Digging for Trouble? Mining Booms, Local Economic Shocks, and Criminal Behavior

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Abstract

Decades of research link natural resource booms to social disorder and rising crime, forming part of the so-called "resource curse". This paper challenges that view by showing that, once compositional changes are accounted for, resource booms can instead reduce criminal behavior. I study the 2004 iron ore boom in Sweden as an exogenous shock to local economic conditions, combining geocoded administrative data on all criminal convictions and demographics from 2000–2015 with a difference-in-differences design. Comparing residents in the mining municipality to those in similar nearby municipalities and exploiting variation in distance to the mines, I distinguish long-term residents from in-migrants to separate genuine local effects from population changes that bias aggregate analyses, and provide new micro-level evidence on how improved labor market opportunities affect individual criminal behavior. Results reveal a 19% reduction in criminal activity among residents during the boom, driven by young, low-educated males employed in the manufacturing, construction, and service sectors. Effects are strongest within 20 kilometers of the mines and are driven by first-time offenders rather than recidivists. These findings overturn the prevailing resource-curse narrative and support rational crime models where improved labor market opportunities increase the returns to legal activity. The evidence indicates that the "resource curse" arises from aggregation, which hides the heterogeneous behavioral adjustments of individuals to local economic shocks. (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. A key factor influencing this decision is the labor market conditions of individuals. Intuitively, if individuals face improved labor markets, the returns to legal activity increase, and individuals should substitute away from illegal activities. Yet empirical evidence at different levels of analysis paints a more complex picture. Local economic shocks that improve labor market conditions have been associated with increases in crime, especially those related to natural resources (James and Smith, 2017; Couttenier et al., 2017; Komarek, 2018). 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. Moreover, the research on the "resource curse" links commodity windfalls to rent-seeking, corruption, and violent conflict (Berman et al., 2017). This puzzle between theory and empirical evidence is difficult to explain in the existing literature, primarily due to aggregate-level analyses that can mask the co-occurrence of different factors.

While aggregate-level (i.e., cross-country and county) and historical 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). The main limitation in aggregate studies that may explain this puzzle is that they are not able to account for migration and compositional changes (Wilson, 2022). This tension motivates my analysis: by examining how criminal behavior responds to local economic shocks for residents and migrants, I contribute to addressing this puzzle in the literature. A challenge in the literature is identifying exogenous local shocks, which I address by studying the 2004 mining boom in Sweden. Given the detailed register data available in Sweden, I differentiate the effects for residents and migrants, separating the effects of population changes that bias aggregate-level results from improved economic opportunity. This is important because a local economic shock that generates labor market opportunities may attract more crime-prone individuals to the area. Moreover, aggregate-level place-based analysis may provide misleading policy decisions because it is difficult to identify and account for mobility across space and economic sectors.

Specifically, I use the boom in iron ore prices in northern Sweden as a plausible exogenous shock to local economic conditions and identify the effect of economic opportunity on individuals' 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. 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 identify the effects using geocoded administrative data on all criminal convictions and demographics in Sweden from 2000 to 2015 and a difference-in-differences framework. I compare residents living in the mining municipality (Gällivare) to residents in the other municipalities in the county. Using the detailed geographical data available, I identify residents as those individuals located in the mining municipality, and migrants as those who moved to Norrbotten County in 2004 or later, assuming that those who migrated to this area after the shock did so in response to improved labor market conditions. This is important because the aggregate 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). Previous literature has shown large migration effects in response to economic conditions (Wilson, 2022). The results provide novel insights into the mechanisms driving the response of criminal behavior to local economic shocks. 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, and demographic groups.

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 case of Gällivare municipality, 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 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).

I follow a simple economics crime model, building on Becker (1968) and Ehrlich (1973), and extend it to feature the impacts of positive local economic shocks, to guide the empirical analysis and interpret the mechanisms driving the relationship between local economic shocks and criminal behavior. Individuals are rational economic agents that choose between legal work and criminal activity depending on the legal work wage and the expected payoff to crime (which depends on the expected gain from crime minus the cost-the product of the probability of being caught and the associated punishment). Therefore, increasing the probability of being caught and/or the resulting punishment may reduce crime. Mining booms may influence crime via several mechanisms, which are not mutually exclusive. First, economic shocks and crime are related via the labor market. A positive economic shock that increases labor market conditions is 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 mining area (Draca and Machin, 2015; Komarek, 2018; Axbard et al., 2021). Nevertheless, by including endogenous migration and compositional changes into the model, aggregate crime levels may increase, decrease, or remain unchanged depending on the characteristics of migrants attracted by the boom. This helps to reconcile the puzzle of contradictory findings in the literature. At the same time, an additional mechanism that suggests an increase in crime due to positive economic shocks, often used in the literature to explain these results, is the increase in the payoff to commit crimes, known as the rapacity effect (Draca and Machin, 2015; James and Smith, 2017). This demonstrates the importance of an empirical analysis of the relationship between a local economic shock and local crime and the mechanisms behind it.

Results show that, contrary to previous literature that finds aggregated crime increases due to resource shocks, when migration and compositional changes are accounted for, residents experience a decrease in criminal activity during the mining boom compared to control residents. The start of the economic expansion led to a statistically significant 0.22 percentage points (19%) reduction in criminal behavior by residents. These results do not appear to be primarily driven by changes in the police force or migrants, addressing concerns about detection and deterrence, and are in line with recent literature that finds reductions in crime due to resource shocks that generate labor market opportunities (Axbard et al., 2021; Street, 2025). Effects are concentrated among young males, who show a decline of 47% in the probability of being convicted of any crime among treated individuals relative to their non-treated counterparts, due to the mining boom. In terms of spatial treatment heterogeneity, the effects are highly localized in space for those individuals located near 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 individuals as a response to the mining boom. Results show that the reduction in criminal behavior is concentrated among first-time offenders. 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. Moreover, the reduction in crime due to the mining boom for young individuals is concentrated in property and other crimes. While there is an increase in drug-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., James and Smith, 2017; Andrews and Deza, 2018).

I also estimate conditional average treatment effects across individuals using causal forest algorithms (Athey and Imbens, 2016; Wager and Athey, 2018; Athey et al., 2019). Predicted treatment effects show that there is important heterogeneity among different population groups. The reductions in criminal convictions due to the mining boom are concentrated among young males with primary and secondary educational levels. Moreover, employed young males reduce their criminal behavior due to the mining boom, and there are significant spillovers in terms of criminal behavior into manufacturing, construction, and service sectors. These findings suggest that the reduction in criminal behavior is concentrated among the population groups that are most sensitive to wage changes and have higher baseline crime propensity (e.g., young males with low-skill levels). These groups are disproportionately represented in mining-related occupations and are more likely to benefit directly from these sector-specific local labor market shocks.

To understand this result, the mechanism analysis suggests that the mining boom improved labor market conditions for individuals living in the Swedish mining municipality. This is consistent with the hypothesis that an important mechanism that may explain these reductions in criminal behavior is local labor market opportunities, which increase the opportunity cost of engaging in criminal activity (in line with Becker (1968)). In addition, evidence suggests that incapacitation effects may explain part of the crime reductions through a higher number of individuals with secondary schooling. Overall, the results suggest that improved labor market conditions through increased opportunity costs or incapacitation effects may deter individuals from engaging in crime for the first time. These effects are driven by existing residents in the area, rather than in-migrants. Moreover, I find no evidence that the mining boom changed the other mechanisms considered in the mining municipality. Specifically, the population composition through migrants and the government's crime prevention capacity (police force) does not show any significant change in the mining municipality due to the mining boom.

Related literature. This paper contributes to different strands of literature. First, this paper adds to a large body of empirical literature on the effect of shocks to economic conditions on crime, recently surveyed by Draca and Machin (2015) and Ferraz et al. (2022). A few studies have examined crime effects from resource shocks in general. Most literature focuses on the oil and gas sector, specifically the effects of the fracking boom in the United States (James and Smith, 2017; Komarek, 2018; Andrews and Deza, 2018). Most previous literature analyzes how aggregate crime changes in response to plausibly exogenous shocks to local economic conditions, generally showing that aggregate-level crime increases with local economic conditions (e.g., Raphael and Winter-Ebmer, 2001; Gould et al., 2002; Dix-Carneiro et al., 2018; James and Smith, 2017).[2] Nevertheless, these studies by being at the aggregate level, are unable to separate the effects of economic shocks on individuals' criminal behavior from the migration caused by the same shocks. I contribute to the empirical literature using individual-level data, as Street (2025), and identify the effect specifically of local economic conditions, separated from migration and compositional changes.

Second, as most literature focuses on fracking, the literature specifically on mining is surprisingly scant. To the best of my knowledge, only three other studies have examined the effects of mining booms on crime (Carrington et al., 2011; Corvalan and Pazzona, 2019; Axbard et al., 2021), finding mixed evidence. I contribute by providing evidence that, once one accounts for population changes and migration that accompany economic expansions, one observes the expected relationship between improved job opportunities and individual criminal behavior. Third, this paper complements a subset of the literature that has highlighted the importance of focusing on people rather than places (Guettabi and James, 2020; Kovalenko, 2023; Jacobsen et al., 2023). Place-based analysis may provide misleading policy decisions because it is difficult to identify and account for mobility across space and economic sectors. The results in this paper complement those of Axbard et al. (2021) and Street (2025), which find that increased mineral wealth and fracking lead to less crime due to changes in employment opportunities created by the industry.

Fourth, I contribute by providing evidence that not all demographic groups are equally affected by these shocks; males, young individuals, and workers in the services sector are the most affected, who are those most likely to benefit from the economic shock. Finally, the findings of the study are also related to the literature on migration and crime (Bell et al., 2013; Miles and Cox, 2014), which finds increases in migration as a response to improved relative economic opportunities (Wilson, 2022). While migration and changing the population composition of a local area might play an important role in determining criminal activity, the effect may depend heavily on who the migrants are. In the specific case of mining, most migrants are young men with low skill levels, who are a crime-prone population. Finally, the study provides empirical support for rational theories of crime (Becker, 1968; Ehrlich,

[2] 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.

1973), which emphasize two main factors as determinants of crime: income and punishment. A stream of papers finds no empirical support for these theories by providing evidence that positive economic shocks increase crime (James and Smith, 2017; Corvalan and Pazzona, 2019), while recent studies find support for an income channel reducing criminal behavior by investigating the effects of these shocks and accounting for compositional changes (Axbard et al., 2021; Street, 2025). Regarding punishment, previous literature focuses mainly on the implications of a greater likelihood of apprehension (e.g., Fella and Gallipoli, 2014; Fu and Wolpin, 2018). I provide supporting evidence for the importance of the income channel in reducing crime levels.

Finally, the study provides empirical support for rational theories of crime. These theories emphasize economic and punishment as main factors in criminal behavior (Becker, 1968). A stream of papers finds support for an income channel by investigating the effects of access to the labor market, job loss, and returns to crime, among others (e.g., Pinotti, 2017; Bennett and Ouazad, 2020; Britto et al., 2022). These papers document an increase (decrease) in criminal activity from the loss (gain) of income that ranges from 20% to 32%, close to the 18% decrease I estimate in response to the mining boom. Seminal studies by Gould et al. (2002) and Machin and Meghir (2004) show that increases in wages or improvements in employment conditions significantly reduce crime, with implied elasticities often ranging between -1 and -2.5. 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. This study contributes to this literature by providing new causal evidence on the elasticity of crime with respect to earnings in the context of a natural resource shock. I estimate that a one percent increase in earnings is associated with a two percent reduction in the likelihood of being convicted of a crime, showing an implied elasticity of -2. This estimate is on the higher end of the existing literature, and reflects the power of high-quality individual-level data to detect treatment effect heterogeneity and overcome limitations common in studies using aggregate crime rates.

The remainder of the paper is organized as follows. In Section 2, the context of the Swedish mining sector and the mining boom is presented. Section 3 develops a theoretical framework. Section 4 presents the data and sample. Section 5 presents empirical methodology. Section 6 reports the empirical results. In Section 7.3, the relevant mechanisms are reviewed. Finally, Section 8 provides a discussion of the findings and conclusions.

