europe differ from the West in the long run? Journal of Comparative Economics, 46(3), 821–837. https://doi.org/10.1016/j.jce.2018.04.001.

Martins-Neto, A., Mathew, N., Mohnen, P., & Treibich, T. (2024). Is there job polarization in developing economies? A review and outlook. World Bank Research Observer, 39(2), 259–288. https://doi.org/10.1093/wbro/lkab046.

Mihaylov, E., & Tijdens, K. G. (2019). Measuring the routine and non-routine task content of 427 four-digit ISCO-08 occupations (Tinbergen Institute Discussion Paper No. 2019-035/V). Tinbergen Institute. https://papers.tinbergen.nl/19035.pdf.

Ministry of Digital Development, Communications and Mass Media of the Russian Federation. (2017). National Program "Digital Economy of the Russian Federation". Retrieved July 2025, from https://digital.gov.ru/ru/activity/directions/858/

Mundlak, Y. (1978). On the pooling of time series and cross section data. Econometrica, 46(1), 69–85. https://doi.org/10.2307/1913646.

Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. Technology in Society, 67, 101679. https://doi.org/10.1016/j.techsoc.2021.101679.

O'Brien, R., Bair, E. F., & Venkataramani, A. S. (2022). Death by robots? Automation and working-age mortality in the United States. Demography, 59(2), 607–628. https://doi.org/10.1215/00703370-9934902.

Park, S., Lee, J.-H., & Lee, J. (2022). Alcohol abuse associated with accumulated periods of precarious employment: A four-year follow-up study of a young population in Korea. International Journal of Environmental Research and Public Health, 19(12), 7380. https://doi.org/10.3390/ijerph19127380.

Patel, P. C., Devaraj, S., Hicks, M. J., & Wornell, E. J. (2018). County-level job automation risk and health: Evidence from the United States. Social Science & Medicine, 202, 54–60. https://doi.org/10.1016/j.socscimed.2018.03.005.

Probst, C., Kilian, C., Sanchez, S., & Lange, S. (2017). The role of economic recessions and unemployment in alcohol consumption and alcohol-related health problems: A systematic review. European Addiction Research, 23(3), 151–161. https://doi.org/10.1159/000452870.

Rehm, J., Kailasapillai, S., Larsen, E., Rehm, M. X., Samokhvalov, A. V., Shield, K. D., & Poznyak, V. (2014). A systematic review of the epidemiology of unrecorded alcohol consumption and the chemical composition of unrecorded alcohol. Addiction, 109(6), 880–893. https://doi.org/10.1111/add.12406.

Sberbank Report. (2024). Digital Leap: The digitalisation of the Russian economy. Sberbank Branch in India. Retrieved July 2025, from https://sberbank.co.in/media/publications/digital-leap-the-digitalisation-of-the-russian-economy.

Shoss, M. K. (2017). Job insecurity: An integrative review and agenda for future research. Journal of Management, 43(6), 1911–1939. https://doi.org/10.1177/0149206317691574.

Vannutelli, S., Scicchitano, S., & Biagetti, M. (2022). Routine-biased technological change and wage inequality: Do workers' perceptions matter? Eurasian Business Review, 12(3), 409–450. https://doi.org/10.1007/s40821-022-00214-z.

Yang, S., Liu, K., Gai, J., & He, X. (2022). Transformation to industrial artificial intelligence and workers' mental health: Evidence from China. Frontiers in Public Health, 10, 881827. https://doi.org/10.3389/fpubh.2022.881827.

Zheng, J., Rohenkohl, B., Barahona, M., & Clarke, J. M. (2024). Automation risk and subjective wellbeing in the UK. [Manuscript in preparation/unpublished manuscript].

World Health Organization. (2018). Global status report on alcohol and health 2018. https://www.who.int/publications/i/item/9789241565639.

World Health Organization. (n.d.). Alcohol levels of consumption. Global Health Observatory. Retrieved July 2025, from https://www.who.int/data/gho/data/themes/topics/indicator-groups/indicator-group-details/GHO/levels-of-consumption.

