The Dark Side of Automation: Robot and Crime*

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Abstract

This study presents the first empirical evidence on the impact of industrial robot adoption on criminal activities, utilizing a comprehensive dataset from more than 2 million court documents in China. We find that a one-standard-deviation increase in robot exposure leads to a 12.8%, a 15.5%, and a 9.1% increase in violent, property, and fraud crimes respectively. These results are likely driven by a decrease in the employment-to-population ratio, an increase in drinking frequency, and the deteriorating mental health of individuals. Finally, we find that unemployment insurance is effective in mitigating the adverse impact of robots on crimes.

Keywords: Industrial Robot, Automation, Crime, China

JEL Codes: O33, K40, J21

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1 Introduction

The rapid advancement of robots and artificial intelligence has brought both new opportunities and challenges for humans, and thus a growing body of economic literature has focused on estimating its social and economic impacts. Among those, the impact of robots on labor markets has received particular attention (e.g., Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021; Adachi et al., 2022). For example, Acemoglu and Restrepo (2020) conduct a seminal study that utilizes robotics data collected by the International Federation of Robotics (IFR) to analyze its impacts on U.S. labor markets. They find that robot penetration significantly reduces the employment and earnings of workers.

This paper focuses on the impact of automation on crime, which, according to the economic theory of crime (Becker, 1968; Ehrlich, 1973), is highly associated with labor market conditions. Crime is one of the most important social outcomes to examine because it generates enormous costs to society (Charles and Luoh, 2010; Agan and Starr, 2017; Anderson, 2021). To our best knowledge, this is the first study on the impact of robot adoption on crimes.

Our empirical setting is China, a country that has heavily invested in robots and automation over the last decades. In its latest Five-Year Plan for 2016–2020, the Chinese government invested billions of Yuan to upgrade its manufacturing sector with advanced technologies, including robots and digitization. Prior to the announcement of this plan, in May 2015, China's Premier Keqiang Li advocated the "Made in China 2025" strategy, which encouraged manufacturing firms to adopt automation and intelligent manufacturing technologies to boost the country's manufacturing productivity. According to the IFR, the usage of industrial robots in

China increased from 550 in 1999 to 649,477 in 2018. Since 2016, China has maintained the largest stock of industrial robots in the world, surpassing the United States, Japan, South Korea, Germany, and other countries, and the trend continues to grow.

Owing to its large population and labor-intensive routine-based industrial structure, the impact of automation may be more significant in China than in developed countries. For example, Frey and Rahbari (2016) estimate that approximately 77% of jobs in China are highly susceptible to automation. Moreover, Zhou et al. (2019) predict that approximately 278 million workers will be replaced by artificial intelligence by 2049, with the manufacturing, transportation, and agriculture sectors having the largest number of jobs being replaced by automation in China.

To investigate the effect of industrial robot adoption on criminal activities, we gather detailed individual-level data on crimes from court documents of criminal trials held between 2014 and 2020 on China Judgements Online, which is the official public platform for the issuance of court documents in China (Supreme People's Court, China, 2013). We use Regular Expressions in Python to extract pertinent information from the text files, including the precise date and type of each incident, trial date, and court location, as well as the defendant's characteristics, such as birth date and gender. Our analysis focuses on three types of crimes: property, violent, and fraud. Our sample consists of approximately 2 million cases, which, to the best of our knowledge, is the most comprehensive crime data available in China. We also utilize data from the IFR to create a Bartik-style city-level measure of exposure to robots, following the approach of Acemogolu and Restrepo (2020). We leverage variation in the preexisting share of industrial employment in Chinese cities (exogenous share), as suggested by Goldsmith-Pinkham et al. (2020), and utilize city-year panel data from 2014 to 2018 by using industry-level robot adoption from other European developed countries as instruments.

Our analysis reveals significant positive effects of robot adoption on almost all types of examined crimes. Specifically, a one-standard-deviation increase in robot exposure raises violent crime rate by 12.8%, the property crime rate by 15.5%, and fraud crime rate by 9.1%. Our unusually large database also allows us to precisely estimate the robots' impact on all types of violent crimes, including those offenses with no specific economic incentive. The results show a significant impact on all types of violent crime, with the effect most pronounced in aggravated assault, followed by affray, intentional homicide, forcible rape, and robbery. Furthermore, our heterogeneity analysis indicates that the impact of robots is most extensive among individuals of prime working age (i.e., 25–44 years old).

We then explore the potential mechanism behind the robots–crime relationship. We find that robot adoption significantly decreases employment in the manufacturing sector but not the service sector. We likewise show that robot adoption increases drinking frequency and worsens mental health among working-age people, especially low-skilled workers. These results suggest that adverse labor market conditions and workers' physical and mental health may be important mechanisms through which robot adoption leads to a larger number of crimes being committed.

Lastly, we explore whether public policy, particularly unemployment insurance (UI), which is the main public policy for aiding displaced workers in China, can mitigate the adverse effect of robot on criminal activity. The results indicate that UI benefits indeed attenuate the impact of robot on criminal activity, even if the level of UI in China is considerably lower than that in developed countries. In particular, the impact of automation on violent crimes will be completely offset if UI benefits can be increased by 50% from the current level. Overall, our results suggest that social insurance can be used as an effective tool to offset the impact of robots on crime to some extent.

The main contribution of this study is to extend the growing literature on the impacts of robots. Previous studies have focused mainly on labor market conditions (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021; Adachi et al., 2022)[1] and income inequality (Hémous and Olsen, 2022; Moll et al., 2022). Recent studies have also analyzed the effects of the increased usage of industrial robots on family outcomes (Anelli et al., 2019; Giuntella et al., 2022), self-reported health (Gunadi and Ryu, 2020), and work-related injuries and mental health outcomes (Gihleb et al., 2022). To the best of our knowledge, this study is the first to examine the causal effect of automation on criminal behaviors. Our estimates indicate that the actual increase in robot exposure in our sample period (2014–2018) leads to 12.16%, 14.73%, and 8.65% increases in violent crime, property crime, and fraud crime rates respectively.[2] These resulting social and economic costs of crimes should be accounted for when evaluating the impacts of robots on society.