2 Context

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

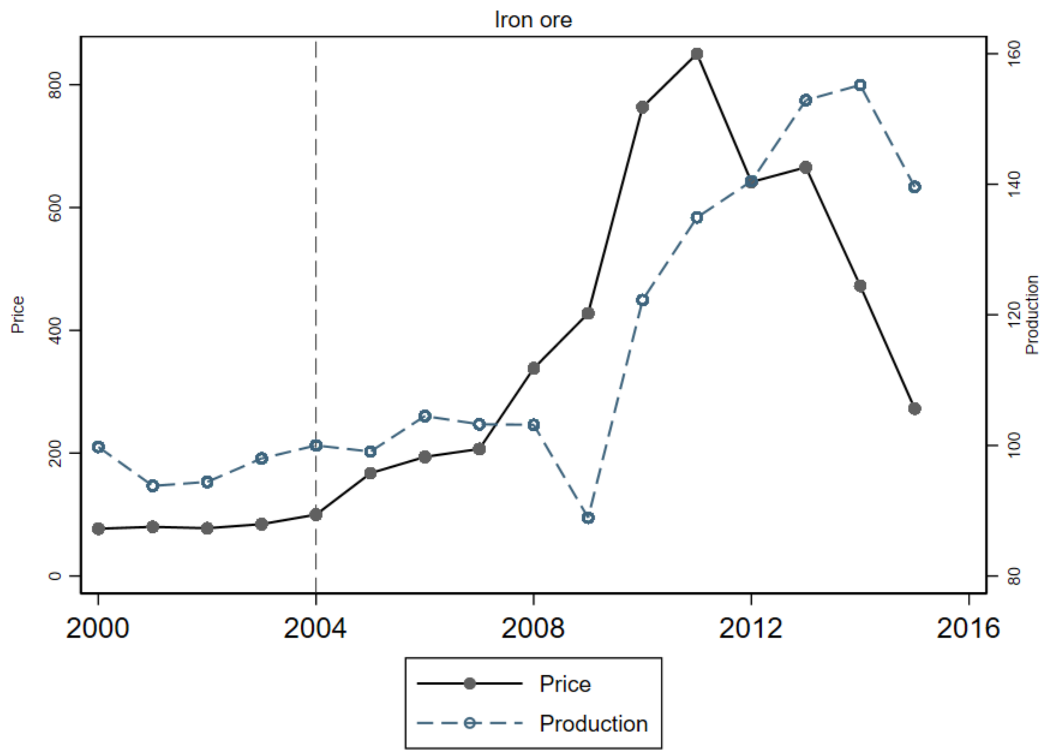
In the last two decades, resource-dependent countries and mining communities have experienced the economic and socioeconomic impacts of resource shocks in the form of price booms. These are characterized by large and persistent increases in international prices of minerals (Fleming and Measham, 2015; 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).[3] According to the literature, 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 crime. 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 international 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

[3] 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.

to high local and international investment in the sector and increasing demand for minerals and metals (Petterson and Knobblock, 2010; SGU, 2014).

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.[4] These are all existing mines, with Kirunavaara opening in the 1860s, and

[4]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

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, they 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 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). Moreover, I exclude Kiruna and consider as treated those individuals living in Gällivare (mining municipality), which is the municipality expected to be more affected by the mining boom. 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; therefore, individuals living in Kiruna are excluded from the analysis to avoid possible bias in the results by confusing the impacts of the mining boom and the decision to relocate the city.

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.

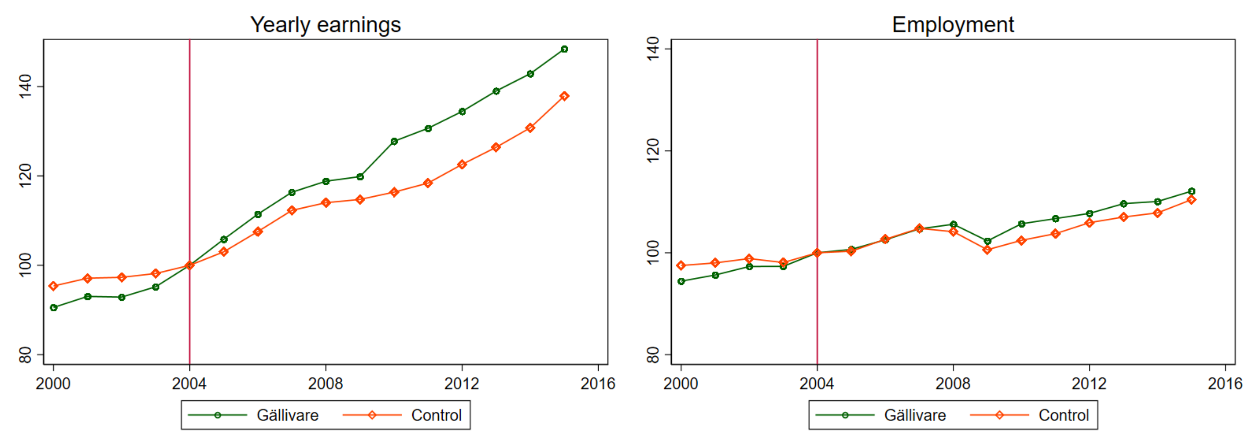
More recent evidence by Rodríguez-Puello and Rickardsson (2024) shows that the local labor market effects of the mining boom in northern Sweden were substantial and spread across space, sectors, and demographic characteristics. The authors find that the mining boom in Sweden affects the labor market 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

private companies operating them and the locations of the mines.

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 7.3.

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



(a) Yearly earnings

(b) Employment

Notes: Treated: Gällivare. 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 The economic model of crime

Building on the canonical model of Becker (1968) and Ehrlich (1973), I present a simple, intuitive static model to guide the empirical analysis and interpret the mechanisms driving the relationship between mining booms and criminal behavior.[5] The model is not meant to be exhaustive and is built to provide intuition to the empirical results. The model incorporates

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

heterogeneous individuals who choose between legal employment and criminal activity.[6] To account for endogenous migration, I extend the framework to allow for migration in response to local economic shocks.

As this is a static model, I assume that time is discrete, individuals live for one period,[7] and choose between legal work, illegal activity, or migrating to a mining region. I abstract from considering different types of crime committed. However, it is intuitive that economically motivated crime is likely to be better understood with this model.[8] If the individual i is employed in a legal work, they receive a legal wage offer in the local labor market w_i. On the contrary, the expected payoff from crime π_i is:

$$\pi_i = (1-p)g_i - ps$$

where p is the exogenous probability of being caught (common across individuals), g_i is the potential gain from crime, and s is the sanction if caught committing a crime. Therefore, if $p = 1$, the individual gets caught for engaging in criminal behavior and receives the sanction s. The probability of being caught depends on police resources and other area characteristics. The individual also has the option of migrating to a mining area with the cost c_i: (fixed and individual-specific). Therefore, if in a non-mining area, the individual may migrate to a mining region and receive a wage w_i^M at a migration cost c_i.

Individuals, as rational economic agents, choose the option that gives the highest expected utility:

$$U_i = \max\{w_i, \pi_i, w_i^M - c_i\}$$

An individual chooses between crime and legal work if the payoff from crime is higher than the wage for becoming a legal worker. Therefore, I observe a threshold rule in which individuals are indifferent between crime and legal work. In other words, I define a threshold individual $\hat{i}$ who is indifferent between crime and legal work:

$$w_i = (1-p)g_i - ps \Rightarrow g_i = \frac{w_i + ps}{1-p}$$

[6]As in the main model of Ehrlich (1973), and on the contrary to Machin and Meghir (2004), I assume that crime and work are substitutes as each takes time and produces income. In other words, the framework assumes, for simplicity, that crime and legal work are mutually exclusive alternatives and, therefore, there is only an extensive-margin choice to engage in crime (Ferraz et al., 2022).

[7]I assume that there are no intertemporal features in the individuals' decisions. This does not appear unrealistic because once individuals participate in the labor market, empirical literature shows that wages grow very slowly due to experience (Gosling et al., 2000).

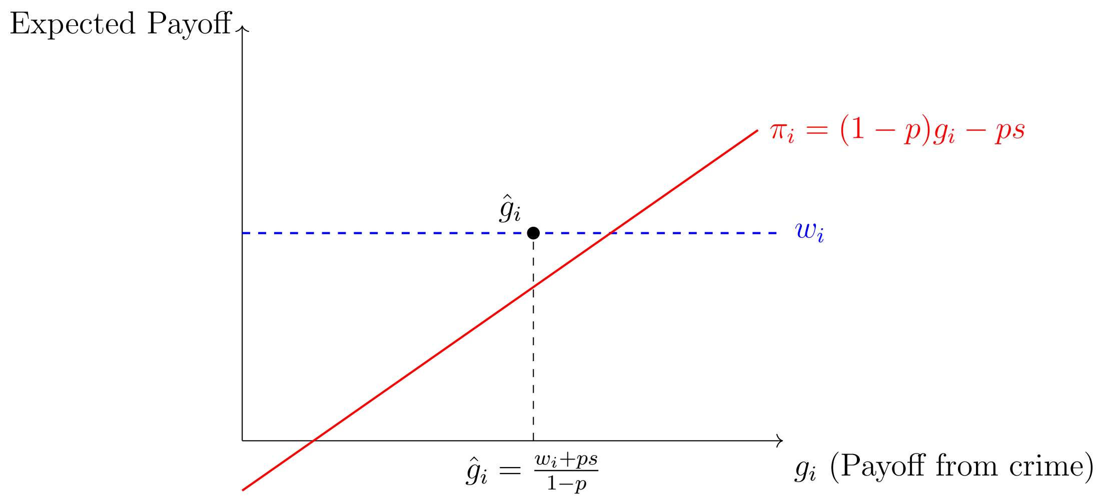
[8]While I keep the model simple, it can be extended toward realism in several ways, without loss of generality and maintaining the same predictions (Draca and Machin, 2015). For example, rather than having a discrete choice between legal work and crime, it can be a time-allocation problem in which work and crime are activities to which individuals allocate time (Lochner, 2004). This modification yields the same kinds of predictions.

Thus, an individual commits a crime if:

$$g_i > \frac{w_i + ps}{1 - p}$$

Figure 3 shows these dynamics and illustrates the individual's decision to engage in criminal activity or legal work based on their potential gain from crime, g_i. The dashed horizontal line represents the legal wage w_i, while the upward-sloping red line shows the expected payoff from committing a crime, $\pi_i = (1-p)g_i - ps$. The point where the two lines cross $\hat{g}_i$ marks the threshold at which the individual is indifferent between legal work and crime. Therefore, individuals with $g_i < \hat{g}_i$ prefer legal employment, while those with $g_i > \hat{g}_i$ choose to commit a crime.

Figure 3: Crime decision threshold: Legal wage vs. expected gain from crime



Mining boom. Next, the question that arises is how a localized positive economic shock (such as a mining boom) affects the crime choice model for those individuals who are treated? I model the mining boom as a positive shock to legal wages in the mining municipality:

$$w_i^B = w_0 + \delta$$

where $\delta > 0$ captures the wage premium induced by the mining boom. I allow heterogeneity in the impact of δ depending on individual characteristics (e.g., gender, age, education), but this is suppressed here for tractability.

With the increase in w_i (due to a mining boom), the threshold rule becomes:

$$g_i > \frac{w_i^B + ps}{1 - p}$$

This new threshold is higher due to the new wage, making crime less attractive. This implies that fewer treated individuals will find it worthwhile to engage in criminal behavior.

In other words, due to the boom, the opportunity cost of treated individuals to commit a crime is higher than it would have been otherwise. Thus, their probability of committing a crime declines as the wage for legal work becomes relatively more attractive. Individuals in the control group, whose labor market conditions do not improve, do not change their behavior because they still face the old w_i and the same threshold. Therefore:

$$\frac{\partial \Pr(\text{Crime}_i)}{\partial w_i} < 0$$

Observing Figure 3, an exogenous increase in the legal wage w_i due to the mining boom, shifts the horizontal line upward. This increases the threshold $\hat{g}_i$, thereby reducing the set of individuals for whom criminal activity is the optimal choice. This mechanism provides the main empirical prediction: *improved labor market conditions reduce crime among residents.*

Migration. Next, I analyze the role of migration and composition effects in the model. As mentioned, if an individual in a non-mining area migrates to a mining region, they receive a wage w_i^M at a migration cost c_i. Individuals located outside the mining municipality decide whether to migrate based on the net benefit of doing so $U_i^{\text{migrate}} = w_i^M - c_i$. w_i^M is the expected wage in the mining municipality after the boom, and c_i is the individual-specific cost of migration. Therefore, an individual migrates if:

$$w_i^M - c_i > \max\{w_i, \pi_i\}$$

That is, an individual decides to migrate to a mining area if the wage minus the migration cost is higher than the highest wage for legal work or the expected payoff for crime in the origin area. If the mining boom increases the wage w_i^M, more individuals will choose to migrate, especially those whose outside options are dominated by the expected gains from moving.