Трудовой кодекс Российской Федерации (ТК РФ) от 30.12.2001 N 197-ФЗ (ред. от 31.07.2025). (Labor Code of the Russian Federation (LC of the RF) dated December 30, 2001 No. 197-FZ (as amended on July 31, 2025)). Retrieved July 2025, from https://www.consultant.ru/document/cons_doc_LAW_34683/

Table S1 – Descriptive statistics stratified by gender: full sample

		Men (n=10,907 obs.)		Women (n=11,274 obs.)		
Variable	Definition	Mean	SD	Mean	SD	t-test
Alcohol use	Abstainer=0, Respondent consumes alcohol=1	0.773	0.419	0.711	0.453	***
Active drinker	Abstainer or potential drinker=0, Active drinker=1	0.573	0.495	0.432	0.495	***
Automation risk	High automation risk (>70% of routine tasks)=1, Otherwise=0	0.142	0.349	0.148	0.355	
Age	Age (number of full years)	39.400	10.248	39.115	9.129	**
Marital status	Married or cohabiting=0, Otherwise=1	0.205	0.404	0.317	0.465	***
Children	Respondent has children under 18=0, Otherwise=1	0.493	0.500	0.480	0.500	*
Education	Postsecondary or less=0, Tertiary or more=1	0.287	0.452	0.441	0.497	***
Income	Monthly individual income adjusted for inflation (kRUR)	35.194	18.947	27.151	15.280	***
Nationality	Russian=0, Otherwise=1	0.101	0.301	0.094	0.292	
SRH	Good or very good self-reported health=0, Otherwise=1	0.453	0.498	0.526	0.499	***
Settlement	Type of settlement (dummies):	1.773	0.767	1.764	0.773	
Area_1	City=1, Otherwise=0	0.434	0.496	0.444	0.497	
Area_2	Town or semi-urban settlement (PGT)=1, Otherwise=0	0.360	0.480	0.347	0.476	*
Area_3	Rural area=1, Otherwise=0	0.207	0.405	0.208	0.406	
Company size	Large company (Headcount>=250 ppl.) =1, Otherwise=0	0.266	0.442	0.177	0.382	***
Industry	Industrial sector (dummies):	3.724	1.726	3.766	1.861	*
Sector_1	Trade and consumer services=1, Otherwise=0	0.165	0.371	0.253	0.434	***
Sector_2	Agriculture + wood, timber, and forestry=1, Otherwise=0	0.056	0.229	0.023	0.149	***
Sector_3	Industrial complex=1, Otherwise=0	0.283	0.450	0.142	0.349	***
Sector_4	Construction=1, Otherwise=0	0.113	0.317	0.020	0.140	***
Sector_5	Social services=1, Otherwise=0	0.156	0.363	0.413	0.492	***
Sector_6	Commercial services=1, Otherwise=0	0.228	0.420	0.149	0.356	***
OPI	High physical exposure index=1, Otherwise=0	0.608	0.488	0.303	0.460	***
OSI	High psychosocial exposure index=1, Otherwise=0	0.552	0.497	0.411	0.492	***
Job insecurity	Concerned about future job loss=1, Otherwise=0	0.633	0.482	0.627	0.484	
Labor market unviability	Uncertain about finding a job if laid off=1, Otherwise=0	0.382	0.486	0.395	0.489	*
Dissatisfaction (growth)	Unsatisfied with growth opportunities at work=1, Otherwise=0	0.220	0.414	0.220	0.414	
Federal district	Federal district (dummies):	3.772	2.270	3.764	2.259	
District_1	Center=1, Otherwise=0	0.277	0.447	0.273	0.445	
District_2	North-West=1, Otherwise=0	0.098	0.297	0.103	0.303	
District_3	South=1, Otherwise=0	0.111	0.315	0.112	0.316	
District_4	North Caucasus=1, Otherwise=0	0.032	0.177	0.036	0.185	
District_5	Volga=1, Otherwise=0	0.238	0.426	0.235	0.424	
District_6	Ural=1, Otherwise=0	0.096	0.295	0.096	0.295	
District_7	Siberia=1, Otherwise=0	0.110	0.313	0.109	0.311	
District_8	Far East=1, Otherwise=0	0.037	0.190	0.036	0.187	
COVID-19	Year of the COVID-19 pandemic lockdown=1, Otherwise=0	0.394	0.489	0.389	0.488	