This study also contributes to the literature on the impacts of technological advances and creative destruction on the well-being of populations. While

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[1] Most previous studies have focused on developed countries and provide mixed evidence from different contexts. For instance, Graetz and Michaels (2018) find no significant effects of robots on employment in 17 OECD countries. Acemoglu and Restrepo (2020) analyze regional labor markets in the U.S. and find that an increasing number of robot adoptions decreases the employment-to-population ratio and earnings of all workers. Dauth et al. (2021) study German labor markets and find that increasing robot usage decreases employment in the manufacturing sector but increase employment in the service sector. However, Adachi et al. (2022) demonstrate that robots and labor are gross complements in Japan, finding that the decline in Japan's robot prices increases the number of robots available and the employment rate.

[2] According to Chen and Liu (2013), criminal offenses in China resulted in social costs of at least 1.3 trillion yuan in 2010, which accounted for approximately 4% of China's GDP.

technological innovation can improve social welfare and increase human life expectancy in the long run, in the short run, it can lead to job loss and income decline, which can negatively impact subjective well-being, particularly when UI policies are less generous (Aghion et al., 2016). For example, Case and Deaton (2015, 2017) show that the economic and social costs of job loss are significant, revealing that the mortality rate of non-Hispanic whites aged 50–54 years in the US began to rise in the early 21st century after a long period of decline and accelerated significantly from 2011 onward, particularly for low-skilled groups. This increase in “deaths of despair” led to increased drug abuse, alcoholism, liver disease, and suicide risks due to the loss of work. Our study provides evidence that automation in China could decrease industrial employment and increase drinking frequency and mental disorders among low-skilled workers, leading to more criminal activities. More importantly, our study provides empirical evidence that UI policies can mitigate the adverse consequences of negative labor market shocks on criminal behavior. Therefore, policy-makers may consider providing more generous welfare policies as a tool with which to reduce crime and social unrest.

Finally, our study contributes to the broad literature on the determinants of crime. According to Becker’s (1968) classic economic theory of crime, individuals decide whether to engage in crime based on a cost-benefit analysis under uncertainty. When the expected return from legal activity or the sanction imposed by the justice system decreases, individuals on the margin of crime may opt for criminal activity. Therefore, improvements in labor market conditions could lower the crime rate. Abundant evidence supports this prediction, including those related to wages (Grogger, 1998; Machin and Meghir, 2004), unemployment (Freeman, 1999; Lin, 2008), employment opportunities (Schnepel, 2016; Freedman et al., 2018), and welfare-related income

(Foley, 2011). In the current paper, we provide empirical evidence on how industrial policies, such as increasing the use of industrial robots, can affect criminal behavior. We find that an increase in robot usage significantly raises both acquisitive (measured by property and fraud) and non-acquisitive (violent) crimes.

2 Empirical Model and Data

2.1 Identification Strategy

To identify the causal effect of robot adoption on crime rates, we estimate the following econometric model:

$$y_{c,t} = \alpha + \beta ExposuretoRobots_{c,t} + X_{c,t}\boldsymbol{\delta} + \gamma_c + \theta_t + \epsilon_{c,t} \tag{1}$$

where $y_{c,t}$ represents the different types of crimes, and we take the natural logarithm of the number of crimes per 10,000 (or per 100,000) people in city c at year t.[3] The explanatory variable of interest is $ExposuretoRobots_{c,t}$, which represents a city-year measure of exposure to industrial robots. To facilitate interpretation, we standardize exposure to robots using z-scores. $X_{c,t}$ is the vector of control variables, including urbanization rate, GDP per capita, the secondary industry as a percentage of GDP, and public security expenditure, all of which may affect both robot penetration and criminal propensity. γ_c and θ_t are city and year fixed effects, respectively, which account for all time-invariant city characteristics and aggregate shocks across cities. Finally, $\epsilon_{c,t}$ represents an idiosyncratic error term and is clustered at the city level to account for the potential correlations within cities.

The exposure to robots for each city is measured according to Acemoglu and

[3] We also provide estimation results using crime rates (unlogged) as dependent variables in Appendix Table A3. Our findings are robust to crime rate measurement.

Restrepo (2020) as follows:

$$ExposuretoRobots_{c,t} = \sum_{k \epsilon K} g_{c,k}^{2000} \left(\frac{R_{k,t}}{L_{k,2000}} \right) \quad (2)$$

where $g_{c,k}^{2000}$ represents the share of the city c's employment in industry sector k in 2000, $R_{k,t}$ is the stock number of robots used in sector k and year t, and $L_{k,2000}$ is the total number of workers (in thousands) employed in sector k in the year 2000, which is the initial year to construct exogenous shares (Giuntella et al., 2022).[4] By exploiting the preexisting distribution of employment across cities and industries, we can avoid the problem of reverse causality.

To further address concerns about the potential endogeneity issue, such as our measure of robot exposure being related to other observed or unobserved factors that also affect crime activities, we follow Acemoglu and Restrepo (2020) and Giuntella et al. (2022) and use industry-level robot adoption in other countries as external shocks. Specifically, we utilize the average robot exposure in nine European countries (Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom) over the same period. Our instrument is defined as follows:

$$ExposuretoRobots_{c,t}^{IV} = \sum_{k \epsilon K} g_{c,k}^{2000} \left(\frac{R_{k,t}^{EU}}{L_{k,2000}^{EU}} \right) \quad (3)$$

where $g_{c,k}^{2000}$ denotes the distribution of employment across cities and industries in the year 2000 in China. $\frac{R_{k,t}^{EU}}{L_{k,2000}^{EU}}$ represents the average robot adoption rate (number of

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[4] We acknowledge the possibility of the instrument being correlated with crime through preexisting industrial distribution in 2000, although the rise of industrial robots in China generally took place after 2010. To address this concern, we also use 1990 as the base year to reconstruct the instrumental variable. As shown in Appendix Table A4, the results remain highly significant.

robots per thousand workers) among European countries in sector k and year t. Thus, our identification largely relies on the exogenous variation in robot adoption across industries in other European countries.[5]

2.2 Data

The primary data used in this study consist of individual-level crime data. We compile the crime database by extracting information from court documents of criminal trials that occurred between 2014 and 2020 in China. The data on the stock of industrial robots are obtained from the IFR. We also utilize survey data from the China Labor-force Dynamic Survey (CLDS) for mechanism analysis, which is described in Section 4.