The individuals who choose to migrate are not a random sample of the population. The composition of migrants depends on the joint distribution of g_i, c_i, and w_i. Specifically, if individuals with higher g_i and lower w_i are more likely to migrate, the inflow could increase the crime rate in the mining region—even as it falls among original residents. Previous studies show that migrants, attracted by local economic shocks, are likely to be young and mobile (lower migration costs c_i), low-skilled (with lower w_i in origin), and more risk-tolerant or with higher baseline crime returns g_i (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. If the volume and composition of migration are large enough, the aggregate crime rate in the mining area may rise, despite falling crime rates among original residents. This creates a potential divergence between *aggregate* and *resident-specific* crime responses to the boom, helping to reconcile seemingly contradictory findings in the literature.[9] This mechanism provides the second empirical prediction: *aggregate crime may increase, decrease, or remain unchanged depending on the characteristics of migrants attracted by the boom.*

Heterogeneity. Finally, the responses to the mining boom in terms of criminal behavior might differ for different population groups. Let $F(\cdot)$ be the cumulative distribution of g_i. Then the probability of committing a crime is:

$$\Pr(\text{Crime}_i) = 1 - F(\hat{g}_i)$$

and the effect of a wage shock is:

$$\frac{\partial \Pr(\text{Crime}_i)}{\partial w_i} = -f(\hat{g}_i) \cdot \frac{1}{1-p}$$

where $f(\cdot)$ is the density function of g_i. This implies that the marginal deterrent effect of a wage increase is stronger for individuals who are close to the threshold $\hat{g}_i$. Empirically, certain demographic groups (e.g., males, young, low-educated) have features that make them more likely to be located near the crime threshold. For example, they tend to have lower legal wages w_i, face higher potential crime returns g_i due to fewer employment opportunities or higher risk tolerance, and are more sensitive to changes in income (higher wage elasticity). Therefore, as a result, they are more likely to change their behavior in response to an increase in the legal work wage. On the contrary, individuals with high education or strong aversion to crime are already well below the threshold and are thus less responsive to wage changes. This mechanism provides the third empirical prediction: *effects are strongest among individuals with certain characteristics (e.g., young, low-skilled, and males) who are most sensitive to wage changes and have higher baseline crime propensity (g_i).*

4 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.

[9] Formally, the total crime rate in the mining municipality is:

$$\text{Crime}_t^{\text{agg}} = \frac{1}{N_t}\left(\sum_{i\in R}\Pr(\text{Crime}_i^R) + \sum_{j\in M}\Pr(\text{Crime}_j^M)\right)$$

where R denotes residents, M denotes migrants, and $N_t = |R| + |M|$. It is possible for:

$$\Pr(\text{Crime}_i^R)\downarrow \quad \text{and} \quad \text{Crime}_t^{\text{agg}}\uparrow$$

if the inflow of migrants M is large and/or has a higher crime propensity than the original population.

The data also includes information on employment, occupation, industry, and region of residence and work, and I focus on the period 2000-2015.[10] These data have been linked to the Swedish Conviction Register and the Crime Suspicion Register, both 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 individuals older than 18 years and under 65 years who appear in five or more annual observations consecutively in the sample. Moreover, I consider individuals located in Gällivare municipality, in Norrbotten County, as treated due to the high presence of mining in the territory and labor market, and because it 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 in the county are considered controls.[11] As mentioned, individuals in Kiruna are also excluded due to the movement of the city. 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.1 shows the spatial location of the treated 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 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

[10]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.

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

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.[12]

In the main analysis, the main outcome of interest is being convicted of any crime for each individual per year. In additional analyses, I divide the crimes into five broad categories: (1) violent crimes, (2) property crimes, (3) drug-related crimes, (4) traffic crimes, and (5) other crimes. Violent crimes include violations of life and health, violations of freedom and peace, defamation, sexual offenses, and crimes against family. Property crimes include theft, robbery, and other assaults, fraud and other misconduct, embezzlement and other faithlessness, offenses against creditors, and crimes of damage. Other crimes include crimes against the public, crimes against the state, and other special categories (e.g., smuggling, tax crimes, terrorist crimes). See Table A.2 in the Online Appendix for a detailed description of each category and subcategory of crime. 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 166,849 individuals (1,979,481 individuals-year observations). Moreover, I identify 52,213 migrants (565,977 migrant-year observations).

5 Empirical framework

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

[12] Online Appendix Figure B.2 shows the distribution of individuals in space according to their location and distance to the nearest mine and their distribution in the rings.

other municipalities in the county, before and after the mining boom, to identify the average treatment effect (ATE) on the treated in Gällivare. Formally, I estimate the effects of local economic shocks on local residents' criminal behavior using the following linear probability model:[13]

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

where Y_{ijmt} is equal to 1 if individual i located in grid j and in municipality m in year t is convicted of any crime. $Treated_{imt}$ is a binary variable that takes the value of 1 if individuals are located in Gällivare 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. In some specifications, I control for time-varying individual level factors (X_{it}), 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).

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

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

where the outcome Y_{ijt} is equal to 1 if individual i located in grid j in year t is convicted of any 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. As before, I have X_{it} as a vector of time-varying individual characteristics as controls for other underlying factors that may influence the outcome variable. $Ring(d)_{ijt}$ 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: $d \in \{(0, 20], (20, 40], (40, 60], (60, 80], (80, 237]\}$. $Post_t$ is a binary indicator equal to 0 before the mining

[13] While logit and probit models are also used for binary outcomes, they add their own assumptions, often don't have closed-form solutions, and their interpretation is more complex, especially with large amounts of fixed effects (Huntington-Klein, 2021).

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. 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).

5.1 Identifying assumptions

The assumptions behind the DID approach are that, in the absence of the mining boom, residents' criminal behavior in Gällivare municipality 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:

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

where Y_{ijmt} is equal to 1 if individual i located in grid j and in municipality m in year t is convicted of any crime. $Treated_{imt}$ is a binary variable that takes the value of 1 if individuals are located in Gällivare 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 βs, 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.[14] Third, I assume that 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 location after 2004 (migrants) (Benshaul-Tolonen et al., 2019; Jacobsen et al., 2023).

6 Results: Mining boom and crime

6.1 Main results

I begin by estimating the overall effect of local economic shocks on crimes committed by residents. Table 1 reports the DID coefficients. Columns (1)-(3) use the binary treatment equal to one for residents in Gällivare municipality and zero otherwise, and show the coefficients from equation (1). Column (1) does not include control variables and is the preferred specification since some controls could be endogenous to the mining boom and criminal behavior (Allcott and Keniston, 2018). To evaluate the robustness of the results, in column (2) I present the results with controls, and column (3) excludes individual fixed effects.

The results suggest a negative and significant reduction in the probability of being convicted of any crime after the mining boom for treated individuals.[15] The preferred

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

[15] In an earlier version of the paper, I used the number of crimes reported to the police per 100,000 inhabitants in the 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

specification in column (1) indicates a decline of 0.23 percentage points in the probability of being convicted of any crime among treated individuals relative to their non-treated counterparts. From a baseline sample mean of 0.012, this estimate translates to a 19% drop in individuals convicted and is statistically significant at the 1% level. This effect remains robust to the different specifications in columns (2)-(3). Overall, 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). Moreover, the results are in line with recent literature that finds reductions in crime due to mining shocks (Axbard et al., 2021; Street, 2025). 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, isolating local economic effects from changing composition, finds similar reductions in criminal behavior (14-17.5% drop in cases filed) (Street, 2025).

Columns (4)-(6) use 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 any crime after the mining boom for 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. This effect remains robust to the different specifications in columns (5)-(6). The specification in column (4) indicates a decline of 0.25 percentage points in the probability of being convicted of any crime among treated individuals relative to their non-treated counterparts. From a baseline sample mean of 0.012, this estimate translates to a 20% drop in individuals convicted and is statistically significant at the 1% level. Overall, these results suggest that the mining boom benefited the most (crime fell more) for 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.

Table 1: Impact of the mining boom on being convicted of any crime, 2000-2015

	(1)	(2)	(3)	(4)	(5)	(6)

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).

Post*Gällivare	-0.0023***	-0.0023***	-0.0031***			
	(0.0008)	(0.0008)	(0.0009)			
Post*≤ 20 km				-0.0025***	-0.0025***	-0.0034***
				(0.0009)	(0.0009)	(0.0010)
Post* 20 - 40 km				-0.0006	-0.0004	-0.0019
				(0.0028)	(0.0028)	(0.0025)
Post*40 - 60 km				-0.0010	-0.0008	-0.0002
				(0.0020)	(0.0020)	(0.0023)
Post*60 - 80 km				-0.0023	-0.0022	-0.0018
				(0.0014)	(0.0014)	(0.0013)
Controls	No	Yes	No	No	Yes	No
Individual FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Nxt	1979481	1979481	1979481	1979481	1979481	1979481
N	123718	123718	123718	123718	123718	123718
Mean dep. var (2003)	0.0123	0.0123	0.0123	0.0122	0.0122	0.0122
Effect relative to the mean (%)	-18.84	-18.53	-25.13	-20.36	-20.30	-27.52
R-squared	0.2407	0.2410	0.0142	0.2407	0.2410	0.0142
Within R-squared	0.0000	0.0004	0.0000	0.0000	0.0004	0.0000

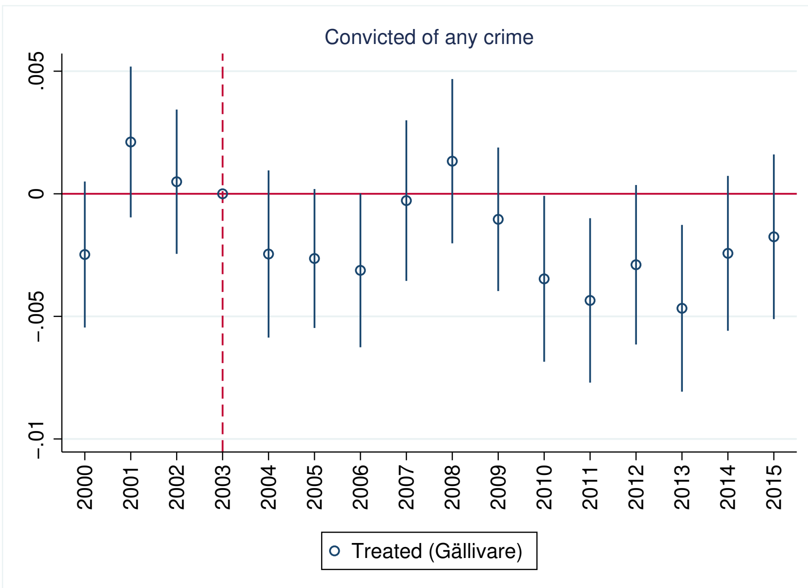
Notes: Two-way fixed effects panel data regression. Controls include marital status, having children under 18, educational levels, and economic sectors. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

For the remainder of the paper, I focus on the treatment definition based on residing in Gällivare 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 86% of Gällivare 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 9 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 4 shows the dynamic treatment effect computed using the same specification of column 1 (Table 1), that is, the effect of the mining boom on the probability of being convicted of any crime 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 crime decreases for individuals located in Gällivare municipality compared to those in the control group. This effect disappears in 2007, 2008, and 2009, becoming statistically insignificant, which coincides with the timing of the global financial crisis. Between 2010 and 2013, I again observe an decrease in criminal behavior, suggesting a renewed response to economic conditions. However, this effect fades and becomes statistically insignificant in the years that follow. These findings complement the ones in Table 1 showing negative effects of the boom on criminal behavior.[16]

Figure 4: Event study of the impact of the mining boom on being convicted of any 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 first prediction from the theory: crime among residents declines following the mining boom, consistent with an increase in legal wage opportunities (w_i) that raises the threshold for engaging in criminal activity. The reduction in convictions 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.

[16]In addition, I estimate a dynamic DID to validate the parallel trends assumption for the spatial heterogeneity treatment (Column 4 Table 1), which is in the Online Appendix Figure B.3. 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 crime decreases for individuals located within 20 kilometers of the nearest mine compared to those in the control ring.

This supports the idea that economic opportunity can serve as an effective crime-reduction mechanism. More discussion on the mechanisms in Section 7.3.

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 men. Moreover, according to the empirical literature, young males participate in a disproportionate amount of violent and property crimes (Komarek, 2018). Figure 5 shows this descriptive pattern for my data. In both the pre-boom and boom periods, young men 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.

Figure 5: Conviction rates of any crime by age and gender, before vs after

Notes: The sample excludes the migrants to the mining area.

This is further confirmed in Table 2, which confirms that the effects of the mining boom on being convicted of any crime are concentrated among males (Column (1)) and young (Column (3)). Column (6) shows a large effect on young males. Specifically, for males, I observe a decline of 0.46 percentage points in the probability of being convicted of any crime among treated individuals relative to their non-treated counterparts during the boom. From a baseline sample mean of 0.020, this estimate translates to a 23% drop in males convicted of any crime during the mining boom. Regarding young individuals (18-30), I observe a decline of 1.07 percentage points in the probability of being convicted of any crime among treated individuals relative to their non-treated counterparts during the boom. From a baseline sample mean of 0.022, this estimate translates to a 48% drop in young residents convicted of any crime during the mining boom. For young males, there is a decline of 1.7

percentage points in the probability of being convicted of any crime among treated individuals relative to their non-treated counterparts. From a baseline sample mean of 0.035, this estimate translates to a 47% drop in young males convicted and is statistically significant at the 1% level. Females and older age groups show no meaningful changes in criminal behavior due to the mining boom. These large effects are in line with previous empirical literature in terms of the demographic composition of the mining sector, which is primarily young and male (e.g., Kearney and Wilson, 2018; Chávez and Rodríguez-Puello, 2022). Moreover, 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, in the rest of the paper, 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. Results for the full sample are shown in Online Appendix C.