*Note: *p-value<0.10, **p-value<0.05, ***p-value<0.01*

Table S2 – Descriptive statistics stratified by gender: active drinkers

Variable	Definition	Men (n=6,245 obs.) Mean	Men SD	Women (n=4,873 obs.) Mean	Women SD	t-test
Alcohol consumption	Total monthly consumption of pure ethanol (grams)	354.572	474.625	136.782	183.936	***
Automation risk	High automation risk (>70% of routine tasks)=1, Otherwise=0	0.154	0.361	0.163	0.370	
Age	Age (number of full years)	39.633	9.833	39.206	8.787	**
Marital status	Married or cohabiting=0, Otherwise=1	0.179	0.384	0.305	0.461	***
Children	Respondent has children under 18=0, Otherwise=1	0.462	0.499	0.466	0.499	
Education	Postsecondary or less=0, Tertiary or more=1	0.297	0.457	0.452	0.498	***
Income	Monthly individual income adjusted for inflation (kRUR)	36.402	19.223	29.908	16.665	***
Nationality	Russian=0, Otherwise=1	0.088	0.284	0.075	0.263	***
SRH	Good or very good self-reported health=0, Otherwise=1	0.463	0.499	0.551	0.497	***
Settlement	Type of settlement (dummies):	1.702	0.742	1.679	0.747	
Area_1	City=1, Otherwise=0	0.469	0.499	0.491	0.500	**
Area_2	Town or semi-urban settlement (PGT)=1, Otherwise=0	0.360	0.480	0.339	0.473	**
Area_3	Rural area=1, Otherwise=0	0.171	0.376	0.170	0.376	
Company size	Large company (Headcount>=250 ppl.) =1, Otherwise=0	0.284	0.451	0.205	0.404	***
Industry	Industrial sector (dummies):	3.666	1.727	3.724	1.874	*
Sector_1	Trade and consumer services=1, Otherwise=0	0.174	0.379	0.259	0.438	***
Sector_2	Agriculture + wood, timber, and forestry=1, Otherwise=0	0.051	0.221	0.022	0.147	***
Sector_3	Industrial complex=1, Otherwise=0	0.297	0.457	0.154	0.361	***
Sector_4	Construction=1, Otherwise=0	0.115	0.319	0.021	0.142	***
Sector_5	Social services=1, Otherwise=0	0.141	0.348	0.388	0.487	***
Sector_6	Commercial services=1, Otherwise=0	0.222	0.416	0.156	0.363	***
OPI	High physical exposure index=1, Otherwise=0	0.597	0.490	0.292	0.455	***
OSI	High psychosocial exposure index=1, Otherwise=0	0.544	0.498	0.400	0.490	***
Job insecurity	Concerned about future job loss=1, Otherwise=0	0.633	0.482	0.606	0.489	***
Labor market unviability	Uncertain about finding a job if laid off=1, Otherwise=0	0.357	0.479	0.362	0.481	
Dissatisfaction (growth)	Unsatisfied with growth opportunities at work=1, Otherwise=0	0.246	0.431	0.256	0.436	
Federal district	Federal district (dummies):	3.739	2.292	3.650	2.344	**
District_1	Center=1, Otherwise=0	0.300	0.458	0.324	0.468	***
District_2	North-West=1, Otherwise=0	0.097	0.296	0.116	0.320	***
District_3	South=1, Otherwise=0	0.085	0.278	0.063	0.242	***
District_4	North Caucasus=1, Otherwise=0	0.024	0.154	0.019	0.137	*
District_5	Volga=1, Otherwise=0	0.242	0.429	0.211	0.408	***
District_6	Ural=1, Otherwise=0	0.110	0.312	0.115	0.319	
District_7	Siberia=1, Otherwise=0	0.116	0.320	0.133	0.340	***
District_8	Far East=1, Otherwise=0	0.027	0.162	0.019	0.137	***
COVID-19	Year of the COVID-19 pandemic lockdown=1, Otherwise=0	0.377	0.485	0.368	0.482	

*Note: *p-value<0.10, **p-value<0.05, ***p-value<0.01*

Table S3 – Descriptive statistics stratified by gender and automation risk: full sample