2.2.1 Crime Data

To obtain individual-level crime data, we collect court documents of criminal trials that occurred between 2014 and 2020 from China Judgements Online.[6] China Judgements Online is the official national public platform for the issuance of court documents in China. In practice, case files of offenses handled by the police are transferred to the office of the prosecutor. The prosecutor then disposes cases by either forwarding them to the courts or withdrawing them due to lack of evidence. Following the guideline titled "Provisions of the Supreme People's Court on the Issuance of Judgements on the Internet by the People's Courts," which came into force on January 1, 2014, the people's courts, especially for higher and intermediate

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[5] Note that we also find consistent results when using U.S. robot adoption to construct the instrument, and these results are available upon request.

[6] See http://wenshu.court.gov.cn.

people's courts, should disclose and upload effective court documents online as quickly as possible. Documents before 2014 do not require mandatory disclosure. By the end of 2021, the platform had over 100 million judicial documents. This high-quality data source has increasingly attracted the attention of scholars and has been gradually used in social science research in recent years (e.g., Liang and Jiang, 2020; Michelson, 2019). We access the court documents that contain all types of crimes occurring between 2014 and 2020.

We utilized Regular Expressions in the Python programming language to extract relevant information, such as the exact date and type of each incident, trial date and location of judgement, the number of offenders, and the defendant's characteristics, such as birthdate and gender, from court documents. We focus on three types of criminal convictions, namely, property, fraud, and violent crimes. To ensure an adequate number of cases, we limit our analysis to those crimes committed between 2014 and 2018 because of the time-lag between the time of crime and court conviction.[7] We focus on the sample of individuals aged between 18 and 59 (working age) since they are most likely to be affected by automation.

Note that the number of crimes based on court convictions is likely to be underestimated. For instance, some criminal cases may go undetected due to various observed and unobserved factors. While the ideal measure of criminal activity is the number of offenses reported to the police, this measure also underestimates the actual incidence of crime in any country, as not all offenses are reported to law enforcement agencies. Unfortunately, police-reported crime data are not available in China. While the measurement of crime based on court judgements is far from perfect, it remains

[7] The mean duration between the time of the crime and court conviction is roughly 240 days for property crimes, 368 days for violent crimes, and 475 days for fraud crimes.

the best one available and will only bias the estimates downward.

Our final sample contains approximately 845,000 violent, 782,000 property, and 207,000 fraud crimes. We aggregate the individual-level data to obtain the total number of crimes by incident city and year. Our analysis includes 325 Chinese cities during the period between 2014 and 2018, which represent approximately 95% of the national population and employment.

2.2.2 Robot Data

We utilize robot data from the IFR, a professional organization of robot suppliers. These data are obtained through yearly surveys of IFR members, who provide information on the number of robots sold in a given industry and country. The data cover 70 countries from 1993 to 2019, accounting for more than 90% of the global market for robots. According to the IFR's definition, an industrial robot is a machine that can be automatically controlled and repeatedly programmed and is capable of performing multiple tasks and replacing human labor in some monotonous, complicated, and long-term jobs.

The operational stock of industrial robots in China has grown exponentially since 2010. Appendix Figure A1 presents the comparison of the total operational stock of robots among China, Japan, the U.S., and nine European countries. As illustrated in the figure, China's operational stock of industrial robots has surpassed those of the world's major developed economies, making it the economy with the highest stock of robots worldwide.

The IFR data cover 13 manufacturing sectors and 6 nonmanufacturing sectors. We amalgamate the automotive and other vehicle industries based on the work of Giuntella et al. (2022), resulting in a total of 18 distinct industrial sectors. The contribution of different industries to the extension of industrial robot penetration in China has varied in recent years. Appendix Figure A2 illustrates the extension of robot penetration across these 18 industries in China. Three industries, namely, automotive and other vehicle, electronics, and basic metals, are responsible for 88% of the increase in robot penetration, while the remaining 15 industries contributed less than 12%.

While IFR data have been used widely in the empirical literature (Acemogolu and Restrepo, 2020; Giuntella et al., 2022; Graetz and Michaels, 2018), it is not without shortcomings. First, the categorization of robots is predominantly grouped into broad industry classifications without finer granularity, and the data on the use of robots outside of manufacturing are restricted to six broad categories. Second, geographical information on the distribution of robots is available only at the country level, and there is no information on the within-country distribution of robots. The difficulty of quantifying real robot penetration at the regional level led prior studies to rely on the preexisting industrial composition within a given region and multiply it by the national-level evolution of the number of robots across industries (Acemoglu and Restrepo, 2020).

2.2.3 Descriptive Statistics

Table 1 presents the descriptive statistics at the city-year level. The first section outlines the outcome variables, which comprise crime data: violent crime with six subcategories, property crime, and fraud crime data. To account for the relatively low number of cases of intentional homicide and forcible rape, these crime rates are presented per 100,000 people, while the other crime rates are presented per 10,000 people. The second section displays our variable of interest, i.e., robot exposure. The average robot exposure in our sample period is 0.81 robots per 1,000 workers. Note we standardize this in estimation. The third section of the table reports the control variables, which include urbanization rate, GDP per capita, and percentage of secondary industry in GDP.

3 Results

We analyze the impact of violent crime, which is presented in Table 2. The sample consists of approximately 845,000 cases of violent crime across 325 Chinese cities during the period 2014–2018. Column (1) reports estimates for overall (log) violent crime rates, and Columns (2)–(6) report estimates for subcategories of violent crime, including defiance and affray, robbery, aggravated assault, intentional homicide, and forcible rape. Panel A presents the OLS estimates, indicating that robot exposure has a significant positive impact on almost all types of violent crime, except for robbery. Panel B presents the IV estimates, with the first-stage KP *F*-statistics displayed at the bottom of the table and the first-stage regression coefficients in Appendix Table A1. Compared with the OLS results, the 2SLS estimates are larger and the coefficients are significant for all types of violent crime at the 1% level. Since the independent variable "Robot Exposure" has been standardized, the coefficients can be interpreted as follows: a one-standard-deviation increase in robot exposure raises the overall rate of violent crime by 12.8%; and for its subtypes, robot adoption raises the rate of affray by 8.8%, of robbery by 3.1%, of aggravated assault by 8.9%, of intentional homicide by 7.5%, and of rape by 8.6%.

