Digging for Trouble?
Mining and Criminal Behavior of Young Males

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Abstract

This paper studies how a large, localized resource boom affects the criminal behavior of young males. I exploit the 2004 iron ore boom in Northern Sweden as an exogenous shock to local economic conditions and combine geocoded administrative data on all criminal convictions and demographics from 2000–2015 with a difference-in-differences design. Comparing young males living in the mining municipalities to young males of similar nearby municipalities, and exploiting fine-grained variation in distance to the mines, I identify the causal impact of improved local labor market opportunities on crime. The results show that the mining boom led to a large decline (52%) in property crime among young male residents aged 18–29, with no effects for older individuals. The reduction is concentrated within 20 kilometers of the mines and driven primarily by first-time offenders. In contrast, the probability of being convicted of substance-related crimes increases (181%) among young males, particularly among repeat offenders and individuals directly employed in the mining sector. There is no evidence of effects on violent or traffic crimes. Mechanism analysis shows that the boom substantially improved employment and earnings for local residents, while changes in migration patterns, policing, and income inequality do not explain the results. Overall, the findings provide new micro-level evidence that positive local labor market shocks can reduce economically motivated crime, while simultaneously increasing certain non-economic offenses. (JEL R11, K42, Q33, O13)

Keywords: criminal behavior, economic opportunities, mining, Sweden

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1 Introduction

Starting with the seminal economic theory of crime (Becker, 1968; Ehrlich, 1973), criminal behavior is viewed as a rational decision-making process in which individuals weigh the costs and benefits of engaging in both legal and illegal activities. Therefore, economic theory predicts that improvements in local labor market conditions reduce crime by increasing the returns to legal activity and the opportunity cost of illegal activity. Consistent with this intuition, a large empirical literature documents that job loss, wage declines, and adverse economic shocks increase criminal behavior. However, evidence on the crime effects of positive economic shocks paints a more complex picture. In particular, local economic booms—often driven by natural resource discoveries or commodity price shocks—have been associated with both reductions and increases in crime (James and Smith, 2017; Couttenier et al., 2017; Komarek, 2018). Furthermore, historically, natural resources have been commonly associated with disorder, lawlessness, and crime. For example, gold rushes are often associated with boomtown violence and weak social control. This puzzle between theory and empirical evidence is difficult to explain in the existing literature, perhaps due to the co-occurrence of different factors.

While previous studies often highlight increases in crime due to positive economic shocks (James and Smith, 2017; Komarek, 2018), more recent micro-level work shows that local labor market opportunities created by resource shocks can instead reduce crime (in line with Becker (1968)) (Axbard et al., 2021; Street, 2025). There are different possible explanations for these mixed results. A key challenge in addressing this question is that positive local economic shocks simultaneously affect individual incentives and population composition. Improved labor market opportunities may reduce economically motivated crime among existing residents, while at the same time attracting in-migration, changing local exposure to economic activity, and altering the mix of behaviors observed in a place. For instance, Street (2025) finds that after the fracking boom in the US, aggregate-level crime increases in resource areas due to migration and compositional changes, while crime decreases among pre-existing residents due to better economic opportunities. As a result, aggregate crime statistics may conflate behavioral responses with compositional changes, complicating the interpretation of the social consequences of place-based economic development policies.

This tension motivates my analysis: I study how the criminal behavior of young males responds to positive local economic shocks, and by distinguishing between existing residents and in-migrants, I contribute to this puzzle in the previous literature. There are also empirical challenges in establishing the causal effects of economic opportunities and criminal behavior, due to the difficulty in identifying plausibly exogenous variation in local economic opportunities, which I address by exploiting a large commodity-price-driven mining boom.

This paper studies how a large, plausibly exogenous local economic boom affects individual criminal behavior, using the 2004 iron ore price boom in northern Sweden as a laboratory.

This allows me to identify the effect of economic opportunity on individuals' (young males) criminal behavior. Moreover, the mechanisms by which the boom may affect crime are analyzed, including the effect of the boom on local economies' labor market conditions and crime prevention capacity. In general, mining booms improve the labor market, attract in-migrants to the areas, and increase local purchasing power. In Sweden specifically, Rodríguez-Puello and Rickardsson (2024) find that individuals located close to the mines experienced higher employment and earnings after the boom, driven by the mining sector, but also by spillovers into manufacturing, construction, and services. I combine detailed geocoded administrative data on criminal convictions with rich individual-level information on employment, earnings, and residential mobility over the period 2000–2015. The empirical design exploits spatial variation in exposure to mining activity and temporal variation induced by the global commodity price shock in a difference-in-differences framework, allowing me to isolate how improved local economic conditions shape criminal behavior while explicitly accounting for residential mobility and spatial heterogeneity. Moreover, the size and richness of the data set allow me to characterize the heterogeneity of treatment effects across individuals using causal forests. I contribute by focusing on people rather than places, and estimating the effect more in depth across time, economic sectors, types of crime, and demographic groups.

Northern Sweden and the mining boom are ideal contexts for this study for several reasons. First, Sweden has a long tradition of iron ore mining, specifically in the North of the country (Nordregio, 2009; Haley et al., 2011; Tano et al., 2016).[1] The unexpected mining boom analyzed in this paper started circa 2004 when mining prices tripled (Baffes and Haniotis, 2010). The mining sector in the country is concentrated in a few municipalities in the north, which have been experiencing decades of disinvestment and population decline (Adjei et al., 2023). I focus on the cases of Gällivare and Kiruna municipalities, where the workers in the mining sector represent around 20% of the total employment. Research on the localized effect of a resource boom on criminal activity in a developed country is scarce (Komarek, 2018), especially in a context such as Northern Sweden, where boomtowns have these characteristics. This is despite crime being considered an obstacle to development and a serious threat to the well-being of individuals (The World Bank, 2011). Second, the shock was largely unforeseen and generated outside of Sweden. The mining boom is assumed to be plausibly exogenous since it was generated by global demand, such as China's increasing demand for commodities, and speculation in the stock markets, rather than shifts in the supply of minerals (Radetzki et al., 2008; Farooki and Kaplinsky, 2013; Singleton, 2014). In addition, empirical literature considers the location of natural resources as exogenous because it depends on local geology. Together, these support the assumption that the mining boom affected local labor markets for

[1] Estimates indicate that in 2013, the mining industry contributed almost SEK 44 billion (1.3 percent) to Swedish GDP, and it is considered one of the most attractive mining countries in the world (Swedish Agency for Growth Policy Analysis, 2015).

reasons unrelated to prior local conditions and individuals' behaviors, overcoming common critiques of the difference-in-differences research design (Besley and Case, 2000).

Young males are an important population group to analyze the effect of economic opportunity on individuals' criminal behavior for several reasons. First, it is well established in previous empirical literature on crime that conviction rates are substantially higher among males than females, and they peak in early adulthood before declining steadily with age (e.g., Elonheimo et al., 2014; Epper et al., 2022). For example, Epper et al. (2022) shows that crime is heavily male-dominated, especially among young males. Moreover, according to the empirical literature, young males participate in a disproportionate amount of violent and property crimes (Komarek, 2018). Second, the mining sector worldwide and in Sweden is composed primarily of young and male workers (e.g., Kearney and Wilson, 2018; Chávez and Rodríguez-Puello, 2022). Finally, Rodríguez-Puello and Rickardsson (2024) finds evidence that the benefits from the mining boom in Sweden, through higher earnings and more employment opportunities, are large for males and young individuals located close to the mines. Therefore, I focus on young males because (i) they are the group with the highest baseline crime rates, and (ii) they are the most responsive to local labor market improvements generated by the boom.

Theoretically, individuals are rational economic agents that choose between legal work and criminal activity by comparing the legal work wage in the labor market and the expected payoff to crime (which depends on the expected gain from crime minus the cost, which is the product of the probability of being caught and the associated punishment), choosing crime whenever the former exceeds the legal wage (Becker, 1968; Ehrlich, 1973). Positive local economic shocks may influence crime via several mechanisms, which are not mutually exclusive. First, improvements in the labor market conditions are expected to decrease crime for residents due to increases in the returns to legal activity. That is, individuals with higher wages or better employment opportunities experience an increase in the opportunity cost of engaging in criminal activity, reducing local crime levels for individuals residing in the local area (Komarek, 2018; Axbard et al., 2021; Street, 2025). Intuitively, I expect that economically motivated crimes (property crimes) are likely to be better understood with this mechanism.[2] Nevertheless, an additional mechanism also related to the improved labor market that suggests opposite effects, and often used in the literature to explain increases in crime due to resource shocks, is the increase in the payoff to commit crimes, known as the rapacity effect (Draca and Machin, 2015; James and Smith, 2017). Intuitively, the positive shock generates increases in earnings, providing individuals with more disposable income and criminals with higher incentives to commit crimes.

Second, there are indirect channels, such as changes in migration patterns, income

[2]See Draca and Machin (2015) and Ferraz et al. (2022) for review articles on how economic incentives and economic shocks can affect crime.

inequality, and crime-prevention capacity, that may influence how a positive economic shock affects crime. Positive local economic shocks attract individuals looking for better economic opportunities (Wilson, 2022), especially those whose outside options are dominated by the expected gains from moving. By analyzing migrants to the mining areas, their characteristics, and how the combination of the boom and their relocation affects their criminal behavior, I provide insights into how different population groups respond to economic opportunities. Moreover, previous studies show that migrants, attracted by local economic shocks, are likely to be young and mobile (lower migration costs), low-skilled, and more risk-tolerant or with higher baseline crime returns (Dustmann and Glitz, 2011; Gröger, 2021; Wilson, 2022). Therefore, due to selection, migrants may have a higher average probability of committing crimes upon arrival, even if their own likelihood declines due to higher local wages. Finally, the probability of being caught depends on police resources and other area characteristics, affecting the final individual decision to commit crimes. This demonstrates the importance of an empirical analysis of the relationship between a positive local economic shock and local crime and the mechanisms behind it.

Although the analysis focuses on a specific mining boom in northern Sweden, the mechanisms studied in this paper are not unique to this context. The theoretical channels linking economic opportunities to criminal behavior—through changes in labor market returns, opportunity costs, disposable income, and population mobility—are central to a wide range of local economic shocks. Mining booms provide a particularly clean laboratory to study these mechanisms because they generate large, localized, and plausibly exogenous changes in economic conditions. However, similar dynamics arise in other settings characterized by rapid local economic expansion, including energy booms, infrastructure investments, manufacturing expansions, and large place-based development programs. At the same time, institutional features such as labor market regulation, social insurance, and law enforcement capacity may shape how these mechanisms operate, implying that the magnitude of the effects may vary across contexts even when the underlying behavioral responses are similar.

Results show that young male residents aged 18-29 experience a substantial decline in property crime during the mining boom relative to comparable young male residents in control municipalities. The start of the economic expansion leads to a statistically significant reduction of 0.66 percentage points (52 percent) in the probability of being convicted of a property crime. This decline is economically meaningful and consistent with recent evidence showing that positive resource-driven labor market shocks can reduce economically motivated crime by increasing legal employment opportunities (Corvalan and Pazzona, 2019; Axbard et al., 2021; Street, 2025). The results are also consistent with the Becker (1968) model of crime, in which improved labor market conditions raise the opportunity cost of engaging in economically motivated illegal activity. Importantly, these effects do not appear to be driven by changes in police presence or enforcement intensity, alleviating concerns related to detection or deterrence.

Exploiting the panel structure of the data and the detailed criminal information, I further show that the reduction in property crime is concentrated among first-time offenders. The mining boom significantly lowers the probability that young males commit a property crime for the first time, while having no detectable effect on the probability of re-offending. This pattern suggests that improved labor market opportunities primarily deter entry into economically motivated criminal activity, rather than altering the behavior of individuals with established criminal histories, suggesting that individuals with prior convictions are less responsive to local economic changes. Consistent with this interpretation, conditional average treatment effects estimated using flexible machine-learning methods, such as causal forest algorithms (Athey et al., 2019), reveal that the reductions in property crime are concentrated among young males with low educational attainment, weak labor market attachment prior to the boom, and low pre-boom earnings—groups that are plausibly most responsive to changes in economic opportunity.

In contrast to property crime, the mining boom is associated with a statistically significant increase in substance-related convictions among young male residents. The probability of being convicted of a substance-related offense increases by 0.46 percentage points, corresponding to a 181 percent increase relative to the pre-boom mean. The increase in substance-related crime is driven almost entirely by narcotics-related offenses. Moreover, a decomposition of narcotics-related offenses indicates that the increase is driven primarily by possession and use rather than production or trafficking. This result is related to a line of literature on the positive effect of resource shocks on risky behaviors, such as an increase in the demand for various goods and services, including alcohol, narcotics, and entertainment activities provided by the adult entertainment industry (e.g., Wilson, 2012; Tynan et al., 2017; **?**). Additional analyses, that should be read with caution due to data limitations, do not reveal significant effects on alcohol-related offenses, intoxicated driving, gender-based violence, or health-related outcomes, indicating that the increase in substance-related crime is specific to narcotics-related offenses.

Further analysis reveals that the increase in substance crime among young males is concentrated among repeat offenders rather than first-time offenders. This pattern contrasts sharply with the results for property crime and suggests that the mining boom intensifies substance-related criminal activity among individuals with pre-existing involvement in substance offenses, rather than inducing new entry. Heterogeneity analysis indicates that these effects are strongest among young males employed in the mining sector and among individuals in the upper tail of the pre-boom earnings distribution, consistent with a channel operating through increased disposable income and engagement in risky consumption behaviors rather than labor market opportunity costs.

Across both property and substance crimes, the estimated effects are highly localized and demographic-specific. The responses are concentrated among individuals residing within

20 kilometers of the mines and are driven by existing residents rather than in-migrants. No statistically significant effects are observed for violent crimes, traffic crimes, or among older young male cohorts aged 30–39. These patterns underscore that the crime response to positive local economic shocks is both crime-specific and concentrated among population groups most directly exposed to changes in local labor market conditions. The effects are not confounded by changes in the population composition through migrants, the government's crime prevention capacity (police force), and income inequality due to the mining boom. The estimates are also robust to several changes in assumptions and estimation.

I also examine how the mining boom affects the criminal behavior of young male migrants, in order to assess the role of population mobility in shaping observed crime patterns. Migrants differ systematically from residents along several dimensions, including weaker pre-boom labor market attachment and higher baseline conviction rates, highlighting the potential importance of compositional changes following local economic expansions. The results show that the mining boom does not generate broad increases in criminal behavior among migrants. For most crime categories, changes in criminal activity following migration are similar in mining and non-mining municipalities, suggesting that they are largely driven by migration itself rather than exposure to mining activity. An exception arises for substance-related offenses, where migrants relocating to mining municipalities experience higher conviction rates relative to migrants settling in non-mining areas. Overall, these findings indicate that while migration matters for interpreting aggregate crime outcomes, the crime effects of the mining boom among migrants are narrow and crime-type specific rather than generalized.

To assess the welfare implications of these opposing crime responses, I translate the estimated effects into implied social costs by combining my estimates with available literature on the costs of crime (Heeks et al., 2018). Reductions in property crime generate sizeable local welfare gains, reflecting lower victimization costs and reduced criminal justice expenditures. These gains are partially offset by increases in substance-related crime, which impose social costs through enforcement, health, and broader social harms. While the net welfare effects are modest relative to national aggregates, they are economically meaningful at the local level and closely mirror the heterogeneous crime responses documented in the main analysis.

Taken together, the results indicate that improved local labor market opportunities substantially reduce economically motivated crime, while being associated with increases in certain non-economic offenses. These findings underscore that positive economic shocks can generate heterogeneous social effects, and that evaluations based solely on aggregate crime measures may obscure important offsetting mechanisms. Overall, the evidence is consistent with improved economic opportunities reducing entry into property crime, even as other dimensions of criminal behavior respond differently to local economic expansion.

Related literature. This paper contributes to several strands of literature on crime, labor markets, and local economic shocks. First, it adds to a large empirical literature studying the relationship between economic conditions and criminal behavior, surveyed by Draca and Machin (2015) and Ferraz et al. (2022). While much of the earlier literature documents that adverse labor market shocks increase crime, evidence on the effects of positive economic shocks is more mixed. In particular, studies exploiting resource-driven booms often find increases in aggregate crime, especially in the context of oil and gas extraction and fracking in the United States (e.g., Raphael and Winter-Ebmer, 2001; Gould et al., 2002; James and Smith, 2017; Dix-Carneiro et al., 2018).[3] More recent micro-level work, however, shows that improved labor market opportunities generated by resource shocks can reduce criminal behavior, consistent with rational models of crime (Axbard et al., 2021; Street, 2025). This paper contributes to this literature by providing individual-level causal evidence that positive local labor market shocks substantially reduce economically motivated crime once compositional changes are accounted for.

Second, the paper contributes to a relatively small literature on mining booms and crime, as most literature focuses on fracking. Existing studies on mining yield mixed results (Carrington et al., 2011; Corvalan and Pazzona, 2019; Axbard et al., 2021), and most analyses rely on aggregate crime outcomes. I show that focusing on individual behavior among residents reveals a clear decline in property crime driven by improved labor market opportunities, suggesting that population mobility might play an important role in shaping observed aggregate crime patterns following mining expansions.

Third, the paper contributes to a growing literature emphasizing the importance of distinguishing people from places when evaluating local economic shocks (Guettabi and James, 2020; Kovalenko, 2023; Jacobsen et al., 2023). While aggregation is an interesting margin, by separating residents from migrants and exploiting detailed migration histories, I show that changes in aggregate crime need not reflect changes in individual behavior. While migration is associated with changes in criminal activity, the mining boom does not generate broad increases in crime among migrants, and its effects are largely concentrated in specific crime categories. These findings highlight how place-based analyses can be misleading when population mobility is ignored.

Fourth, the paper provides new evidence on heterogeneity in crime responses to economic opportunities. The decline in property crime is concentrated among young, low-skilled males and among first-time offenders—groups most responsive to changes in labor market conditions—while substance-related crime increases are concentrated among repeat offenders and higher-earning individuals. By documenting sharply different responses across crime types and demographic groups, the paper shows that treating crime as a single outcome masks important variation in the social effects of economic shocks.

[3] Stretesky and Grimmer (2020) provides a systematic review of the literature relating shale gas development and crime, concluding that most studies provide clear evidence that shale gas development increases crime, especially in the United States.

Finally, the paper contributes to the literature on rational theories of crime (Becker, 1968; Ehrlich, 1973) by providing new causal evidence on the income channel. I estimate that a one percent increase in earnings reduces the likelihood of a property crime conviction by approximately two percent, an elasticity at the upper end of existing estimates (Gould et al., 2002; Machin and Meghir, 2004). More recent work, including Agan and Makowsky (2023), further supports the view that better access to economic opportunities can lower recidivism and overall criminal activity. These findings show the importance of labor market dynamics in shaping social outcomes. At the same time, the results demonstrate that improved economic opportunities do not uniformly reduce all forms of criminal behavior, underscoring the importance of distinguishing economically motivated offenses from other types of crime when assessing the welfare consequences of labor market policies and place-based economic development.

Roadmap. The remainder of the paper is structured as follows. In Section 2, the background of the Swedish mining sector, the mining booms, and the first-stage effects of the shock on the labor market are presented. Section 3 presents the data and sample. Section 4 presents the empirical framework and identification assumptions. Section 5 reports the empirical results. In Section 6.3, the results are compared to the literature and the relevant mechanisms are reviewed. Finally, Section 7 provides a discussion of the findings and conclusions.

2 Background and institutional setting

This section provides background on the mining boom, the mining sector in Sweden, and its local economic effects. First, I describe the evolution of the mining boom and the geographic distribution of the mining sector. Second, I present evidence on how the shock affected local labor markets, serving as the first stage for the analysis of crime responses.

2.1 Mining booms and the mining sector in Sweden

In the last two decades, resource-dependent countries and mining communities have experienced the economic and socioeconomic impacts of resource shocks in the form of price booms. These are characterized by large and persistent increases in international prices of minerals (Fleming and Measham, 2015; Álvarez et al., 2021). I analyze the global mining boom that started during the first years after the new millennium (2004) when international mining prices suddenly tripled (Baffes and Haniotis, 2010).[4] According to the literature,

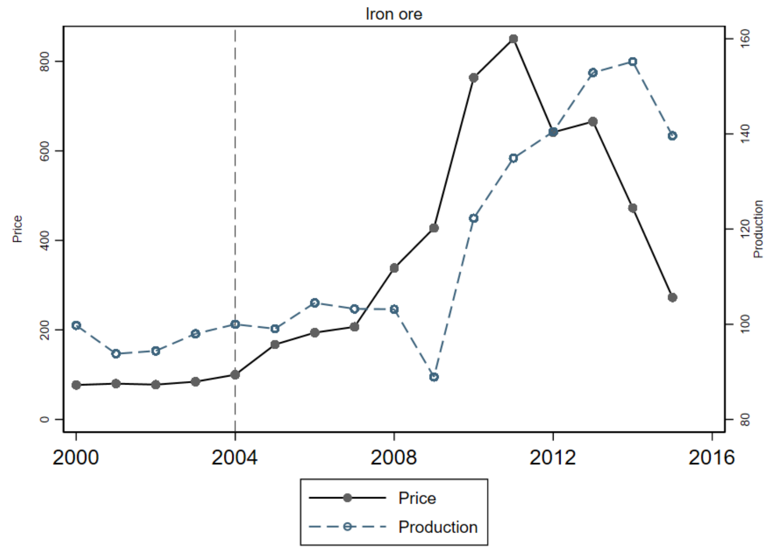
[4]It is difficult to choose the timing of the mining boom because of the complex fluctuations of international prices of different minerals (Rossen, 2015). Following Tano et al. (2016), I use 2004 as the starting point because it is the year when the price of minerals started to rapidly increase; for example, the price of iron ore increased by 67% from 2004 to 2005. In addition, the number of mining jobs had a negative trend until 2003, started to increase in 2004, and continued to grow over the coming years (SGU, 2014; Knobblock and Pettersson, 2010). This trend was accompanied by an increase in investment in the Swedish mining sector.

this shock can be considered a quasi-experiment and plausibly exogenous if it fulfills four conditions: large, variable, temporary, and generated outside an industry or country. It was generated by China's increasing demand for commodities (Radetzki et al., 2008; Farooki and Kaplinsky, 2013) and speculation in stock markets that generated investor flow (Singleton, 2014; Erten and Ocampo, 2013), rather than shifts in the supply of minerals. Therefore, it was generated outside of the country. In addition, it must be large and variable enough to affect municipalities' local conditions and temporary to identify the phases and years in which it occurred. Since this external demand shock is exogenous to the Swedish mining industry, it allows me to identify causal effects of labor market shocks on criminal behavior. Moreover, being able to track individuals over a long period provides a unique setting to examine how criminal behavior responds to changes in local economic conditions.

This boom is especially relevant for Sweden because the country has a long tradition of mining. During the mining boom, the main minerals and metals exploited in the country were iron ore, copper, zinc, and gold (Tano et al., 2016). I focus on iron ore because it is the most important mineral in the Swedish mining economy, in which the country is dominant at the European level, producing approximately 90% of the total iron ore production in the European Union (SGU, 2016). Figure 1 shows the international prices and Swedish production of iron ore for the period 2000-2015. As can be seen, prices began to increase in 2004, reaching the maximum level in 2011. The price of iron ore increased by 67% from 2004 to 2005 and continued to grow rapidly in the following years (Tano et al., 2016). At the same time, observing the rise in prices, mining companies employed strategies to increase their production before a probable fall in prices, showing some changes in production between those same years after the increase in prices. In addition, the start of the mining boom coincides with a dramatic increase in exploration activities and production in Northern Sweden due to high local and international investment in the sector and increasing demand for minerals and metals (Petterson and Knobblock, 2010; SGU, 2014).

In addition to changes in prices and production, the mining boom was highly salient in the public debate. Using information from the newspaper archive *Retriever Mediearkivet*, I construct the annual number of articles in Swedish newspapers mentioning LKAB (Luossavaara–Kiirunavaara Aktiebolag), the state-owned iron ore company operating the major mines in Kiruna and Gällivare (Online Appendix Figure B.1). Media coverage closely tracks the evolution of international iron ore prices, increasing sharply after 2004 and peaking during the height of the boom. This pattern suggests that the mining boom was widely perceived and discussed at the national level, reinforcing the view that the shock was not only economically significant but also highly visible to local communities.

Figure 1: Price and production values for iron ore in overall Swedish production, 2000–2015



Notes: Price and production are normalized to 2004 values (2004=100). The vertical dashed line shows the year of the start of the mining boom (2004). Data are obtained from SGU (2021) and International Monetary Fund.

In Sweden, mining activity is spatially concentrated in northern municipalities, with a few exceptions in the South of the country. The North of the country is part of the *Fennoscandinavian Shield*, a region considered rich in minerals (Nordregio, 2009; Haley et al., 2011). Most mines, mining jobs, and exploration are concentrated in the two northernmost counties: Norrbotten and Västerbotten (SGU, 2014), representing 93% of total mining employment in Sweden in 2013 (Moritz et al., 2017). There are mainly three large iron ore mines that were continuously operating during the mining boom period: the Malmberget mine located in Gällivare municipality and the Kirunavaara and Gruvberget mines in Kiruna municipality.[5] These are all existing mines, with Kirunavaara opening in the 1860s, and Malmberget in the 1820s. I focus on existing mines instead of the opening or closing of mines since that was rare during this period and does not provide sufficient variation for empirical analysis. Moreover, these mines are central to the labor market dynamics of these municipalities, employing a substantial share of the workforce.