	Men					Women				
	Low risk (n=9,354)		High risk (n=1,553)			Low risk (n=9,608)		High risk (n=1,666)		
Variable	Mean	SD	Mean	SD	t-test	Mean	SD	Mean	SD	t-test
Alcohol use	0.770	0.421	0.791	0.407	*	0.703	0.457	0.756	0.429	***
Active drinker	0.565	0.496	0.619	0.486	***	0.424	0.494	0.477	0.500	***
Age	39.595	10.261	38.227	10.092	***	39.228	9.110	38.462	9.213	***
Marital status	0.196	0.397	0.257	0.437	***	0.311	0.463	0.354	0.478	***
Children	0.490	0.500	0.509	0.500		0.483	0.500	0.462	0.499	
Education	0.312	0.463	0.133	0.339	***	0.470	0.499	0.275	0.447	***
Income	35.365	19.350	34.161	16.271	***	27.389	15.612	25.781	13.127	***
Nationality	0.103	0.304	0.086	0.280	**	0.097	0.296	0.078	0.268	***
SRH	0.454	0.498	0.448	0.497		0.525	0.499	0.532	0.499	
Settlement	1.778	0.774	1.742	0.723	*	1.771	0.777	1.723	0.744	**
Area_1	0.435	0.496	0.423	0.494		0.443	0.497	0.453	0.498	
Area_2	0.351	0.477	0.411	0.492	***	0.343	0.475	0.370	0.483	**
Area_3	0.213	0.410	0.165	0.372	***	0.214	0.410	0.176	0.381	***
Company size	0.251	0.433	0.359	0.480	***	0.170	0.376	0.219	0.414	***
Industry	3.838	1.751	3.035	1.376	***	3.841	1.843	3.334	1.902	***
Sector_1	0.160	0.367	0.192	0.394	***	0.244	0.430	0.301	0.459	***
Sector_2	0.059	0.235	0.037	0.190	***	0.022	0.146	0.028	0.166	
Sector_3	0.242	0.428	0.533	0.499	***	0.119	0.323	0.279	0.448	***
Sector_4	0.112	0.315	0.120	0.325		0.022	0.146	0.010	0.101	***
Sector_5	0.179	0.383	0.019	0.138	***	0.452	0.498	0.190	0.393	***
Sector_6	0.249	0.433	0.099	0.299	***	0.142	0.349	0.191	0.394	***
OPI	0.565	0.496	0.867	0.339	***	0.283	0.451	0.417	0.493	***
OSI	0.525	0.499	0.713	0.452	***	0.401	0.490	0.473	0.499	***
Job insecurity	0.634	0.482	0.632	0.482		0.624	0.484	0.643	0.479	
Labor market unviability	0.381	0.486	0.387	0.487		0.386	0.487	0.442	0.497	***
Dissatisfaction (growth)	0.218	0.413	0.231	0.422		0.206	0.404	0.304	0.460	***
Federal district	3.792	2.279	3.651	2.210	**	3.807	2.248	3.517	2.305	***
District_1	0.272	0.445	0.305	0.460	**	0.264	0.441	0.323	0.468	***
District_2	0.099	0.299	0.089	0.285		0.099	0.298	0.125	0.331	***
District_3	0.115	0.319	0.090	0.286	***	0.116	0.320	0.094	0.292	***
District_4	0.033	0.180	0.026	0.160		0.038	0.190	0.023	0.151	***
District_5	0.232	0.422	0.278	0.448	***	0.240	0.427	0.211	0.408	***
District_6	0.095	0.294	0.100	0.301		0.099	0.298	0.082	0.274	**
District_7	0.112	0.316	0.094	0.292	**	0.108	0.311	0.109	0.312	
District_8	0.041	0.197	0.018	0.133	***	0.037	0.189	0.032	0.177	
COVID-19	0.395	0.489	0.389	0.488		0.389	0.487	0.391	0.488	

*Note: *p-value<0.10, **p-value<0.05, ***p-value<0.01*

Table S4 – Descriptive statistics stratified by gender and automation risk: active drinkers