We proceed to examine the effect of robot exposure on property and fraud crime in Columns (7) and (8), respectively. The sample comprises approximately 782,000 property crime cases and 207,000 fraud crime cases. Compared with violence, the propensity for property crime is more likely to be affected by economic incentives, as such crime is directly associated with criminal earnings in the economic model of crimes, such as the value of loot (Draca and Machin, 2015). We therefore expect a larger impact on property crime when the mechanism behind robot adoptions operates through labor market opportunities. For a comparison with property crime, we also examine the effects of fraud crime, which is indeed associated with economic incentives but requires more criminal techniques and is more difficult to commit.

The 2SLS estimates indicate significantly positive effects of robot exposure on property and fraud crimes. Specifically, a one-standard-deviation increase in robot exposure raises the rate of property crime by 15.5% and of fraud crime by 9.1%. In addition, these estimates, particularly the estimate on property crime, are larger than the estimates for most violent crimes, indicating the significance of worsening labor market conditions.

Overall, robots have both statistically and economically significant effects on all types of crimes. The standard deviation of robot exposure in the raw data is 1.03 over the sample period. From 2014 to 2018, the mean value increases from 0.38 to 1.36, indicating an average increase of 0.95 standard deviation in robot exposure during the sample period. Through simple calculation, we can obtain that the actual increase in robot exposure results in an average increase of 12.16% in the rate of violent crime, 14.73% in the rate of property crime, and 8.65% in the rate of fraud crime.

In Table 3, we investigate the heterogeneity of these effects by age group. We divide the full sample into three groups based on age: 18–24 (Panel A), 25–44 (Panel B), and 45–59 (Panel C) years old. We then report the 2SLS results for violent, property, or fraud crimes for each group. As in the overall analysis results reported in

Table 2, the positive impact of robot exposure on property crimes is the largest in all age groups. Among them, those aged 25–44 years are most affected by robot exposure, followed by those aged 18–24 years, while those aged 45–59 years are least affected. This result again indicates the importance of worsening labor market conditions as the group aged 25–44 years old is the primary working-age group.

We conduct a few robustness checks as follows: A) calculate the Rotemberg weights for each industry (Appendix Table A2) using the procedure provided by Goldsmith-Pinkham et al. (2020) and remove *other manufacturing* industry from the calculation of robot exposure as its weight is the largest among all industries; B) exclude the *automotive and other vehicle* industry from the calculation of robot exposure since this industry has experienced the largest penetration of robots compared to other sectors; C) use year 1990 rather than year 2000 as the initial year to construct the instrument; D) include province-specific time trends in the baseline specification to account for any time-varying unobserved factors that may be correlated with both robot exposure and provincial characteristics; E) exclude four municipal cities (Beijing, Shanghai, Tianjin, and Chongqing) since central government policies may favor municipalities more than they do other prefecture cities; and F) include city-specific minimum wage in the regression model as prior studies suggest that rising labor costs are an important determinant of the rise in robot adoptions in China (Cheng et al., 2019). Our results are robust to these checks, as shown in Appendix Table A4.

4 Mechanism Analysis

4.1 City-level Results

To investigate the mechanism by which an increase in exposure to industrial robots affects crime, we first examine the changes that occur at the city level in response to the rise in the prevalence of robots. According to the economic model of crime (Becker, 1968), individuals decide to participate in criminal activities based on the potential earnings from successful crime outweighing the benefits of legal work. Therefore, an important mechanism by which increasing robot adoption may affect crime is through its impact on labor market opportunities, especially for property crime.

In this section, we replicate the baseline specification analysis at the city-year level by replacing the dependent variable with employment outcomes. Columns (1)–(4) of Table 4 present the 2SLS estimates. Column (1) reports the number of manufacturing employees (in 10 thousands) as the dependent variable, Column (2) reports the number of service employees (in 10 thousands), Column (3) reports the manufacturing employment-to-population ratio, and Column (4) refers to Acemoglu and Restrepo (2020) using the employment-to-population ratio. Consistent with recent empirical studies focusing on China's context (e.g., Giuntella et al., 2022; Wang and Dong, 2020), we observe a decrease in employment level in the manufacturing sector with increasing exposure to robots. The effects on service employment are relatively small and insignificant, which implies that workers displaced in the manufacturing sector cannot easily transfer to the service sector. We likewise find that robot penetration into the labor market significantly decreases both the manufacturing employment-to-population ratio and the total employment-to-population ratio. These findings suggest that adverse labor demand effects may be an important mechanism through which robot adoption leads to an increased number of crimes.

4.2 Individual-level Results

Compared with property crime, the determinants of violent crime are more complex and may be driven by both economic and non-economic factors. The adoption of industrial robots may have negative impacts on workers' well-being due to the labor market pressure and fears they induce, which in turn affect violent crime participation. Recent research by Gihleb et al. (2022) shows that robot penetration leads to a significant increase in drug- or alcohol-related deaths and mental health problems among U.S. workers. To further investigate individual behaviors in response to robot adoption, we use CLDS data to explore whether the rise in robot adoption affects mental health and alcohol use at the individual level. The CLDS is a nationally representative longitudinal survey launched by Sun Yat-sen University. It employs a rotating panel design and collects four waves of data every two years. The surveys provide comprehensive information on the socioeconomic characteristics of the labor force, including social stratification, mobility, social networks and involvement, entrepreneurship, rights and interests, subjective status, and health. The baseline survey was conducted in 2012 and included interviews with approximately 10,000 families and 16,000 individuals in about 300 communities.