Table 2: Impact of the mining boom on being convicted of any crime by demographic groups, 2000-2015

	(1) Male	(2) Female	(3) Age 18-30	(4) Age 31-50	(5) Age 51-65	(6) Male 18-30
Post*Treated	-0.0046***	0.0001	-0.0107***	-0.0011	-0.0005	-0.0166***
	(0.0014)	(0.0005)	(0.0038)	(0.0011)	(0.0009)	(0.0060)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Nxt	1029022	950459	408843	839569	731069	225492
N	64314	59404	25553	52473	45692	14093
Mean dep. var (2003)	0.0203	0.0035	0.0222	0.0122	0.0068	0.0355
Effect relative to the mean (%)	-22.57	3.68	-48.09	-9.07	-7.13	-46.92
R-squared	0.2475	0.1982	0.3255	0.2498	0.2234	0.3367
Within R-squared	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001

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

6.2 Detailed criminal behavior

Additional crime outcomes. 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 individuals as a response to the mining boom (Table C.1). I construct five 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. Third, a binary indicator reflecting those individuals convicted of any crime and not sentenced to prison, which represents the majority of convicted individuals. Fourth, 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 fifth, post-prison reoffense identifies individuals who reoffend in any year following a previous prison sentence, isolating patterns of reentry into criminal activity post-incarceration.[17] Individuals with no convictions across all years constitute the reference group for these outcomes. The outcomes of being convicted of any crime and not sentenced to prison, conviction with prison, and post-prison reoffense are mutually exclusive. All 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, repeat offending, and the role of incarceration.

The results reveal important heterogeneity. First, the reduction in criminal behavior for young males due to the mining boom is concentrated among first-time offenders, suggesting that improved labor market conditions through increased opportunity costs or incapacitation effects 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. 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. Second, the probability of being convicted without receiving a prison sentence, which may be considered a proxy for lower-severity crimes, also significantly decreases due to the mining boom. Specifically, convictions not resulting in prison decline by around 61% relative to the 2003 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. 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.[18]

Table 3: Impact of the mining boom on different crime outcomes, 2000-2015

	(1)	(2)	(3)	(4)	(5)

[17]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.

[18]Online Appendix Table C.1 shows the results for the full sample. The results are similar to those for young males. Interestingly, convictions resulting in prison, which may indicate more serious offenses, decline by around 69% relative to the 2003 mean, highlighting a particularly strong response in this category. Finally, the probability of post-prison reoffense increases modestly and significantly during the boom, possibly reflecting limitations in reintegration or rehabilitation for formerly incarcerated individuals.

	First-time convicted	Re-offense	Convicted + no prison	Convicted + in prison	Post-prison reoffense
Post*Treated	-0.0163***	-0.0006	-0.0192***	-0.0011	0.0036
	(0.0042)	(0.0041)	(0.0053)	(0.0018)	(0.0029)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes
Nxt	225492	225492	225492	225492	225492
N	14093	14093	14093	14093	14093
Mean dep. var (2003)	0.0219	0.0135	0.0313	0.0020	0.0022
Effect relative to the mean (%)	-74.24	-4.13	-61.36	-54.64	161.64
R-squared	0.1547	0.3822	0.2844	0.1557	0.4280
Within R-squared	0.0001	0.0000	0.0001	0.0000	0.0000

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

Types of crime. To better understand the type of crime affected by local economic shocks, I explore treatment effects separately for the five crime categories: property (e.g., theft, fraud, damage), violent (e.g., assault, kidnapping, defamation), drug, traffic, and others (e.g., public order offenses, treason, misconduct). These exercises are viewed as exploratory to understand the overall crime results better and generally lack precision, which is common when disaggregating rare outcomes. Therefore, all other analyses in the paper focus on the overall criminal behavior. Results are shown in Table 4 for the sample of young male residents.[19] Column (1) reports a significant decrease in property crime convictions for treated residents compared to controls, due to the mining boom. Specifically, I observe a decline of 0.92 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 0.015, this estimate translates to a 62% drop in individuals convicted and is statistically significant at the 5% level. Similarly, estimates are negative and of similar magnitude for "other" crimes. Moreover, more in line with expectations, there is no significant effect on violent crimes, suggesting that positive local economic shocks do not directly change interpersonal violence. There is no effect on traffic-related crimes, and the coefficients are small and imprecise. Finally, drug-related crimes increase due to the mining boom. 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 entertainment and illegal activities provided by the adult entertainment industry (e.g., Wilson, 2012; Beleche and Cintina, 2018;

[19] Online Appendix Table C.2 shows the results for the full sample, and Online Appendix Figure B.4 validates the parallel trends assumption for these outcomes and shows their temporal dynamics before and after the mining boom. Residents in the mining and non-mining municipalities do not diverge prior to the mining boom across the crime types, and residents exposed to the mining boom are not more likely to have a criminal charge than their non-exposed counterparts, except for the "other" crimes category.

Cunningham et al., 2020).

Overall, these results provide evidence that the reduction in crime due to the mining boom for young individuals is concentrated in property and other crimes. While there is an increase in drug-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., James and Smith, 2017; Andrews and Deza, 2018). Regarding the reduction in "other" crimes, there may be several reasons for this finding; nevertheless, due to low statistical power, I am not able to empirically assess them. For example, other crimes include forgery, such as fake permits, false ID, or counterfeiting, which may decrease with formal employment and strong institutions. Moreover, the relationship between local economic shocks and crime may be highly context-specific.

Table 4: Impact of the mining boom on being convicted by types of crime, 2000-2015

	(1) Property crime	(2) Violent crime	(3) Drug crime	(4) Traffic crime	(5) Other crimes
Post*Treated	-0.0092**	0.0027	0.0066**	-0.0033	-0.0092***
	(0.0039)	(0.0022)	(0.0028)	(0.0027)	(0.0032)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes
Nxt	225492	225492	225492	225492	225492
N	14093	14093	14093	14093	14093
Mean dep. var (2003)	0.0149	0.0065	0.0049	0.0102	0.0121
Effect relative to the mean (%)	-61.60	41.52	135.59	-31.85	-76.08
R-squared	0.2939	0.2167	0.3790	0.2739	0.2362
Within R-squared	0.0001	0.0000	0.0001	0.0000	0.0001

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

6.3 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 crime 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). Due to sample size, I estimate the CATE using the full sample; however, in this subsection, the GATEs focus on young males.[21] Appendix D provides additional details on the estimation procedure.

The ATE estimate using the causal forest is similar to the one in Column (1) Table 1, negative and statistically significant. The magnitude of the effect ranges between -0.041 and 0.041, with a mean of -0.002. 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 any crime in the first decile of the effect size distribution to a 0.8 percentage point increase in the last decile (see Online Appendix Figure B.5).

Figure 6 shows how the effect varies with individual characteristics. The results show important heterogeneity among different population groups.[22] Panel (a) shows the heterogeneous effect of the mining boom for primary, secondary, and tertiary educational levels. The reductions in criminal convictions due to the mining boom are concentrated among young males with primary and secondary educational levels. 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). Panel (b) shows the heterogeneous effect of the mining boom across the income distribution. While the effects are not significant for most earnings deciles, the reduction in the probability of being convicted of any crime is observed for the young males in deciles 5 to 9.

In panels (c) and (d), I examine whether the effects are concentrated among employed or unemployed young males, 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

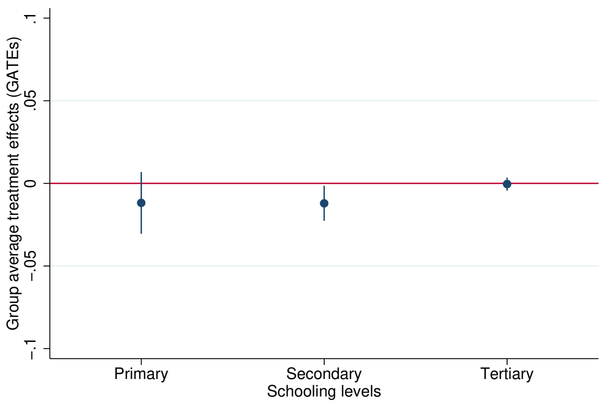
[20] To avoid endogenous movement across categories, individuals are classified in their education level, earnings decile, employment status, and economic sector according to their information in 2003.

[21] Specifically, to ensure sufficient within-leaf variation and maintain treatment–control balance under the honest-splitting procedure, I estimate the causal forest using the full sample. Although the young-male subsample is relatively large (around 14,000 individuals and 225,000 person-year observations), the combination of honest sample splitting, a high-dimensional covariate space, and a relatively sparse treatment assignment substantially reduces the effective sample size (Wager and Athey, 2018). For this reason, the model is trained on the full population, while the GATEs reported below focus on young males.

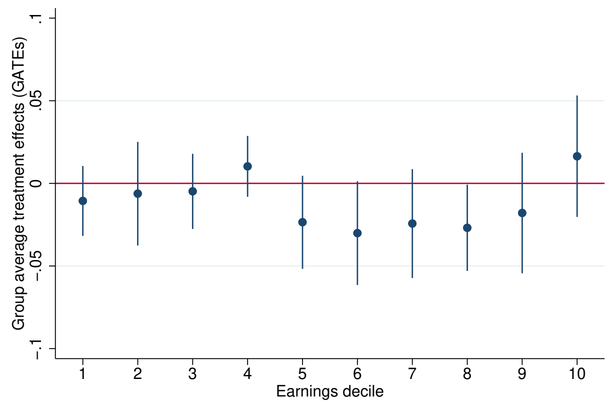
[22] Online Appendix Figure C.1 shows the results for the full sample.

economic sectors into mining, manufacturing, construction, services, and others (including agriculture, public, and healthcare). Results show that employed young males reduce their criminal behavior due to the mining boom, and there are significant spillovers in terms of criminal behavior into manufacturing, construction, and service sectors. On the other hand, the criminal behavior of young male workers in the mining and other sectors is not affected. These results align with previous studies that find evidence of local spillover effects from resources into labor market conditions of workers in industries directly related to mining, such as manufacturing, and indirectly related, such as services (Tano et al., 2016; Allcott and Keniston, 2018).

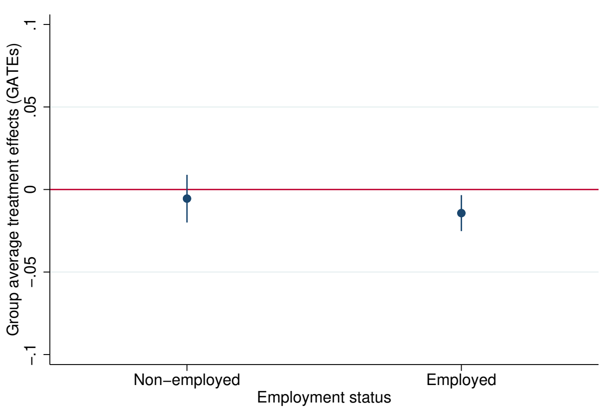
Figure 6: Group average treatment effects (GATEs) by characteristics, 2000-2015



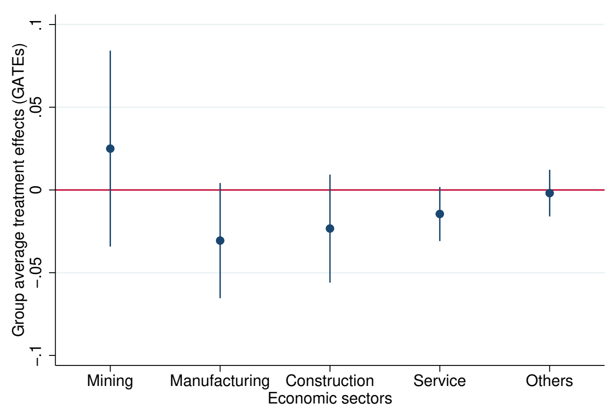
(a) Schooling levels



(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. GATE are estimated using causal forest algorithms. 95% confidence interval shown.

Overall, these results support the third prediction from the theory: the reduction in criminal behavior is concentrated among males, individuals aged 18–30, and those with low-skill levels, who are most sensitive to wage changes and have higher baseline crime propensity (g_i). These groups are disproportionately represented in mining-related occupations and are more likely to benefit directly from these sector-specific local labor market shocks.