	Men					Women				
	Low risk (n=5,283)		High risk (n=962)			Low risk (n=4,078)		High risk (n=795)		
Variable	Mean	SD	Mean	SD	t-test	Mean	SD	Mean	SD	t-test
Alcohol consumption	358.004	480.990	335.727	437.778		132.832	178.392	157.042	209.041	***
Age	39.789	9.835	38.774	9.778	***	39.357	8.733	38.433	9.022	***
Marital status	0.169	0.375	0.236	0.425	***	0.296	0.457	0.351	0.478	***
Children	0.456	0.498	0.494	0.500	**	0.467	0.499	0.464	0.499	
Education	0.327	0.469	0.130	0.336	***	0.486	0.500	0.279	0.449	***
Income	36.693	19.635	34.807	16.695	***	30.307	17.137	27.861	13.822	***
Nationality	0.090	0.286	0.081	0.273		0.078	0.268	0.059	0.236	**
SRH	0.462	0.499	0.468	0.499		0.556	0.497	0.528	0.500	
Settlement	1.702	0.750	1.703	0.702		1.681	0.753	1.668	0.714	
Area_1	0.475	0.499	0.439	0.496	**	0.494	0.500	0.475	0.500	
Area_2	0.349	0.477	0.420	0.494	***	0.331	0.471	0.381	0.486	***
Area_3	0.176	0.381	0.141	0.349	***	0.175	0.380	0.143	0.351	**
Company size	0.273	0.446	0.345	0.476	***	0.203	0.402	0.218	0.413	
Industry	3.788	1.750	2.996	1.419	***	3.798	1.857	3.343	1.915	***
Sector_1	0.168	0.373	0.207	0.405	***	0.250	0.433	0.308	0.462	***
Sector_2	0.051	0.221	0.050	0.218		0.022	0.146	0.023	0.149	
Sector_3	0.257	0.437	0.515	0.500	***	0.132	0.338	0.268	0.443	***
Sector_4	0.117	0.322	0.104	0.305		0.023	0.149	0.011	0.106	**
Sector_5	0.163	0.370	0.019	0.136	***	0.425	0.494	0.199	0.399	***
Sector_6	0.243	0.429	0.106	0.308	***	0.149	0.356	0.191	0.393	***
OPI	0.545	0.498	0.884	0.321	***	0.273	0.445	0.391	0.488	***
OSI	0.513	0.500	0.713	0.453	***	0.390	0.488	0.449	0.498	***
Job insecurity	0.633	0.482	0.628	0.484		0.602	0.489	0.626	0.484	
Labor market unviability	0.353	0.478	0.383	0.486	*	0.354	0.478	0.404	0.491	***
Dissatisfaction (growth)	0.245	0.430	0.254	0.435		0.239	0.426	0.343	0.475	***
Federal district	3.752	2.301	3.668	2.244		3.701	2.336	3.389	2.370	***
District_1	0.295	0.456	0.324	0.468	*	0.313	0.464	0.379	0.485	***
District_2	0.101	0.301	0.078	0.268	**	0.114	0.318	0.126	0.332	
District_3	0.088	0.284	0.064	0.246	***	0.064	0.244	0.058	0.234	
District_4	0.026	0.158	0.017	0.128	*	0.021	0.143	0.010	0.100	**
District_5	0.232	0.422	0.299	0.458	***	0.216	0.411	0.189	0.391	*
District_6	0.110	0.313	0.108	0.311		0.120	0.325	0.088	0.284	***
District_7	0.120	0.325	0.090	0.287	***	0.133	0.339	0.135	0.342	
District_8	0.028	0.166	0.019	0.136	**	0.020	0.139	0.016	0.127	
COVID-19	0.376	0.485	0.379	0.485		0.363	0.481	0.396	0.489	*

*Note: *p-value<0.10, **p-value<0.05, ***p-value<0.01*

Table S5 – Comparison of gender-, risk group-, and occupation-specific means for binary outcome variables (full sample)