Due to the lack of an official classification for mining and non-mining municipalities in Sweden, I consider those municipalities highly specialized in mining, with a high mining

[5]There are other small mines in other municipalities, not considered in the study due to their size and because they are located in different parts of Sweden in terms of demographics and labor market. Other than Gällivare and Kiruna, the other eight municipalities that have mines during the mining boom period are Lycksele, Malå, Norsjö, Skellefteå, Sorsele, and Storuman in Västerbotten County, Askersund in Örebro County, and Hedemora in Dalarna County. Online Appendix Table A.1 shows some basic information about the mines, municipalities, and their employment share in the mining sector. Tano et al. (2016) and SGU (2021) provide a more detailed description of the mines opening and closing in Sweden, the public and private companies operating them, and the locations of the mines.

employment share in 2003, which can be classified as industrial mining and focused on the exploitation of iron ore: Gällivare and Kiruna. Choosing treated units based on their high share of employment in the industry is a common approach in the empirical literature about resource booms (Black et al., 2005; Kumar, 2017; Jacobsen et al., 2023). Therefore, I consider individuals living in Gällivare and Kiruna (mining municipalities) as treated, which are the municipalities expected to be more affected by the mining boom.

Gällivare and Kiruna are small municipalities with approximately 18,000 and 23,000 residents in 2015, respectively, characterized by very low population density and compact urban centers surrounded by sparsely populated land. In both municipalities, large-scale iron ore mines are located in close proximity to the urban centers, and local commuting patterns, employment opportunities, and economic activity are tightly linked to mining operations. Although neither municipality is a classic company town, mining represents the dominant economic sector in both Gällivare and Kiruna, directly and indirectly employing a substantial share of the local workforce. Moreover, prior to the mid-2000s mining boom, crime rates in both Gällivare and Kiruna were relatively stable and comparable to those in similar northern municipalities, with no pronounced differential trends relative to the control areas used in the analysis. Although the institutional environment of Swedish mining is specific, Gällivare and Kiruna share features with mining towns worldwide, such as copper-mining municipalities in northern Chile (Corvalan and Pazzona, 2019; Rodríguez-Puello, 2025), including geographic concentration of extraction activity, reliance on mainly one economic sector, and high sensitivity to global commodity price fluctuations, suggesting that comparative analyses across mining regions could help assess the external validity of the findings.

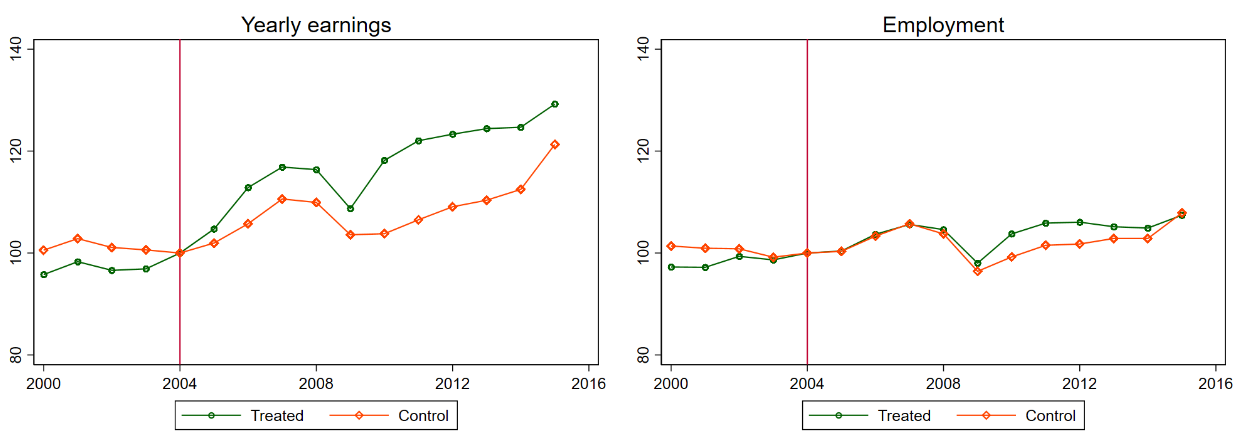
2.2 First-Stage effects on local labor markets

Several studies have examined how the Swedish mining boom reshaped local labor markets, documenting sizable income and employment gains concentrated in mining areas. Tano et al. (2016) analyzes the effects of the mining boom on labor income in Northern Sweden and finds rapid income growth among mining and construction workers, along with moderate spillover effects into other sectors such as manufacturing and services. This pattern suggests that the mining boom generated broader local multipliers beyond direct extraction activities. Similarly, Moritz et al. (2017) provides evidence of strong employment effects both within the mining sector and across related industries. Haikola and Anshelm (2020) highlights how the volatility of global iron ore prices influenced local attitudes toward state involvement and economic policy in mining communities.

More recent evidence by Rodríguez-Puello and Rickardsson (2024) shows that the local labor market effects of the mining boom in northern Sweden were substantial and spread across space, sectors, and demographic characteristics. The authors find that the mining boom affects the labor market conditions of individuals located as far as 27 km during the boom and 83 km in later years. Residents living near mines experienced around 5% higher annual earnings, equivalent to roughly 8,400 SEK in 2004. Moreover, these individuals experienced higher employment and earnings after the boom, driven by the mining sector, but also by spillovers into manufacturing, construction, and services. Individuals who migrated to the mining area after the boom were predominantly young, unmarried, and highly educated, and experienced large gains in earnings and employment, especially those who moved to work directly in mining.

Consistent with these findings, Figure 2 shows that both employment and earnings increased sharply in Gällivare after 2004 relative to nearby municipalities in the county (controls). This findings provide evidence suggesting that the mining boom created a powerful, geographically concentrated labor-demand shock that improved local economic conditions and serves as the first stage for analyzing its broader social consequences, including effects on crime. This is a first approximation to the first stage effects of the mining boom on the labor market conditions of residents; more discussion on this mechanism is in Section 6.3.

Figure 2: Earnings and employment evolution for mining and comparison municipalities, 2000-2015



(a) Yearly earnings (b) Employment

Notes: Treated: Gällivare and Kiruna. Earnings and employment are normalized to 2004 values (2004=100). The vertical line shows the year of the start of the mining boom (2004).

3 Data and sample

To examine the role of the mining boom on criminal behavior in Sweden, I rely on geocoded register data that originate from various administrative registers managed by Statistics Sweden. The data is of yearly frequency, and the outcomes are measured in November each year. The dataset is rich and contains information on all individuals above the age of 16, including age, gender, education, region of origin, income, and household characteristics. The data also includes information on employment, occupation, economic sector, and region of residence and work, and I focus on the period 2000-2015.[6] These data have been linked to the Swedish Conviction Register, maintained by the National Council for Crime Prevention (Brottsförebyggande rådet - BRÅ). These data contain comprehensive details concerning criminal convictions at the individual level during this period. It includes information on the type of crime and the date of the crime, among other information. A single conviction may encompass multiple crimes, and I observe all crimes within a given conviction. It excludes minor offenses such as speeding tickets, but includes offenses such as driving without a license and DUI.

I restrict the sample to young males: males older than 18 years and under 39 years who appear in five or more annual observations consecutively in the sample.[7] Moreover, I consider individuals located in Gällivare and Kiruna municipalities, in Norrbotten County, as treated due to the high presence of mining in the territory and labor market, and because they had at least one operating iron ore mine during the mining boom period, representing more than 10% of employment in the mining sector. To ensure that individuals in the treated and control groups are not only similar but also geographically close, I define the control group as those located in Norrbotten County. Therefore, all individuals located in municipalities other than Gällivare and Kiruna in the county are considered controls.[8] Finally, I exclude individuals who moved to Norrbotten County in 2004 or later in the main specification, whom I call migrants. Therefore, the main analysis focuses on residents. I assume that those who migrated to this area after the shock did so in response to improved labor market conditions. This is important because the results may be a combination of the effects of the mining boom on crime and endogenous movement decisions made by individuals who migrated to the mining areas (Winters et al., 2021). Nevertheless, for robustness, I also present the results with all individuals. Online Appendix Figure B.3 shows the spatial location of the treated

[6]The analysis ends in 2015 for several reasons. First, statistics of reported crimes might not be entirely comparable for a large period of time due to changes in the counting and judicial system. In addition, at about this time, Europe and Sweden experienced the start of a migration crisis (Puschmann et al., 2019; Gamalerio et al., 2023), where refugees were disproportionately placed in peripheral and rural areas (Wennström and Oner, 2019); therefore, including this period in the analysis could lead to confusion about the impact of the mining boom and the migration crisis.

[7]I focus on young males because it is well established in previous empirical literature on crime that conviction rates are substantially higher among males than females, and they peak in early adulthood before declining steadily with age (e.g., Elonheimo et al., 2014; Epper et al., 2022). Online Appendix Figure B.2 shows this descriptive pattern for the Swedish data, and all types of crimes. In both the pre-boom and boom periods, young males stand out as the group with the highest conviction rates, several times greater than those of women or older cohorts. Therefore, young males are disproportionately responsible for overall crime levels, and most variation in criminal activity is concentrated in this demographic.

[8]Norrbotten County has 14 municipalities: Arjeplog, Arvidsjaur, Boden, Gällivare, Haparanda, Jokkmokk, Kalix, Kiruna, Luleå, Pajala, Piteå, Älvsbyn, Överkalix, and Övertorneå.

and control municipalities.

Individuals residing closer to the mines may be the most affected by the mining boom. That is, individuals close to mines may be more affected than those further away (even within Gällivare and Kiruna), and the previous treatment definition may mask this large spatial heterogeneity. Therefore, as a second treatment, I incorporate treatment intensity by constructing a measure of the distance in kilometers from the individual's residential location to the nearest mine, depending on the coordinates of the grid where she/he is located. I consider the three large iron ore mines that were continuously operating during the mining boom period, as mentioned in Section 2. The grids in the data are 250 by 250 meters in size in urban areas and 1000 by 1000 meters in size in rural areas. Individuals are located in these grids according to their place of residence. This variable exploits within-municipality variation in exposure to the mining boom and uncovers spatial heterogeneity in crime responses. I use distance to construct a categorical treatment indicator, assigning individuals into different treatment groups (rings) based on their proximity to the mines. The approach of defining exposure to mining as being geographically close to a mine is commonly used in the literature and is also known as the "ring method" (e.g., Wilson, 2012; Benshaul-Tolonen et al., 2019; Rodríguez-Puello and Rickardsson, 2024). I classify individuals in 20-kilometer rings, obtaining five rings in total, where those individuals located farther away serve as controls.[9]

In the main analysis, the main outcomes of interest that reflect the criminal behavior of individuals are: (1) being convicted of property crime, (2) violent crime, (3) traffic crimes, and (4) substance-related crimes, per year. Property crimes include theft, robbery, and other assaults, fraud and other misconduct, embezzlement and other faithlessness, offenses against creditors, and crimes of damage. Violent crimes include violations of life and health, violations of freedom and peace, defamation, sexual offenses, and crimes against family. Traffic crimes include a broad range of road- and maritime-traffic offenses such as reckless or negligent driving, unlawful driving, driving under the influence, hit-and-run, speeding, safety violations, and other traffic- and navigation-related offenses.[10] Substance-related crimes include convictions under Swedish legislation governing narcotics, doping substances, alcohol, tobacco, and nicotine products, covering offenses related to possession, use, production, and distribution of these substances.[11] See Table A.2 in the Online Appendix for a detailed

[9]Online Appendix Figure B.4 shows the distribution of individuals in space according to their location and distance to the nearest mine and their distribution in the rings.

[10]Traffic crime is identified using convictions under the Traffic and Maritime Offences Acts. The data do not allow for a consistent separation between driving under the influence and other traffic offenses within this category.

[11]The administrative conviction records do not allow for a consistent separation between possession, use, and distribution within narcotics offenses. As a result, substance-related crime is analyzed as a composite outcome.

description of each category and subcategory of crime.[12] Online Appendix Table A.3 presents summary statistics for treated and controls before (2000-2003) and after (2004-2015) the mining boom. The two groups are balanced in terms of demographics and job characteristics, confirming the expectations about the similarity of individuals in the treatment and control groups before the boom. The summary statistics show similar crime levels among treated and controls. The main sample consists of 27,525 individuals (440,402 individuals-year observations). Moreover, I identify 15,108 migrants (241,725 migrant-year observations).

4 Empirical framework

Understanding the effects of economic opportunity from mining on criminal behavior is challenging from an empirical standpoint. Empirical literature often argues that resource endowments are exogenous because they occur due to chance and not so much to the political and economic environment in the host country. Therefore, according to Brunnschweiler and Bulte (2008) and Van der Ploeg and Poelhekke (2010), they are considered good measures of exogenous variation in resource wealth. Nevertheless, recent literature challenges this view. Although the location of natural resources is considered exogenous since it is determined by local geology and natural characteristics (Brunnschweiler and Poelhekke, 2021), the opening of mines and finding these resources is not completely exogenous, as it often relies on foreign firms to provide capital and expertise or on local governments' investment in exploration (Cust and Harding, 2020; Brunnschweiler and Poelhekke, 2021). Moreover, minerals are typically found in places that are remote and rugged; therefore, settlements driven by natural resources are highly heterogeneous from other communities (Asher and Novosad, 2023). Those features are not orthogonal to the labor market conditions or crime; hence, regressions of such outcomes on mining availability may be biased due to omitted variables and/or reverse causality.

I exploit the unexpected rise in iron ore prices that generated the global mining boom in 2004, coupled with variation in individuals' exposure to mining activity, driven by their geographical residential location. These provide a plausibly exogenous shock to local economic conditions, based on the assumption that the location of mines is exogenous because it depends on the local geology (Pelzl and Poelhekke, 2021; Christian and Barrett, 2024). Using a generalized difference-in-differences framework that exploits both temporal and spatial variation in exposure, I compare the criminal behavior of treated individuals to residents in other municipalities in the county, before and after the mining boom, to identify the average treatment effect (ATE) on the treated in mining municipalities. Formally, I estimate the effects of local economic shocks on local residents' criminal behavior using the following linear probability model:[13]

[12] Other types of crimes, such as crimes against the public, crimes against the state, and other special categories (e.g., smuggling, tax crimes, terrorist crimes), are excluded due to their low frequency.

[13] While logit and probit models are also used for binary outcomes, they add their own assumptions, often

$$Y_{ijmt} = \alpha_i + \alpha_j + \alpha_t + \beta(Post_t \times Treated_{imt}) + \epsilon_{ijmt} \quad (1)$$

where Y_{ijmt} is equal to 1 if individual i located in grid j and in municipality m in year t is convicted of a crime (property, violent, traffic, or substance crime). $Treated_{imt}$ is a binary variable that takes the value of 1 if individuals are located in the mining municipalities and 0 if individuals reside in other municipalities in the county (control). $Post_t$ is a binary indicator equal to 0 before the mining boom (2000-2003) and 1 after (2004-2015). The coefficient of interest is the β, which identifies the difference-in-differences estimate (ATE) of the effects of the mining boom on the outcome Y_{ijmt}. I include α_i, α_j, and α_t, which are individual, grid, and time fixed effects, respectively, to account for omitted variables and isolate the effect of the event. Individual fixed effects account for any static differences in the propensity to commit a crime across individuals. Year fixed effects control for factors that affect the criminal behavior of all individuals in a given year, such as the Great Recession. Grid fixed effects account for any static differences in the propensity to commit a crime across geographical locations. Moreover, in the empirical analysis, I present results separately for individuals aged 18–29 and 30–39 to account for potentially different crime-related behaviors and life-cycle stages across younger and early-middle-aged adults.[14] In all estimations, I cluster standard errors at the grid level, allowing for an arbitrary covariance structure over time within each grid, and accounting for the serial correlation in the error term (Bertrand et al., 2004; Miller, 2023).

As mentioned, to incorporate treatment intensity and explore spatial heterogeneity in the ATE, I estimate the following specification using a second measure of treatment:

$$Y_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta(Post_t \times Ring(d)_{ijt}) + \epsilon_{ijt} \quad (2)$$

where the outcome Y_{ijt} is equal to 1 if individual i located in grid j in year t is convicted of a crime. α_i, α_j, and α_t are individual, grid, and time fixed effects, respectively, which are included to control for confounding omitted variables that vary at the unit or time level. $Ring(d)_{ijt}$ is the treatment variable, measured as a set of indicators equal to 1 if individual i located in grid j belongs in the following distance rings (in kilometers) from the nearest mine: $d \in \{(0, 20], (20, 40], (40, 60], (60, 80], (80, 236]\}$. $Post_t$ is a binary indicator equal to 0

don't have closed-form solutions, and their interpretation is more complex, especially with large amounts of fixed effects (Huntington-Klein, 2021).

[14]In the robustness checks, I include time-varying individual-level controls, such as being married, having children under 18, education categories (primary, secondary, and tertiary), and economic sector which distinguishes between non-employed, primary (extraction and agriculture), secondary (manufacturing and construction), and tertiary (services, healthcare, public sector, and other). I do not include the control variables in the main specification because some of the controls could be endogenous to the mining boom (Allcott and Keniston, 2018; Pérez-Trujillo and Rodríguez-Puello, 2022; Rodríguez-Puello, 2025), becoming bad controls. The main results are robust.

before the mining boom (2000-2003) and 1 after (2004-2015). The coefficient of interest is the β, which identifies the difference-in-differences estimate (ATE) of the effects of the mining boom on the outcome Y_{ijmt} for each ring compared to ring 5.

4.1 Identifying assumptions

The assumptions behind the DID approach are that, in the absence of the mining boom, residents' criminal behavior in mining municipalities would have changed similarly over time with residents' criminal behavior in control municipalities (parallel trends) (Meyer, 1995), pre-periods are not affected by treatment (no anticipation), and an individual's treatment status does not affect the potential outcome of another ("stable unit treatment value assumption", SUTVA). I check these assumptions in several ways.

First, regarding the parallel trends assumption, a violation of this assumption would imply that the observed effects might be a result of preexisting trends instead of the boom. To empirically assess the validity of the "parallel trends" assumption, I estimate the following dynamic DID equation:

$$Y_{ijmt} = \alpha_i + \alpha_j + \alpha_t + \sum_{t}^{T} \beta_t \times I_t \times Treated_{imt} + \epsilon_{ijmt} \tag{3}$$

where Y_{ijmt} is equal to 1 if individual i located in grid j and in municipality m in year t is convicted of a crime. $Treated_{ijmt}$ is a binary variable that takes the value of 1 if individuals are located in mining municipalities and 0 if individuals reside in other municipalities in the county (control). The I_t's represent each year, accounting for the dynamic nature of the approach. The coefficients of interest are the β_ts, which identify the per-period difference-in-differences estimate of the effects of mining on the outcome Y_{ijmt}. I normalize β_{2003} to zero; thus, all the coefficients are interpreted as changes relative to that year. In this dynamic DID approach, the first difference is between the reference period $t = 2003$ and the period $t + x$, while the second difference is between the treated and control individuals. The β_ts for $t > 2003$ capture the dynamic effects of the treatment. On the other hand, the β_ts for $t \leq 2003$ provide a placebo or falsification test for the parallel trend assumption. In this specification, I include the same fixed effects to account for omitted variables and isolate the effect of the event.

Second, if there are spillovers to neighboring control municipalities, the SUTVA assumption would be violated, and the parameters of interest in the main model would be biased toward zero. In other words, I assume that there is no interference between units, and the individuals in the control municipalities are not affected by the treatment via spatial spillover effects (Sinclair et al., 2012). As a robustness check, I remove residents located in the four neighboring municipalities, which are most prone to spillovers.[15] Third, I assume that

[15] The four neighboring municipalities are Jokkmokk, Pajala, Överkalix, and Boden.

there are no time-varying omitted variables at the treatment level correlated with the boom and the outcomes. Specifically, I assume that individuals in treated and control locations are similar in the time-varying evolution of observed and unobserved characteristics (Von der Goltz and Barnwal, 2019). The fact that there is little to no change in the results when including the control variables supports this assumption. Moreover, although the DID design only requires that treatment and control groups exhibit the same trends (not necessarily the same levels) in the absence of treatment, one could worry that the control group does not provide an adequate counterfactual in light of the level gap. Online Appendix Table A.3 shows that individuals in the pre-boom years are close to each other in observed characteristics. More importantly, in terms of trends, Online Appendix Table A.4 shows the changes in individual characteristics between 2000 and 2003 for treated individuals compared with control individuals and the mean difference test. I do not find any economically meaningful differences in trends across groups, and only a few characteristics have p-values less than 0.05. Finally, an additional concern is endogenous self-selection, where individuals may have chosen to migrate to the mining area, anticipating that the move would improve their living conditions. To address this concern, the main specification excludes individuals who moved to the treated or control locations after 2004 (migrants) (Benshaul-Tolonen et al., 2019; Jacobsen et al., 2023).

5 Results: Mining boom and crime

5.1 Main results

I begin by estimating the overall effect of local economic shocks on the different types of crimes committed by residents. Table 1 reports the DID coefficients from equation (1) for 18-29-year-old residents in Panel A and for 30-39-year-old residents in Panel B. All estimations include individual, year, and grid fixed effects, do not include control variables, and are the preferred specification since some controls could be endogenous to the mining boom and criminal behavior (Allcott and Keniston, 2018). All robustness tests, including controls and different fixed effects, among others, are in subsection 5.6.

Column (1) shows the results for being convicted of property crime, column (2) violent crime, column (3) traffic crimes, and column (4) substance-related crimes. Starting with Panel A (young males between 18 and 29 years old), the results suggest a negative and significant reduction in the probability of being convicted of property crime after the mining boom for treated young residents. I observe a decline of 0.66 percentage points in the probability of being convicted of property crime among treated individuals relative to their non-treated counterparts. From a baseline sample mean of 0.012, this estimate translates to a 52% drop in individuals convicted and is statistically significant at the 5% level. In line with expectations, there is no significant effect on violent crimes (Column (2)), suggesting that positive local economic shocks do not directly change interpersonal violence. There is no effect on traffic-related crimes (Column (3)), and the coefficients are small and imprecise. These findings suggest that

Finally, there is a positive and significant increase in the probability of being convicted of a substance-related crime after the mining boom for treated young male residents (Column (4)). I observe an increase of 0.46 percentage points in the probability of being convicted of a substance crime among treated individuals relative to their non-treated counterparts. From a baseline sample mean of 0.002, this estimate translates to a 181% increase in individuals convicted and is statistically significant at the 5% level. Approximately 95% of substance-related convictions in the sample fall under the Narcotics Law, which includes offenses related to possession, use, production, and distribution of narcotic substances, and the conviction data does not allow to separate between them. I provide a decomposition of substance-related crimes using suspicion data in subsection 5.5. On the contrary, a very small share of convictions are alcohol-, tobacco-, and doping-related offenses. This result is related to a line of literature on the positive effect of resource shocks on risky behaviors, such as an increase in the demand for various goods and services, including alcohol, narcotics, and entertainment activities provided by the adult entertainment industry (e.g., Wilson, 2012; Tynan et al., 2017; Beleche and Cintina, 2018; Cunningham et al., 2020). There is no significant effect of the mining boom on young males between 30 and 39 years old (Panel B).[16]

Table 1: Impact of the mining boom on criminal behavior, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Panel A: 18-29 years old				
Post*Treated	-0.0066**	0.0018	-0.0017	0.0046**
	(0.0027)	(0.0016)	(0.0020)	(0.0018)
Nxt	230480	230480	230480	230480
N	14405	14405	14405	14405
Mean dep. var (2000-03)	0.0125	0.0060	0.0097	0.0025
Effect relative to the mean (%)	-52.40	29.18	-17.06	181.24
R-squared	0.2929	0.2195	0.2708	0.3759
Within R-squared	0.0001	0.0000	0.0000	0.0000

[16]In an earlier version of the paper, I used the number of crimes reported to the police per 100,000 inhabitants in Gällivare municipality, and the synthetic control method to consider the relationship between mining booms and crime rates. I found similar results, but less precise and significant: the mining boom improves the labor market conditions of mining municipalities, which translates to reductions in total crime at the end of the sample period (2013, 2014, and 2015). However, using aggregate data may introduce bias to the results, such as measurement error in crime reports, unobserved omitted factors, given the large heterogeneity between mining municipalities and other municipalities considered for the synthetic control, and compositional changes due to migration. This reinforces the benefit of using detailed administrative data on criminal convictions, which allows addressing several identification challenges and analyzing in depth both mechanisms and treatment effect heterogeneity. Results are available in Rodrıguez-Puello (2024).

Panel B: 30-39 years old				
Post*Treated	0.0002	0.0004	0.0008	-0.0008
	(0.0012)	(0.0011)	(0.0015)	(0.0006)
Nxt	209922	209922	209922	209922
N	13120	13120	13120	13120
Mean dep. var (2000-03)	0.0055	0.0036	0.0067	0.0019
Effect relative to the mean (%)	3.11	11.27	12.66	-42.73
R-squared	0.3088	0.2396	0.3071	0.4397
Within R-squared	0.0000	0.0000	0.0000	0.0000
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Overall, these results provide evidence that there is a reduction in property crime convictions due to the mining boom for young males. While there is an increase in substance-related crimes. The observed reductions in property crime are consistent with Becker (1968) model, where improved legal labor market opportunities raise the opportunity cost of engaging in economically motivated offenses, and in line with previous literature (e.g., Andrews and Deza, 2018; Axbard et al., 2021; Street, 2025). Moreover, these findings suggest that economic opportunities from a resource shock reduce crime for those already living in these areas, despite the aggregate increase in crime that has been documented in the literature in other contexts (e.g., James and Smith, 2017; Komarek, 2018). For example, Axbard et al. (2021) finds that increased mineral wealth in South Africa leads to less crime due to changes in employment opportunities generated by the mining industry. A recent study that also focuses on residents in fracking counties in the US and finds reductions in criminal behavior (14-17.5% drop in cases filed) (Street, 2025).