6.4 Robustness checks

The estimated impacts of the mining boom on criminal behavior are robust to various alternative specifications and robustness checks. The robustness checks in this section consider the full sample. Online Appendix Tables A.5 and A.6 show the robustness checks for the municipality and rings treatments, respectively, both using being convicted of any crime as the outcome. Column (1) reports the results from the baseline specification for reference, focusing only on the sample of 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 estimate the results by also including migrants. As noted above, by separating the effect for residents and migrants, I can exclude crimes committed in Gällivare municipality 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 (4), I restrict the sample to individuals under 55 years old, which corresponds to the end of their "prime" working years. I do this to make sure the results are based on exogenous changes in economic opportunities and not on endogenous household-level choices related to retirement (Jacobsen et al., 2023). This change has little effect on the coefficient estimates.

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. 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. Finally, in column (8), I analyze the effects of the mining boom specifically for Kiruna municipality, which is excluded from the main analysis due to the large-scale relocation of its city center during the boom period. Kiruna is also a major mining municipality in Sweden, but the relocation process due to the mining activity 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 positive effects of improved labor market opportunities. As expected, there is no reduction in criminal behavior among residents in Kiruna municipality due to the mining boom. On the contrary, point estimates suggest a small increase in convictions during the boom. However, the dynamic DID estimates (Online Appendix Figure B.6) show no good pre-trends, with negative and imprecise coefficients already present in the pre-boom period, suggesting that the positive post-boom estimate is largely driven by pre-existing downward trends and noise. Therefore, the Kiruna results should be interpreted with caution.

As an additional robustness check, I consider an alternative outcome: being suspected of a crime. These data come from the Crime Suspicion Register, maintained by BRÅ. It provides information about individuals who are regarded as likely suspects following a criminal investigation conducted by the police or prosecutor. As Grenet et al. (2024), the individuals suspected of a crime can also be known as having been "arrested", following closely how the terminology is used in many other countries. As an additional outcome, I create the dummy variable of being suspected of any crime in a given year. This measure captures earlier involvement in the criminal justice process and may reflect a broader set of behaviors, though it is potentially more prone to measurement error. Online Appendix Table A.7 shows the results, which are consistent with the main findings using convictions. This reinforces the interpretation that the mining boom affected criminal behavior, rather than judicial outcomes or conviction thresholds alone.

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. The estimated effects for being convicted of any crime are virtually unchanged, compared to those of Column (4) 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 any crime after the mining boom for residents located within 20 minutes by car of the mines.

Finally, 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).[23] 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,

[23] 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.

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). The results, in Online Appendix Figure B.7, show that the findings are robust to this empirical strategy.[24]

7 Contextualization and mechanisms

7.1 Social cost effects

Online Appendix Table A.9 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 Table 4 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 11.8 million during the boom. The reductions in “other crimes” also translate into sizeable social savings, amounting to SEK 2.6 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. Drug crimes increase significantly during the boom, leading to social losses of roughly SEK 9.5 million. This pattern mirrors the conviction results and suggests that mining-driven shocks may have unintended spillovers into illicit drug 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 and other crimes, which dominate the aggregate social savings. At the same time, the rise in drug-related crime partly offsets these benefits.

7.2 Literature comparison

Online Appendix Figure B.8 compares the baseline mining boom effect estimates with 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. I distinguish between aggregate- and individual-level

[24] I do not use this strategy as a robustness check rather than the main empirical approach because using it, I lose the time dimension of the data, comparing the average values of the outcome before and after the shock.

studies. 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.

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; Street, 2025) and null effects in Chile (Corvalan and Pazzona, 2019), which are contrary to expectations on Becker (1968) model. These studies explain these contradicting effects based on increases in criminal opportunities, access to disposable income for activities that complement crime, and population changes due to migration (Street, 2025). When the migration of crime-prone individuals is accounted for, recent studies find that residents reduce their criminal behavior due to better economic opportunities (in line with Becker (1968)). The baseline result of this paper on the effect of the mining boom (19% reduction) is comparable to the effects from other resource shocks papers in South Africa (Axbard et al., 2021) and the US (Street, 2025), which account for endogenous migrations to the resource areas. Notably, the 95% confidence interval from my main specification overlaps with that of Street (2025) for the fracking boom in North Dakota in the US. Together, these comparisons show that resource shocks that account for endogenous migration decisions and isolate the impact of economic opportunity on criminal behavior generate similar 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 C.4), I divide the effect on crime by the 9.3% increase in labor income and estimate an implied elasticity of crime to earnings equal to -2. That is, a 1% increase in earnings is associated with a 2% decrease in crime conviction probability.[25] This suggests that 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).[26]

[25]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 7.3).

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

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

7.3 Why does the mining boom affect crime?

Generally, the estimates are reduced-form effect that encompasses 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.9 presents a Directed Acyclic Graph (DAG) that maps out the main hypothesized mechanisms. The diagram highlights how the mining boom may reduce crime through an opportunity cost channel via improved labor market conditions, but also through other indirect channels such as changes in migration patterns, income inequality, schooling (via incapacitation), and crime prevention capacity.

In this section, I use the same empirical design described in Section 5 (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.[27] I start by examining the effect of the mining boom on the criminal behavior of migrants to the area. Next, I analyze the role of the opportunity cost channel via labor market improvements and then follow with the other indirect channels.

Migration. 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

[27] 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.

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. These contribute to answering the question posed by James and Smith (2017) and Street (2025), which is whether I may observe an increase in aggregate crime rates in mining areas due to possible criminally prone individuals disproportionately migrating to resource areas due to the boom. 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 that align with the hypothesis that certain population characteristics can drive aggregate crime dynamics after a mining boom (Online Appendix Table A.10). First, I find that a higher share of migrants are convicted of any crime, compared to residents in Gällivare. 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, younger, more likely to be male, less likely to be married, and have lower educational attainment, which are demographic traits commonly associated with higher baseline crime risk in the literature. Their employment rates and earnings are also lower compared to 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). These differences help explain why an influx of migrants due to the mining boom, even during a period of economic expansion, might increase overall crime rates at the municipality level, in line with previous empirical evidence (e.g., James and Smith, 2017; Street, 2025). The observed higher conviction rates among migrants—particularly in the early period—support the view that compositional effects play a key role in shaping the crime response to local labor market shocks.

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.[28] The table presents results from several model specifications that differ in comparison groups and estimation approaches. Columns (1)–(2) and (3)–(4) estimate conventional two-way fixed-effects regressions: the first two columns compare migrants to Gällivare or the control municipalities to themselves before migration (the estimation includes two post-migration interaction dummies, with "pre-migration years" as the omitted category), while columns (3)–(4) contrast migrants to Gällivare with migrants to the control municipalities. Columns (5)–(6) use a staggered difference-in-differences estimator, reporting average treatment effects on the treated (ATT)

[28] Online Appendix Table C.3 shows the results for the full sample.

that compare migrants to Gällivare or the control municipalities to those who have not yet migrated (Callaway and Sant'Anna, 2021). All specifications include individual and year fixed effects, and some include controls or grid fixed effects as indicated. These specifications allow me to estimate the combined impact of migration and the mining boom on individual criminal behavior. Across all models, the estimated coefficients are small in magnitude and statistically insignificant, suggesting that migrating to Gällivare or other municipalities in the county after the mining boom does not significantly alter the likelihood of being convicted of any crime. These results suggest that the mining boom did not systematically alter criminal behavior among migrants, consistent with the notion that improved economic opportunities in booming regions may offset potential crime-inducing factors.

Table 5: Impact of the mining boom on being convicted of crime of migrants, 2000-2015

	(1)	(2)	(3)	(4)	(5)	(6)
Post*Gällivare	0.0078	0.0079	0.0043	0.0046	0.0119	
	(0.0127)	(0.0129)	(0.0150)	(0.0151)	(0.0116)	
Post*Control mun.	0.0041	0.0046				-0.0005
	(0.0044)	(0.0044)				(0.0039)
Controls	No	Yes	No	Yes	No	No
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	No	No
Nxt	163197	163197	50166	50166	121020	148521
N	10200	10200	3135	3135	7564	9283
Mean dep. var (2003)	0.1206	0.1206	0.0394	0.0394	0.0388	0.0411
Effect relative to the mean, Gällivare (%)	6.47	6.58	10.79	11.58	30.67	
Effect relative to the mean, Control mun. (%)	3.37	3.83				-1.22
R-squared	0.5526	0.5528	0.4685	0.4686		
Within R-squared	0.0000	0.0005	0.0000	0.0002		

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) and (2) compare migrants to Gällivare or the control municipalities to themselves before the migration event. Columns (3) and (4) compare migrants to Gällivare to migrants to the control municipalities. Columns (5) and (6) consider the staggered nature of the migration event and show average treatment effect on the treated (ATT) comparing migrants to Gällivare or the control municipalities to not yet treated migrants. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Overall, while the descriptive evidence comparing demographic characteristics of migrants and residents provides suggestive evidence supporting the hypothesis that an influx of potentially higher-risk individuals (i.e., young, low-education, male migrants) into booming mining regions could elevate crime rates at the aggregate level, the micro-level empirical results discard this idea. The mining boom does not alter the probability of migrants committing crimes after the migration event. This 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. These results underscore the importance of distinguishing between individual- and aggregate-level analyses in evaluating the impacts of local economic shocks.

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).[29] Several empirical papers find positive effects on employment (Black et al., 2005; Pérez-Trujillo and Rodríguez-Puello, 2022) and earnings (Black et al., 2005; Weber, 2012; Tano et al., 2016). 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 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 residents in the mining municipality and discuss its relative importance in explaining the changes in crime as a result of the resource shock (Table 6).[30] Columns (1), (2), (3), and (4) show the results for disposable income, labor income (earnings), employment overall, and employment in the mining sector, respectively.[31] Consistent with previous work in other contexts, the mining boom has a positive effect on the labor market conditions of young male residents in the mining municipality, with a significant increase in disposable and labor income, and the probability of being employed directly in the mining sector due to the shock. Specifically, yearly disposable income increases by 18,304 SEK for treated residents after the mining boom compared with control residents. This represents a 16% increase from the baseline mean disposable income. The observed increase in labor income is higher. While there is no overall

[29] 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). 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.

[30] Online Appendix Table C.4 shows the results for the full sample.

[31] 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).

effect on employment, a substantial increase is observed in the probability of being employed in the mining sector, with significant spillover effects into related sectors (e.g., manufacturing and construction) (Rodríguez-Puello and Rickardsson, 2024). 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. 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 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 (4) and (5) Table 6).[32] 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

[32]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%.

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 aggregate changes in crime.

Table 6: Mechanisms: impact of the mining boom on different mechanisms, 2000-2015

	(1) Disposable income	(2) Labor income	(3) Employment	(4) Employment mining	(5) Police occupation	(6) Police industry	(7) Top earning tercile	(8) Secondary educ. (18-24)
Post*Treated	183.0490***	280.3299***	-0.0073	0.1119***	-0.0006	-0.0007	-0.0020	0.0930***
	(18.6333)	(30.5062)	(0.0123)	(0.0108)	(0.0024)	(0.0026)	(0.0022)	(0.0185)
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	225492	225492	225492	225492	183812	225492	129392	97967
N	14093	14093	14093	14093	14139	14093	8087	6123
Mean dep. var (2003)	1114.3322	1174.6761	0.6248	0.0212	0.0027	0.0063	0.2360	0.5788
Effect relative to the mean (%)	16.43	23.86	-1.16	527.26	-23.64	-10.98	-0.84	16.07
R-squared	0.6093	0.7409	0.5628	0.6834	0.5673	0.5356	0.9720	0.7544
Within R-squared	0.0004	0.0014	0.0000	0.0123	0.0000	0.0000	0.0000	0.0015

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

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 crime increases due to the mining boom, 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 (6) Table 6) show that the mining boom does not affect the probability of being at the top of the income distribution. 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.

Incapacitation effects. The crime reductions may be in part due to changes in incapacitation effects from high school attendance. There is a large body of literature exploring the effects of resource booms on human capital accumulation (e.g., Mejía, 2020; Pérez-Trujillo and Rodríguez-Puello, 2022; Kovalenko, 2023). This literature finds that mining booms reduce schooling attendance due to better labor market opportunities that increase the opportunity cost of attending school. Therefore, residents might drop out of school during the mining boom, and they may miss out on human capital accumulation. On the contrary, a mining boom that improves labor market opportunities may indirectly increase schooling by providing individuals with the monetary and time resources to spend on their education, or by improving the public good provision in education (Paredes and Rivera, 2017; Rodríguez-Puello, 2025). Previous literature argues that education reduces the probability of engaging in activities that generate negative externalities, such as criminal activities (Moretti, 2004; Lochner, 2004, 2020). Therefore, the mining boom that increases educational attainment may generate incapacitation effects, because young individuals have less time available for participating in criminal activities (Anderson, 2014).