isco_4d	Title	Obs.	Alcohol use (gender-specific mean)	Alcohol use (risk group mean)	Alcohol use (isco_4d mean)	Active drinker (gender-specific mean)	Active drinker (risk group mean)	Active drinker (isco_4d mean)
				Men: High-risk group				
7212	Welders and Flame Cutters	315	0.773	0.791	0.759	0.573	0.619	0.571
4321	Stock Clerks	228	0.773	0.791	0.829	0.573	0.619	0.689
8211	Mechanical Machinery Assemblers	199	0.773	0.791	0.829	0.573	0.619	0.613
7223	Metal Working Machine Tool Setters and Operators	125	0.773	0.791	0.824	0.573	0.619	0.600
				Men: Low-risk group				
8332	Heavy Truck and Lorry Drivers	881	0.773	0.770	0.772	0.573	0.565	0.539
5419	Protective Services Workers Not Elsewhere Classified	549	0.773	0.770	0.761	0.573	0.565	0.495
7233	Agricultural and Industrial Machinery Mechanics and Repairers	340	0.773	0.770	0.741	0.573	0.565	0.532
8322	Car, Taxi and Van Drivers	327	0.773	0.770	0.771	0.573	0.565	0.599
7411	Building and Related Electricians	316	0.773	0.770	0.785	0.573	0.565	0.589
3322	Commercial Sales Representatives	293	0.773	0.770	0.826	0.573	0.565	0.604
3122	Manufacturing Supervisors	285	0.773	0.770	0.867	0.573	0.565	0.656
8331	Bus and Tram Drivers	281	0.773	0.770	0.790	0.573	0.565	0.580
7126	Plumbers and Pipe Fitters	270	0.773	0.770	0.656	0.573	0.565	0.544
9333	Freight Handlers	269	0.773	0.770	0.799	0.573	0.565	0.639
7231	Motor Vehicle Mechanics and Repairers	265	0.773	0.770	0.728	0.573	0.565	0.528
5412	Police Officers	182	0.773	0.770	0.786	0.573	0.565	0.544
1321	Manufacturing Managers	160	0.773	0.770	0.781	0.573	0.565	0.631
7412	Electrical Mechanics and Fitters	157	0.773	0.770	0.847	0.573	0.565	0.682
8341	Mobile Farm and Forestry Plant Operators	156	0.773	0.770	0.622	0.573	0.565	0.340
8342	Earthmoving and Related Plant Operators	155	0.773	0.770	0.729	0.573	0.565	0.503
5223	Shop Sales Assistants	147	0.773	0.770	0.850	0.573	0.565	0.558
2141	Industrial and Production Engineers	138	0.773	0.770	0.732	0.573	0.565	0.543

1349	Professional Services Managers Not Elsewhere Classified	129	0.773	0.770	0.853	0.573	0.565	0.713
8311	Locomotive Engine Drivers	128	0.773	0.770	0.703	0.573	0.565	0.477
3123	Construction Supervisors	123	0.773	0.770	0.764	0.573	0.565	0.569
2514	Applications Programmers	111	0.773	0.770	0.739	0.573	0.565	0.505
				Women: High-risk group				
3343	Administrative and Executive Secretaries	248	0.711	0.756	0.810	0.432	0.477	0.560
5230	Cashiers and Ticket Clerks	244	0.711	0.756	0.709	0.432	0.477	0.443
4321	Stock Clerks	174	0.711	0.756	0.724	0.432	0.477	0.414
9321	Hand Packers	137	0.711	0.756	0.759	0.432	0.477	0.438
4110	General Office Clerks	114	0.711	0.756	0.807	0.432	0.477	0.544
				Women: Low-risk group				
5223	Shop Sales Assistants	896	0.711	0.703	0.704	0.432	0.424	0.402
3313	Accounting Associate Professionals	545	0.711	0.703	0.734	0.432	0.424	0.486
3221	Nursing Associate Professionals	463	0.711	0.703	0.674	0.432	0.424	0.367
2342	Early Childhood Educators	413	0.711	0.703	0.678	0.432	0.424	0.419
9112	Cleaners and Helpers in Offices, Hotels and Other Establishments	377	0.711	0.703	0.690	0.432	0.424	0.419
2330	Secondary Education Teachers	375	0.711	0.703	0.571	0.432	0.424	0.267
3322	Commercial Sales Representatives	364	0.711	0.703	0.761	0.432	0.424	0.500
2411	Accountants	267	0.711	0.703	0.768	0.432	0.424	0.487
5120	Cooks	253	0.711	0.703	0.715	0.432	0.424	0.482
2631	Economists	237	0.711	0.703	0.759	0.432	0.424	0.464
5312	Teachers' Aides	184	0.711	0.703	0.630	0.432	0.424	0.402
2341	Primary School Teachers	169	0.711	0.703	0.568	0.432	0.424	0.278
3359	Government Regulatory Associate Professionals Not Elsewhere Classified	153	0.711	0.703	0.778	0.432	0.424	0.444
2619	Legal Professionals Not Elsewhere Classified	136	0.711	0.703	0.610	0.432	0.424	0.287
4323	Transport Clerks	129	0.711	0.703	0.705	0.432	0.424	0.481
3312	Credit and Loans Officers	119	0.711	0.703	0.756	0.432	0.424	0.378