We begin our investigation by examining the relationship between robot adoption and alcohol use. Prior research has established that alcohol consumption may directly or indirectly impact criminal behavior, particularly concerning violent crime. For instance, alcohol abuse has direct pharmacological effects on aggression and can motivate the intention to commit crimes. The CLDS, conducted between 2014 and 2016, includes questions related to personal drinking behaviors, thereby providing us with comprehensive data for our analysis. Specifically, we generate a categorical outcome variable based on the question regarding drinking frequency. This variable assigns a value of 3 to drinking alcohol 5 or more times per week, 2 to drinking alcohol 3–4 times per week, 1 to drinking alcohol 1–2 times per week, and 0 to no alcohol consumption. Our sample is limited to respondents aged 16–59 years residing in urban areas who participated in the 2014–2016 CLDS survey. The econometric model is formulated as follows:

$$y_{i,c,t} = \alpha + \beta ExposuretoRobots_{c,t} + X_{i,t}\boldsymbol{\delta} + \delta_i + \gamma_c + \theta_t + \upsilon_{c,t} \tag{4}$$

The equation shows that $y_{i,c,t}$ represents the drinking frequency for individual i in city c in year t. Similarly, $ExposuretoRobots_{c,t}$ is the exposure to robots, which is normalized with Z-scores. Individual-level characteristics, including gender, age, and educational attainment, are represented by $X_{i,t}$. Individual fixed effects are represented by δ_i, city fixed effects are represented by γ_c, and survey fixed effects are represented by θ_t. Finally, $\upsilon_{c,t}$ represents the error term and is clustered at city level.

Column (5) of Table 4 presents the impact of robot exposure on drinking frequency for all individuals. Column (6) reports the impact for low-skilled individuals, proxied by education level (high school graduation or below), while Column (7) reports the impact for high-skilled individuals (college degree or above). Our findings reveal that individuals residing in cities with higher levels of robot exposure tend to drink more frequently. In addition, the results are primarily driven by low-skilled individuals.

We analyze the relationship between robot use and mental health, focusing on the Center for Epidemiologic Studies Depression Scale (CES-D) question in the CLDS questionnaire in Columns (8)–(10). Originally introduced by Radloff (1977), the CES-D is a 20-item measure that asks respondents to rate the frequency with which they experienced symptoms associated with depression, such as restless sleep, poor appetite, and feelings of loneliness, over the past week. Response options range from 0 to 3 for each item, with 0 indicating rarely or none of the time, and 3 indicating most or almost all of the time. Scores range from 0 to 60, with higher scores indicating greater depressive symptoms. We use a cutoff score of 16, designating individuals with scores above 16 as 1, indicating mild depression, and 0 otherwise (Radloff, 1977). We include only respondents aged 16–59 years living in urban areas in the 2016 survey because the CES-D question is not investigated in the 2014 survey.[8] Column (8) shows that robot adoption has a significant positive impact on the probability of moderate depression, with an increase of 2.0 percentage points. The effects are also larger for low-skilled individuals (Column (9)) but not high-skilled ones (Column (10)). Together, these results suggest that adverse labor market conditions, increased drinking frequency, and the deteriorating mental health of workers may be important mechanisms through which robot adoption leads to a larger number of crimes being committed.

5 Moderating Effect of Unemployment Insurance

The results in previous sections establish that job displacement exerted by the rise of industrial robots has an adverse impact on criminal behavior. In this section, we aim to examine whether public policy can mitigate such adverse impacts. Specifically, we study the moderating effect of UI on the relationship between robot adoption and crime rate.

[8] Accordingly, we cannot control for individual- and city-level fixed effects due to the nature of cross-sectional data.

As in most countries, the UI system in China is the main labor protection intervention for supporting displaced workers who lose their job for reasons outside their control. Notably, China's overall level of social security is insufficient, and its UI benefits are far behind those of developed countries such as France, Germany, and the U.S. As noted by Liang and Ji (2020), the proportion of social security expenditure in GDP in 2016 was the largest in France, as high as 24.7%, while that in China was only 0.1%. Moreover, they show that UI in China will increase the job search efforts of the unemployed by compensating their search costs, thus promoting the re-employment rate. The results are completely contrary to those observed in developed countries. For example, Katz and Meyer (1990) find that UI significantly decreases labor supply in the U.S. by lowering job search efforts. Therefore, in the context of China, eligible workers are unlikely to spend more leisure time in illegal activity; instead, the limited UI benefits may reduce the crime rate through both (welfare-related) income incentive and the incapacitation effect of employment.

To identify the moderating effect of UI, we construct a database that contains detailed UI standards in 269 Chinese cities. These data are obtained from local government official websites. We then estimate the following econometric model:

$$\begin{aligned} y_{c,t} = \alpha + \beta_1 ExposuretoRobots_{c,t} + \beta_2 UI_{c,t} \\ + \beta_3 ExposuretoRobots_{c,t} \times UI_{c,t} + X_{c,t}\delta + \gamma_c + \theta_t + \epsilon_{c,t} \end{aligned} \quad (5)$$

where $UI_{c,t}$ denotes UI benefits, defined as the proportion of the maximum monthly UI standards to the monthly average wage in the city c at year t. Therefore, it can be used as a proxy to capture the UI generosity. Compared with the benchmark specification, here we add the UI variable and interaction term between robot adoption and UI in the model. If UI can mitigate the adverse impacts of job automation, we expect the estimated coefficient β_3 to be negative. Note that China's

UI standard is highly dependent on the financial capacity of the local government. Given the substantial regional disparities in China, the generosity of UI also varies across cities. The average UI benefits in our sample period is about 0.2, of which the minimum value observed is only 0.036 and the maximum value is 0.328.

In Table 5, we present the 2SLS estimation results, namely, the moderating effect of UI benefits on violent, property, and fraud crimes.[9] First, we find that the coefficient on the interaction term is negative and significant on the violent crime, indicating that UI benefits may attenuate the adverse consequences of robot adoption on criminal behavior. Given that the average UI benefits in our sample period is about 0.2, the magnitude implies that if the average generosity of UI can be raised to 0.3, then the impact of automation on violent crime will be completely offset. In addition, the interactions for property and fraud crime rates are insignificant, indicating that the main effect of the UI is in mitigating the negative impact of robot exposure on violent crime.

Taken together, these results suggest that labor market reforms such as UI policies can be used as an effective tool to alter the association between job automation and crime. Our results are also consistent with prior research showing that social assistance policies decrease the time allocation to illegal activity (e.g., Yang, 2017; Britto et al., 2022). In particular, Britto et al. (2022) document that unemployment benefit eligibility completely offsets potential crime increases upon job loss by alleviating liquidity constraints and psychological stress in Brazil.

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[9] The variable “Robot Exposure” is instrumented using robot exposure in nine European countries, and the variable “Robot Exposure×UI” is instrumented using the interaction between robot exposure in nine European countries and UI.