Given that there is no significant effect on the criminal behavior of the 30-39-year-old male sample due to the mining boom (consistent throughout the paper), for the remainder of the paper, I show the results only for the 18-29-year-old male sample. All the results for the 30-39-year-old male sample are in Online Appendix C.

Spatial heterogeneity. Table 2 shows the results using the categorical treatment measure (rings) to explore spatial heterogeneity and show the estimated coefficients from equation (2). I observe a large spatial heterogeneity in crime responses. There is a negative and significant reduction in the probability of being convicted of property crime after the mining boom for young male residents located within 20 kilometers of the mines. There is no significant effect for those individuals located farther away from the mines. These results provide evidence of the large spatial localization of the mining boom effects. Additionally, the increase in substance-related crimes is also concentrated among those young male residents located within 20 kilometers of the mines. The specification in column (1) indicates a decline of 0.76 percentage points in the probability of being convicted of property crime among treated individuals relative to their non-treated counterparts. From a baseline sample mean of 0.012, this estimate translates to a 61% drop in individuals convicted of property crime and is statistically significant at the 1% level. Overall, these results suggest that the mining boom had the most effect on those closer to mines. This goes in line with Rodríguez-Puello and Rickardsson (2024), which shows greater job opportunities and higher earnings closer to the mines. In addition, a large part of the treated individuals are located within 27 kilometers of the mines. This provides evidence suggesting high heterogeneous treatment effects by geography: crime effects depend on proximity to the mine. Results for the 30-39-year-old males sample are shown in Online Appendix C Table C.3.

Table 2: Impact of the mining boom on criminal behavior by distance to the mines, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Post*≤ 20 km	-0.0076***	0.0015	-0.0018	0.0055***
	(0.0029)	(0.0017)	(0.0021)	(0.0020)
Post* 20 - 40 km	-0.0019	-0.0002	-0.0046	-0.0072*
	(0.0057)	(0.0036)	(0.0116)	(0.0042)
Post*40 - 60 km	0.0078	0.0090	-0.0024	0.0000
	(0.0089)	(0.0060)	(0.0125)	(0.0015)
Post*60 - 80 km	0.0007	0.0027	-0.0046	-0.0008
	(0.0051)	(0.0039)	(0.0078)	(0.0017)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	230480	230480	230480	230480
N	14405	14405	14405	14405
Mean dep. var (2000-03)	0.0125	0.0060	0.0097	0.0025
R-squared	0.2929	0.2195	0.2708	0.3759
Within R-squared	0.0001	0.0000	0.0000	0.0001

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

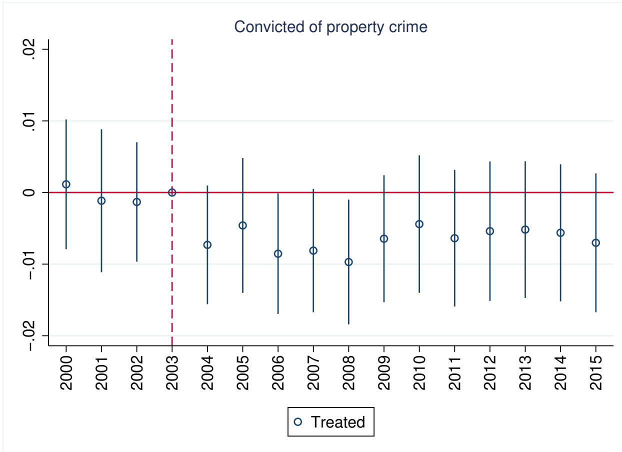
For the remainder of the paper, I focus on the treatment definition based on residing in a mining municipality. The results are very similar when instead defining treatment by proximity within 20 kilometers of the mine, and the two measures are highly overlapping in practice: over 87% of Gällivare and Kiruna residents in the sample live within 20 kilometers of the mine. Moreover, for Gällivare residents, the average distance from the mine in the sample is approximately 8 kilometers. Therefore, the municipality-based treatment captures essentially the same population as the proximity definition. Using the municipality definition has the advantage of being more transparent and easier to interpret, while still capturing essentially the same population as the proximity-based measure.

Development over time. The credibility of the DID estimation hinges crucially on the parallel trends assumption. That is, the pre-2004 time trends in the outcome follow the same trend over time between the residents in the treated and control municipalities until 2004, when the mining boom started. To validate the parallel trends assumption and analyze the temporal dynamics of criminal behavior after the mining boom, I estimate a dynamic DID (equation (3)). Figure 3 shows the dynamic treatment effect computed using the same specifications as Panel A in Table 1, that is, the effect of the mining boom on the probability of being convicted of the different crime types by year. The coefficients for years 2000-2002 (before the shock) allow us to test the presence of parallel pretrends. Importantly, these coefficients are not significantly different from zero, providing evidence supporting the identifying assumption that the treated and control individuals followed the same economic trajectory before the boom. Thus, they provide support for the use of a DID empirical strategy.

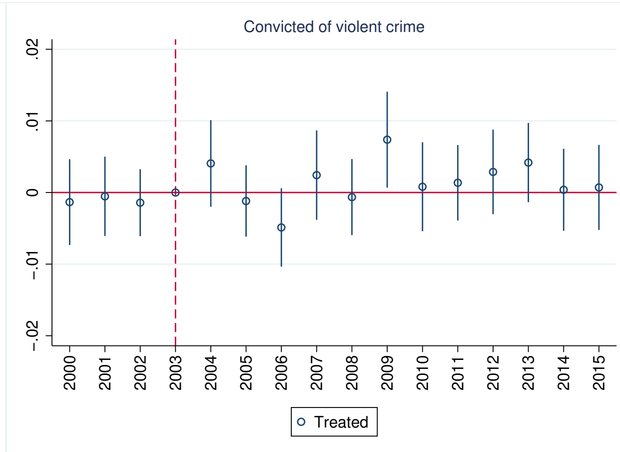
After 2004, I observe that the probability of being charged with a property crime decreases for individuals located in the mining municipalities compared to those in the control group. This effect disappears after 2009, becoming statistically insignificant, which coincides with the timing of the global financial crisis. Regarding substance crimes, I observe an increase in the probability of being charged with a substance-related crime after 2004, becoming insignificant after 2008. These findings complement the ones in Table 1 showing negative effects of the boom on property crimes and positive effects on substance crimes. Results for the 30-39-year-old males sample are shown in Online Appendix C Figure C.1. Importantly, the coefficients for years 2000-2002 (before the shock), which allow us to test the presence of parallel pretrends, are not significantly different from zero.[17]

[17] In addition, I estimate a dynamic DID to validate the parallel trends assumption for the spatial heterogeneity treatment (Table 2), which is in the Online Appendix Figure B.5. Importantly, the coefficients for years 2000-2002 (before the shock), which allow us to test the presence of parallel pretrends, are not significantly different from zero. Moreover, after 2004, I observe that the probability of being charged with a property crime decreases and increases for substance crimes for individuals located within 20 kilometers of the nearest mine compared to those in the control ring.

Figure 3: Event study of the impact of the mining boom on criminal behavior, 2000-2015

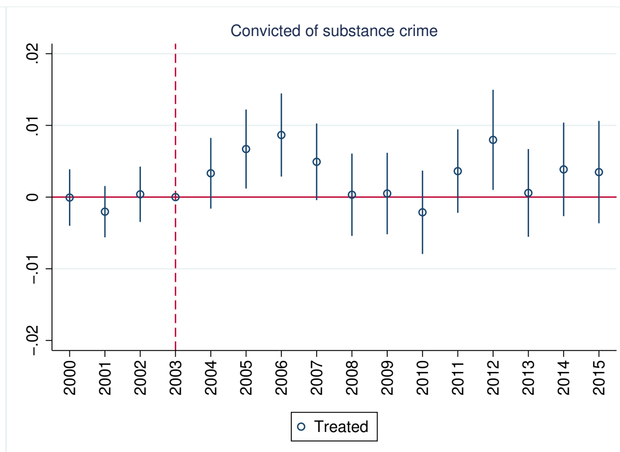


(a) Property crime



(b) Violent crime

(c) Traffic crime



(d) Substance crime

Notes: Year 2003 is the reference. 95% confidence interval shown. Estimations include individuals, grid, and time fixed effects. The sample excludes the migrants to the mining area. Standard errors are clustered at the grid level.

Overall, these results support the theory of Becker (1968), in which crime among residents declines following the mining boom, consistent with an increase in legal wage opportunities that raises the opportunity cost of engaging in criminal activity. The reduction in convictions of property crimes after the boom, as shown in both the main and dynamic specifications, suggests that improved local labor market conditions deter criminal behavior among residents in the area. This supports the idea that economic opportunity can serve as an effective crime-reduction mechanism. More discussion on the mechanisms in Section 6.3.

5.2 Detailed criminal behavior

I take advantage of the panel structure of the data and the detailed criminal information to construct additional outcomes that reflect more in detail the criminal behavior of young males as a response to the mining boom (Table 3). I focus on property crimes and substance-related crimes. I construct two distinct binary outcomes capturing different types of criminal behavior (e.g., Britto et al., 2022; Grenet et al., 2024). First, I classify individuals as first-time offenders, which is an indicator equal to one in the first year in which an individual is convicted, with no prior convictions in the panel. Second, re-offense captures subsequent convictions following an earlier conviction and reflects persistent or repeated criminal behavior. Individuals with no convictions across all years constitute the reference group for these outcomes. These outcomes allow for a richer analysis of how the mining boom affects the nature and intensity of criminal activity, differentiating between initial criminal engagement and repeat offending.

The results reveal important heterogeneity. First, the reduction in property crime convictions for young males due to the mining boom is concentrated among first-time offenders, suggesting that improved labor market conditions through increased opportunity costs may deter individuals from engaging in economically-motivated crimes for the first time. On the contrary, there is no effect on the probability of re-offending, suggesting no broader behavioral responses that include repeat offenders, and individuals with prior convictions are less responsive to local economic changes. This result is contrary to Britto et al. (2022), who finds that crime increases for both first-time offenders and re-offenders after a job loss. However, regarding substance-related crimes, I observe the opposite pattern. The increase in substance crime convictions for young males due to the mining boom is concentrated among re-offenders, suggesting that the boom primarily intensifies criminal activity among individuals with pre-existing involvement in substance-related offenses, rather than inducing new entry. This pattern is consistent with substance crimes being less responsive to changes in legitimate labor market opportunities and more closely linked to persistent criminal behavior, potentially amplified by higher local incomes and demand during the boom.

Table 3: Impact of the mining boom on detailed criminal behavior, 2000-2015

	(1) First-time convicted Property crime	(2) Re-offense Property crime	(3) First-time convicted Substance crime	(4) Re-offense Substance crime
Post*Treated	-0.0060**	-0.0006	0.0012	0.0034**
	(0.0025)	(0.0014)	(0.0012)	(0.0014)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	230480	230480	230480	230480
N	14405	14405	14405	14405
Mean dep. var (2000-03)	0.0102	0.0023	0.0020	0.0006
Effect relative to the mean (%)	-58.87	-24.94	62.27	586.46
R-squared	0.1605	0.3358	0.1710	0.3654
Within R-squared	0.0001	0.0000	0.0000	0.0000

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, I create three additional binary outcomes capturing different types of criminal behavior and the role of incarceration (e.g., Britto et al., 2022; Grenet et al., 2024). First, a binary indicator reflecting those individuals convicted of any crime and not sentenced to prison, which represents the majority of convicted individuals. Second, conviction with prison indicates individuals who are convicted and simultaneously receive a prison sentence in that year, serving as a proxy for more serious offenses or incapacitation. And third, post-prison reoffense identifies individuals who reoffend in any year following a previous prison sentence, isolating patterns of reentry into criminal activity post-incarceration.[18] Individuals with no convictions across all years constitute the reference group for these outcomes, which are mutually exclusive.

Table 4 shows the results, uncovering important heterogeneity. The reduction in property crimes of young males due to the mining boom is concentrated among those convicted without receiving a prison sentence, which may be considered a proxy for lower-severity crimes. Specifically, property crime convictions not resulting in prison decline by around 53% relative to the pre-boom mean. On the contrary, there is no effect on convictions resulting in prison, which may indicate more serious offenses, and in the probability of post-prison reoffense. Similar results are observed for substance-related crimes. The increase in substance crimes of young males due to the mining boom is concentrated among those convicted without receiving a prison sentence, with an increase of around 142% relative to the pre-boom mean. Overall, these results suggest that local economic shocks, such as the mining boom, reduce new and low-severity criminal activity, while persistent criminal behavior among those with prior incarceration may be less elastic to local labor market conditions.[19]

Table 4: Impact of the mining boom on detailed criminal behavior (the role of prison), 2000-2015

	(1) Convicted + no prison Property crime	(2) Convicted + in prison Property crime	(3) Post-prison reoffense Property crime	(4) Convicted + no prison Substance crime	(5) Convicted + in prison Substance crime	(Post- reo Substan
Post*Treated	-0.0060**	-0.0002	-0.0004	0.0026*	0.0004	0.0
	(0.0026)	(0.0005)	(0.0009)	(0.0014)	(0.0004)	(0.0
Individual FE	Yes	Yes	Yes	Yes	Yes	Y
Year FE	Yes	Yes	Yes	Yes	Yes	Y
Grid FE	Yes	Yes	Yes	Yes	Yes	Y
Nxt	230480	230480	230480	230480	230480	23

[18] It is important to note that this measure of recidivism is an "ever recidivist" measure within the panel window, not a rate conditional on release timing or sentence length. Therefore, I do not observe the post-prison reoffense of those individuals who are imprisoned late in the sample period, because I only observe a few years afterward.

[19] Online Appendix Tables C.1 and C.2 shows the results for the 30-39-year-old male sample.

N	14405	14405	14405	14405	14405	14
Mean dep. var (2000-03)	0.0113	0.0006	0.0006	0.0019	0.0003	0.0
Effect relative to the mean (%)	-53.20	-24.92	-66.84	142.47	150.95	38
R-squared	0.2390	0.1617	0.3567	0.3215	0.1418	0.3
Within R-squared	0.0000	0.0000	0.0000	0.0000	0.0000	0.0

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Heterogeneous treatment effects using causal forests

The average treatment effects mask significant heterogeneity in criminal behavior across individuals. The size and richness of our data set provide a unique opportunity for characterizing this heterogeneity using causal forest estimators via machine learning (Athey and Imbens, 2016; Wager and Athey, 2018; Athey and Imbens, 2019). By using these methods, I rely on data-driven sample splits, thus limiting the researcher's discretion when selecting the relevant dimensions of heterogeneity (Britto et al., 2022).

I estimate Conditional Average Treatment Effects for each individual based on baseline levels of observed characteristics included in the registry data (educational level, earnings, employment status, and economic sector).[20] It is important to differentiate the effects of the boom on property and substance-related crimes by population groups because different groups of people are more or less likely to commit crimes. The method estimates conditional average treatment effects (CATEs), which are average treatment effects (ATEs) conditional on a set of variables for which the treatment effects may vary. I focus on two different estimates: individual average treatment effects (IATEs) and group average treatment effects (GATEs). Appendix D provides additional details on the estimation procedure.

While these results have limited power due to low sample, the ATE estimate using the causal forest (see Online Appendix Figure B.6) is higher for property crimes than the effect observed in Table 1, which highlights high heterogeneity. In the case of substance crimes, the ATE estimate using the causal forest is similar to the one in Column (4) Table 1, positive and statistically significant. The magnitude of the effect ranges between -0.02 and 0.04, with a mean of 0.004. Moreover, by analyzing the distribution of IATEs in deciles, I observe that the magnitude of the effect ranges between a 1.3 percentage point decline in the probability of being convicted of substance crimes in the first decile of the effect size distribution to a 0.03 percentage point increase in the last decile (see Online Appendix Figure B.6).

Online Appendix Figures B.7 and B.8 show how the effect varies with individual characteristics for property and substance crimes, respectively. I analyze heterogeneity in educational levels (primary, secondary, and tertiary), across the income distribution, among

[20] To avoid endogenous movement across categories, individuals are classified in their education level, earnings decile, employment status, and economic sector according to their information in 2003.

employed or unemployed, and regarding employed individuals, whether those who are affected are those in sectors that are directly related to mining extraction, or whether these effects (positive or negative) are experienced in other sectors as well. This analysis is important since previous literature has found significant spillover effects of resource shocks in terms of earnings and employment to other sectors of the economy (Feyrer et al., 2017). I classify economic sectors into mining, manufacturing, construction, services, and others (including agriculture, public, and healthcare).

The results show important heterogeneity among different population groups. The observed reduction in the probability of being convicted of property crime due to the mining boom is concentrated among young males with primary educational levels, non-employed, and in the low tail of the earnings distribution in 2003. This goes in line with previous literature, which affirms that employment in the mining sector is composed primarily of low- or medium-low-skilled workers (Reeson et al., 2012; Pérez-Trujillo and Rodríguez-Puello, 2022). Regarding substance-related crimes, the observed increase in the probability of being convicted of substance crimes due to the mining boom is concentrated among young males with primary educational levels, employed directly in the mining sector, and in the high tail of the earnings distribution in 2003. On the contrary, there is a reduction in the probability of being convicted of substance crimes due to the mining boom for young males with a tertiary educational level. According to the economic model of crime (Becker, 1968), young males with low-skill levels are most sensitive to wage changes and have higher baseline crime propensity, making them more likely to change their criminal behavior after a boom. In addition, these groups are disproportionately represented in mining-related occupations and are more likely to be affected directly by these sector-specific local labor market shocks.

5.4 Effects on migrants

Local economic shocks attract individuals looking for better labor market opportunities (Black et al., 2005; Komarek, 2016; Wilson, 2022). The consequences of positive economic shocks may be exploited by migrants rather than residents (Guettabi and James, 2020; Winters et al., 2021; Wilson, 2022). Moreover, as the mining sector is predominantly composed of young male individuals (a more crime-prone demographic) (James and Smith, 2017; Pérez-Trujillo and Rodríguez-Puello, 2022), improved labor market conditions may lead to a shift in population composition in mining municipalities, as a resource boom attracts workers, which could impact criminal behavior. Therefore, I describe the demographic characteristics of migrants to the mining area and empirically analyze the effects of the mining boom on the criminal behavior of young male migrants. Since I do not observe the reasons for migrating, I make a series of conservative assumptions to analyze migrants. As mentioned above, I define migrants as those individuals who moved to Norrbotten County in 2004 or later. I assume that those who migrated to this area after the boom did so in response to improved labor market conditions.

There are notable differences in demographic characteristics between residents and migrants to the mining area (Online Appendix Table A.5).[21] First, I find that a higher share of migrants to the county are convicted of crimes, compared to residents in the mining municipalities. This is descriptive and a rough estimate, but it can be thought of as a conservative estimate of the difference in criminal propensity between groups. Second, migrants are, on average, less likely to be married and have higher educational attainment. Their employment rates and earnings are also lower compared to those of residents, particularly before 2004, suggesting more limited economic opportunities. These findings are similar to those found on migrants to US states due to fracking, who are primarily young, male, unmarried, and white (Wilson, 2022).

While the main specification estimates the effect of the mining boom on the criminal behavior of residents, Table 5 shifts focus to young male migrants and shows the effects of the mining boom on their probability of being convicted of any crime.[22] The table presents results from several model specifications that differ in comparison groups and estimation approaches. Columns (1)–(4) estimate conventional two-way fixed-effects regressions comparing migrants to the mining municipalities or the control municipalities to themselves before migration (the estimation includes two post-migration interaction dummies, with "pre-migration years" as the omitted category). Columns (5)–(8) contrast migrants to the mining municipalities with migrants to the control municipalities. These specifications allow me to estimate the combined impact of migration and the mining boom on individual criminal behavior.

The results indicate that migration is associated with changes in criminal behavior, but the role of the mining boom differs across crime types. Columns (1)–(4) show that, following migration, young male migrants experience an increase in property crime convictions both in mining and in control municipalities. The magnitude is slightly larger in mining municipalities, but a statistically significant increase is also present for migrants to the control areas, suggesting that the rise in property crime is largely driven by migration itself rather than by exposure to the mining boom. For violent crime, post-migration convictions increase for migrants in the control municipalities. A similar pattern emerges for substance crime: post-migration convictions decrease for migrants in the control municipalities, while no significant change is observed in mining municipalities. This suggests no meaningful differential effect attributable to mining activity. For traffic crimes, there is no evidence of systematic changes following migration in either type of municipality.

Columns (5)–(8) directly compare migrants who move to mining municipalities with those who move to non-mining municipalities, isolating the additional effect of the mining boom. These estimates show no statistically significant differential effect of mining exposure on property, violent, or traffic crime convictions among young male migrants. In contrast,

[21] The full sample (18-39-year-old males) is included in this table.

[22] Online Appendix Table C.4 show the results for the 30-39-year-old male sample.

column (8) reveals a positive and statistically significant effect on substance-related crime convictions: migrants relocating to mining municipalities are more likely to be convicted of substance crimes relative to migrants settling in control municipalities. While the baseline probability of substance convictions among migrants is low, the relative effect is sizeable, suggesting that mining-driven local conditions amplify substance-related criminal activity among migrants.

Table 5: Impact of the mining boom on criminal behavior of migrants, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime	(5) Property crime	(6) Violent crime	(7) Traffic crime	(8) Substance crime
Post*Migrants (Mining mun.)	0.0107**	0.0041	-0.0084	-0.0006	0.0017	-0.0039	-0.0081	0.0105*
	(0.0052)	(0.0033)	(0.0052)	(0.0051)	(0.0058)	(0.0039)	(0.0058)	(0.0057)
Post*Migrants (Control mun.)	0.0093***	0.0070***	0.0010	-0.0078***				
	(0.0033)	(0.0022)	(0.0028)	(0.0029)				
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nxt	155753	155753	155753	155753	50603	50603	50603	50603
N	9735	9735	9735	9735	3163	3163	3163	3163
Mean dep. var (2000-03)	0.0616	0.0205	0.0446	0.0466	0.0169	0.0063	0.0108	0.0058
Effect relative to the mean, Treated (%)	17.32	19.82	-18.78	-1.20	9.92	-61.02	-74.81	181.32
Effect relative to the mean, Control mun. (%)	15.12	34.27	2.26	-16.69	0.00			
R-squared	0.4892	0.3494	0.4901	0.5258	0.4455	0.3270	0.3891	0.4634
Within R-squared	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001

Notes: Two-way fixed effects panel data regression. Migrants before the move are the references. Standard errors (in parentheses) are clustered at the grid level. Columns (1)-(4) compare migrants to the mining municipalities or the control municipalities to themselves before the migration event. Columns (5)-(8) compare migrants to the mining municipalities to migrants to the control municipalities. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Overall, these results imply that the mining boom does not broadly increase criminal behavior among migrants across all crime categories. Instead, its effects are concentrated in substance-related offenses, consistent with mechanisms related to increased local income, demand, or illicit market activity in mining areas, rather than generalized increases in criminality driven by migration alone. Regarding other types of crime, the evidence suggests that the economic benefits associated with the boom—such as increased employment and earnings opportunities, as documented in Rodríguez-Puello and Rickardsson (2024)—mitigate potential criminal behavior among migrants to the mining municipalities. These results underscore the importance of distinguishing between individual- and aggregate-level analyses in evaluating the impacts of local economic shocks.

5.5 Additional evidence

Alcohol-related offenses. Given the observed increase in substance-related crime, a natural question is whether the mining boom also affected alcohol-related criminal behavior, including intoxicated driving (Tynan et al., 2017). To explore this, I separately analyze convictions under alcohol-related legislation, which include illegal production, possession, or sale of alcohol. Regarding intoxicated driving, those are included under traffic crimes, encompassing driving under the influence alongside other driving-related offenses under the Traffic Offenses Act, which the data does not allow to separate. The results show no statistically significant effects of the mining boom on alcohol-related convictions, alcohol-related suspicions, or on traffic crime. Moreover, alcohol-related offenses account for only a very small share of substance-related convictions in the data, with the vast majority falling under the Narcotics Law (approximately 95%). Together, these findings indicate that the increase in substance-related crime documented in the main analysis is not driven by alcohol-related offenses or intoxicated driving, but instead reflects changes in narcotics-related convictions. While the data do not allow for a more granular separation of alcohol consumption or intoxication intensity, the absence of effects on alcohol-related and traffic crimes suggests that alcohol-related behavior is unlikely to explain the main substance-related crime results.

Decomposing narcotics-related crime. As mentioned, the substance-related crime increase is driven by narcotics convictions. To further understand the increase in narcotics-related crime, I use information from the Crime Suspicion Register, maintained by the National Council for Crime Prevention. I decompose narcotics-related suspicions into production, selling, and holding/use offenses.[23] Table 6 that the overall increase is driven primarily by holding and use, with smaller increases in distribution and production from very low baseline levels. This pattern is consistent with increased local demand and market activity rather than widespread entry into drug production or trafficking. Importantly, these findings

[23]The outcomes are based on police suspicion records and capture suspected involvement in narcotics-related offenses. Base rates for production and distribution are very low; estimates should be interpreted with caution.

align with the main results showing that substance-related convictions increase primarily among repeat offenders and are concentrated among residents most directly exposed to the mining boom. Together, the evidence suggests that improved local economic conditions lead to an intensification of substance use and related activity among a subset of individuals, rather than a broad shift toward criminal entrepreneurship. This interpretation is consistent with existing evidence that positive resource shocks can increase engagement in risky or addictive behaviors, even as they reduce economically motivated crimes such as property offenses (e.g., James and Smith, 2017; Cunningham et al., 2020; Axbard et al., 2021).