3119	Physical and Engineering Science Technicians Not Elsewhere Classified	111	0.711	0.703	0.721	0.432	0.424	0.414
1349	Professional Services Managers Not Elsewhere Classified	106	0.711	0.703	0.708	0.432	0.424	0.443
1420	Retail and Wholesale Trade Managers	104	0.711	0.703	0.712	0.432	0.424	0.452
3333	Employment agents and contractors	104	0.711	0.703	0.740	0.432	0.424	0.471
5321	Health Care Assistants	102	0.711	0.703	0.735	0.432	0.424	0.412
3116	Chemical Engineering Technicians	100	0.711	0.703	0.600	0.432	0.424	0.350

Table S6 – Comparison of gender-, risk group-, and occupation-specific means for a continuous outcome variable (active drinkers)

isco_4d	Title	Obs.	Alcohol consumption (gender-specific mean)	Alcohol consumption (risk group mean)	Alcohol consumption (isco_4d mean)
			Men: High-risk group		
7212	Welders and Flame Cutters	180	354.572	335.727	332.748
4321	Stock Clerks	157	354.572	335.727	306.144
8211	Mechanical Machinery Assemblers	122	354.572	335.727	289.906
			Men: Low-risk group		
8332	Heavy Truck and Lorry Drivers	475	354.572	358.004	341.381
5419	Protective Services Workers Not Elsewhere Classified	272	354.572	358.004	400.296
8322	Car, Taxi and Van Drivers	196	354.572	358.004	372.695
3122	Manufacturing Supervisors	187	354.572	358.004	315.203
7411	Building and Related Electricians	186	354.572	358.004	389.541
7233	Agricultural and Industrial Machinery Mechanics and Repairers	181	354.572	358.004	381.194
3322	Commercial Sales Representatives	177	354.572	358.004	306.306
9333	Freight Handlers	172	354.572	358.004	481.859
8331	Bus and Tram Drivers	163	354.572	358.004	390.816
7126	Plumbers and Pipe Fitters	147	354.572	358.004	473.333
7231	Motor Vehicle Mechanics and Repairers	140	354.572	358.004	288.460
7412	Electrical Mechanics and Fitters	107	354.572	358.004	362.247
1321	Manufacturing Managers	101	354.572	358.004	339.614
			Women: High-risk group		
3343	Administrative and Executive Secretaries	139	136.782	157.042	163.636
5230	Cashiers and Ticket Clerks	108	136.782	157.042	185.370
			Women: Low-risk group		
5223	Shop Sales Assistants	360	136.782	132.832	162.206
3313	Accounting Associate Professionals	265	136.782	132.832	97.751
3322	Commercial Sales Representatives	182	136.782	132.832	155.136
2342	Early Childhood Educators	173	136.782	132.832	136.098
3221	Nursing Associate Professionals	170	136.782	132.832	97.179
9112	Cleaners and Helpers in Offices, Hotels and Other Establishments	158	136.782	132.832	191.428
2411	Accountants	130	136.782	132.832	130.139
5120	Cooks	122	136.782	132.832	164.345
2631	Economists	110	136.782	132.832	94.961
2330	Secondary Education Teachers	100	136.782	132.832	85.386

Table S7 – List of occupations (four-digit ISCO-08 code) subject to pre-shift alcohol testing