6 Conclusion

This study provides novel evidence on the positive causal relationship between automation or industrial robots and criminal activities in the context of a developing country, using over 2 million criminal cases from the court documents of criminal trials. We combine city-level crime data with robot adoption data from the IFR and find that increases in robot usage significantly raise both acquisitive and non-acquisitive crimes in China between 2014 and 2018. Specifically, a one-standard-deviation increase in robot exposure raises the property crime rate by 15.5%, the violent crime rate by 12.8%, and the fraud crime rate by 9.1%. Our mechanism analysis suggests that these results are likely driven by adverse labor conditions, increased drinking frequency, and deteriorating mental health of working-age individuals. More importantly, by collecting UI standard data from local government websites, we show that UI benefits may mitigate the impact of industrial robot adoption on criminal activity. As automation technology rapidly develops, policy-makers need to refine crime reduction policies to include labor market activation measures. Such measures could include the provision of more generous welfare-related programs, such as UI policies, which may reduce the opportunity costs of committing a crime.

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Table 1. Summary Statistics

	Mean	SD	Min	Max
Dependent Variables:				
Violent crime per 10,000 people	1.229	0.977	0	9.480
---Intentional homicide per 100,000 people	0.435	0.679	0	11.872
---Affray per 10,000 people	0.367	0.362	0	4.484
---Aggravated assault per 10,000 people	0.658	0.512	0	5.315
---Forcible rape per 100,000 people	0.264	0.508	0	8.321
---Robbery crime per 10,000 people	0.135	0.257	0	3.879
Property crime per 10,000 people	1.121	1.061	0	10.851
Fraud crime per 10,000 people	0.290	0.340	0	3.449
Independent Variable				
Robot exposure (robots per 1,000 workers)	0.810	1.030	0.080	11.140
Control Variables:				
Urbanization rate (%)	55.537	13.360	22.345	100.000
GDP per capita (10,000 yuan)	5.627	5.205	0.512	50.456
Secondary industry as a percentage of GDP (%)	0.441	0.105	0.092	0.755
Public security expenditure (100 million yuan)	352.700	234.820	55.630	1,355.530

Notes**:** N=1,625. Unit of observation is city-year. Crime data are aggregated from case-level data obtained from China Judgements Online. Robot data are obtained from the International Federation of Robotics at industry-year level, and then disaggregate to city-year level based on preexisting distribution of employment across cities and industries in year 2000. The table reports raw measure of robot exposure, and we standardize it in estimation to facilitate interpretation.

Table 2. Effect of Robot Exposure on Crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Violent Crime						Property Crime	Fraud Crime
	All	Defiance and Affray	Robbery	Aggravated Assault	Intentional Homicide	Forcible Rape		
	Panel A: OLS Estimates							
Robot Exposure	0.092***	0.062***	0.018	0.063***	0.047*	0.087***	0.123***	0.073***
	(0.02)	(0.011)	(0.011)	(0.014)	(0.026)	(0.021)	(0.024)	(0.013)
	Panel B: IV Estimates							
Robot Exposure	0.128***	0.088***	0.031***	0.089***	0.075***	0.086***	0.155***	0.091***
	(0.034)	(0.019)	(0.011)	(0.024)	(0.025)	(0.025)	(0.046)	(0.023)
Observations	1,625	1,625	1,625	1,625	1,625	1,625	1,625	1,625
First-stage KP *F*-statistics	101.7	101.7	101.7	101.7	101.7	101.7	101.7	101.7

Notes**:** The sample contains about 845,000 violent crimes, 782,000 property crimes, and 207,000 fraud crimes across 325 Chinese cities from 2014 to 2018. The outcome variable is the natural logarithm of crimes per 10,000 (or 100,000) people in a given city and year. All estimates include city fixed effects, year fixed effects, and control variables (urbanization rate, GDP per capita, secondary industry as a percentage of GDP, and public security expenditure). The instrumental variable is average robot exposure in nine European countries (Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom) following Acemoglu and Restropo (2020) and Giuntella et al. (2022). See Appendix Table A1 for first-stage estimates. All regressions are weighted by city population. Standard errors are clustered by city and in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 3. Effect of Robot Exposure on Crime: By Age Groups

	(1) Violent Crime	(2) Property Crime	(3) Fraud Crime
	Panel A: Aged from 18-24		
Robot Exposure	0.061***	0.077***	0.042***
	(0.017)	(0.022)	(0.011)
	Panel B: Aged from 25-44		
Robot Exposure	0.114***	0.135***	0.065***
	(0.026)	(0.035)	(0.016)
	Panel C: Aged from 45-59		
Robot Exposure	0.044***	0.073***	0.013***
	(0.011)	(0.015)	(0.004)
Observations	1,625	1,625	1,625
First-stage KP *F*-statistics	101.701	101.701	101.701

***Notes*:** The table presents the 2SLS estimates of the impact of exposure to robots on the city-level crime rate of violent, property, and fraud crimes across different age groups. Three age groups, 18–24, 25–44, and 45–59 years old, are separately estimated. The outcome variable is the natural logarithm of crimes per 10,000 (or 100,000) people in a given city and year. All estimates include city fixed effects, year fixed effects, and control variables (urbanization rate, GDP per capita, secondary industry as a percentage of GDP, and public security expenditure). The instrumental variable is average robot exposure in nine European countries (Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom) following Acemoglu and Restropo (2020) and Giuntella et al. (2022). See Appendix Table A1 for first-stage estimates. All regressions are weighted by city population. Standard errors are clustered by city and in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 4. Mechanism Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Robot Exposure on Employment				Robot Exposure on Drinking Frequency			Robot Exposure on Mental Health		
	Employment in Manu. (10,000)	Employment in Serv. (10,000)	Emp. Manu./Population	Emp./Population	Full Sample	Low Skilled	High Skilled	Full Sample	Low Skilled	High Skilled
Robot Exposure	-3.183***	0.971	-0.019***	-0.022***	0.042**	0.048***	0.010	0.020***	0.021***	0.007
	(0.798)	(1.297)	(0.005)	(0.007)	(0.018)	(0.017)	(0.061)	(0.008)	(0.008)	(0.016)
Observations	1,395	1,395	1,395	1,395	4,826	3,494	1,162	6,696	4,825	1,871
First-stage KP *F*-stat.	155.701	155.701	155.701	155.701	113.593	115.448	69.881	1044.085	930.731	725.654