The first evidence for this mechanism is in the heterogeneity analysis by age groups in

Table 2. I estimate treatment effects on criminal behavior only for young individuals who are around school age (18-30 years old), when the incapacitation effect is more relevant. The incapacitation effect only holds when individuals are actually in school instead of out committing crimes. The fact that the larger reductions in crime due to the mining boom are among the youth provides evidence supporting this mechanism. Moreover, I specifically test the first-stage of this mechanism by examining the effect of the mining boom on the probability of young male residents completing secondary education (Table 6).[33] I focus on males between 18 and 24 years old in 2003 (pre-treatment year), as these are school-age youth and likely to be in or just completing secondary school. The results show a significant increase in the probability of having a secondary education for young male individuals. This provides suggestive evidence for the incapacitation effect mechanism, in which young individuals are in school and have less time available to commit crimes.

Overall, the evidence suggests that the observed reduction in crime following the mining boom is likely driven by a combination of improved labor market conditions and increased school attendance. On the one hand, better labor market opportunities raise the opportunity cost of engaging in criminal behavior. On the other hand, higher school participation during the boom period may reduce crime through incapacitation effects, particularly among school-age youth. Selective migration and improvements in crime prevention capacity do not drive the results. These complementary mechanisms highlight how localized economic shocks can influence criminal behavior through both direct and indirect channels.

8 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 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. Moreover, as a contribution from previous work, I differentiate the effects for residents and migrants, separating the effects of population changes that bias aggregate-level results.

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

[33] I define as having completed secondary education those individuals with educational levels of upper secondary 3 years or more than upper secondary less than 2 years in the Swedish educational system.

criminal convictions and demographics in Sweden from 2000 to 2015, I estimate the effect of improvement in labor market conditions on criminal behavior using difference-in-differences and event study models. As mentioned, 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 economic sectors and demographic groups. 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, contrary to previous literature that finds aggregated crime increases due to resource shocks, when migration and compositional changes are accounted for, local residents do not experience a similar increase but rather have a decrease in criminal activity during the mining boom. Specifically, I find a decline of 0.22 percentage points in the probability of being convicted of any crime among treated individuals relative to their non-treated counterparts. From a baseline sample mean of 0.012, this estimate translates to a 19% 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). Effects are concentrated among young males with low education levels and the workers in the manufacturing, construction, and services sectors. These effects are driven by existing residents in the area, rather than in-migrants. For young males, there is a decline of 47% in the probability of being convicted of any crime among treated individuals relative to their non-treated counterparts, due to the mining boom.

In addition, 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 individuals as a response to the mining boom. Results show that the reduction in criminal behavior for young males due to the mining boom is concentrated among first-time offenders, suggesting that improved labor market conditions through increased opportunity costs or incapacitation effects 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. Moreover, the reduction in crime due to the mining boom for young individuals is concentrated in property and other crimes. While there is an increase in drug-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., 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 municipality. In addition, evidence suggests that incapacitation effects may explain part of the crime reductions through a higher number of individuals with secondary schooling. On the other hand, I find no evidence that changes in the population composition through migrants and the government's crime prevention capacity (police force) due to the mining boom drive the crime reductions. Therefore, an important mechanism that may explain these reductions in 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 crime, highlighting the role of compositional changes on the aggregate effects on crime observed in the literature.

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Online Appendix

Digging for Trouble? Mining Booms, Local Economic Shocks, and Criminal Behavior

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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. 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 any crime	0.012	0.014	0.012	0.013	0.013	0.013
	(0.107)	(0.118)	(0.107)	(0.114)	(0.113)	(0.113)
Convicted property crime	0.004	0.004	0.004	0.004	0.004	0.004
	(0.060)	(0.063)	(0.060)	(0.062)	(0.060)	(0.061)
Convicted violent crime	0.002	0.002	0.002	0.002	0.002	0.002
	(0.042)	(0.045)	(0.042)	(0.046)	(0.049)	(0.046)
Convicted drug crimes	0.001	0.001	0.001	0.002	0.002	0.002
	(0.028)	(0.023)	(0.027)	(0.047)	(0.044)	(0.046)
Convicted traffic crimes	0.003	0.005	0.003	0.004	0.004	0.004
	(0.057)	(0.068)	(0.058)	(0.061)	(0.066)	(0.061)
Convicted other crimes	0.005	0.006	0.005	0.005	0.004	0.005
	(0.070)	(0.075)	(0.069)	(0.070)	(0.066)	(0.069)
Married	0.450	0.397	0.444	0.413	0.336	0.405
	(0.497)	(0.489)	(0.497)	(0.492)	(0.472)	(0.491)
Children under 18	0.379	0.364	0.378	0.351	0.334	0.350
	(0.485)	(0.481)	(0.485)	(0.477)	(0.472)	(0.477)
Primary education	0.551	0.644	0.562	0.464	0.538	0.472
	(0.497)	(0.479)	(0.496)	(0.499)	(0.499)	(0.499)
Secondary education	0.319	0.278	0.316	0.374	0.364	0.374
	(0.466)	(0.448)	(0.465)	(0.484)	(0.481)	(0.484)
Tertiary education	0.130	0.078	0.122	0.163	0.098	0.154
	(0.336)	(0.268)	(0.328)	(0.369)	(0.297)	(0.361)
Non-employed	0.287	0.282	0.285	0.238	0.203	0.230
	(0.452)	(0.450)	(0.452)	(0.426)	(0.402)	(0.421)
Primary sector	0.017	0.135	0.035	0.023	0.181	0.047
	(0.131)	(0.341)	(0.185)	(0.149)	(0.385)	(0.211)
Secondary sector	0.153	0.099	0.143	0.156	0.117	0.149

	(0.360)	(0.299)	(0.350)	(0.363)	(0.321)	(0.356)
Tertiary sector	0.543	0.484	0.536	0.584	0.500	0.574
	(0.498)	(0.500)	(0.499)	(0.493)	(0.500)	(0.494)
Nxt	472116	44552	570708	1339878	122935	1614443
N	118029	11138	142677	111656	10245	134537

Notes: The table shows mean and standard deviations in parentheses. Treated: Gällivare, 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 any crime	0.00	-0.00
Convicted property crime	0.00	0.00
Convicted violent crime	0.00	0.00
Convicted drug crime	0.00	0.00
Convicted traffic crime	0.00	-0.00
Convicted other crimes	-0.00	-0.00*
Married	-0.00	0.01***
Children under 18	-0.03	-0.03
Primary education	-0.02	-0.03*
Secondary education	0.02	0.01***
Tertiary education	0.01	0.02***
Non-employed	0.00	0.01
Primary sector	0.00	-0.00***
Secondary sector	-0.00	-0.00
Tertiary sector	-0.00	-0.00

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: Robustness checks: impact of the mining boom on being convicted of any crime with first treatment, 2000-2015

	(1) Residents	(2) Residents (treated 2003)	(3) Residents and migrants	(4) Population less 55 years	(5) Balanced panel	(6) Exclude neigh. municipalities	(7) Municipality fixed-effect	(8) Treated Kiruna municipality
Post*Treated	-0.0023***		-0.0025***	-0.0031***	-0.0032***	-0.0026***	-0.0022***	
	(0.0008)		(0.0008)	(0.0011)	(0.0010)	(0.0008)	(0.0008)	
Post*Treated (2003)		-0.0026***						
		(0.0008)						
Post*Kiruna								0.0010*
								(0.0005)
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	No	Yes
Municipality FE	No	No	No	No	No	No	Yes	No
Nxt	1979481	1769671	2111042	1495446	1207918	1604312	1979481	2017664
N	123718	110604	131940	93465	75495	100270	123718	126104
Mean dep. var (2003)	0.0123	0.0122	0.0126	0.0143	0.0119	0.0121	0.0123	0.0121
Effect relative to the mean (%)	-18.84	-21.32	-19.41	-21.72	-27.24	-21.35	-17.55	7.98
R-squared	0.2407	0.2153	0.2489	0.2554	0.1905	0.2442	0.2349	0.2372
Within R-squared	0.0000	0.0000	0.0000	0.0000	0.0000	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Robustness checks: impact of the mining boom on being convicted of any crime with second treatment, 2000-2015

	(1) Residents	(2) Residents (treated 2003)	(3) Residents and migrants	(4) Population less 55 years	(5) Balanced panel	(6) Exclude neigh. municipalities	(7) Municipality fixed-effect
Post*≤ 20 km	-0.0025***		-0.0026***	-0.0034***	-0.0035***	-0.0028***	-0.0023***
	(0.0009)		(0.0009)	(0.0011)	(0.0011)	(0.0009)	(0.0009)
Post* 20 - 40 km	-0.0006		0.0001	0.0005	-0.0000	-0.0009	-0.0003
	(0.0028)		(0.0027)	(0.0035)	(0.0029)	(0.0028)	(0.0025)
Post*40 - 60 km	-0.0010		-0.0018	-0.0015	-0.0016	-0.0012	-0.0013
	(0.0020)		(0.0022)	(0.0029)	(0.0027)	(0.0022)	(0.0021)
Post*60 - 80 km	-0.0023		-0.0022	-0.0035*	-0.0030*	-0.0084	-0.0023*
	(0.0014)		(0.0014)	(0.0019)	(0.0017)	(0.0084)	(0.0013)
Post*≤ 20 km		-0.0009*					
		(0.0005)					
Post* 20 - 40 km		0.0036*					
		(0.0018)					
Post*40 - 60 km		-0.0013					
		(0.0018)					
Post*60 - 80 km		-0.0014					
		(0.0013)					
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
Nxt	1979481	1953364	2111042	1495446	1207918	1604312	1979481
N	123718	122085	131940	93465	75495	100270	123718
Mean dep. var (2003)	0.0122	0.0122	0.0126	0.0143	0.0119	0.0121	0.0122
Effect relative to the mean (%)	-20.36	-7.75	-20.28	-23.96	-29.47	-22.76	-18.57
R-squared	0.2407	0.2111	0.2489	0.2554	0.1905	0.2442	0.2349
Within R-squared	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Two-way fixed effects panel data regression. Treated: 20-kilometer rings. Standard errors (in parentheses) are clustered at the grid level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Robustness check: impact of the mining boom on being suspect of any crime, 2000-2015

	(1)	(2)	(3)	(4)	(5)	(6)
Post*Gällivare	-0.0032***	-0.0031***	-0.0040***			
	(0.0009)	(0.0009)	(0.0012)			
Post*$\leq$ 20 km				-0.0030***	-0.0030***	-0.0042***
				(0.0010)	(0.0010)	(0.0014)
Post* 20 - 40 km				-0.0025	-0.0023	-0.0042
				(0.0035)	(0.0035)	(0.0035)
Post*40 - 60 km				-0.0044	-0.0042	-0.0015
				(0.0029)	(0.0029)	(0.0028)
Post*60 - 80 km				-0.0024	-0.0022	-0.0022
				(0.0015)	(0.0015)	(0.0017)
Controls	No	Yes	No	No	Yes	No
Individual FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Nxt	1979481	1979481	1979481	1979481	1979481	1979481
N	123718	123718	123718	123718	123718	123718
Mean dep. var (2003)	0.0159	0.0159	0.0159	0.0160	0.0160	0.0160
Effect relative to the mean (%)	-20.00	-19.85	-25.41	-19.02	-19.09	-26.06
R-squared	0.2963	0.2966	0.0189	0.2963	0.2966	0.0189
Within R-squared	0.0000	0.0004	0.0000	0.0000	0.0004	0.0000

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

Table A.8: Robustness check: impact of the mining boom on being convicted of any crime using time duration for treatment, 2000-2015

	(1)	(2)	(3)
Post*$\leq$ 20 min	-0.0023***	-0.0023***	-0.0031***
	(0.0009)	(0.0009)	(0.0010)
Post* 20 - 40 min	0.0025	0.0026	0.0019
	(0.0018)	(0.0018)	(0.0019)
Post*40 - 60 min	0.0004	0.0005	-0.0002
	(0.0005)	(0.0005)	(0.0006)
Post*60 - 80 min	-0.0038	-0.0034	-0.0031
	(0.0025)	(0.0025)	(0.0023)
Controls	No	Yes	No
Individual FE	Yes	Yes	No
Year FE	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes
Nxt	2185151	2185151	2185151
N	136572	136572	136572
Mean dep. var (2003)	0.0123	0.0123	0.0123
Effect relative to the mean (%)	-19.05	-19.10	-25.57
R-squared	0.2363	0.2366	0.0136
Within R-squared	0.0000	0.0004	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 A.9: Social cost effects of the mining boom

	Property crime	Violent crime	Drug crime	Traffic crime	Other crime
	Total social cost effect (1000s SEK)				
Post	-11831.99**	8190.78	9530.24**	-1786.32	-2592.05***
	(4982.76)	(6576.84)	(4023.26)	(1459.47)	(908.24)