Table 6: Impact of the mining boom on narcotics-related suspicions by offense type, 2000-2015

	(1) Narcotic suspicion	(2) Narcotic production	(3) Narcotic distribution	(4) Narcotic use-holding
Post*Treated	0.0055**	0.0009**	0.0014*	0.0049**
	(0.0023)	(0.0004)	(0.0007)	(0.0023)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	230480	230480	230480	230480
N	14405	14405	14405	14405
Mean dep. var (2000-03)	0.0045	0.0000	0.0006	0.0017
Effect relative to the mean (%)	122.92	2603.78	209.61	290.00
R-squared	0.4056	0.1691	0.2194	0.4025
Within R-squared	0.0000	0.0000	0.0000	0.0000

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Gender-based violence. Another natural concern is whether the increase in substance-related crime during the mining boom translated into higher levels of gender-based violence, particularly given the highly male-dominated nature of the mining sector. Theoretically, the expected effects are ambiguous: increases in substance use or risky behavior could raise the incidence of violence, while improved labor market opportunities could reduce stress and lower the risk of violent behavior. To explore this possibility, I use information from the Crime Suspicion Register, which includes individuals reasonably suspected of a crime and provides information on victim gender, allowing identification of suspected offenses involving violence against women.[24] I find no statistically significant effects of the mining boom on suspected

[24] This approach is necessary because the conviction register does not consistently identify the gender of the victim. A limitation is that the data do not allow for a more precise separation of intimate partner violence from other forms of violence against woman. The outcome is equal to one if the individual is suspected of the following crimes: assault against a woman, (attempted) murder of woman, unlawful threat against a woman, stalking of a woman, molestation of a woman, sexual molestation of a woman, (attempted) rape of a woman or a person of unspecified gender, and violation of the restraining order act.

violence against women. Moreover, such cases are relatively rare in the sample, accounting for less than one percent of young males, which limits statistical power. Taken together, these results suggest no detectable impact of the mining boom on gender-based violence, while highlighting the need for future research using richer data to better understand how local economic shocks affect different forms of violence.

Health-related outcomes. Given the increase in substance-related crime, an additional concern is whether the mining boom affected health-related outcomes, including mental health or risky behavior that may not result in criminal convictions. For example, Shandro et al. (2011) finds increases in pregnancies, sexually transmitted infections, and mine related injuries during booming mine activities, while mental health issues such as depression and anxiety were reported during bust periods. While I do not have health data to analyze this in detail, I explore it by examining employer-paid sick leave spells exceeding two weeks, which capture more serious or prolonged health episodes and are available in the administrative data. While sick leave is an imperfect proxy for health and mental health, prior work has used extended sickness absence as an indicator of underlying health shocks. The analysis reveals no statistically significant effects of the mining boom on the incidence of long-term sick leave or sickness benefit payments among young male residents. These results suggest no detectable impact of the boom on severe health-related work absences during the study period, although more granular health data would be required to identify specific mental health or substance-related conditions.

5.6 Robustness checks

The estimated impacts of the mining boom on criminal behavior are robust to various alternative specifications and robustness checks.

By treated municipality. As the first alternative specification, I estimate the main results individually for Gällivare and Kiruna (Online Appendix Table A.6). This is important because, while both municipalities are heavily dependent on mining, they are different in other aspects. For instance, in Kiruna, in 2004, the government made a plan to move the city of Kiruna 4 kilometers east, a process that started in 2013. The main reason was the security of the population because years of mining had caused the town to sink into the ground. This policy may affect individuals' behavior, the labor market, and crime in the municipality. It may have created substantial social and demographic disruption, including population displacement, new housing construction, and temporary inflows of workers. Therefore, I expect weaker or even opposite effects relative to Gällivare, as the relocation may offset the effects of improved labor market opportunities. There is no significant effect on the criminal behavior among young male residents in Kiruna municipality due to the mining boom. The effect observed is concentrated among the residents of Gällivare.[25]

[25] Online Appendix Table C.5 show the results for the 30-39-year-old male sample.

Data-driven rings. A concern when using distance to construct a categorical treatment indicator and assigning individuals into different treatment groups (rings) is the choice of distance cutoffs to construct the treatment intensity. According to Butts (2023), the wrong choice of cutoff biases the results, while the correct identification of the cutoff enables an enhanced understanding of the spatial propagation of the treatment effects. I use an alternative nonparametric estimator that provides a more complete picture of how the shock affects units at different distances, proposed by Butts (2023).[26] It estimates a curve that represents the effect as a function of distance by using many rings. In addition, it selects the rings in a data-driven procedure, eliminating the need to specify a cutoff where the treatment effects become zero to estimate the average treatment effect (Cattaneo et al., 2019), thereby avoiding potential specification searching (Andrews and Kasy, 2019). Using this method, I obtain ten rings grouping the young males sample according to their distance to the nearest mine. The results, in Online Appendix Table A.7, show that the findings are robust to this empirical strategy.[27]

Travel time treatment. Next, as an alternative to defining treated individuals based on geographical distance, I redefined treatment using travel time by car, measured with OpenStreetMap data using the Open Source Routing Machine (OSRM). I classify individuals into 20-minute rings, obtaining a total of five rings, where individuals located farther away serve as controls. Online Appendix Table A.8 reports the results.[28] The estimated effects for being convicted of property and substance-related crime are virtually unchanged, compared to those of Panel A Table 1, confirming that the findings are robust to this alternative treatment definition. Specifically, there is a negative and significant reduction in the probability of being convicted of property crime after the mining boom for young male residents located within 20 minutes by car of the mines, and an increase in substance crimes for the same treated individuals.

Triple difference-in-differences. I estimate a triple difference-in-differences (DDD) model to further account for unobserved municipality-level shocks (Online Appendix Table A.9). This approach compares changes in criminal behavior before and after the mining boom between treated and non-treated areas, and additionally across employment sectors (public vs. non-public). The triple interaction term isolates whether the mining boom had a differential effect on crime for individuals employed in the public sector relative to others, netting out common time trends, area-specific shocks, and baseline sectoral differences. Following Rodríguez-Puello and Rickardsson (2024), workers in the public sector do not experience any labor market effect from the mining boom, providing a good group for this

[26] According to Butts (2023), this method is similar to using the distance to the nearest mine as a continuous measure to estimate the "dosage-response" function proposed by Callaway et al. (2024) in the difference-in-differences approach with continuous treatment.

[27] Online Appendix Table C.6 show the results for the 30-39-year-old male sample.

[28] Online Appendix Table C.7 show the results for the 30-39-year-old male sample.

placebo analysis. As expected, there is no evidence that public-sector workers in mining-exposed areas experienced crime changes that differ systematically from those of non-public workers. The absence of a triple-difference effect implies that public-sector employees are insulated from the mining shock, consistent with greater income stability and weaker exposure to local labor market fluctuations.[29]

Additional robustness checks. Online Appendix Table A.10 shows the robustness checks for the main results of young males (18-29 years old).[30] Column (1) reports the results from the baseline specification for reference, focusing only on the sample of young male residents. In Column (2), I limit the movement of individuals across treated and control municipalities by defining their treated/control status on the municipality of residence in 2003. This change has little effect on the coefficient estimates. In Column (3), I include time-varying individual-level controls, such as being married, having children under 18, education categories (primary, secondary, and tertiary), and economic sector, which distinguishes between non-employed, primary (extraction and agriculture), secondary (manufacturing and construction), and tertiary (services, healthcare, public sector, and other). I do not include the control variables in the main specification because some of the controls could be endogenous to the mining boom (Allcott and Keniston, 2018; Pérez-Trujillo and Rodríguez-Puello, 2022; Rodríguez-Puello, 2025), becoming bad controls. The main results are robust. In Column (4), I estimate the results by also including migrants. As noted above, by separating the effect for residents and migrants, I can exclude crimes committed in the mining municipalities by new individuals who migrated to the relatively stronger labor markets looking for better opportunities. In this way, I can distinguish the effect of the economic shock from the impact of the changing demographics on overall crime rates. The inclusion of migrants in the analysis of the individuals' behavioral change in crime does not change the results.

In Column (5), I restrict the sample to a balanced panel to improve the stability across time in the sample size and follow individuals throughout the whole period. The results are robust to this restriction. In Column (6), I exclude residents located in the four neighboring municipalities, which are most prone to spillovers, to check for the SUTVA assumption. The results remain robust, providing evidence of no spillover effects to neighboring municipalities. A possible reason is that population density in northern Sweden is low, and the municipalities cover large geographical areas. Finally, in column (7), grid fixed effects are replaced with municipality fixed effects to account for possible confounding omitted variables at the municipality level, and the results remain robust.

[29] Online Appendix Table C.8 show the results for the 30-39-year-old male sample.

[30] Online Appendix Table C.9 show the results for the 30-39-year-old male sample.

6 Contextualization and mechanisms

6.1 Social cost effects

Online Appendix Table A.11 translates the main crime effect estimates into estimates of the effect of the mining boom on social costs of crime for young males, as Alsan et al. (2025). Specifically, I calculate the total unit cost for each crime category, which includes the costs for anticipation (e.g., defensive expenditure), consequence (e.g., physical and emotional harm), and response (e.g., police costs) to the crime, as reported in Heeks et al. (2018). I multiply the estimated coefficients of Panel A Table 1 by the cost of crime and add it by the number of treated young male individuals during the boom, obtaining the aggregate social cost effect (total welfare implication) of the mining boom.

The results show a mixed picture. Consistent with the regression estimates, reductions in property crimes translate into sizeable social savings, amounting to SEK 17.8 million during the boom. These savings are meaningful at the local level, even if modest relative to national figures. However, other categories reveal offsetting costs. The effects on violent and traffic crimes are statistically insignificant. substance crimes increase significantly during the boom, leading to social losses of roughly SEK 14.1 million. This pattern mirrors the conviction results and suggests that mining-driven shocks may have unintended spillovers into illicit substance activity. Taken together, the social cost estimates underscore that the mining boom had heterogeneous welfare implications. On balance, the largest and most robust effects come from reductions in property crimes, which dominate the aggregate social savings. At the same time, the rise in substance-related crime partly offsets these benefits.

6.2 Literature comparison

Online Appendix Figure B.9 shows a comparison of other comparable quasi-experimental estimates that analyze the effects of resource shocks and crime in the literature, such as mining and fracking booms. See Online Appendix E for details on the papers and effect size construction. Each point indicates the estimated effect of treatment (direct percent change) on criminal behavior for treated areas or individuals relative to controls as a percent of the control mean. When not specified, the outcome in the paper is all types of crime.

As can be seen, previous literature finds mixed evidence of resource shocks on crime. On the one side, most aggregate-level studies on resource shocks find increases in crime levels in local communities in the US (James and Smith, 2017; Komarek, 2018; Andrews and Deza, 2018) and null effects in Chile (Corvalan and Pazzona, 2019), which are contrary to expectations on Becker (1968) model. These studies explain these crime increases based on increases in criminal opportunities, access to disposable income for activities that complement crime, and population changes due to migration. On the contrary, recent studies find that residents in resource areas reduce their criminal behavior due to better economic opportunities (in line with Becker (1968)) (Axbard et al., 2021; Street, 2025). Which is in line with the evidence provided in this paper for young males. The baseline result of this paper on the effect of the mining boom (reduction in property crime) is comparable to the effects from other resource shocks papers in South Africa (Axbard et al., 2021) and the US (Street, 2025). One possible reason for the mixed results in previous literature is that aggregate-level studies do not account for the migration of crime-prone individuals to the resource areas attracted by the boom. When this is accounted for, Axbard et al. (2021) and Street (2025) find reductions in crime among residents. Together, these comparisons show that resource shocks that come close to isolating the impact of economic opportunity on criminal behavior generate the expected reductions in crime in other environments and countries.

A more general comparison to previous literature on economic shocks and criminal behavior can be made by using the effect of the shock on crime and relating it to the effect on earnings. This provides an implied elasticity of crime with respect to earnings, which is more comparable among studies. Specifically, by considering the effect of the mining boom on labor income (Column 2 Table 7), I divide the effect on property crime by the 24.8% increase in labor income and estimate an implied elasticity of property crime to earnings equal to -2. That is, a 1% increase in earnings is associated with a 2% decrease in property crime conviction probability.[31] This suggests that property crime convictions are relatively elastic to income shocks in this context, in comparison to Britto et al. (2022), who uses job loss as a shock and finds an implied elasticity of crime to earnings equal to -0.58. On the contrary, it goes in line with previous literature, which finds that higher wages reduce crime with an implied elasticity roughly between -1 to -2.5 (e.g., Gould et al., 2002; Machin and Meghir, 2004; Agan and Makowsky, 2023).

Earlier studies have found that natural resources can lead to increased violent grabbing, appropriation, conflict, and civil war (e.g., Collier and Hoeffler, 2005; Berman et al., 2017).[32] Recent studies have explored these dynamics at the subnational level, often focusing on developing countries, where state capacity is weak and conflict events are more prevalent (Lei and Michaels, 2014; Maystadt et al., 2014). (Axbard et al., 2021) analyzes the crime and conflict responses to natural resource wealth in South Africa, observing effects for crime and not conflict. The authors argue that the causal effect of resource value on crime is different from the effect on conflict. The Swedish case differs in two important respects. First, Sweden is a stable democracy with strong institutions and no recent history of armed conflict, making violent appropriation an unlikely channel. Second, instead of conflict, local

[31] It is important to note that I do not attach a causal interpretation to the elasticity, as this would require that the mining boom affects criminal behavior only through (higher) earnings. This is not the case, as the effect could occur through other mechanisms, such as crime prevention capacity, migration, and so on (I discuss these mechanisms in detail in Section 6.3).

[32] See Vanden Eynde and Vargas (2025) for a recent review on the theoretical and empirical literature about how natural resource dynamics contribute to conflict.

responses to resource shocks are more likely to manifest in socioeconomic outcomes such as crime, migration, and labor market adjustments.

6.3 Why does the mining boom affect crime?

Generally, the estimates are reduced-form effects that encompass multiple potential mechanisms. However, I claim that the estimates are consistent with an opportunity cost mechanism from an improvement in labor market conditions. To illustrate the potential pathways linking the mining boom to changes in criminal behavior, Online Appendix Figure B.10 presents a Directed Acyclic Graph (DAG) that maps out the main hypothesized mechanisms. The diagram highlights how the mining boom may affect crime through an opportunity cost channel via improved labor market conditions, but also through other indirect channels such as income inequality, and crime prevention capacity.

In this section, I use the same empirical design described in Section 4 (using the variables capturing these mechanisms as outcomes) to explore the first-stage effect for the mechanisms via which a mining boom might affect criminal behavior, even though I cannot definitively distinguish across them or rule out the possibility that there are other intermediating variables at work.[33] I analyze the role of the opportunity cost channel via labor market improvements and then follow with the other indirect channels.

Labor market opportunity cost. Established literature shows that local communities exposed to resource shocks tend to experience improvements in labor market conditions (Corden and Neary, 1982; Sachs and Warner, 2001; Allcott and Keniston, 2018).[34] Several empirical papers find positive effects on employment (Black et al., 2005; Pérez-Trujillo and Rodríguez-Puello, 2022) and earnings (Weber, 2012; Tano et al., 2016; Rodríguez-Puello and Rickardsson, 2024). The link between labor market conditions and crime has also been explored (e.g., Raphael and Winter-Ebmer, 2001; Edmark, 2005; Öster and Agell, 2007; Fougère et al., 2009; Nordin and Almén, 2017; Dix-Carneiro et al., 2018). Therefore, labor market conditions constitute a natural channel through which a mining boom may have

[33] Another approach to evaluate mechanisms in the literature is to include the variable on the right-hand side as a control to see how the main treatment effect changes and test mediation or partial channeling. Nevertheless, the main concern why I do not apply it is that mediators (e.g., earnings) are bad controls and bias the treatment effect.

[34] When there is a mining boom, due to an increase in international prices, revenues in the resource sector will increase, generating a shift from the nontradable sector to the export-oriented tradable (resource) sector. This economic movement would cause a positive shift in the demand for labor in the resource sector. As a result, employment, wages, and earnings are expected to increase in local communities affected by the boom (Corvalan and Pazzona, 2019; Chávez and Rodríguez-Puello, 2022), especially in the resource sector. Due to spillover effects between economic sectors, the boom may affect sectors beyond extraction. For example, sectors directly linked to the extractive sector as input providers would eventually experience an increase in demand due to the higher employment in the area, leading to an overall positive effect on the labor market of residents extended throughout the local economy.

affected crime. According to Becker (1968), if individuals face improved labor markets, the returns to legal activity increase, and individuals should substitute away from illegal activities.

I start by examining how the mining boom affects the labor market conditions of young male residents in the mining municipalities and discuss its relative importance in explaining the changes in crime as a result of the resource shock (Table 7).[35] Columns (1), (2), (3), (4), and (5) show the results for disposable income, labor income (earnings), labor income conditional on being employed, employment overall, and employment in the mining sector, respectively.[36] Consistent with previous work, the mining boom raises labor market opportunities on both the extensive and intensive margins. Specifically, the mining boom has a positive effect on the labor market conditions of young male residents in the mining municipalities, with a significant increase in disposable and labor income, and the probability of being employed, especially directly in the mining sector. Yearly disposable income increases by 17,923 SEK for treated young male residents after the mining boom compared with control residents. This represents a 17% increase from the baseline mean. The observed increase in labor income is higher. While there is no clear effect on employment due to different effects for different economic sectors, a substantial increase is observed in the probability of being employed in the mining sector.[37] The results show that a mining boom has positive effects on labor market conditions in the Swedish case, as noted in previous literature (Tano et al., 2016; Rodríguez-Puello and Rickardsson, 2024). This may increase the opportunity cost of engaging in criminal activity, thereby reducing local crime levels (Draca and Machin, 2015; Edmark, 2005; Axbard et al., 2021). This mechanism seems to be dominating over the one that suggests that a mining boom that increases earnings generates higher benefits to committing crimes because now people are wealthier, increasing the payoff of crime.

Government's crime prevention capacity. Becker (1968) highlights that the probability of detection is an important factor to consider when examining factors influencing an individual's decision to commit a crime. Increasing the probability of being caught and/or the resulting punishment may reduce crime according to theory. Previous literature has shown that crime decreases when there is an increase in police presence (Di Tella and Schargrodsky, 2004; Machin and Marie, 2011). Therefore, a concern in interpreting the main results is that the reductions in crime may be due to improvements in the government's

[35] Online Appendix Table C.10 show the results for the 30-39-year-old male sample.

[36] Disposable income is the sum of all incomes, including other benefits (e.g., child allowances, social benefits, and housing benefits) minus final tax. All income variables are adjusted to real values with the base year 2000 using the national CPI. To avoid typical problems of zeros in the outcome variables (Chen and Roth, 2024; Mullahy and Norton, 2024), I measure income in levels. Therefore, the coefficients can be interpreted as the effect on income as measured directly in 100 Swedish krona (in 100 SEK).

[37] Rodríguez-Puello and Rickardsson (2024) finds that the mining boom in Sweden increased employment in mining and manufacturing, while there is a reduction in service employment due to high competition for workers.

crime prevention capacity. A mining boom increases resource wealth through higher revenues from mining operations in local communities, thereby enhancing the provision of public goods (e.g., security and policing resources) and the capacity of local governments to combat crime (Foley, 2011; Axbard et al., 2021). This is especially important in countries where the government implements revenue-sharing schemes to ensure that locals benefit from resource booms. For example, in Chile, a mineral tax is expected to benefit municipalities hosting the extraction directly. By law, this wealth must be allocated toward enhancing the residents' welfare (Paredes and Rivera, 2017).

As an approximation to this mechanism and as a proxy of the government's crime prevention capacity, I test for changes in the police force by examining the effect of the mining boom on the probability of young male residents becoming a police worker (Columns (5) and (6) Table 7).[38] The results indicate that there is no increase in police forces due to the mining boom. The observed no change in police in Sweden is expected since police resources are funded by the state alone, not by the state and local authorities as it is in other countries (Lindström, 2015), and it does not depend on the crime level or economic conditions in each municipality. As a result, changes in the police force are unlikely to be driving the significant crime reduction. Consistent with this result, James and Smith (2017) and Axbard et al. (2021) find that changes in fracking activities and mining value did not affect police operations, ruling it out as a driving mechanism behind the observed changes in crime.

[38]There are two ways of classifying residents as police workers using data from Statistics Sweden. Since neither of them is a perfect classification, I use both to compare the results. I classify as police those individuals working in the security sector using the Swedish Standard Industrial (SNI) Classification from 2007, specifically classified in the codes 74900, 80100, 80200, 80300, and 84240. I use this data because they are available for the whole period of analysis. As a comparison, I use data from the "Swedish Occupational Register with Statistics" (Statistics Sweden) for the period 2001-2015. The data are available only after 2001, and those for the years 2014 and 2015 are not comparable. As police officers, I consider patrol officers, criminal investigators, and community police officers (Lindström, 2015). The correlation of the police per capita variables for the period 2001-2013 among the two measures is 90%.

Table 7: Mechanisms: impact of the mining boom on different mechanisms, 2000-2015

	(1) Disposable income	(2) Labor income	(3) Lab. inc. employed	(4) Employment	(5) Employment mining	(6) Police occupation	(7) Police industry	(8) Top earning tercile
Post*Treated	179.2325***	283.6183***	261.9730***	0.0186**	0.0869***	0.0033	0.0026	0.0071*
	(14.4637)	(22.0785)	(22.9279)	(0.0094)	(0.0068)	(0.0023)	(0.0021)	(0.0040)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nxt	230480	230480	152308	230480	230480	187619	230480	124267
N	14405	14405	9519	14405	14405	11726	14405	7767
Mean dep. var (2000-03)	1076.8738	1145.6519	1724.7957	0.6225	0.0219	0.0019	0.0052	0.2197
Effect relative to the mean (%)	16.64	24.76	15.19	2.99	396.29	170.34	50.07	3.23
R-squared	0.6161	0.7432	0.7152	0.5618	0.6831	0.5546	0.5200	0.9176
Within R-squared	0.0007	0.0025	0.0024	0.0000	0.0083	0.0001	0.0000	0.0001

Notes: Two-way fixed effects panel data regression. Disposable income and labor income expressed in 100 SEK and in real values with the base year 2000. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Income inequality. According to the economics literature on crime, there are rational incentives to commit crimes when there are lower-income people near high-income people in a community (Deller and Deller, 2010), and the economic gains of a mining boom may be concentrated among specific population groups, such as extraction workers rather than other residents (Hardy and Kelsey, 2015). There is empirical literature linking resource booms with income inequality (e.g., Reeson et al., 2012; Loayza et al., 2013) and income inequality with crime and violence (e.g., Kelly, 2000; Bourguignon et al., 2003; Neumayer, 2005). Therefore, combining both pieces of evidence, a mining boom that increases local income inequality may indirectly generate incentives to commit crime. While I do not observe property crime increases due to the mining boom, only increases in substance-related crimes, it is important to examine this mechanism to discard its role in the main results.

Measuring income inequality at the individual level is a challenge. I examine the effect of the mining boom on the probability of moving into (or out of) the top of the income distribution. Specifically, using the labor income in 2003, I classify individuals by year and municipality of residence into terciles, and use a binary outcome equal to one if the individual is in the third tercile (top of the income distribution). The results (Column (7) Table 7) show weak evidence that the mining boom increases the probability of being at the top of the income distribution. Nevertheless, the effect is only statistically significant at the 10% level, and the relative effect is small. Therefore, there is no evidence suggesting that income inequality played a role in the changes in criminal behavior. This result is contrary to James and Smith (2017), who finds descriptive evidence for this mechanism in the case of the impact of an energy boom on regional crime in the United States, where the resource shock increased crime rates in shale-rich counties, and this coincided with a rise in income inequality.

Overall, the evidence suggests that the observed reduction in property crime and increase in substance crimes following the mining boom is likely driven by improved labor market conditions. Better labor market opportunities raise the opportunity cost of engaging in criminal behavior (Becker, 1968). Selective migration, improvements in crime prevention capacity, and income inequality do not drive the results.

7 Conclusions

The present study provides evidence of the local effects of a mining boom that started in 2004 on criminal behavior in Sweden. Sweden is a developed country with a long tradition of mining, especially in the North of the country, and, therefore, is subject to both the positive and negative effects of commodity price volatility. The Becker (1968) and Ehrlich (1973) economic theory of crime, and the discussed mechanisms, suggest that there are competing effects that could result in an increase, decrease, or null changes (canceling each other) in the criminal behavior of residents in mining municipalities as a result of the mining boom. These competing theoretical predictions highlight the importance of the empirical analysis of the relationship between a mining boom and local criminal behavior.

More specifically, I exploit the boom in iron ore prices in northern Sweden as a plausibly exogenous shock to local economic conditions, which is similar to local stimulus from large construction or manufacturing projects. Using detailed geocoded administrative data on all criminal convictions and demographics in Sweden from 2000 to 2015, I estimate the effect of improvement in labor market conditions on the criminal behavior of young males using difference-in-differences and event study models. An important strength of this study is that by focusing the analysis on residents already living in the area before the boom, I distinguish the effect of improved economic opportunity from the effect of population inflows on aggregate crime, as Street (2025). Moreover, I contribute by focusing on people rather than places, and estimating the effect more in-depth in different types of crime and demographic sectors. Place-based analysis may provide misleading policy decisions because it is difficult to identify and account for mobility across space and economic sectors.