***Notes*:** The table presents the estimates of the impact of exposure to robots on city-year employment in manufacturing (unit=10,000 people) in Column (1), employment in service sector (unit=10,000 people) in Column (2), employment in manufacturing over total population in Column (3), and total employment over total population in Column (4), individual drinking frequency (0–3 with higher number indicating high frequency) for full sample in Column (5), individual drinking frequency for low-skilled group (high school graduation or below) in Column (6), individual drinking frequency for high-skilled group (college degree or above) in Column (7), individual mental health (CES-D score above 16 with depression) for full sample in Column (8), low-skilled group in Column (9), and high-skilled group in Column (10). All estimates include city fixed effects, year fixed effects, and control variables including urbanization rate, GDP per capita, secondary industry as a percentage of GDP, and public security expenditure. The instrumental variable is average robot exposure in nine European countries (Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom) following Acemoglu and Restropo (2020) and Giuntella et al. (2022). See Appendix Table A1 for first-stage estimates. All regressions are weighted by city population. Standard errors are clustered by city and in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

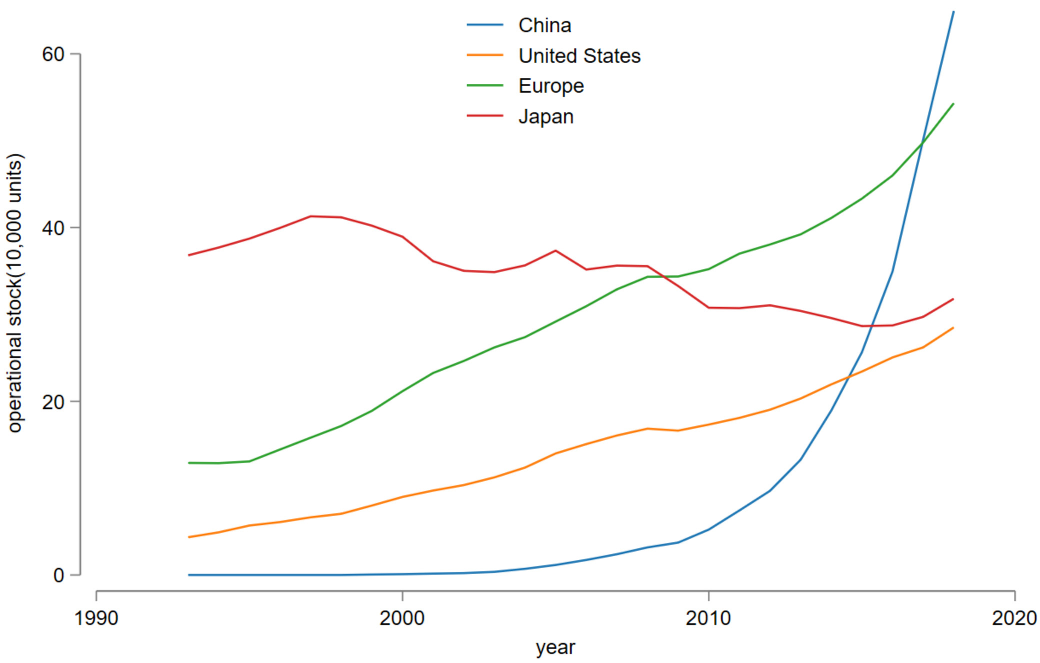
Table 5. Moderating Effect of Unemployment Insurance (UI)

	(1)	(2)	(3)
	Violent Crime	Property Crime	Fraud Crime
Robot Exposure	0.275***	0.267***	0.083*
	(0.081)	(0.096)	(0.043)
Robot Exposure×UI	-0.914**	-0.731	-0.099
	(0.377)	(0.472)	(0.214)
Observations	1,344	1,344	1,344
First-stage KP *F*-statistics	28.567	28.567	28.567

Notes**:** The UI data are sourced from the Human Resources and Social Security Office of Local Government in China. The table presents estimates regarding the moderating effect of UI benefits. The sample consists of approximately 269 Chinese cities, spanning the period from 2014 to 2018. All estimates include city fixed effects, year fixed effects, and control variables (urbanization rate, GDP per capita, secondary industry as a percentage of GDP, and public security expenditure). The variable "Robot Exposure" is instrumented using robot exposure in nine European countries, and the variable "Robot Exposure×UI" is instrumented using the interaction between robot exposure in nine European countries and UI. All regressions are weighted by city population. Standard errors are clustered by city and in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

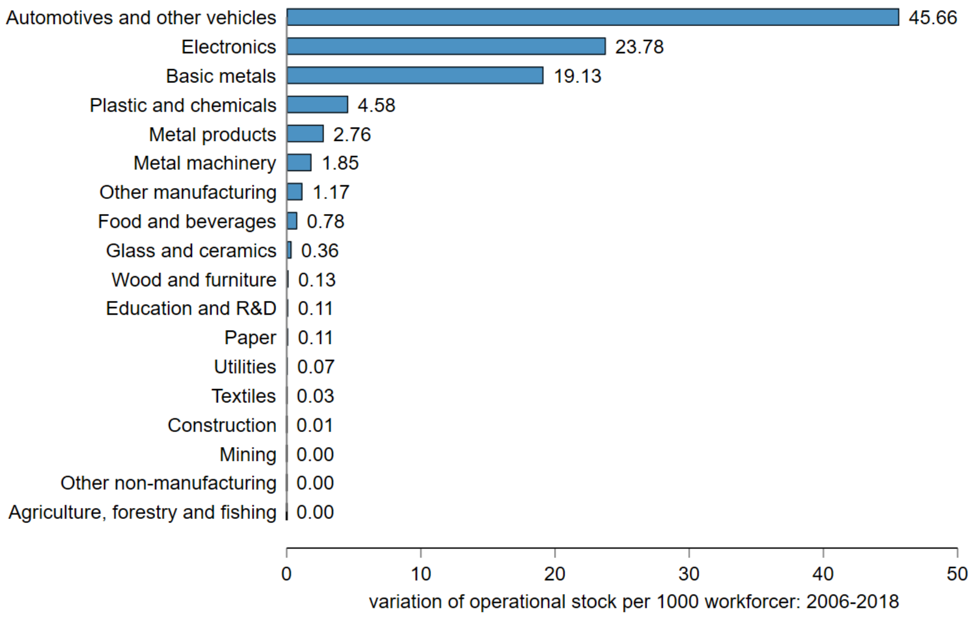
Online Appendix: Supplementary Figures and Tables

Figure A1. Operational Stocks Across Four Economies



Notes: Data are drawn from the International Federation of Robotics (IFR), utilizing the operational stock of industrial robots in China, Japan, the US, and aggregation of nine European countries, including Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom.