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, violent, and other 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 other crimes, I use the 17,358 SEK related to crimes of fraud. For drug crimes, I use the estimated cost of 89,523 SEK, which only accounts for the cost of arrest. For the traffic crimes, I use the estimated cost of 33,936 SEK, which accounts for a damage-only accident. I multiply the estimated coefficients of Table 4 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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: 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 (Gällivare) 2000-2003	Migrants (Gällivare) post-migration-2015
	Mean/SD	Mean/SD	Mean/SD	Mean/SD	Mean/SD	Mean/SD
Convicted of any crime	0.01	0.01	0.10	0.06	0.04	0.02
	(0.12)	(0.11)	(0.30)	(0.24)	(0.18)	(0.15)
Disposable income (100SEK)	1514.75	1932.28	1222.23	1443.08	1063.32	1802.00
	(689.15)	(1665.89)	(2972.41)	(8869.54)	(635.97)	(1162.75)
Yearly earnings (100SEK)	1486.35	2065.23	1012.13	1317.33	1012.83	1965.93
	(1251.45)	(1535.74)	(1820.35)	(1599.53)	(1044.05)	(1511.48)
Employment	0.72	0.80	0.52	0.60	0.63	0.80
	(0.45)	(0.40)	(0.50)	(0.49)	(0.48)	(0.40)
Male	0.53	0.54	0.66	0.59	0.53	0.51
	(0.50)	(0.50)	(0.47)	(0.49)	(0.50)	(0.50)
18–30 years old	0.17	0.21	0.46	0.52	0.68	0.44
	(0.37)	(0.41)	(0.50)	(0.50)	(0.47)	(0.50)
31–50 years old	0.47	0.40	0.37	0.36	0.24	0.46
	(0.50)	(0.49)	(0.48)	(0.48)	(0.43)	(0.50)
51–65 years old	0.36	0.39	0.17	0.12	0.08	0.11
	(0.48)	(0.49)	(0.37)	(0.33)	(0.27)	(0.31)
Married	0.40	0.34	0.10	0.02	0.06	0.03
	(0.49)	(0.47)	(0.30)	(0.14)	(0.24)	(0.17)
Children under 18	0.36	0.33	0.25	0.26	0.33	0.34
	(0.48)	(0.47)	(0.44)	(0.44)	(0.47)	(0.47)
Primary education	0.64	0.54	0.49	0.31	0.35	0.27
	(0.48)	(0.50)	(0.50)	(0.46)	(0.48)	(0.44)
Secondary education	0.28	0.36	0.39	0.44	0.57	0.43
	(0.45)	(0.48)	(0.49)	(0.50)	(0.50)	(0.49)
Tertiary education	0.08	0.10	0.12	0.26	0.08	0.30
	(0.27)	(0.30)	(0.33)	(0.44)	(0.26)	(0.46)
Non-employed	0.28	0.20	0.48	0.40	0.37	0.20
	(0.45)	(0.40)	(0.50)	(0.49)	(0.48)	(0.40)
Primary economic sector	0.13	0.18	0.01	0.01	0.04	0.13
	(0.34)	(0.38)	(0.10)	(0.12)	(0.20)	(0.33)
Secondary economic sector	0.10	0.12	0.11	0.09	0.08	0.11
	(0.30)	(0.32)	(0.32)	(0.29)	(0.27)	(0.32)
Tertiary economic sector	0.48	0.50	0.40	0.49	0.51	0.56
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)

Notes: The table shows mean and standard deviations in parentheses. The full sample is included in this table. Residents in Gällivare. Migrants to Norbotten County in columns 3 and 4, and migrants to Gällivare municipality 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).

B Appendix: Additional figures

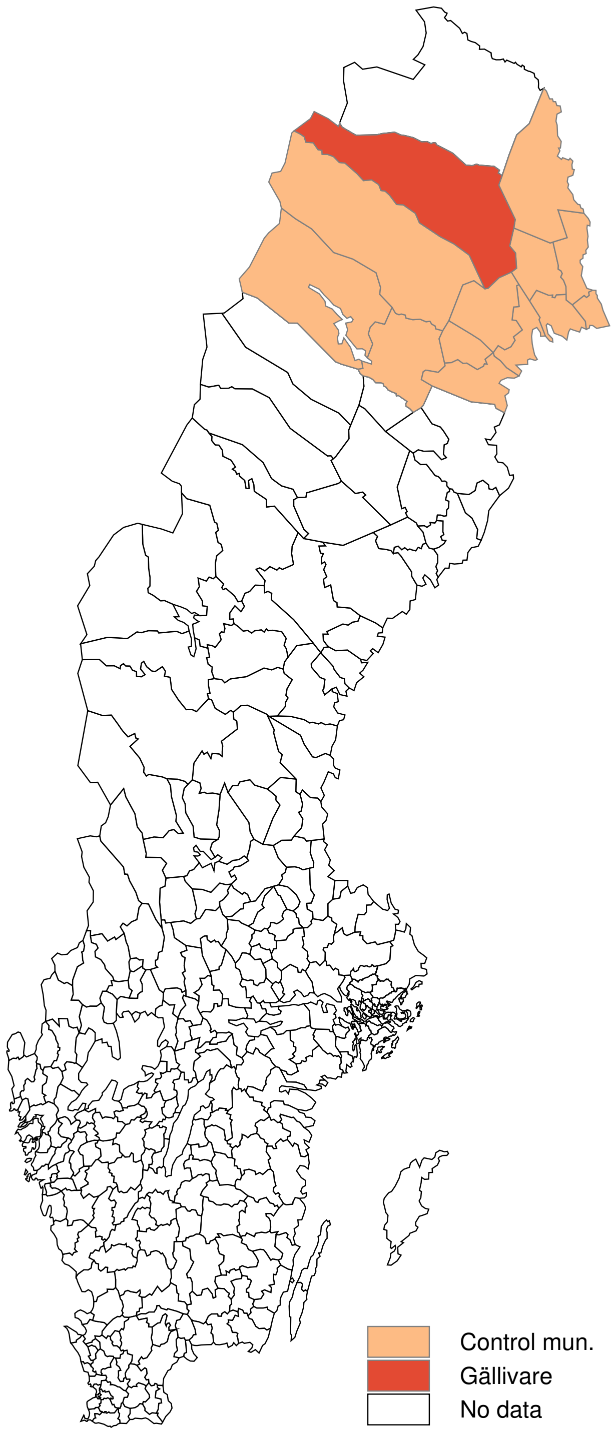


Figure B.1: Treated (Gällivare) and control municipalities

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

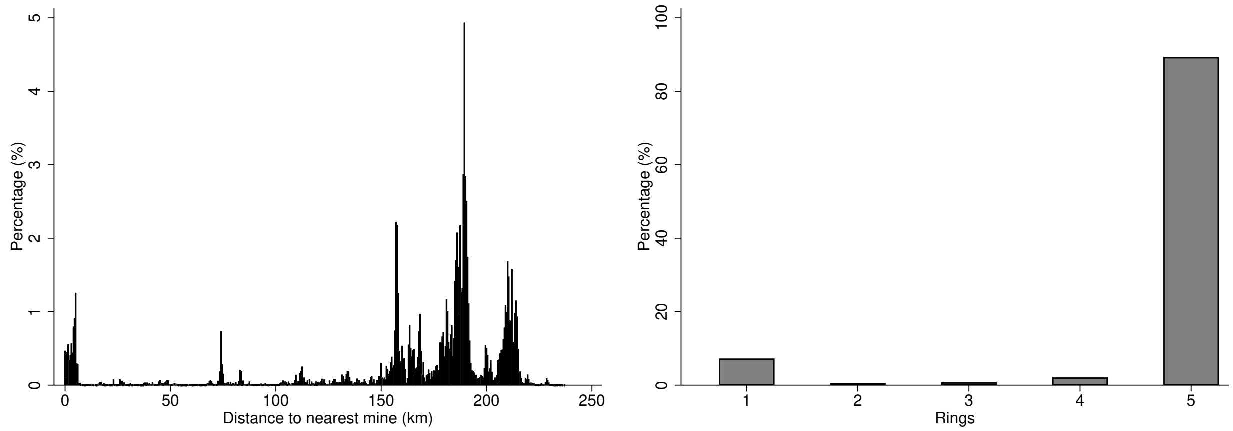
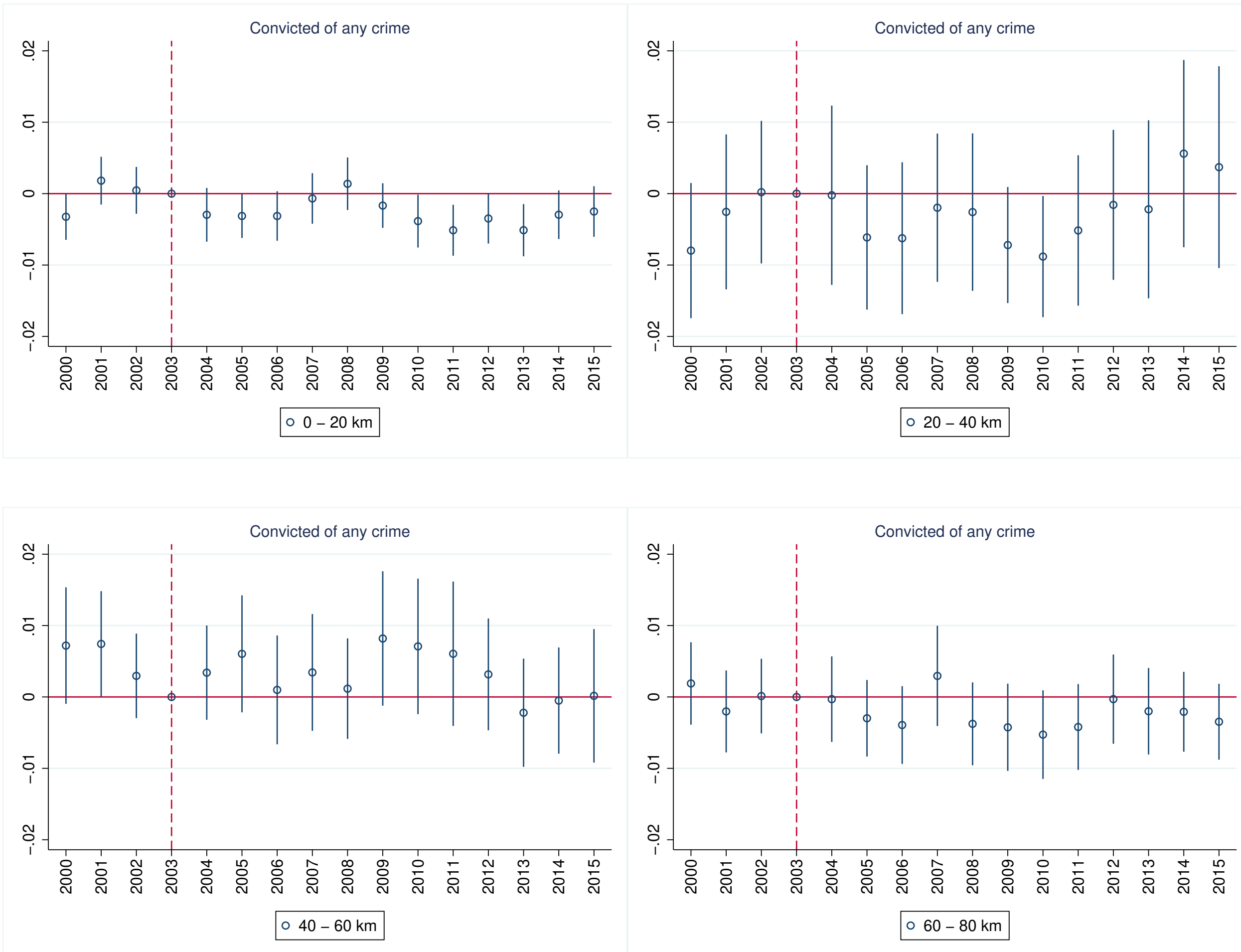


Figure B.2: Distribution of individuals according to their distance to the nearest mine and in the rings

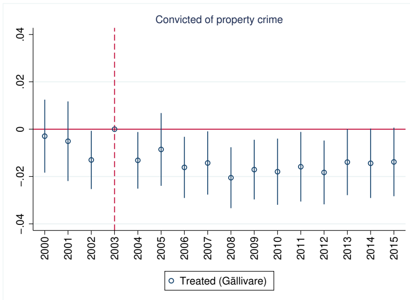
Notes: The figure shows the distribution of individuals according to their distance to the nearest mine and in the rings.

Figure B.3: Event study of the impact of the mining boom on being convicted of any crime by rings, 2000-2015

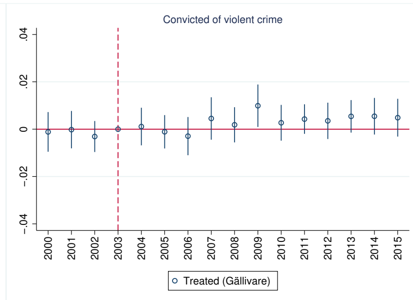


Notes: Year 2003 is the reference. 95% confidence interval shown. Four figures come from the same estimation. Estimations include individuals, grid, and time fixed effects. The sample excludes the migrants to the mining area. Standard errors are clustered at the grid level.