Results indicate that local young male residents (18-29 years old) experience a decrease in criminal activity during the mining boom. Specifically, I find a decline of 0.66 percentage points in the probability of being convicted of property crimes among treated young males relative to their non-treated counterparts. From a baseline sample mean of 0.012, this estimate translates to a 52% drop in individuals convicted. These results are consistent with recent literature that finds reductions in crime due to resource shocks that generate labor market opportunities (Corvalan and Pazzona, 2019; Axbard et al., 2021; Street, 2025). In addition, there is a positive and significant increase in the probability of being convicted of a substance-related crime after the mining boom for treated young male residents. I observe an increase of 0.46 percentage points in the probability of being convicted of a substance crime among treated individuals relative to their non-treated counterparts. From a baseline sample mean of 0.002, this estimate translates to a 181% increase in individuals convicted. There is no significant effect of the mining boom on young males aged 30-39. These effects are driven by existing residents in the area, rather than in-migrants, and are concentrated among young males located within 20 km of the mines.

In addition, I take advantage of the panel structure of the data and the detailed criminal information to construct additional outcomes that reflect in more detail the criminal behavior of young males as a response to the mining boom. Results show that the reduction in property crimes for young males due to the mining boom is concentrated among first-time offenders, suggesting that improved labor market conditions through increased opportunity costs may deter individuals from engaging in crime for the first time. On the contrary, there is no effect on the probability of re-offending, suggesting no broader behavioral responses that include repeat offenders, and individuals with prior convictions are less responsive to local economic changes. Regarding substance crimes, I observe the opposite pattern. The increase in substance crime convictions for young males due to the mining boom is concentrated among re-offenders, suggesting that the boom primarily intensifies criminal activity among individuals with pre-existing involvement in substance-related offenses, rather than inducing new entry. The observed reductions in property crime are consistent with Becker (1968) model, where improved legal labor market opportunities raise the opportunity cost of engaging in economically motivated offenses, and in line with previous literature (e.g., James and Smith, 2017; Andrews and Deza, 2018).

To understand this result, the analysis of mechanisms suggests that the mining boom had a direct, significant effect on the labor market, improving the labor market conditions for individuals living in the Swedish mining municipalities. On the other hand, I find no evidence that changes in the population composition through migrants, the government's crime prevention capacity (police force), and income inequality due to the mining boom drive the crime results. Therefore, an important mechanism that may explain these reductions in property crime levels is the improvement in labor market conditions, thereby increasing the opportunity cost of engaging in criminal activity (in line with Becker (1968)). Taken together, these results are consistent with economic opportunities reducing economically motivated crimes. Nevertheless, I also observe an increase in substance-related crimes, which may be driven by a high disposable income available for young males willing to expend in risky behaviors.

While this study focuses on a developed-country mining context, the results highlight general mechanisms through which local economic shocks affect criminal behavior. The focus on the mining boom as a laboratory to study the effects of economic conditions on criminal behavior is an important natural experiment that works as an opportunity to address concerns about economic shocks in general. Natural experiments classified as exogenous and that occurred in clearly specified local areas are difficult to find, but the mining boom is one such case. The mining boom provides a useful laboratory for studying how localized economic shocks affect criminal behavior, similar to other resource-dependent communities worldwide. Future work could examine how these mechanisms operate in settings with different institutional environments, such as developing countries or regions with weaker labor market protections and enforcement capacity.

References

Adjei, E. K., Eriksson, R., and Lundberg, J. (2023). The effects of a large industrial investment on employment in a remote and sparsely populated area using a synthetic control approach. *Regional Science Policy & Practice*, 15(7):1553–1576.

Agan, A. Y. and Makowsky, M. D. (2023). The minimum wage, EITC, and criminal recidivism. *Journal of Human Resources*, 58(5):1712–1751.

Allcott, H. and Keniston, D. (2018). Dutch disease or agglomeration? the local economic effects of natural resource booms in modern America. *The Review of Economic Studies*, 85(2):695–731.

Alsan, M., Barnett, A., Hull, P., and Yang, C. S. (2025). "something works" in US jails: Misconduct and recidivism effects of the IGNITE program. *The Quarterly Journal of Economics*, 140(2):1367–1415.

Álvarez, R., García-Marín, Á., and Ilabaca, S. (2021). Commodity price shocks and poverty reduction in Chile. *Resources Policy*, 70:101177.

Andrews, I. and Kasy, M. (2019). Identification of and correction for publication bias. *American Economic Review*, 109(8):2766–2794.

Andrews, R. J. and Deza, M. (2018). Local natural resources and crime: Evidence from oil price fluctuations in Texas. *Journal of Economic Behavior & Organization*, 151:123–142.

Asher, S. and Novosad, P. (2023). Rent-seeking and criminal politicians: Evidence from mining booms. *Review of Economics and Statistics*, 105(1):20–39.

Athey, S. and Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, 113(27):7353–7360.

Athey, S. and Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics*, 11(1):685–725.

Athey, S., Tibshirani, J., and Wager, S. (2019). Generalized random forests. *The Annals of Statistics*, 47(2):1148–1178.

Axbard, S., Benshaul-Tolonen, A., and Poulsen, J. (2021). Natural resource wealth and crime: The role of international price shocks and public policy. *Journal of Environmental Economics and Management*, 110:102527.

Baffes, J. and Haniotis, T. (2010). Placing the recent commodity boom into perspective. *Food prices and rural poverty*, pages 40–70.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2):169–217.

Beleche, T. and Cintina, I. (2018). Fracking and risky behaviors: Evidence from Pennsylvania. *Economics & Human Biology*, 31:69–82.

Benshaul-Tolonen, A., Chuhan-Pole, P., Dabalen, A., Kotsadam, A., and Sanoh, A. (2019). The local socioeconomic effects of gold mining: Evidence from Ghana. *The Extractive Industries and Society*, 6(4):1234–1255.

Berman, N., Couttenier, M., Rohner, D., and Thoenig, M. (2017). This mine is mine! how minerals fuel conflicts in Africa. *American Economic Review*, 107(6):1564–1610.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1):249–275.

Besley, T. and Case, A. (2000). Unnatural experiments? estimating the incidence of endogenous policies. *The Economic Journal*, 110(467):672–694.

Black, D., McKinnish, T., and Sanders, S. (2005). The economic impact of the coal boom and bust. *The Economic Journal*, 115(503):449–476.

Bourguignon, F., Nuñez, J., and Sanchez, F. (2003). A structural model of crime and inequality in Colombia. *Journal of the European Economic Association*, 1(2-3):440–449.

Britto, D. G., Pinotti, P., and Sampaio, B. (2022). The effect of job loss and unemployment insurance on crime in Brazil. *Econometrica*, 90(4):1393–1423.

Brunnschweiler, C. N. and Bulte, E. H. (2008). The resource curse revisited and revised: A tale of paradoxes and red herrings. *Journal of Environmental Economics and Management*, 55(3):248–264.

Brunnschweiler, C. N. and Poelhekke, S. (2021). Pushing one's luck: Petroleum ownership and discoveries. *Journal of Environmental Economics and Management*, 109:102506.

Brå, T. S. N. C. f. C. P. (2023). Crime and statistics. Accessed = 2023-05-12.

Butts, K. (2023). JUE insight: Difference-in-differences with geocoded microdata. *Journal of Urban Economics*, 133:103493.

Callaway, B., Goodman-Bacon, A., and Sant'Anna, P. H. (2024). Difference-in-differences with a continuous treatment. Technical report, National Bureau of Economic Research.

Carrington, K., Hogg, R., and McIntosh, A. (2011). The resource boom's underbelly: Criminological impacts of mining development. *Australian & New Zealand Journal of Criminology*, 44(3):335–354.

Cattaneo, M. D., Crump, R. K., Farrell, M. H., and Feng, Y. (2019). Binscatter regressions. *arXiv preprint arXiv:1902.09615*.

Chávez, A. and Rodríguez-Puello, G. (2022). Commodity price shocks and the gender wage gap: Evidence from the metal mining prices super-cycle in Chile. *Resources Policy*, 76:102497.

Chen, J. and Roth, J. (2024). Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics*, 139(2):891–936.

Christian, P. and Barrett, C. B. (2024). Spurious regressions and panel IV estimation: revisiting the causes of conflict. *The Economic Journal*, 134(659):1069–1099.

Collier, P. and Hoeffler, A. (2005). Resource rents, governance, and conflict. *Journal of Conflict Resolution*, 49(4):625–633.

Corden, W. M. and Neary, J. P. (1982). Booming sector and de-industrialisation in a small open economy. *The Economic Journal*, 92(368):825–848.

Corvalan, A. and Pazzona, M. (2019). Persistent commodity shocks and transitory crime effects. *Journal of Economic Behavior & Organization*, 158:110–127.

Couttenier, M., Grosjean, P., and Sangnier, M. (2017). The wild west is wild: The homicide resource curse. *Journal of the European Economic Association*, 15(3):558–585.

Cunningham, S., DeAngelo, G., and Smith, B. (2020). Fracking and risky sexual activity. *Journal of Health Economics*, 72:102322.

Cust, J. and Harding, T. (2020). Institutions and the location of oil exploration. *Journal of the European Economic Association*, 18(3):1321–1350.

Davis, J. M. and Heller, S. B. (2017). Using causal forests to predict treatment heterogeneity: An application to summer jobs. *American Economic Review*, 107(5):546–550.

Deller, S. C. and Deller, M. A. (2010). Rural crime and social capital. *Growth and Change*, 41(2):221–275.

Di Tella, R. and Schargrodsky, E. (2004). Do police reduce crime? estimates using the allocation of police forces after a terrorist attack. *American Economic Review*, 94(1):115–133.

Dix-Carneiro, R., Soares, R. R., and Ulyssea, G. (2018). Economic shocks and crime: Evidence from the Brazilian trade liberalization. *American Economic Journal: Applied Economics*, 10(4):158–195.

Draca, M. and Machin, S. (2015). Crime and economic incentives. *Annual Review of Economics*, 7(1):389–408.

Dustmann, C. and Glitz, A. (2011). Migration and education. In *Handbook of the Economics of Education*, volume 4, pages 327–439. Elsevier.

Edmark, K. (2005). Unemployment and crime: Is there a connection? *Scandinavian Journal of Economics*, 107(2):353–373.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy*, 81(3):521–565.

Elonheimo, H., Gyllenberg, D., Huttunen, J., Ristkari, T., Sillanmäki, L., and Sourander, A. (2014). Criminal offending among males and females between ages 15 and 30 in a population-based nationwide 1981 birth cohort: Results from the FinnCrime study. *Journal of Adolescence*, 37(8):1269–1279.

Epper, T., Fehr, E., Hvidberg, K. B., Kreiner, C. T., Leth-Petersen, S., and Nytoft Rasmussen, G. (2022). Preferences predict who commits crime among young men. *Proceedings of the National Academy of Sciences*, 119(6):e2112645119.

Erten, B. and Ocampo, J. A. (2013). Super cycles of commodity prices since the mid-nineteenth century. *World Development*, 44:14–30.

Farooki, M. and Kaplinsky, R. (2013). *The impact of China on global commodity prices: The global reshaping of the resource sector*, volume 57. Routledge.

Ferraz, E., Soares, R., and Vargas, J. (2022). Unbundling the relationship between economic shocks and crime. In *A Modern Guide to the Economics of Crime*, pages 184–204. Edward Elgar Publishing.

Feyrer, J., Mansur, E. T., and Sacerdote, B. (2017). Geographic dispersion of economic shocks: Evidence from the fracking revolution. *American Economic Review*, 107(4):1313–1334.

Fleming, D. A. and Measham, T. G. (2015). Income inequality across Australian regions during the mining boom: 2001–11. *Australian Geographer*, 46(2):203–216.

Foley, C. F. (2011). Welfare payments and crime. *The Review of Economics and Statistics*, 93(1):97–112.

Fougère, D., Kramarz, F., and Pouget, J. (2009). Youth unemployment and crime in France. *Journal of the European Economic Association*, 7(5):909–938.

Gamalerio, M., Luca, M., Romarri, A., and Viskanic, M. (2023). Refugee reception, extreme-right voting, and compositional amenities: evidence from Italian municipalities. *Regional Science and Urban Economics*, 100:103892.

Gould, E. D., Weinberg, B. A., and Mustard, D. B. (2002). Crime rates and local labor market opportunities in the United States: 1979–1997. *Review of Economics and Statistics*, 84(1):45–61.

Grenet, J., Grönqvist, H., and Niknami, S. (2024). The effects of electronic monitoring on offenders and their families. *Journal of Public Economics*, 230:105051.

Gröger, A. (2021). Easy come, easy go? economic shocks, labor migration and the family left behind. *Journal of International Economics*, 128:103409.

Guettabi, M. and James, A. (2020). Who benefits from an oil boom? evidence from a unique Alaskan data set. *Resource and Energy Economics*, 62:101200.

Haikola, S. and Anshelm, J. (2020). Evolutionary governance in mining: Boom and bust in peripheral communities in Sweden. *Land Use Policy*, 93:104056.

Haley, S., Klick, M., Szymoniak, N., and Crow, A. (2011). Observing trends and assessing data for Arctic mining. *Polar Geography*, 34(1-2):37–61.

Hardy, K. and Kelsey, T. W. (2015). Local income related to Marcellus shale activity in Pennsylvania. *Community Development*, 46(4):329–340.

Heeks, M., Reed, S., Tafsiri, M., and Prince, S. (2018). The economic and social costs of crime second edition. *Home Office Research report99*.

Huntington-Klein, N. (2021). *The effect: An introduction to research design and causality*. Chapman and Hall/CRC.

Jacobsen, G. D., Parker, D. P., and Winikoff, J. B. (2023). Are resource booms a blessing or a curse?: Evidence from people (not places). *Journal of Human Resources*, 58(2):393–420.

James, A. and Smith, B. (2017). There will be blood: Crime rates in shale-rich US counties. *Journal of Environmental Economics and Management*, 84:125–152.

Kearney, M. S. and Wilson, R. (2018). Male earnings, marriageable men, and nonmarital fertility: Evidence from the fracking boom. *Review of Economics and Statistics*, 100(4):678–690.

Kelly, M. (2000). Inequality and crime. *Review of Economics and Statistics*, 82(4):530–539.

Knobblock, E. A. and Pettersson, Ö. (2010). Restructuring and risk-reduction in mining: employment implications for northern Sweden. *Fennia-International Journal of Geography*, 188(1):61–75.

Komarek, T. M. (2016). Labor market dynamics and the unconventional natural gas boom: Evidence from the Marcellus region. *Resource and Energy Economics*, 45:1–17.

Komarek, T. M. (2018). Crime and natural resource booms: evidence from unconventional natural gas production. *The Annals of Regional Science*, 61:113–137.

Kovalenko, A. (2023). Natural resource booms, human capital, and earnings: Evidence from linked education and employment records. *American Economic Journal: Applied Economics*, 15(2):184–217.

Kumar, A. (2017). Impact of oil booms and busts on human capital investment in the USA. *Empirical Economics*, 52(3):1089–1114.

Lei, Y.-H. and Michaels, G. (2014). Do giant oilfield discoveries fuel internal armed conflicts? *Journal of Development Economics*, 110:139–157.

Lindström, P. (2015). Police and crime in rural and small Swedish municipalities. *Journal of Rural Studies*, 39:271–277.

Loayza, N., Mier y Teran, A., and Rigolini, J. (2013). Poverty, inequality, and the local natural resource curse. *World Bank Policy Research Working Paper*, (6366).

Machin, S. and Marie, O. (2011). Crime and police resources: The street crime initiative. *Journal of the European Economic Association*, 9(4):678–701.

Machin, S. and Meghir, C. (2004). Crime and economic incentives. *Journal of Human Resources*, 39(4):958–979.

Maystadt, J.-F., De Luca, G., Sekeris, P. G., and Ulimwengu, J. (2014). Mineral resources and conflicts in DRC: a case of ecological fallacy? *Oxford Economic Papers*, 66(3):721–749.

Meyer, B. D. (1995). Natural and quasi-experiments in economics. *Journal of Business & Economic Statistics*, 13(2):151–161.

Miller, D. L. (2023). An introductory guide to event study models. *Journal of Economic Perspectives*, 37(2):203–230.

Moritz, T., Ejdemo, T., Söderholm, P., and Wårell, L. (2017). The local employment impacts of mining: an econometric analysis of job multipliers in northern Sweden. *Mineral Economics*, 30:53–65.

Mullahy, J. and Norton, E. (2024). Why transform Y? the pitfalls of transformed regressions with a mass at zero. *Oxford Bulletin of Economics and Statistics*, 86(2):417–447.

Neumayer, E. (2005). Inequality and violent crime: Evidence from data on robbery and violent theft. *Journal of Peace Research*, 42(1):101–112.

Nordin, M. and Almén, D. (2017). Long-term unemployment and violent crime. *Empirical Economics*, 52:1–29.

Nordregio (2009). North norden: a new mining era.

Öster, A. and Agell, J. (2007). Crime and unemployment in turbulent times. *Journal of the European Economic Association*, 5(4):752–775.

Paredes, D. and Rivera, N. M. (2017). Mineral taxes and the local public goods provision in mining communities. *Resources Policy*, 53:328–339.

Pelzl, P. and Poelhekke, S. (2021). Good mine, bad mine: Natural resource heterogeneity and Dutch disease in Indonesia. *Journal of International Economics*, 131:103457.

Pérez-Trujillo, M. and Rodríguez-Puello, G. (2022). Economic shocks and their effect on the schooling and labor participation of youth: evidence from the metal mining price boom in Chilean counties. *The Annals of Regional Science*, 68(1):65–93.

Petterson, O. and Knobblock, E. (2010). Restructuring and risk-reduction in mining: employment implications for northern Sweden: 3rd Nordic geographers meeting special issue. *Fennia (Helsinki, 2010)*, 188(1):61–75.

Puschmann, P., Sundin, E., De Coninck, D., and d'Haenens, L. (2019). Migration and integration policy in Europe: Comparing Belgium and Sweden. *Images of immigrants and refugees in Western Europe: Media representations, public opinion and refugees' experiences*, pages 21–36.

Radetzki, M., Eggert, R. G., Lagos, G., Lima, M., and Tilton, J. E. (2008). The boom in mineral markets: How long might it last? *Resources Policy*, 33(3):125–128.

Raphael, S. and Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. *The Journal of Law and Economics*, 44(1):259–283.

Reeson, A. F., Measham, T. G., and Hosking, K. (2012). Mining activity, income inequality and gender in regional Australia. *Australian Journal of Agricultural and Resource Economics*, 56(2):302–313.

Rodrıguez-Puello, G. (2024). Digging for trouble? uncovering the link between mining booms and crime. *OSF*.

Rodríguez-Puello, G. (2025). Socioeconomic well-being in the face of commodity price shocks: Evidence from Chile. *The Journal of Development Studies*, 61(7):1081–1109.

Rodríguez-Puello, G. and Rickardsson, J. (2024). Spatial diffusion of economic shocks in the labor market: Evidence from a mining boom and bust. *Center for Open Science*.

Rossen, A. (2015). What are metal prices like? co-movement, price cycles and long-run trends. *Resources Policy*, 45:255–276.

Sachs, J. D. and Warner, A. M. (2001). The curse of natural resources. *European Economic Review*, 45(4-6):827–838.

SGU (2014). Statistics of the swedish mining industry 2013.

SGU (2016). Statistics of the swedish mining industry 2015.

SGU (2021). Statistics of the swedish mining industry 2021.

Shandro, J. A., Veiga, M. M., Shoveller, J., Scoble, M., and Koehoorn, M. (2011). Perspectives on community health issues and the mining boom–bust cycle. *Resources Policy*, 36(2):178–186.

Sinclair, B., McConnell, M., and Green, D. P. (2012). Detecting spillover effects: Design and analysis of multilevel experiments. *American Journal of Political Science*, 56(4):1055–1069.

Singleton, K. J. (2014). Investor flows and the 2008 boom/bust in oil prices. *Management Science*, 60(2):300–318.

Street, B. (2025). The impact of economic opportunity on criminal behavior: Evidence from the fracking boom. *Journal of Public Economics*, 248:105402.

Stretesky, P. and Grimmer, P. (2020). Shale gas development and crime: A review of the literature. *The Extractive Industries and Society*, 7(3):1147–1157.

Swedish Agency for Growth Policy Analysis, G. (2015). Sverige – ett attraktivt gruvland i världen? en internationell jämförelse.

Tano, S., Pettersson, Ö., and Stjernström, O. (2016). Labour income effects of the recent "mining boom" in northern Sweden. *Resources Policy*, 49:31–40.

The World Bank, W. (2011). World development report. tech. rep.

Tynan, R. J., Considine, R., Wiggers, J., Lewin, T. J., James, C., Inder, K., Kay-Lambkin, F., Baker, A. L., Skehan, J., Perkins, D., et al. (2017). Alcohol consumption in the Australian coal mining industry. *Occupational and environmental medicine*, 74(4):259–267.

Van der Ploeg, F. and Poelhekke, S. (2010). The pungent smell of "red herrings": Subsoil assets, rents, volatility and the resource curse. *Journal of Environmental Economics and Management*, 60(1):44–55.

Vanden Eynde, O. and Vargas, J. (2025). Theme 5 path-finding paper: Climate change, natural resources, and conflict. *Economic Policy*, page eiaf007.

Von der Goltz, J. and Barnwal, P. (2019). Mines: The local wealth and health effects of mineral mining in developing countries. *Journal of Development Economics*, 139:1–16.

Wager, S. and Athey, S. (2018). Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*, 113(523):1228–1242.

Weber, J. G. (2012). The effects of a natural gas boom on employment and income in Colorado, Texas, and Wyoming. *Energy Economics*, 34(5):1580–1588.

Wennström, J. and Oner, O. (2019). Political hedgehogs: The geographical sorting of refugees in Sweden.

Wilson, N. (2012). Economic booms and risky sexual behavior: evidence from Zambian copper mining cities. *Journal of Health Economics*, 31(6):797–812.

Wilson, R. (2022). Moving to economic opportunity: the migration response to the fracking boom. *Journal of Human Resources*, 57(3):918–955.

Winters, J. V., Cai, Z., Maguire, K., and Sengupta, S. (2021). Causal effects of the fracking boom on long-term resident workers. *Journal of Regional Science*, 61(2):387–406.

Online Appendix

Digging for Trouble? Mining and Criminal Behavior of Young Males

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A Appendix: Additional tables

Table A.1: Mining municipalities, mines and mining employment share

County	Municipality	Mine(s) and main product(s)	Population 2015	Mining employment share 2003	2010	2015
Norrbotten	Gällivare	Malmberget (Iron ore) and Aitik (Copper)	18,123	17.44%	20.89%	22.56%
Norrbotten	Kiruna	Kirunavaara (Iron ore) and Gruvberget (Iron ore)	23,178	13.94%	16.51%	18.44%
Västerbotten	Lycksele	Kristineberg (Copper/zinc) and Svartliden (Gold)	12,177	1.50%	1.97%	1.70%
Västerbotten	Malå	Storliden (Zinc/copper)	3,109	4.93%	6.10%	7.64%
Västerbotten	Norsjö	Maurliden (Copper/zinc) and Maurliden Ö (Copper/zinc)	4,176	2.92%	2.68%	4.69%
Västerbotten	Skelleftea	Björkdal (Gold) and Renström (Copper/zinc)	72,031	1.82%	1.88%	2.61%
Västerbotten	Sorsele	Blaiken (Zinc)	2,516	0.52%	1.37%	0.99%
Västerbotten	Storuman	Svartliden (Gold) and Blaiken (Zinc)	5,943	0.75%	0.80%	1.07%
Örebro	Askersund	Zinkgruvan (Zinc)	11,151	7.24%	7.39%	7.75%
Dalarna	Hedemora	Garpenberg (Zinc)	15,235	3.24%	3.35%	4.40%

Notes: Information from Statistics Sweden, Nordregio (2009), SGU (2014), Tano et al. (2016), and SGU (2021). Following Tano et al. (2016), municipalities are considered if they had an operating mine during the mining boom ranging from 2004 to 2010. Only individuals located in Norrbotten County are included in the paper, either as treated or control. Employment in the mining sector via the Swedish Standard Industrial (SNI) Classification 2002 includes the codes 10100, 10200, 10301, 10302, 12000, 13100, 13200, 14110, 14120, 14130, 14210, 14220, 14300, 14400, 14500, 29520, and 51820.

Table A.2: Description of crime variables

Crime category	Description
Total violations of the criminal code	Violent crimes Property crimes Crimes against the public Crimes against the state
Violent crimes	1+2+3+4+5
1. Violations of life and health	Completed murder, manslaughter, or assault with fatal outcome. Attempt, preparation, and branding for murder or manslaughter. Child killing.
2. Violations of freedom and peace	Kidnapping, human trafficking, human exploitation. Illegal restraint. Child welfare violation. Unlawful coercion. Serious breach of peace, serious breach of women's peace, unlawful persecution. Unlawful threats. Unlawful use of identity. Illegal invasion of privacy. Molestation. Urge to commit suicide. Reckless solicitation of suicide. Data breach, illegal wiretapping.
3. Defamation	Crime of defamation. Slander, insult, slander of the deceased.
4. Sexual offenses	Rape incl. Bearish. Negligent rape. Rape against children incl. Bearish. Sexual assault incl. gross, negligent sexual assault. Sexual exploitation of children under the age of 18. Sexual assault incl. violently against children under the age of 18. Intercourse with offspring or siblings. Purchase of sexual services, pimping of persons 18 years and older. Exploitation of children for sexual posing, purchase of sexual act of children under 18 years. Sexual harassment, exhibitionism. Contact to meet a child for sexual purposes.
5. Crimes against family	Bigamy, illicit marriage; Undue influence in the adoption of children adoption of children; Distortion of family status.
Property crimes	1+2+3+4+5
1. Theft, robbery and other assault	Theft of motor-driven means of transport. Theft of non-motorized means of transportation. Theft (including burglary). Theft by burglary. Theft without breaking and entering. Robbery without a firearm. Robbery with a firearm.