Figure A2. Penetration Extension of China between 2006 and 2018



Notes: Data are drawn from the International Federation of Robotics (IFR) and China Census 2000.

Table A1. First stage: Impacts of Robot Exposure in Nine European Countries on Robot Exposure in China

	(1)	(2)
	Robot Exposure IV (2000)	Robot Exposure IV (1990)
Robot Exposure	0.397***	0.190***
	(0.033)	(0.031)
Observations	1,625	1,590

Notes**:** This table presents the first-stage estimates, i.e., the impacts of standardized robot exposure in nine European countries (Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom) on standardized robot exposure in China following Acemoglu and Restropo (2020) and Giuntella et al. (2022). Column (1) uses preexisting distribution of employment across cities and industries in year 2000, and Column (2) uses year 1990. Standard errors are clustered in city and in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A2. Rotemberg Weights

Industry Name	Rotemberg Weight
Other manufacturing	0.585
Basic metals	0.194
Electronics	0.105
Automotives and other vehicles	0.056
Metal products	0.052
Metal machinery	0.017
Food and beverages	0.003
Other non-manufacturing	0.002
Agriculture, forestry and fishing	0.001
Plastic and chemicals	0.001
Paper	<0.001
Glass and ceramics	<0.001
Education and R&D	<0.001
Utilities	>-0.001
Construction	>-0.001
Mining	>-0.001
Wood and furniture	-0.001
Textiles	-0.017

Notes**:** We calculated Rotemberg weights by year and sector following the procedure introduced by Goldsmith-Pinkham et al. (2020). The table displays the average weight of each sector in our sample periods.

Table A3. Effect of Robot Exposure on Unlogged Crime Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Violent Crime						Property Crime	Fraud Crime
	All	Defiance and Affray	Robbery	Aggravated Assault	Intentional Homicide	Forcible Rape		
	Panel A: OLS Estimates							
Robot Exposure	0.309***	0.136***	0.026	0.117***	0.163	0.141***	0.472***	0.129***
	(0.060)	(0.026)	(0.018)	(0.028)	(0.129)	(0.044)	(0.065)	(0.023)
	Panel B: IV Estimates							
Robot Exposure	0.441***	0.184***	0.031***	0.183***	0.156**	0.138***	0.629***	0.166***
	(0.083)	(0.039)	(0.011)	(0.040)	(0.068)	(0.045)	(0.119)	(0.039)
Observations	1,625	1,625	1,625	1,625	1,625	1,625	1,625	1,625
First-stage KP *F*-statistics	101.7	101.7	101.7	101.7	101.7	101.7	101.7	101.7

***Notes*:** This table complements Table 2 and reports the effect of robot exposure on raw crime rates (unlogged). The sample contains about 845,000 violent crimes, 782,000 property crimes, and 207,000 fraud crimes across 325 Chinese cities from 2014 to 2018. The outcome variable is crimes per 10,000 (or 100,000) people in a given city and year. All estimates include city fixed effects, year fixed effects, and control variables (urbanization rate, GDP per capita, secondary industry as a percentage of GDP, and public security expenditure). The instrumental variable is average robot exposure in nine European countries (Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom) following Acemoglu and Restropo (2020) and Giuntella et al. (2022). See Appendix Table A1 for first-stage estimates. All regressions are weighted by city population. Standard errors are clustered by city and in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A4. Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Violent Crime						
Robot Exposure	0.128***	0.103***	0.105***	0.107***	0.083***	0.111***	0.120***
	(0.034)	(0.031)	(0.034)	(0.039)	(0.028)	(0.035)	(0.036)
	Panel B: Property Crime						
Robot Exposure	0.155***	0.144***	0.127***	0.124***	0.121***	0.141***	0.142***
	(0.046)	(0.033)	(0.047)	(0.041)	(0.038)	(0.049)	(0.048)
	Panel C: Fraud Crime						
Robot Exposure	0.091***	0.075***	0.080***	0.088***	0.074***	0.086***	0.084***
	(0.023)	(0.016)	(0.025)	(0.022)	(0.018)	(0.025)	(0.024)
Observations	1,625	1,625	1,625	1,590	1,625	1,605	1,555
First-stage KP *F*-statistics	101.7	95.801	58.300	21.116	58.024	94.548	94.868
Excluding other manufacturing	No	Yes	No	No	No	No	No
Excluding automation industry	No	No	Yes	No	No	No	No
IV using the 1990 employment share	No	No	No	Yes	No	No	No
Including province trend	No	No	No	No	Yes	No	No
Excluding four municipalities	No	No	No	No	No	Yes	No
Including minimum wage	No	No	No	No	No	No	Yes

Notes**:** The table presents robustness checks on estimation method. Column (1) is the baseline model, which corresponds to Columns (1) for violent crime, Column (7) for property crime, and Column (8) for fraud crime in Table 2. Column (2) excludes other manufacturing when constructing the instrumental variable, which has the largest Rotemberg weight. Column (3) excludes automotive and other vehicles from constructing the instrumental variable, which has the largest extension of robot penetration in our sample period. Column (4) uses the distribution of industrial employment in 1990 to construct instrumental variable. Column (5) adds province-specific linear time trends. Column (6) exclude four municipalities, i.e., Beijing, Shanghai, Tianjin, and Chongqing. Column (7) includes city-level minimum wage as a control variable. All estimates include city fixed effects, year fixed effects, and control variables including urbanization rate, GDP per capita, secondary industry as a percentage of GDP, and public security expenditure. The instrumental variable is average robot exposure in nine European countries (Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom) following Acemoglu and Restropo (2020) and Giuntella et al. (2022). See Appendix Table A1 for first-stage estimates. All regressions are weighted by city population. Standard errors are clustered by city and in parentheses. * p<0.10, ** p<0.05, *** p<0.01.