Low risk		High risk	
ISCO-08	Title	ISCO-08	Title
3114	Electronics Engineering Technicians	3132	Incinerator and Water Treatment Plant Operators
3115	Mechanical Engineering Technicians	3135	Metal Production Process Controllers
3116	Chemical Engineering Technicians	7211	Metal Molders and Coremakers
3117	Mining and Metallurgical Technicians	7212	Welders and Flame Cutters
3121	Mining Supervisors	7221	Blacksmiths, Hammersmiths and Forging Press Workers
3122	Manufacturing Supervisors	7223	Metal Working Machine Tool Setters and Operators
3123	Construction Supervisors	7315	Glass Makers, Cutters, Grinders and Finishers
3131	Power Production Plant Operators	8111	Miners and Quarriers
3151	Ships' Engineers	8112	Mineral and Stone Processing Plant Operators
3153	Aircraft Pilots and Related Associate Professionals	8114	Cement, Stone and Other Mineral Products Machine Operators
3154	Air Traffic Controllers	8121	Metal Processing Plant Operators
3258	Ambulance Workers	8122	Metal Finishing, Plating and Coating Machine Operators
5165	Driving Instructors	8131	Chemical Products Plant and Machine Operators
5411	Fire Fighters		
5413	Prison Guards		
7113	Stonemasons, Stone Cutters, Splitters and Carvers		
7114	Concrete Placers, Concrete Finishers and Related Workers		
7121	Roofers		
7213	Sheet Metal Workers		
7214	Structural Metal Preparers and Erectors		
7224	Metal Polishers, Wheel Grinders and Tool Sharpeners		
7411	Building and Related Electricians		
7412	Electrical Mechanics and Fitters		
7413	Electrical Line Installers and Repairers		
7523	Woodworking Machine Tool Setters and Operators		
8113	Well Drillers and Borers and Related Workers		
8182	Steam Engine and Boiler Operators		
8311	Locomotive Engine Drivers		
8312	Railway Brake, Signal and Switch Operators		
8322	Car, Taxi and Van Drivers		
8331	Bus and Tram Drivers		
8332	Heavy Truck and Lorry Drivers		
8342	Earthmoving and Related Plant Operators		
8343	Crane, Hoist and Related Plant Operators		
8344	Lifting Truck Operators		

Table S8 – Summary of estimates for alternative model specifications

	Full sample								Active drinkers			
	Alcohol use				Active drinker				Total alcohol consumption (ln)			
	Men		Women		Men		Women		Men		Women	
	AME	SE	AME	SE	AME	SE	AME	SE	Coef.	SE	Coef.	SE
Baseline model	0.008	0.013	0.040***	0.013	0.016	0.016	0.034**	0.014	-0.071	0.043	0.090**	0.041
Alternative models:												
Correlated RE probit	-0.013	0.019	0.033*	0.019	-0.017	0.024	0.033	0.021				
FE linear regression									-0.123*	0.069	0.084	0.065
CDH: Intensive margin (coef.)	0.093*	0.051	0.097**	0.045								
CDH: Extensive margin (coef.)	-0.104**	0.048	0.107**	0.048								
AME (CDH)	-8.824	12.257	10.699***	3.685								
Dynamic models:												
High risk	0.015	0.015	0.058***	0.015	0.009	0.018	0.035**	0.017	-0.107**	0.053	0.042	0.054
Outcome (t-1)	0.027*	0.014	0.076***	0.018	0.065***	0.019	0.058***	0.019	0.141***	0.025	0.205***	0.031
Outcome (t=1)	0.336***	0.015	0.304***	0.016	0.359***	0.016	0.322***	0.016	0.395***	0.027	0.321***	0.033
Sensitivity analysis:												
Without Moscow & St. Petersburg	0.005	0.014	0.034**	0.014	0.017	0.017	0.032**	0.015	-0.078*	0.046	0.059	0.045
Without alcohol-prohibiting religion	0.008	0.013	0.042***	0.013	0.014	0.016	0.035**	0.015	-0.066	0.044	0.088**	0.042
Without unofficially employed	0.013	0.013	0.038***	0.013	0.024	0.017	0.036**	0.015	-0.039	0.046	0.085**	0.042
Without Y2017	0.029**	0.014	0.046***	0.015	0.028	0.018	0.049***	0.016	-0.112**	0.051	0.118**	0.047
With pre-shift alcohol testing control:												
High risk	0.008	0.013	0.041***	0.013	0.016	0.016	0.035**	0.014	-0.071	0.043	0.090	0.041
Pre-shift testing	0.000	0.009	-0.077***	0.025	0.000	0.012	-0.058**	0.026	-0.005	0.034	0.014	0.085

*Note: *p-value<0.10, **p-value<0.05, ***p-value<0.01*

All models include controls for age, squared age, marital status, presence of children under age 18, educational attainment, income, nationality, health status, type of settlement, federal district, company size, industrial sector, and the years of the COVID-19 pandemic lockdown.

Robust standard errors are clustered at an individual level.