	Other offenses against the Criminal Code.
2. Fraud and other misconduct	Fraud, petty fraud, gross fraud, gross debt fraud. Other offenses against the Criminal Code.
3. Embezzlement and other faithlessness	Embezzlement, petty embezzlement, gross embezzlement; Wrongful disposal; Misdemeanor; Breach of trust; Abuse of authority.
4. Offenses against creditors, etc.	Misconduct against creditors, gross misconduct against creditors; Aggravation of bankruptcy and executive proceedings; Negligence against creditors; Undue favoring of creditor.
5. Crime of damage	Damage, minor damage, injury, serious damage: on motor vehicles, car fire or other motor vehicle fire, by fire, against state, municipality, county council, other manage, graffiti against public transport.

Notes: Own elaboration using Brå (2023) as a base. For a detailed description of the types of crimes and the Swedish criminal code, consult Brå (2023).

Table A.3: Summary statistics, 2000-2003 and 2004-2015

	Control 2000-2003 Mean SD	Treated 2000-2003 Mean SD	Total 2000-2003 Mean SD	Control 2004-2015 Mean SD	Treated 2004-2015 Mean SD	Total 2004-2015 Mean SD
Convicted property crime	0.009	0.009	0.009	0.011	0.009	0.010
	(0.092)	(0.097)	(0.093)	(0.102)	(0.094)	(0.101)
Convicted violent crime	0.005	0.005	0.005	0.006	0.006	0.006
	(0.069)	(0.068)	(0.069)	(0.076)	(0.076)	(0.076)
Convicted substance crimes	0.002	0.002	0.002	0.007	0.007	0.007
	(0.047)	(0.042)	(0.047)	(0.086)	(0.084)	(0.086)
Convicted traffic crimes	0.008	0.010	0.008	0.009	0.010	0.009
	(0.088)	(0.098)	(0.090)	(0.094)	(0.097)	(0.094)
Married	0.184	0.150	0.178	0.158	0.125	0.153
	(0.387)	(0.357)	(0.383)	(0.365)	(0.331)	(0.360)
Children under 18	0.416	0.411	0.416	0.390	0.375	0.387
	(0.493)	(0.492)	(0.493)	(0.488)	(0.484)	(0.487)
Primary education	0.493	0.602	0.511	0.341	0.390	0.349
	(0.500)	(0.490)	(0.500)	(0.474)	(0.488)	(0.477)
Secondary education	0.409	0.348	0.398	0.551	0.553	0.551
	(0.492)	(0.476)	(0.490)	(0.497)	(0.497)	(0.497)
Tertiary education	0.099	0.050	0.090	0.108	0.057	0.100
	(0.298)	(0.218)	(0.287)	(0.311)	(0.232)	(0.299)
Non-employed	0.270	0.232	0.263	0.251	0.162	0.236
	(0.444)	(0.422)	(0.440)	(0.433)	(0.369)	(0.425)
Primary sector	0.024	0.205	0.054	0.028	0.244	0.064
	(0.152)	(0.404)	(0.226)	(0.164)	(0.429)	(0.244)
Secondary sector	0.268	0.190	0.255	0.269	0.232	0.263
	(0.443)	(0.392)	(0.436)	(0.444)	(0.422)	(0.440)
Tertiary sector	0.439	0.373	0.428	0.452	0.362	0.437
	(0.496)	(0.484)	(0.495)	(0.498)	(0.481)	(0.496)
Nxt	100410	20184	120594	266136	53672	319808

N	25102	5046	30148	22178	4473	26651

Notes: The table shows mean and standard deviations in parentheses. Treated: Gällivare and Kiruna, control: municipalities in Norrbotten County. Individuals who moved to Norrbotten County after 2004 are excluded. Marital status is a dummy variable equal to 1 if married. Education is categorized as primary, secondary, and tertiary. The economic sectors are divided into primary (extraction and agricultural sector), secondary (manufacturing and construction), and tertiary (services, healthcare, public sector, and others).

Table A.4: Mean differences of changes (2000-2003) comparing treated and control individuals

	Treated	Control
Convicted property crime	0.00	0.00
Convicted violent crime	0.00	0.00
Convicted substance crime	0.00	0.00
Convicted traffic crime	0.00	0.00
Married	0.03	0.05***
Children under 18	0.03	0.03
Primary education	-0.06	-0.06
Secondary education	0.05	0.01***
Tertiary education	0.02	0.05***
Non-employed	-0.07	-0.06
Primary sector	0.03	-0.00***
Secondary sector	-0.01	0.02***
Tertiary sector	0.05	0.05

Notes: Each value represents a change between 2000 and 2003. Marital status is a dummy variable equal to 1 if married. Education is categorized as primary, secondary, and tertiary. The economic sectors are divided into primary (extraction and agricultural sector), secondary (manufacturing and construction), and tertiary (services, healthcare, public sector, and others). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Summary statistics of residents and migrants, 2000-2003 and 2004-2015

	Residents 2000-2003	Residents 2004-2015	Migrants (county) 2000-2003	Migrants (county) post-migration-2015	Migrants (Treated mun.) 2000-2003	Migrants (Treated mun.) post-migration-2015
	Mean/SD	Mean/SD	Mean/SD	Mean/SD	Mean/SD	Mean/SD
Convicted of property crime	0.01	0.01	0.07	0.04	0.01	0.01
	(0.10)	(0.09)	(0.25)	(0.19)	(0.11)	(0.11)
Convicted of violent crime	0.00	0.01	0.02	0.01	0.00	0.00
	(0.07)	(0.08)	(0.15)	(0.11)	(0.06)	(0.07)
Convicted of traffic crime	0.01	0.01	0.05	0.03	0.02	0.01
	(0.10)	(0.10)	(0.22)	(0.16)	(0.13)	(0.09)
Convicted of substance crime	0.00	0.01	0.05	0.04	0.00	0.01
	(0.04)	(0.08)	(0.22)	(0.19)	(0.05)	(0.10)
Disposable income(100SEK)	1439.84	1886.59	1080.36	1372.35	1015.39	1907.15
	(792.69)	(1244.01)	(3148.50)	(1321.92)	(1096.85)	(1059.97)
Yearly earnings(100SEK)	1701.11	2278.91	978.01	1367.14	1000.87	2281.41
	(1172.99)	(1453.96)	(1317.49)	(1521.95)	(954.14)	(1487.67)
Employment	0.77	0.84	0.51	0.60	0.59	0.82
	(0.42)	(0.37)	(0.50)	(0.49)	(0.49)	(0.38)
Age	30.13	28.26	27.31	27.57	24.85	29.03
	(6.44)	(6.65)	(6.20)	(5.53)	(5.78)	(5.44)
Married	0.15	0.13	0.11	0.12	0.06	0.14
	(0.36)	(0.33)	(0.31)	(0.33)	(0.23)	(0.34)
Children under 18	0.41	0.37	0.24	0.23	0.30	0.28
	(0.49)	(0.48)	(0.43)	(0.42)	(0.46)	(0.45)
Primary education	0.60	0.39	0.47	0.26	0.34	0.22
	(0.49)	(0.49)	(0.50)	(0.44)	(0.47)	(0.41)
Secondary education	0.35	0.55	0.44	0.52	0.60	0.53
	(0.48)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)
Tertiary education	0.05	0.06	0.10	0.22	0.06	0.25
	(0.22)	(0.23)	(0.29)	(0.42)	(0.23)	(0.43)
Non-employed	0.23	0.16	0.49	0.40	0.41	0.18

	(0.42)	(0.37)	(0.50)	(0.49)	(0.49)	(0.38)
Primary economic sector	0.21	0.24	0.01	0.02	0.04	0.17
	(0.40)	(0.43)	(0.10)	(0.13)	(0.21)	(0.38)
Secondary economic sector	0.19	0.23	0.14	0.13	0.12	0.17
	(0.39)	(0.42)	(0.35)	(0.34)	(0.32)	(0.38)
Tertiary economic sector	0.37	0.36	0.36	0.45	0.43	0.48
	(0.48)	(0.48)	(0.48)	(0.50)	(0.49)	(0.50)

Notes: The table shows mean and standard deviations in parentheses. The full sample (18-39-year-old males) is included in this table. Residents in Gällivare and Kiruna. Migrants to Norbotten County in columns 3 and 4, and migrants to the mining municipalities in columns 5 and 6. Marital status is a dummy variable equal to 1 if married. Education is categorized as primary, secondary, and tertiary. The economic sectors are divided into primary (extraction and agricultural sector), secondary (manufacturing and construction), and tertiary (services, healthcare, public sector, and others).

Table A.6: Impact of the mining boom on criminal behavior by treated municipality, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Panel A: Gällivare				
Post*Gällivare	-0.0101**	0.0033	-0.0048	0.0073**
	(0.0043)	(0.0024)	(0.0031)	(0.0031)
Nxt	209232	209232	209232	209232
N	13077	13077	13077	13077
Mean dep. var (2000-03)	0.0125	0.0060	0.0097	0.0025
Effect relative to the mean (%)	-80.42	54.93	-49.08	287.80
R-squared	0.2976	0.2219	0.2783	0.3821
Within R-squared	0.0001	0.0000	0.0000	0.0001
Panel B: Kiruna				
Post*Kiruna	-0.0037	0.0005	0.0011	0.0024
	(0.0028)	(0.0021)	(0.0024)	(0.0020)
Nxt	213263	213263	213263	213263
N	13329	13329	13329	13329
Mean dep. var (2000-03)	0.0125	0.0060	0.0097	0.0025
Effect relative to the mean (%)	-29.79	7.56	11.47	93.33
R-squared	0.2918	0.2203	0.2731	0.3725
Within R-squared	0.0000	0.0000	0.0000	0.0000
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Impact of the mining boom on criminal behavior by rings, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Post*Ring 1	-0.0105	0.0009	-0.0062	0.0091*
	(0.0086)	(0.0032)	(0.0042)	(0.0049)
Post*Ring 2	-0.0106**	-0.0019	-0.0046	0.0041
	(0.0045)	(0.0049)	(0.0055)	(0.0046)
Post*Ring 3	0.0037	0.0068*	0.0019	0.0061***
	(0.0042)	(0.0039)	(0.0039)	(0.0021)
Post*Ring 4	-0.0097	0.0037	0.0017	0.0050
	(0.0060)	(0.0042)	(0.0033)	(0.0041)
Post*Ring 5	-0.0070	-0.0045	-0.0055	0.0053
	(0.0046)	(0.0033)	(0.0051)	(0.0058)
Post*Ring 6	-0.0148**	0.0038	0.0034	0.0018
	(0.0069)	(0.0025)	(0.0045)	(0.0033)
Post*Ring 7	0.0019	0.0054*	-0.0028	-0.0032**
	(0.0040)	(0.0029)	(0.0074)	(0.0016)
Post*Ring 8	-0.0029	0.0015	-0.0004	0.0009
	(0.0058)	(0.0035)	(0.0055)	(0.0021)
Post*Ring 9	-0.0010	-0.0042	-0.0055	-0.0004
	(0.0057)	(0.0041)	(0.0063)	(0.0017)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	230480	230480	230480	230480
N	14405	14405	14405	14405
Mean dep. var (2000-03)	0.0125	0.0060	0.0097	0.0025
R-squared	0.2929	0.2195	0.2708	0.3759
Within R-squared	0.0001	0.0001	0.0000	0.0001

Notes: Two-way fixed effects panel data regression. Ring 1: 0.00 km-2.74 km, ring 2: 2.75 km-3.37 km, ring 3: 3.38 km-3.82 km, ring 4: 3.83 km-4.26 km, ring 5: 4.27 km-4.86 km, ring 6: 4.87 km-18.34 km, ring 7: 18.35 km-73.67 km, ring 8: 73.68 km-102.47 km, ring 9: 102.48 km-125.37 km, and ring 10: 125.38 km-236.00 km. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Impact of the mining boom on criminal behavior using time duration for treatment, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Post*$\leq$ 20 km	-0.0128***	0.0038	-0.0048	0.0083**
	(0.0046)	(0.0026)	(0.0031)	(0.0035)
Post* 20 - 40 km	0.0056	-0.0008	-0.0025	-0.0061
	(0.0070)	(0.0042)	(0.0120)	(0.0048)
Post*40 - 60 km	-0.0027	-0.0002	-0.0003	0.0029
	(0.0029)	(0.0021)	(0.0026)	(0.0021)
Post*60 - 80 km	0.0025	0.0076	-0.0130	-0.0053***
	(0.0097)	(0.0086)	(0.0166)	(0.0017)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	230480	230480	230480	230480
N	14405	14405	14405	14405
Mean dep. var (2000-03)	0.0125	0.0060	0.0097	0.0025
R-squared	0.2929	0.2195	0.2708	0.3759
Within R-squared	0.0001	0.0000	0.0000	0.0001

Notes: Two-way fixed effects panel data regression. Treated: 20-kilometer rings using travel time duration by car to the nearest mine. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Impact of the mining boom on criminal behavior using DDD approach, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Post*Treated (DID)	-0.0053**	0.0029*	-0.0012	0.0055***
	(0.0026)	(0.0017)	(0.0022)	(0.0020)
Post*Treated*Public (DDD)	0.0027	-0.0019	-0.0023	-0.0004
	(0.0084)	(0.0049)	(0.0056)	(0.0057)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	124267	124267	124267	124267
N	7767	7767	7767	7767
Mean dep. var (2000-03)	0.0125	0.0060	0.0097	0.0025
R-squared	0.2992	0.2084	0.2816	0.3560
Within R-squared	0.0001	0.0000	0.0000	0.0002

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Robustness checks: impact of the mining boom on criminal behavior, 2000-2015

	(1) Baseline Residents	(2) Residents (treated 2003)	(3) Including controls	(4) Residents and migrants	(5) Balanced panel	(6) Exclude neigh. municipalities	(7) Municipality fixed-effect
Panel A: Property crime							
Post*Treated	-0.0066**		-0.0060**	-0.0052**	-0.0061*	-0.0074***	-0.0061**
	(0.0027)		(0.0027)	(0.0024)	(0.0037)	(0.0027)	(0.0025)
Post*Treated (2003)		-0.0045*					
		(0.0027)					
Mean dep. var (2003)	0.0125	0.0125	0.0125	0.0127	0.0139	0.0123	0.0125
Effect relative to the mean (%)	-52.40	-35.86	-48.08	-41.41	-44.04	-60.26	-48.45
R-squared	0.2929	0.2991	0.2932	0.3020	0.2800	0.2951	0.2710
Within R-squared	0.0001	0.0000	0.0005	0.0000	0.0001	0.0001	0.0000
Panel B: Violent crime							
Post*Treated	0.0018		0.0019	0.0014	0.0026	0.0019	0.0014
	(0.0016)		(0.0016)	(0.0015)	(0.0019)	(0.0016)	(0.0016)
Post*Treated (2003)		0.0019					
		(0.0017)					
Mean dep. var (2003)	0.0060	0.0060	0.0060	0.0061	0.0066	0.0059	0.0060
Effect relative to the mean (%)	29.18	31.34	31.30	23.53	39.85	31.77	22.53
R-squared	0.2195	0.2084	0.2196	0.2213	0.2104	0.2219	0.1975
Within R-squared	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
Panel C: Traffic crime							
Post*Treated	-0.0017		-0.0020	-0.0026	-0.0037	-0.0024	-0.0016
	(0.0020)		(0.0020)	(0.0018)	(0.0030)	(0.0020)	(0.0019)
Post*Treated (2003)		-0.0010					
		(0.0020)					
Mean dep. var (2003)	0.0097	0.0097	0.0097	0.0097	0.0112	0.0089	0.0097
Effect relative to the mean (%)	-17.06	-10.45	-20.16	-26.61	-32.71	-27.19	-16.16
R-squared	0.2708	0.2815	0.2711	0.2735	0.2697	0.2744	0.2480
Within R-squared	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000

			Panel D: Substance crime				
Post*Treated	0.0046**		0.0048***	0.0042**	0.0019	0.0047**	0.0039**
	(0.0018)		(0.0018)	(0.0017)	(0.0020)	(0.0018)	(0.0017)
Post*Treated (2003)		0.0046**					
		(0.0018)					
Mean dep. var (2003)	0.0025	0.0025	0.0025	0.0027	0.0028	0.0023	0.0025
Effect relative to the mean (%)	181.24	179.33	188.73	154.33	68.23	202.28	154.28
R-squared	0.3759	0.3560	0.3764	0.3769	0.3662	0.3765	0.3600
Within R-squared	0.0000	0.0001	0.0009	0.0000	0.0000	0.0001	0.0000
Nxt	230480	124267	230480	263626	49698	193151	230480
N	14405	7767	14405	16477	3106	12072	14405
Controls	No	No	Yes	No	No	No	No
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Municipality FE	No	No	No	No	No	No	Yes

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

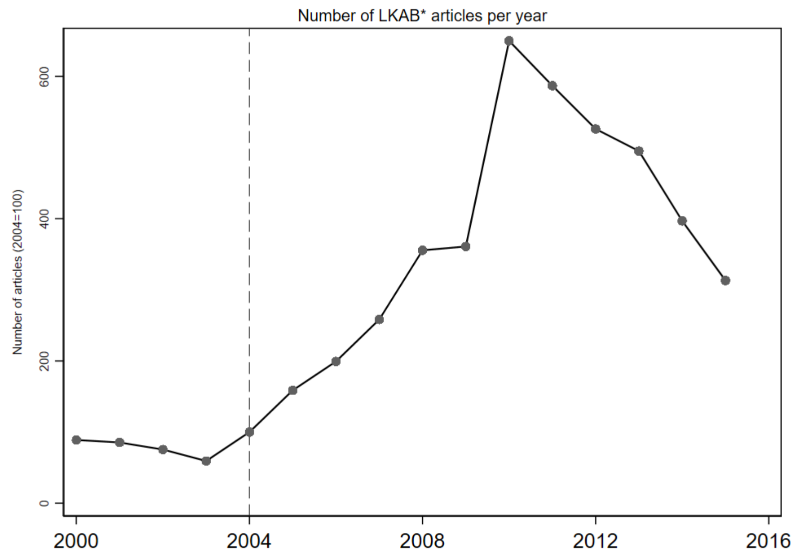
Table A.11: Social cost effects of the mining boom, 18-29-year-old male sample

	Property crime	Violent crime	Traffic crime	Substance crime
	Total social cost effect (1000s SEK)			
Post	-17866.61**	11345.70	-1921.11	14086.18**
	(7223.97)	(10332.34)	(2327.19)	(5473.34)

Notes: The table shows the social costs of effects computed using the DID estimates of the effect of the mining boom on different types of crime for young males. I take the total unit cost for each crime category for the UK using 2015/2016 prices and convert it to SEK using the 2004 exchange rate (1 GBP = 13.45 SEK). The total unit costs for property and violent crimes include the costs for anticipation (e.g., defensive expenditure), consequence (e.g., physical and emotional harm), and response (e.g., police costs) to the crime. The source for the crime costs is Heeks et al. (2018). For property crimes, I use the estimated cost of 79,794 SEK for domestic burglary and dwelling. For violent crimes, I use the estimated cost of 189,057 SEK for violence with injury. For the traffic crimes, I use the estimated cost of 33,936 SEK, which accounts for a damage-only accident. For substance crimes, I use the estimated cost of 89,523 SEK, which only accounts for the cost of arrest. I multiply the estimated coefficients of Panel A Table 1 by the cost of crime and add it by the number of treated young male individuals during the boom, obtaining the aggregate social cost effect for this population (welfare implication). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

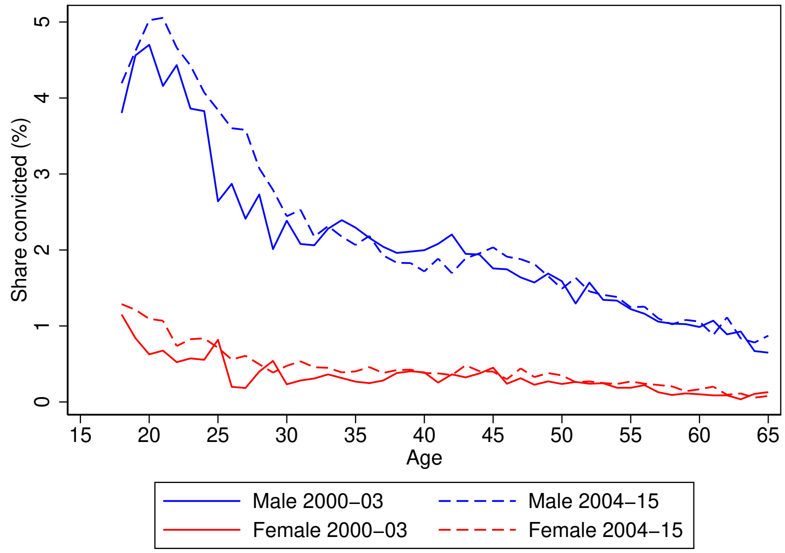
B Appendix: Additional figures

Figure B.1: Media coverage of LKAB in Swedish newspapers, 2000–2015



Notes: The figure reports the annual number of newspaper articles mentioning "LKAB" normalized to 2004 values (2004=100). Articles are identified using the newspaper archive *Retriever Mediearkivet*. Following the literature, we search for articles containing the case-insensitive string "LKAB*", where the asterisk is used as a wildcard. The vertical dashed line marks the start of the mining boom in 2004. LKAB is the main iron ore producer in Sweden and operates the large-scale mines in Kiruna and Gällivare. LKAB is Sweden's state-owned iron ore mining company.

Figure B.2: Conviction rates of any crime by age and gender, before vs after



Notes: The sample excludes the migrants to the mining area. Convictions include all types of crimes.

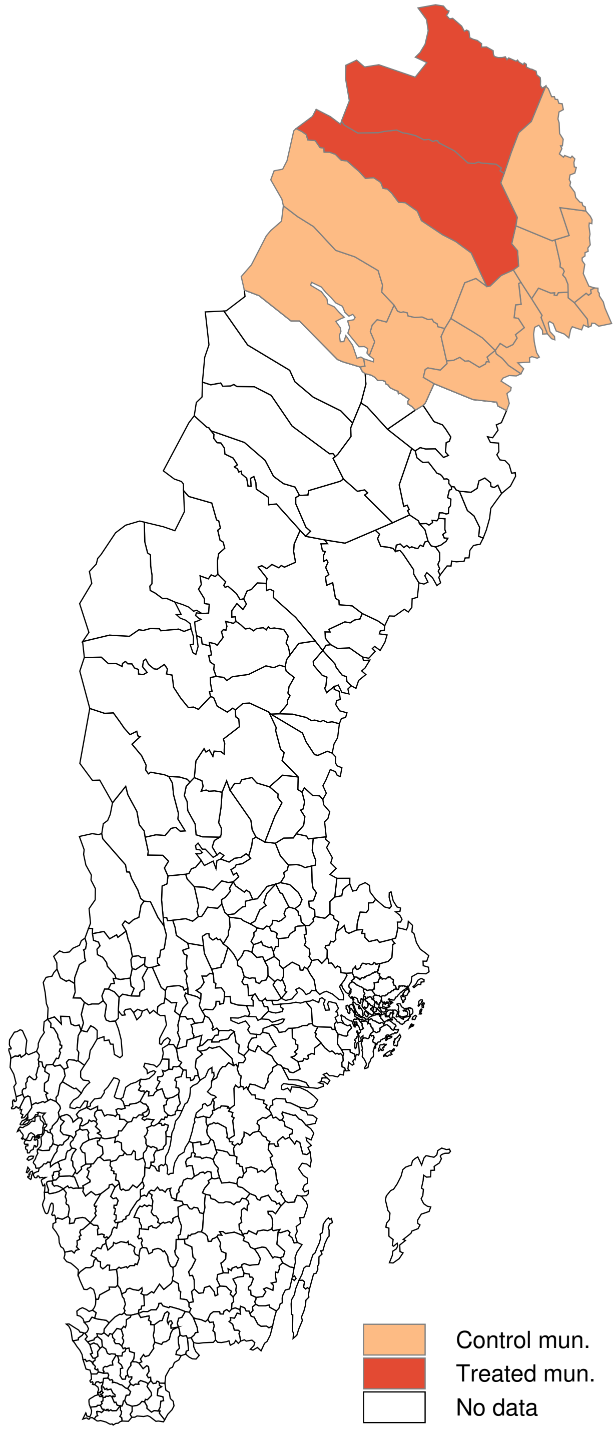


Figure B.3: Treated and control municipalities

Notes: This map shows the spatial location of the treated (Gällivare and Kiruna) and control municipalities. The rest of the municipalities in white are excluded from the sample.

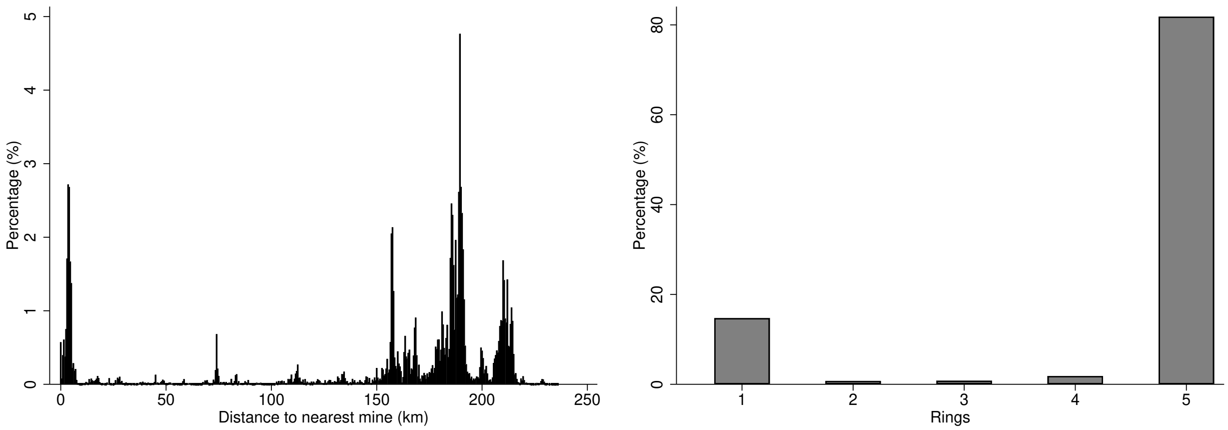
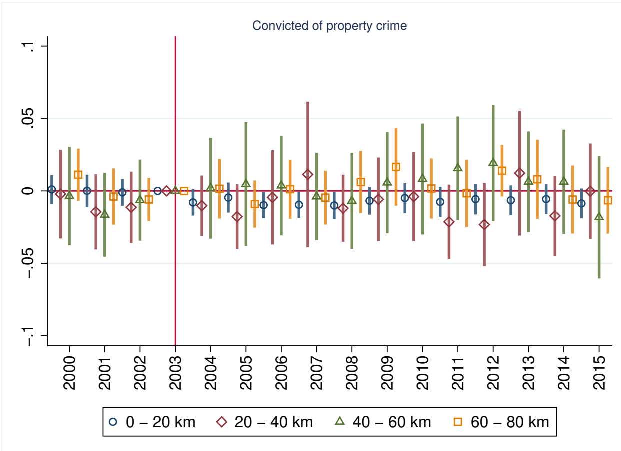


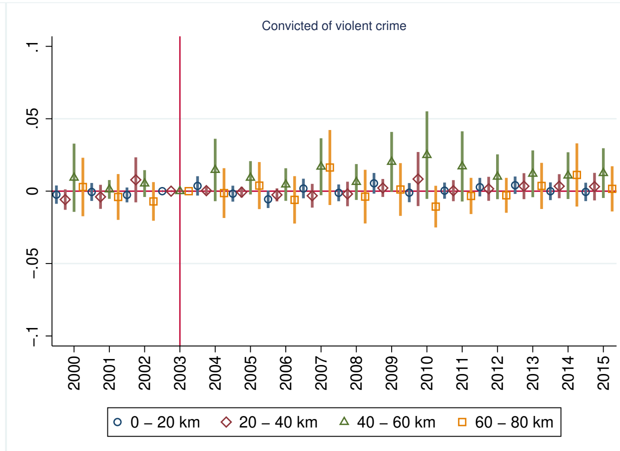
Figure B.4: Distribution of individuals according to their distance to the nearest mine and in the rings

Notes: The figure shows the distribution of individuals according to their distance to the nearest mine and in the rings.

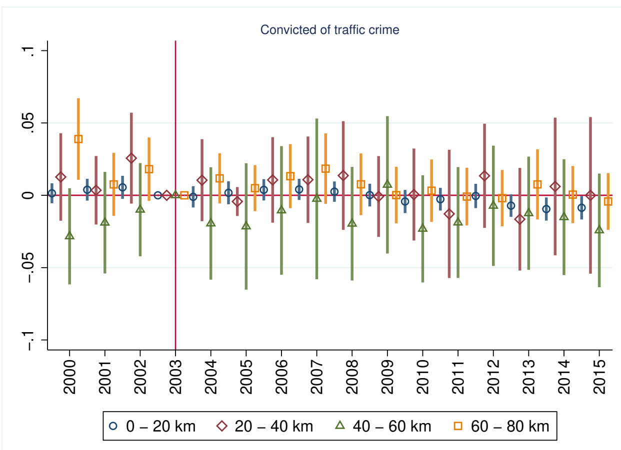
Figure B.5: Event study of the impact of the mining boom on criminal behavior by rings, 2000-2015



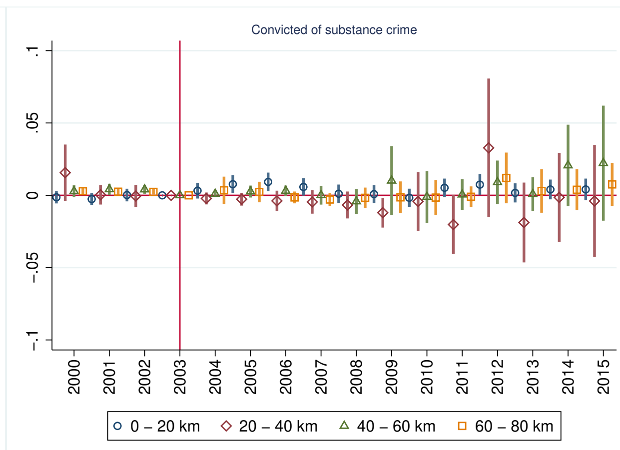
(a) Property crime



(b) Violent crime



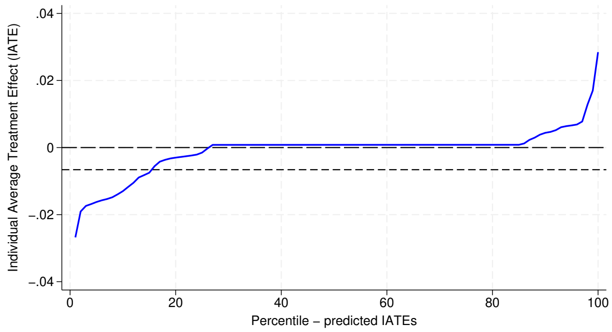
(c) Traffic crime



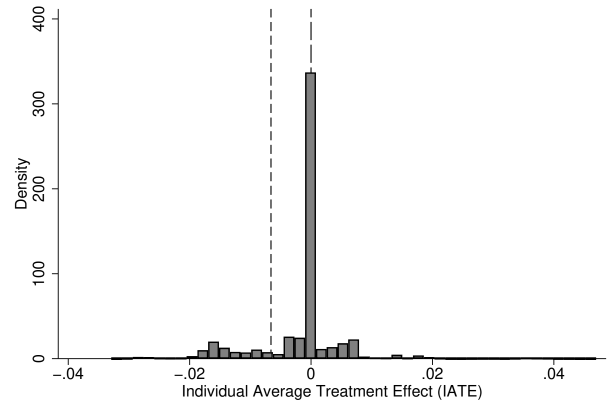
(d) Substance crime

Notes: Year 2003 and > 80 km are the references. is the reference. 95% confidence interval shown. Estimations include individuals, grid, and time fixed effects. The sample excludes the migrants to the mining area. Standard errors are clustered at the grid level.

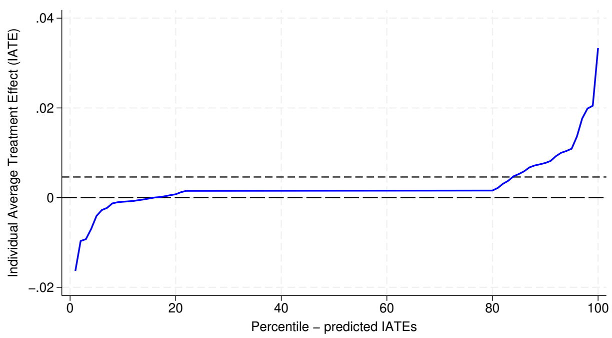
Figure B.6: Distribution predicted individual average treatment effects



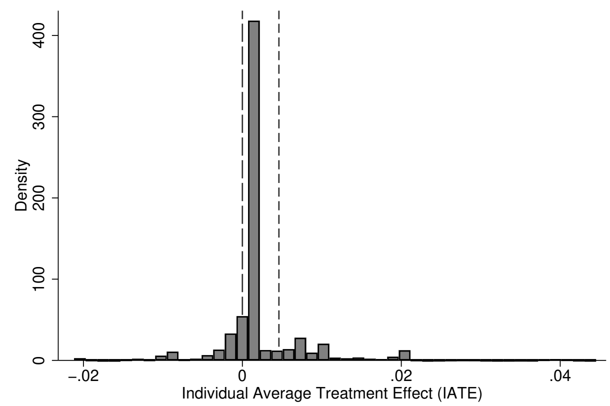
(a) Property crime



(b) Property crime



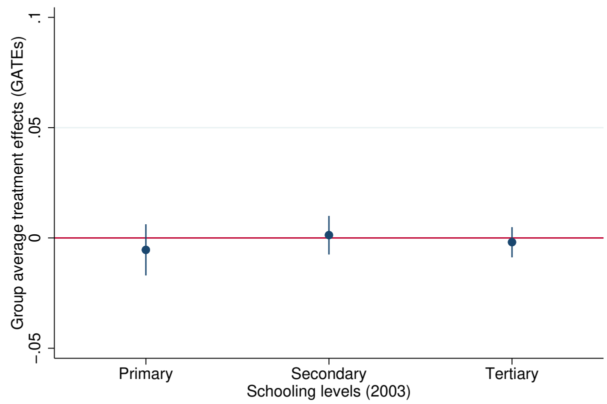
(c) Substance crime



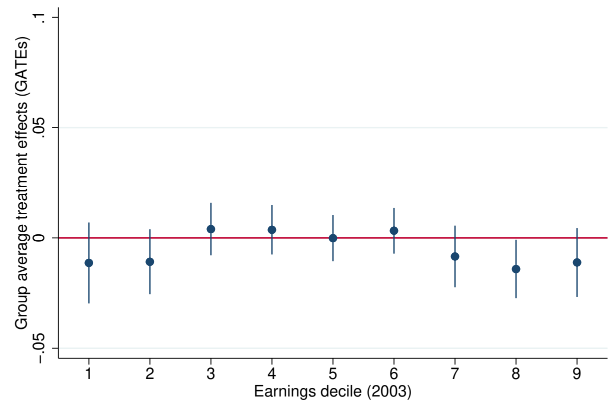
(d) Substance crime

Notes: The figure shows how the predicted Individual Average Treatment Effect (IATE) varies over its rank, aggregated over percentiles (panel a) and its distribution (panel b). A causal forest is implemented to estimate the CATE. Long dash lines show the 0 in both figures. Dash lines show the Average Treatment Effect (ATE) in both figures.

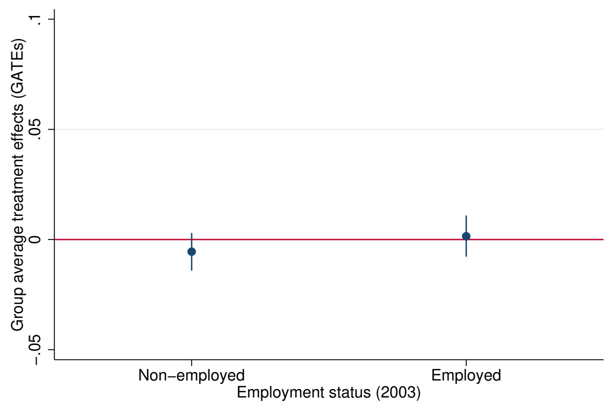
Figure B.7: Group average treatment effects (GATEs) by characteristics for property crime, 2000-2015



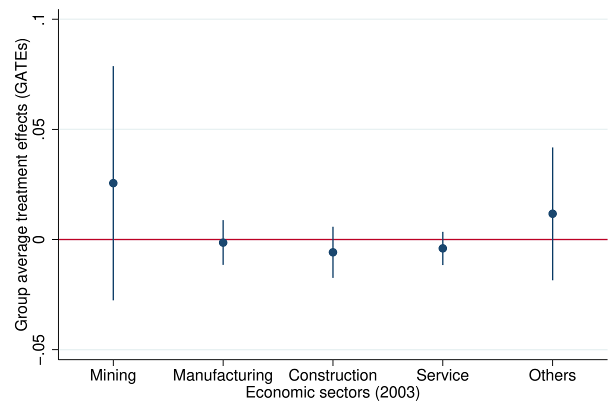
(a) Schooling levels



(b) Yearly earnings decile



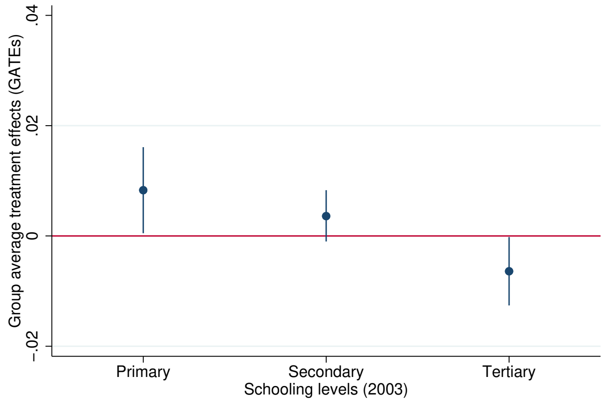
(c) Employment status



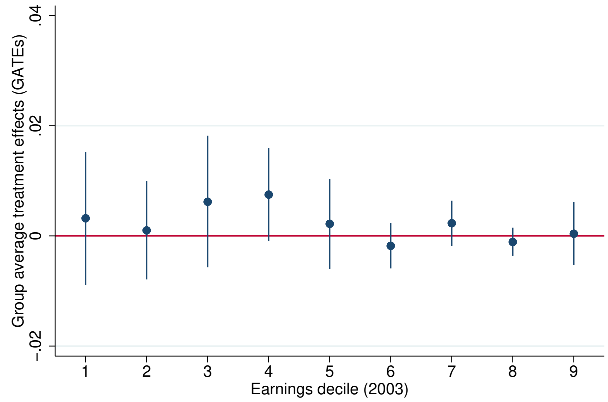
(d) Economic sectors

Notes: This figure shows the mean predicted Conditional Average Treatment Effects (CATE) over individual-level characteristics. GATEs are estimated using causal forest algorithms. 95% confidence interval shown.

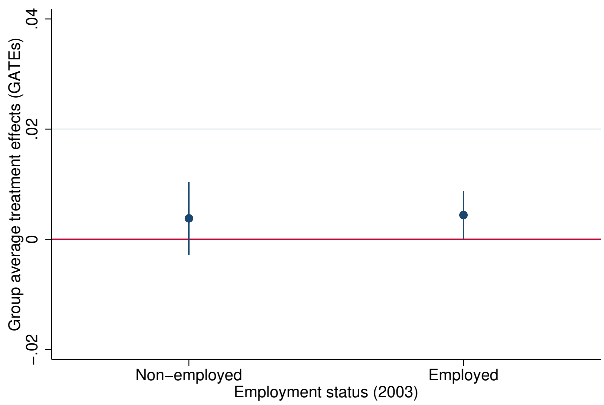
Figure B.8: Group average treatment effects (GATEs) by characteristics for substance crime, 2000-2015



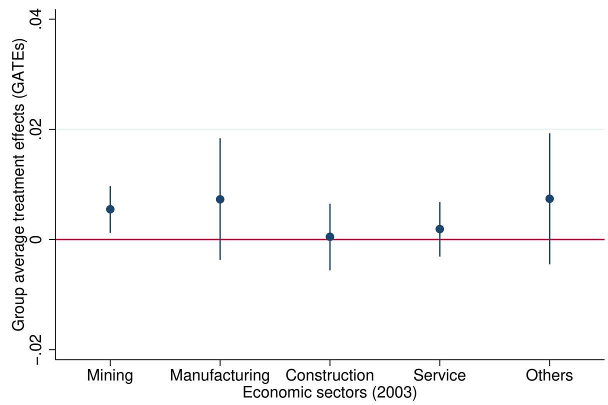
(a) Schooling levels



(b) Yearly earnings decile



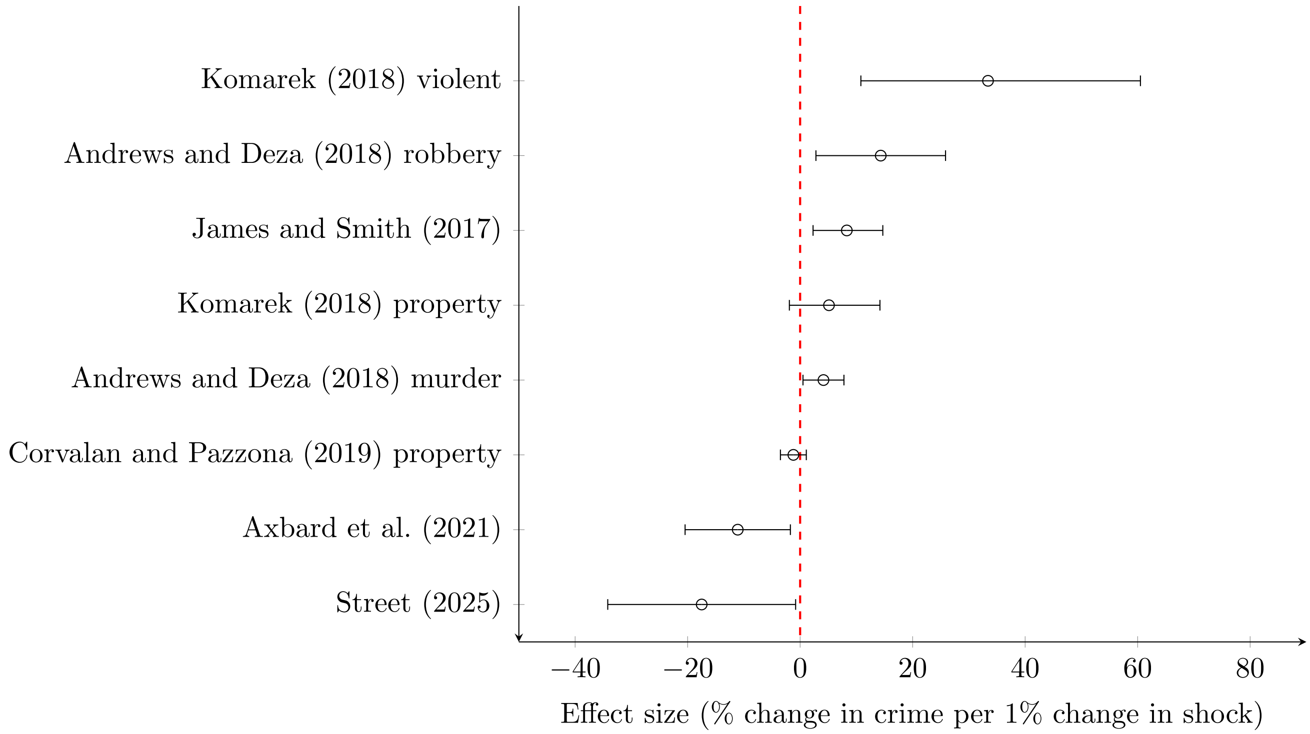
(c) Employment status



(d) Economic sectors

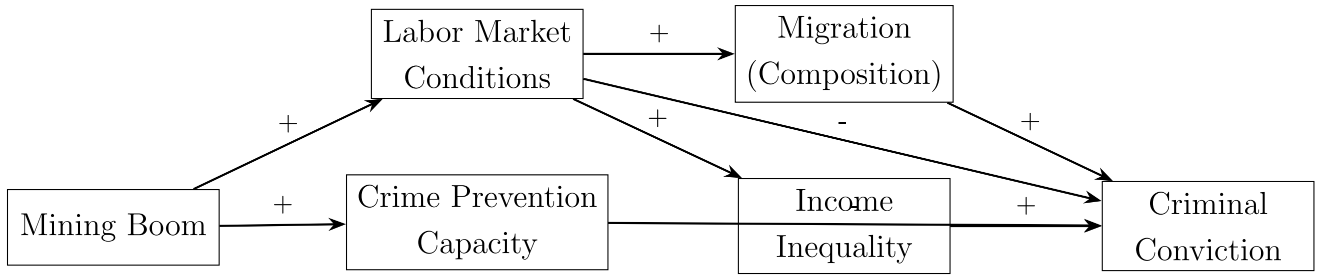
Notes: This figure shows the mean predicted Conditional Average Treatment Effects (CATE) over individual-level characteristics. GATEs are estimated using causal forest algorithms. 95% confidence interval shown.

Figure B.9: Literature comparisons: resource shocks and crime



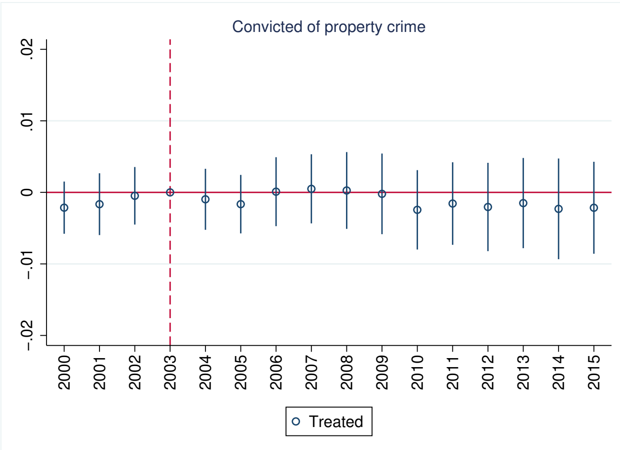
Notes: This figure compares estimated treatment effect sizes in the literature. Each dot shows the estimated effect size (%) with 95% confidence intervals. The figure compares the effect of different resource shocks exposure, such as mining and fracking booms, on criminal behavior. See Online Appendix E for details on the papers and effect size construction. Each point indicates the estimated effect of treatment (direct percent change) on criminal behavior for treated areas or individuals relative to controls as a percent of the control mean. When not specified, the outcome in the paper is all types of crime.

Figure B.10: Directed Acyclic Graph (DAG) of mechanisms linking mining booms to crime

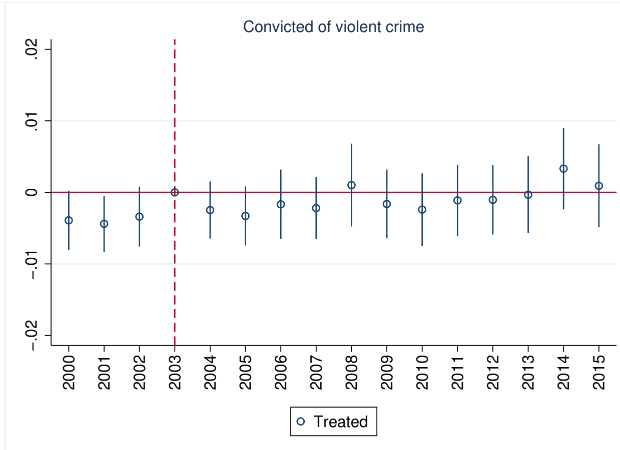


C Appendix: Results for the 30-39-year-old males sample

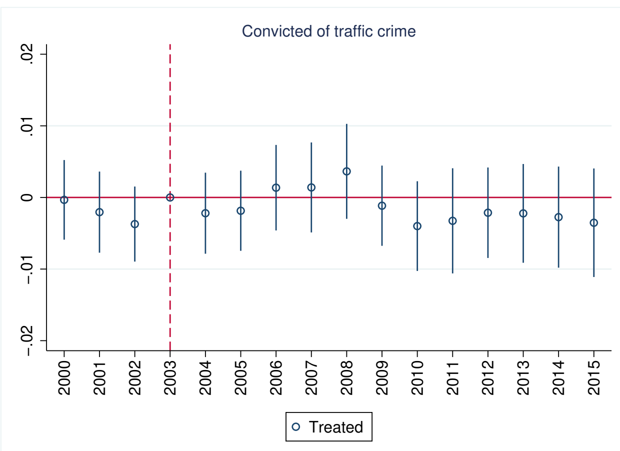
Figure C.1: Event study of the impact of the mining boom on criminal behavior of 30-39-year-old males, 2000-2015



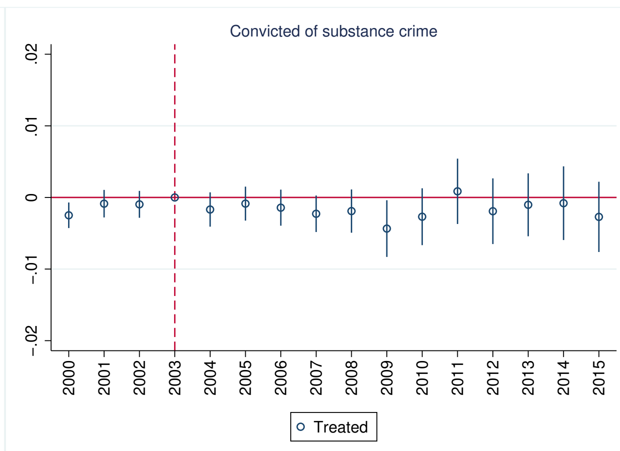
(a) Property crime



(b) Violent crime



(c) Traffic crime



(d) Substance crime

Notes: Year 2003 is the reference. 95% confidence interval shown. Estimations include individuals, grid, and time fixed effects. The sample excludes the migrants to the mining area. Standard errors are clustered at the grid level.

Table C.1: Impact of the mining boom on detailed criminal behavior for 30-39 years old, 2000-2015

	(1) First-time convicted Property crime	(2) Re-offense Property crime	(3) First-time convicted Substance crime	(4) Re-offense Substance crime
Post*Treated	0.0002	-0.0000	-0.0006	-0.0002
	(0.0011)	(0.0007)	(0.0006)	(0.0004)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	209922	209922	209922	209922
N	13120	13120	13120	13120
Mean dep. var (2000-03)	0.0045	0.0010	0.0014	0.0005
Effect relative to the mean (%)	4.15	-4.84	-40.26	-49.88
R-squared	0.1874	0.3943	0.2161	0.4678
Within R-squared	0.0000	0.0000	0.0000	0.0000

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Impact of the mining boom on detailed criminal behavior (the role of prison) for 30-39 years old, 2000-2015

	(1) Convicted + no prison Property crime	(2) Convicted + in prison Property crime	(3) Post-prison reoffense Property crime	(4) Convicted + no prison Substance crime	(5) Convicted + in prison Substance crime	(Post- reo Substan
Post*Treated	-0.0000	-0.0000	0.0002	-0.0007	0.0001	-0.
	(0.0011)	(0.0004)	(0.0006)	(0.0005)	(0.0003)	(0.0
Individual FE	Yes	Yes	Yes	Yes	Yes	Y
Year FE	Yes	Yes	Yes	Yes	Yes	Y
Grid FE	Yes	Yes	Yes	Yes	Yes	Y
Nxt	209922	209922	209922	209922	209922	20
N	13120	13120	13120	13120	13120	13
Mean dep. var (2000-03)	0.0041	0.0008	0.0007	0.0011	0.0004	0.0
Effect relative to the mean (%)	-1.13	-3.56	37.07	-69.08	13.07	-2
R-squared	0.2311	0.2264	0.4059	0.3273	0.2387	0.4
Within R-squared	0.0000	0.0000	0.0000	0.0000	0.0000	0.0

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Impact of the mining boom on criminal behavior by distance to the mines for 30-39 years old, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Post*$\leq$ 20 km	-0.0002	0.0004	0.0012	-0.0007
	(0.0013)	(0.0011)	(0.0016)	(0.0007)
Post* 20 - 40 km	0.0018	-0.0029	-0.0074	-0.0033
	(0.0053)	(0.0027)	(0.0055)	(0.0038)
Post*40 - 60 km	0.0007	-0.0014	0.0032	-0.0005
	(0.0011)	(0.0023)	(0.0060)	(0.0004)
Post*60 - 80 km	-0.0003	-0.0017	-0.0034	-0.0003
	(0.0029)	(0.0026)	(0.0046)	(0.0004)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	209922	209922	209922	209922
N	13120	13120	13120	13120
Mean dep. var (2000-03)	0.0055	0.0036	0.0067	0.0019
R-squared	0.3088	0.2396	0.3071	0.4397
Within R-squared	0.0000	0.0000	0.0000	0.0000

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Impact of the mining boom on criminal behavior of migrants for 30-39-year-old males, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime	(5) Property crime	(6) Violent crime	(7) Traffic crime	(8) Substance crime
Post*Migrants (Mining mun.)	0.0088	-0.0119*	-0.0145	-0.0094	-0.0142	-0.0166*	-0.0306**	-0.0049
	(0.0135)	(0.0068)	(0.0127)	(0.0063)	(0.0162)	(0.0086)	(0.0149)	(0.0065)
Post*Migrants (Control mun.)	0.0178**	0.0069	0.0133**	-0.0056				
	(0.0080)	(0.0055)	(0.0064)	(0.0062)				
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nxt	85972	85972	85972	85972	25977	25977	25977	25977
N	5373	5373	5373	5373	1624	1624	1624	1624
Mean dep. var (2000-03)	0.0797	0.0242	0.0691	0.0537	0.0186	0.0096	0.0173	0.0058
Effect relative to the mean, Treated (%)	11.06	-49.25	-20.96	-17.60	-76.60	-172.59	-176.94	-84.80
Effect relative to the mean, Control mun. (%)	22.35	28.64	19.24	-10.37				
R-squared	0.5680	0.4011	0.5384	0.5718	0.5183	0.3622	0.4389	0.5082
Within R-squared	0.0001	0.0000	0.0001	0.0000	0.0001	0.0002	0.0004	0.0000

Notes: Two-way fixed effects panel data regression. Migrants before the move are the references. Standard errors (in parentheses) are clustered at the grid level. Columns (1)-(4) compare migrants to the mining municipalities or the control municipalities to themselves before the migration event. Columns (5)-(8) compare migrants to the mining municipalities to migrants to the control municipalities. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: Impact of the mining boom on criminal behavior by treated municipality for of 30-39-year-old males, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Panel A: Gällivare				
Post*Gällivare	0.0005	-0.0011	-0.0022	-0.0012
	(0.0021)	(0.0015)	(0.0022)	(0.0012)
Nxt	189753	189753	189753	189753
N	11860	11860	11860	11860
Mean dep. var (2000-03)	0.0055	0.0036	0.0067	0.0019
Effect relative to the mean (%)	9.64	-30.66	-32.49	-65.92
R-squared	0.3141	0.2439	0.3173	0.4444
Within R-squared	0.0000	0.0000	0.0000	0.0000
Panel B: Kiruna				
Post*Kiruna	0.0001	0.0016	0.0030*	-0.0005
	(0.0012)	(0.0014)	(0.0018)	(0.0006)
Nxt	194700	194700	194700	194700
N	12169	12169	12169	12169
Mean dep. var (2000-03)	0.0055	0.0036	0.0067	0.0019
Effect relative to the mean (%)	1.71	42.72	44.94	-29.11
R-squared	0.3103	0.2397	0.3049	0.4397
Within R-squared	0.0000	0.0000	0.0000	0.0000
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6: Impact of the mining boom on criminal behavior by rings for 30-39-year-old males, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Post*Ring 1	0.0031	0.0004	-0.0049*	-0.0009
	(0.0036)	(0.0022)	(0.0027)	(0.0024)
Post*Ring 2	0.0010	-0.0016	-0.0036	-0.0041**
	(0.0033)	(0.0030)	(0.0029)	(0.0020)
Post*Ring 3	-0.0039	0.0060**	0.0055	-0.0008
	(0.0030)	(0.0030)	(0.0037)	(0.0006)
Post*Ring 4	-0.0019	-0.0001	-0.0007	0.0002
	(0.0020)	(0.0018)	(0.0028)	(0.0006)
Post*Ring 5	-0.0018	-0.0002	0.0056	0.0018
	(0.0029)	(0.0022)	(0.0042)	(0.0017)
Post*Ring 6	0.0017	-0.0035	0.0076*	-0.0002
	(0.0018)	(0.0033)	(0.0046)	(0.0008)
Post*Ring 7	-0.0001	0.0004	-0.0047	-0.0015
	(0.0026)	(0.0020)	(0.0041)	(0.0016)
Post*Ring 8	0.0008	-0.0000	0.0069	0.0006
	(0.0030)	(0.0037)	(0.0047)	(0.0011)
Post*Ring 9	-0.0009	-0.0040	-0.0035	0.0004
	(0.0033)	(0.0042)	(0.0040)	(0.0019)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	209922	209922	209922	209922
N	13120	13120	13120	13120
Mean dep. var (2000-03)	0.0055	0.0036	0.0067	0.0019
R-squared	0.3088	0.2396	0.3072	0.4398
Within R-squared	0.0000	0.0001	0.0001	0.0000

Notes: Two-way fixed effects panel data regression. Ring 1: 0.00 km-2.74 km, ring 2: 2.75 km-3.37 km, ring 3: 3.38 km-3.82 km, ring 4: 3.83 km-4.26 km, ring 5: 4.27 km-4.86 km, ring 6: 4.87 km-18.34 km, ring 7: 18.35 km-73.67 km, ring 8: 73.68 km-102.47 km, ring 9: 102.48 km-125.37 km, and ring 10: 125.38 km-236.00 km. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7: Impact of the mining boom on criminal behavior using time duration for treatment for 30-39-year-old males, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Post*$\leq$ 20 km	0.0002	-0.0007	-0.0018	-0.0013
	(0.0023)	(0.0016)	(0.0024)	(0.0014)
Post* 20 - 40 km	-0.0002	-0.0003	-0.0087*	-0.0034
	(0.0053)	(0.0039)	(0.0051)	(0.0037)
Post*40 - 60 km	-0.0003	0.0009	0.0032*	-0.0003
	(0.0013)	(0.0014)	(0.0019)	(0.0005)
Post*60 - 80 km	-0.0053	0.0006	-0.0055	-0.0016
	(0.0065)	(0.0006)	(0.0044)	(0.0010)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	209922	209922	209922	209922
N	13120	13120	13120	13120
Mean dep. var (2000-03)	0.0055	0.0036	0.0067	0.0019
R-squared	0.3088	0.2396	0.3071	0.4397
Within R-squared	0.0000	0.0000	0.0000	0.0000

Notes: Two-way fixed effects panel data regression. Treated: 20-kilometer rings using travel time duration by car to the nearest mine. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8: Impact of the mining boom on criminal behavior using DDD approach for 30-39 years old, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Traffic crime	(4) Substance crime
Post*Treated (DID)	-0.0001	0.0004	0.0013	-0.0010
	(0.0013)	(0.0012)	(0.0016)	(0.0007)
Post*Treated*Public (DDD)	0.0020	-0.0005	-0.0029	0.0006
	(0.0027)	(0.0020)	(0.0032)	(0.0010)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
Nxt	195335	195335	195335	195335
N	12208	12208	12208	12208
Mean dep. var (2000-03)	0.0055	0.0036	0.0067	0.0019
R-squared	0.3013	0.2311	0.3044	0.4445
Within R-squared	0.0000	0.0000	0.0000	0.0000

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.9: Robustness checks: impact of the mining boom on criminal behavior for 30-39-year-old males, 2000-2015

	(1) Baseline Residents	(2) Residents (treated 2003)	(3) Including controls	(4) Residents and migrants	(5) Balanced panel	(6) Exclude neigh. municipalities	(7) Municipality fixed-effect
Panel A: Property crime							
Post*Treated	0.0002		0.0002	-0.0000	0.0000	0.0002	-0.0006
	(0.0012)		(0.0012)	(0.0012)	(.)	(0.0012)	(0.0012)
Post*Treated (2003)		0.0006					
		(0.0012)					
Mean dep. var (2003)	0.0055	0.0055	0.0055	0.0055	.	0.0053	0.0055
Effect relative to the mean (%)	3.11	10.02	3.36	-0.81	.	3.18	-10.41
R-squared	0.3088	0.3013	0.3092	0.3183	0.3708	0.3080	0.2772
Within R-squared	0.0000	0.0000	0.0005	0.0000	0.0000	0.0000	0.0000
Panel B: Violent crime							
Post*Treated	0.0004		0.0003	0.0003	0.0000	0.0006	0.0002
	(0.0011)		(0.0011)	(0.0011)	(.)	(0.0011)	(0.0011)
Post*Treated (2003)		0.0003					
		(0.0011)					
Mean dep. var (2003)	0.0036	0.0036	0.0036	0.0037	.	0.0036	0.0036
Effect relative to the mean (%)	11.27	8.11	9.17	9.16	.	15.60	4.36
R-squared	0.2396	0.2311	0.2397	0.2405	0.2781	0.2477	0.2053
Within R-squared	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
Panel C: Traffic crime							
Post*Treated	0.0008		0.0010	0.0008	0.0000	0.0010	0.0010
	(0.0015)		(0.0015)	(0.0015)	(.)	(0.0015)	(0.0014)
Post*Treated (2003)		0.0005					
		(0.0015)					
Mean dep. var (2003)	0.0067	0.0067	0.0067	0.0067	.	0.0064	0.0067
Effect relative to the mean (%)	12.66	7.76	14.95	11.60	.	16.14	15.42
R-squared	0.3071	0.3044	0.3072	0.3094	0.3126	0.3050	0.2801
Within R-squared	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000

Panel D: Substance crime							
Post*Treated	-0.0008		-0.0008	-0.0009	0.0000	-0.0008	-0.0009
	(0.0006)		(0.0006)	(0.0006)	(.)	(0.0007)	(0.0006)
Post*Treated (2003)		-0.0010					
		(0.0006)					
Mean dep. var (2003)	0.0019	0.0019	0.0019	0.0019	.	0.0017	0.0019
Effect relative to the mean (%)	-42.73	-51.23	-42.76	-48.96	.	-44.33	-50.23
R-squared	0.4397	0.4445	0.4400	0.4351	0.4154	0.4443	0.4062
Within R-squared	0.0000	0.0000	0.0005	0.0000	0.0000	0.0000	0.0000
Nxt	209922	195335	209922	230440	39031	176669	209922
N	13120	12208	13120	14402	2439	11042	13120
Controls	No	No	Yes	No	No	No	No
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Municipality FE	No	No	No	No	No	No	Yes

Notes: Two-way fixed effects panel data regression. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.10: Mechanisms: impact of the mining boom on different mechanisms for 30-39-year-old males, 2000-2015

	(1) Disposable income	(2) Labor income	(3) Lab. inc. employed	(4) Employment	(5) Employment mining	(6) Police occupation	(7) Police industry	(8) Top earning tercile
Post*Treated	85.5493***	185.5795***	190.2128***	0.0087	0.0295***	0.0004	0.0005	0.0071
	(12.3396)	(15.6541)	(14.8165)	(0.0059)	(0.0040)	(0.0011)	(0.0014)	(0.0050)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nxt	209922	209922	180910	209922	209922	174442	209922	195335
N	13120	13120	11307	13120	13120	10903	13120	12208
Mean dep. var (2000-03)	1680.6631	1965.3857	2316.2926	0.8338	0.0476	0.0047	0.0087	0.4723
Effect relative to the mean (%)	5.09	9.44	8.21	1.04	62.12	7.98	5.24	1.50
R-squared	0.5079	0.8284	0.7976	0.6802	0.9087	0.7833	0.8025	0.9081
Within R-squared	0.0001	0.0017	0.0021	0.0000	0.0030	0.0000	0.0000	0.0000

Notes: Two-way fixed effects panel data regression. Treated: Gällivare. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D Appendix: The causal forest approach for heterogeneous treatment effects

Using the causal forest method, I estimate the Conditional Average Treatment Effects (CATE) of the form:

$$CATE \equiv \tau(x) = E[Y_{1i} - Y_{0i} | X_i = x] \tag{4}$$

where Y_{1i} and Y_{0i} are the potential outcomes of interest for the *ith* individual when treated and untreated, respectively, and X is a vector of observable characteristics. The causal forest approach is a form of supervised machine learning techniques that is used for predicting heterogeneity in causal treatment effects (Athey and Imbens, 2016; Wager and Athey, 2018).[39] I follow the generalized random forest implementation developed by Athey et al. (2019). By using these methods, I rely on data-driven sample splits, thus limiting the researcher's discretion when selecting the relevant dimensions of heterogeneity. Given that I have a difference-in-differences setting (e.g., Davis and Heller, 2017; Britto et al., 2022), which is different than most applications based on RCTs, I run the causal forest over first differences, comparing pre- and post-boom averages. By doing this, the unconfoundedness assumption, explained in Wager and Athey (2018), holds because the treatment indicator is orthogonal to the covariates.

The method estimates conditional average treatment effects (CATEs), which are average treatment effects (ATEs) conditional on a set of variables for which the treatment effects may vary. I focus on two different estimates: individual average treatment effects (IATEs) and group average treatment effects (GATEs). IATEs are treatment effects conditional on observation-level characteristics, and there is one IATE for each observation in the sample. GATEs are treatment effects conditional on prespecified groups, and there is a treatment effect for each group. The approach fits an outcome model and a treatment-assignment model. I fit these models using cross-fitting via random forest. The CATEs are estimated using a partialing-out (PO) estimator via random forest. The algorithm randomly partitions the data across a large number of trees to flexibly capture heterogeneity in treatment effects without imposing a parametric structure. By default, the sample is randomly split into two parts ("honest" estimation): one half is used to determine the tree structure (e.g., how the data are partitioned into leaves), and the other half is used to estimate treatment effects within those leaves. This approach prevents overfitting and ensures unbiased estimation of treatment effects. The final CATE prediction for each observation is obtained by averaging over all trees in the forest. The default settings use 2000 trees, with subsampling and minimum leaf sizes chosen automatically by the algorithm to balance bias and variance. In addition, inference

[39] See Athey and Imbens (2019) for a review and discussion on recent machine learning (ML) literature for economics and econometrics.

and confidence intervals are computed using the bootstrap of little bags proposed in Athey et al. (2019).

In my specific case, the main outcomes are the probability of criminal conviction for property or substance-related crimes. The algorithm starts by building trees defined by data-driven sample splits characterizing leafs, which are followed by a prediction of the causal effect over the characteristics X. I believe that the treatment effect of the mining boom could vary based on schooling, earnings, employment status, and economic sectors, which I denote as x. Treatment(1) represents the potential outcomes of being treated, and Treatment(0) represents the potential outcomes of not being treated. I estimate the effects of the mining boom on criminal behavior conditional on the variables x:

$$IATE \equiv \tau(x) = E\{treatment(1) - treatment(0)|x\} \tag{5}$$

As x refers to individual characteristics, this version of the CATE is also known as IATEs. In this approach, I do not assume any functional form of $\tau(x)$, therefore, the data tells us what this function looks like.

If I want to know how the ATEs vary across population groups, I estimate the GATEs. Specifically, if G is a group variable (e.g., schooling levels) and g is a specific level of the group variable (e.g., primary education), I estimate the ATE conditional on belonging to group g, that is:

$$GATE \equiv \tau(g) = E\{treatment(1) - treatment(0)|G = g\} \tag{6}$$

where the function $\tau(g)$ is referred to as the GATE function.

E Appendix: Literature comparisons, resource shocks and crime

I compare the baseline estimated effect of the mining boom on criminal behavior with the effects of other resource shocks evaluated in the literature. To benchmark the findings, I calculate the effect sizes for related work against the control complier mean, the complier mean, the control mean, or the mean value of the criminal behavior measure, in that order of priority based on availability. I apply the same transformations to the confidence intervals. When the outcome is in log points, I interpret the effect as $100 \times (e^{\beta} - 1)$. Below, I detail this calculation for each paper included in the literature comparison plots in Online Appendix Figure B.9.

1. Andrews and Deza (2018) studies how a change in oil reserves in Texas impacts the crime in counties that have reserves. The authors exploit plausibly exogenous changes in the value of reserves and estimate reduced form models to capture the relationship between changes in the value of oil reserves and criminal activity in a given Texas county. As the independent variable of interest is an interaction between the oil price in the previous year and the amount of time-invariant reserves in million barrels of oil in any given county, I use the 26% increase in value of reserves reported in the paper to convert the results into comparable elasticities to the other papers using a DID. As outcomes, the authors have several types of crime. For simplicity, I focus on murder and robbery as proxies for violent and property crimes. The authors find that a 1% increase in the value of oil reserves increases murder by 0.16% and robbery by 0.55%. Using the 26% increase in the value of oil reserves to convert the results, there is a 4.1% (95% CI: 0.5% to 7.8%) increase in murder ([Table 2, Column 1]). Moreover, there is a 14.3% (95% CI: 2.8% to 25.9%) increase in robbery ([Table 2, Column 1]).

2. James and Smith (2017) studies how the energy boom of oil and shale gas in the United States affected regional crime rates throughout the country. The authors use a difference-in-differences design comparing counties for which the geographic center lies above one of the major play formations (treated) against controls, and exploiting the national temporal variation in shale energy production. They find positive effects on rates of various property and violent crimes in shale-rich counties. Focusing on all crimes, the authors find that the shock increased crime in treated counties by 0.080, significant at the 1% level ([Table 3, Column 6]. As the outcome is in log points, I interpret that there is an 8.3% (95% CI: 2.3% to 14.7%) increase in all crime.

3. Corvalan and Pazzona (2019) studies the short- and medium-run effects that an increase in copper price had on the local economy and on criminal activity in Chile. The authors compute the current value of the copper production in the year 2000 in each

municipality, in billions of Chilean pesos, and multiply it by the current price of copper in billions of Chilean pesos. Then, by comparing mining and non-mining municipalities, the authors find that, after a decade of high prices, mining municipalities did not exhibit lower crime rates compared to non-mining municipalities. As an outcome, the authors focus on property crimes and use the number of crime reports to the authorities per 100,000 inhabitants. As the independent variable of interest is an interaction between the copper production in the year 2000 and the price, I use the 400% increase in the international price of copper reported in the paper to convert the results into comparable elasticities to the other papers using a DID. The authors find that a 1 billion CLP increase in the value of copper production reduces property crime by 0.98 per 100,000. Using the 400% increase in the price to convert the results, there is a 1.2% (95% CI: -3.5% to 1.1%) reduction in property crime, which is not statistically significant ([Table 3, Column 6]).

4. Axbard et al. (2021) studies the impact of natural resource wealth on criminal activity in South Africa. The authors exploit price fluctuations in 15 internationally traded minerals as exogenous variation and compare mining police precincts against controls. The outcome of interest is the inverse hyperbolic sine transformed total number of crimes. As the independent variable of interest is the inverse hyperbolic sine transformation of the mineral value, I use the 154% increase in mining value reported in the paper to convert the results into comparable elasticities to the other papers using a DID. The authors find that increased mineral wealth leads to less crime. Specifically, the authors find that a 10% increase in the value of mineral production reduces the total number of crimes by about 0.7% (significant at the 5%-level). Using the 154% increase in mining value to convert the results, there is a 11.1% (95% CI: -20.4% to -1.7%) crime reduction ([Table 1, Column 1]).

5. Komarek (2018) studies the effect of resource extraction on local crime using the fracking boom as a natural experiment in the Marcellus region in the United States. The author uses a difference-in-differences model, exploiting variation in both the timing of fracking activity in a county and the moratorium on fracking natural gas in the State of New York. That is, counties in Pennsylvania can receive the treatment of fracking activity, while similar counties in New York can only serve as controls due to the policy. He finds that areas experiencing a natural gas extraction boom suffer an increase in overall violent crimes, while property crimes remain similar to non-boom areas. Specifically, the author finds that the shock increased violent crime in treated counties by 0.288, significant at the 1% level ([Table 2, Column 2]). For property crimes, the author finds that the shock increased property crime in treated counties by 0.050, which is not statistically significant ([Table 2, Column 4]). As the outcome is transformed using the inverse hyperbolic sine transformation of the number of crimes

per 100,000 residents, I interpret that there is a 33.4% (95% CI: 10.8% to 60.5%) increase in violent crimes and a 5.1% (95% CI: -3.2% to 14.2%) increase in property crimes.

6. Street (2025) studies the effect of the fracking boom in North Dakota, both at the individual and aggregate levels, on criminal behavior. The author uses a generalized difference-in-differences framework, comparing the criminal behavior of resident households in counties within the shale play to residents in counties outside the shale play, before and after the fracking boom. The author considers two periods: leasing (2004–2008) and production (2008–2017). I compare my effects with the effects of the production period. At the aggregate level, the outcome is aggregate cases and charges filed per household population for each county-year, and the author finds large increases in charges and cases filed during the production period. Specifically, there is a 0.0371 percentage point increase in cases per household during the production period, translating to a 44.7% (95% CI: 13.3% to 75.9%) increase, using the baseline mean of 0.083, significant at the 5% level ([Table 3, Column 1]). At the individual level, the outcome is a binary indicator for whether a case was filed for the household each year, and evidence shows a modest decrease in crime for treated individuals. Specifically, there is a 0.35 percentage point decrease during the production period in the probability of having a case filed for treated individuals, translating to a 17.5% (95% CI: -34.2% to -0.8%) decrease, using the baseline mean of 0.02, significant at the 5% level ([Table 2, Column 2]).

References

Andrews, R. J. and Deza, M. (2018). Local natural resources and crime: Evidence from oil price fluctuations in Texas. *Journal of Economic Behavior & Organization*, 151:123–142.

Athey, S. and Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, 113(27):7353–7360.

Athey, S. and Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics*, 11(1):685–725.

Athey, S., Tibshirani, J., and Wager, S. (2019). Generalized random forests. *The Annals of Statistics*, 47(2):1148–1178.

Axbard, S., Benshaul-Tolonen, A., and Poulsen, J. (2021). Natural resource wealth and crime: The role of international price shocks and public policy. *Journal of Environmental Economics and Management*, 110:102527.

Britto, D. G., Pinotti, P., and Sampaio, B. (2022). The effect of job loss and unemployment insurance on crime in Brazil. *Econometrica*, 90(4):1393–1423.

Brå, T. S. N. C. f. C. P. (2023). Crime and statistics. Accessed = 2023-05-12.

Corvalan, A. and Pazzona, M. (2019). Persistent commodity shocks and transitory crime effects. *Journal of Economic Behavior & Organization*, 158:110–127.

Davis, J. M. and Heller, S. B. (2017). Using causal forests to predict treatment heterogeneity: An application to summer jobs. *American Economic Review*, 107(5):546–550.

Heeks, M., Reed, S., Tafsiri, M., and Prince, S. (2018). The economic and social costs of crime second edition. *Home Office Research report99*.

James, A. and Smith, B. (2017). There will be blood: Crime rates in shale-rich US counties. *Journal of Environmental Economics and Management*, 84:125–152.

Komarek, T. M. (2018). Crime and natural resource booms: evidence from unconventional natural gas production. *The Annals of Regional Science*, 61:113–137.

Nordregio (2009). North norden: a new mining era.

SGU (2014). Statistics of the swedish mining industry 2013.

SGU (2021). Statistics of the swedish mining industry 2021.

Street, B. (2025). The impact of economic opportunity on criminal behavior: Evidence from the fracking boom. *Journal of Public Economics*, 248:105402.

Tano, S., Pettersson, Ö., and Stjernström, O. (2016). Labour income effects of the recent "mining boom" in northern Sweden. *Resources Policy*, 49:31–40.

Wager, S. and Athey, S. (2018). Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*, 113(523):1228–1242.