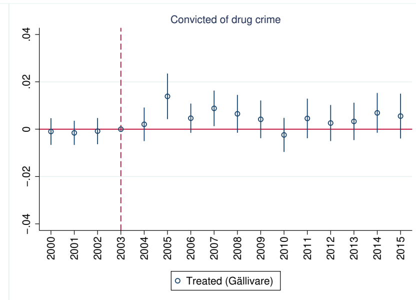
Figure B.4: Event study of the impact of the mining boom on crime convictions by type of crime, 2000-2015



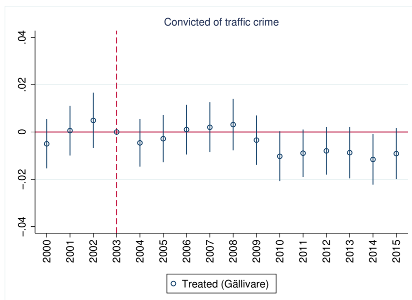
(a) Property crime



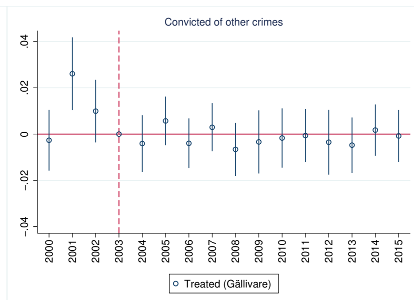
(b) Violent crime



(c) Drug crime



(d) Traffic crime



(e) Other crimes

Notes: Treated: Gällivare. All the estimations include individual, grid, and time fixed effects. Standard errors are clustered at the grid level. The year 2003 is the reference. 95% confidence interval shown.

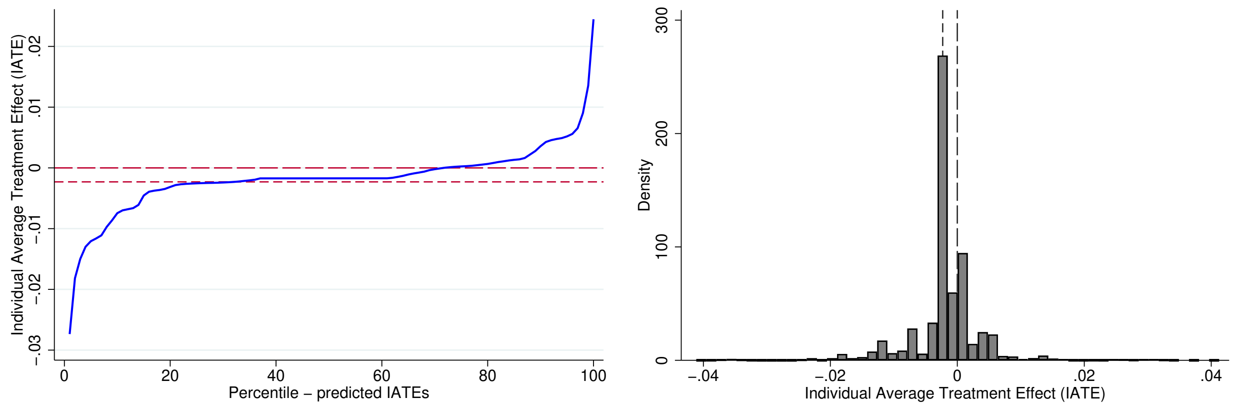
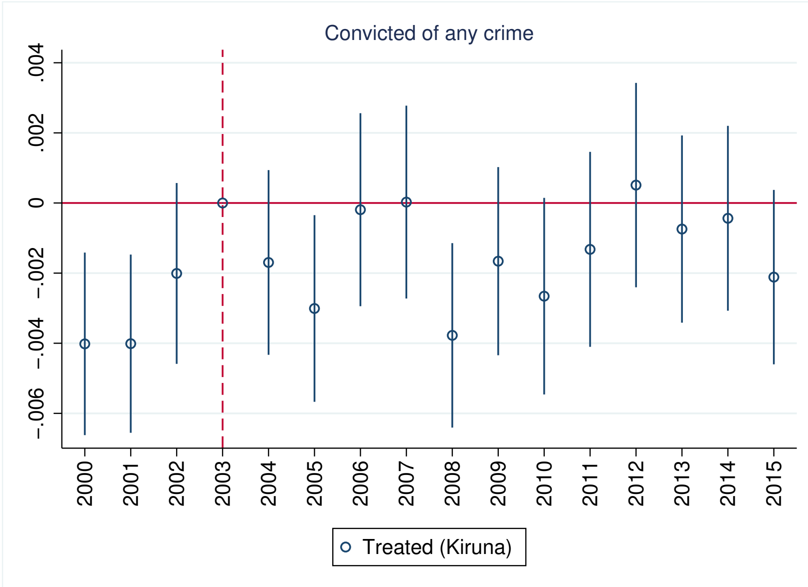


Figure B.5: Distribution predicted individual average treatment effects

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). The figure considers the full sample. 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.6: Event study of the impact of the mining boom on being convicted of any crime for Kiruna



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.

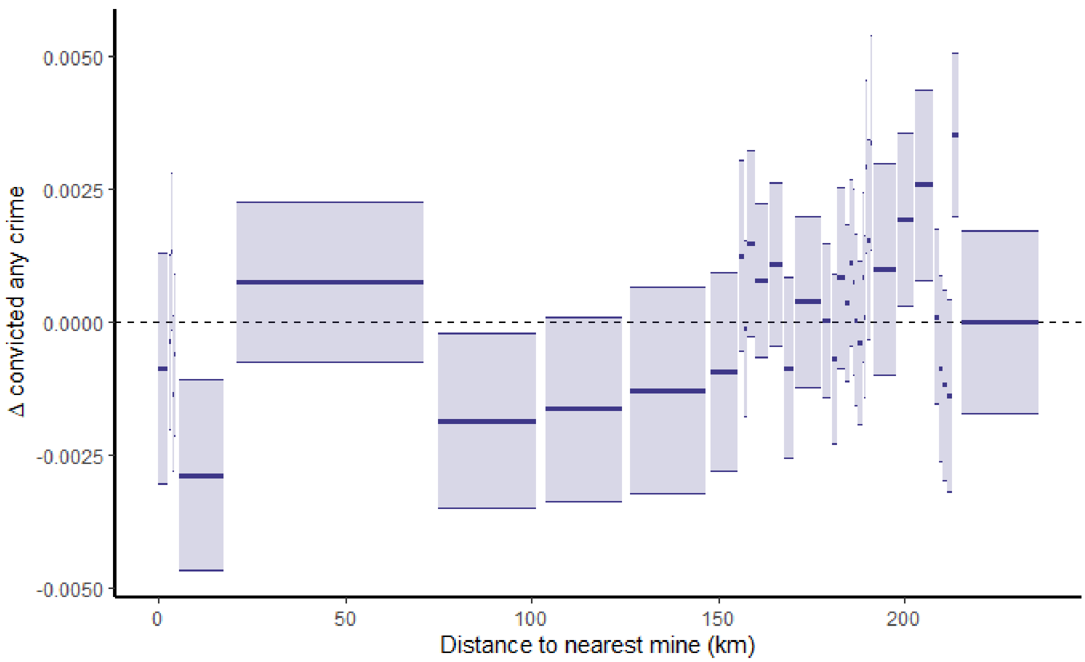
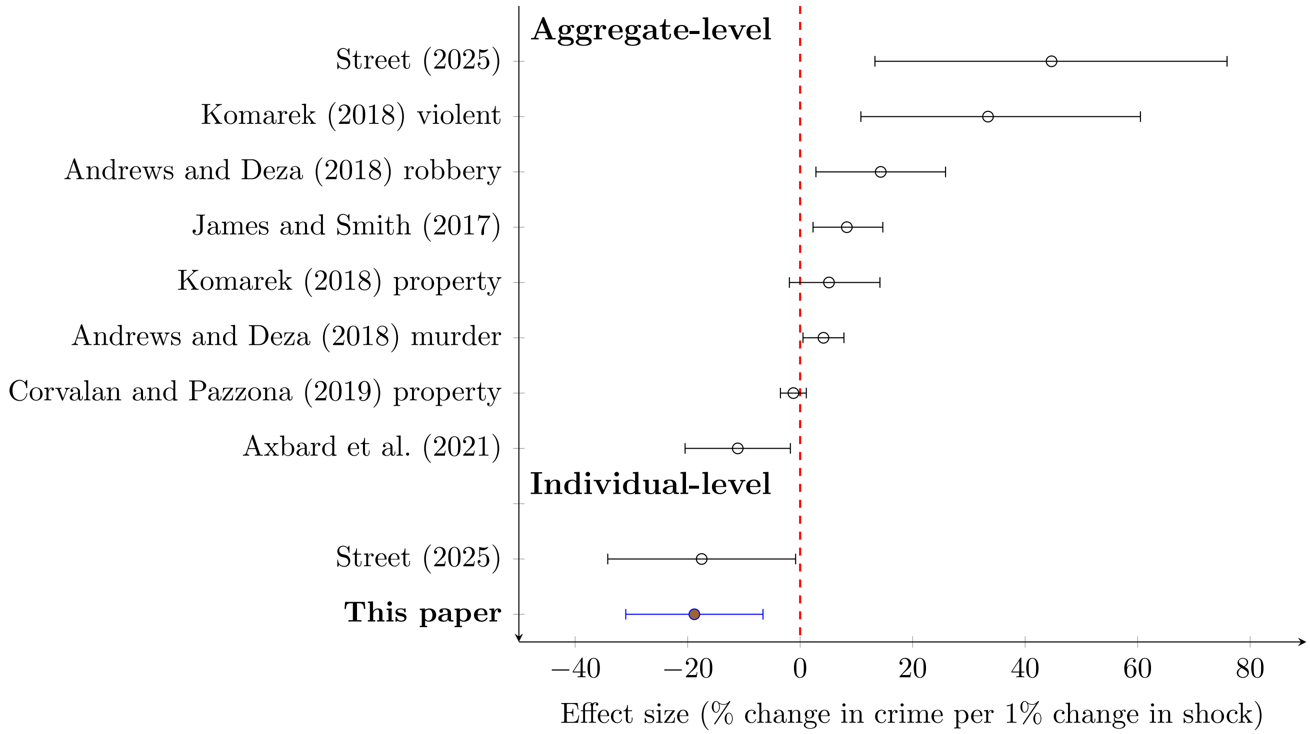


Figure B.7: Nonparametric estimation of the change in convictions of any crime, 2000-2003 vs 2004-2015

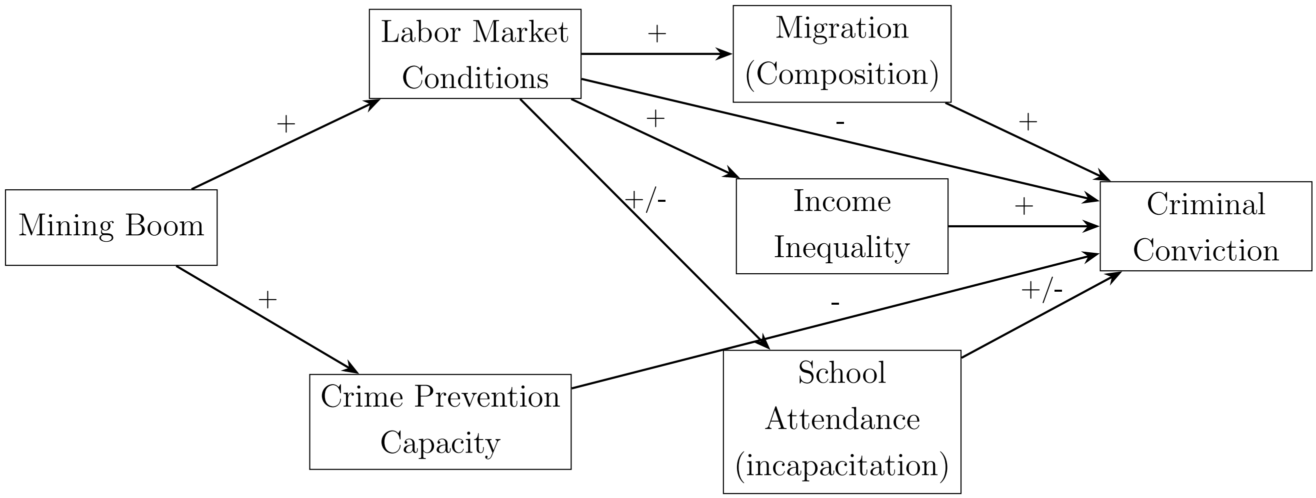
Notes: I use the distance from each individual to the nearest mine in kilometers. 95% confidence interval shown.

Figure B.8: Literature comparisons: resource shocks and crime



Notes: This figure compares estimated treatment effect sizes from this paper to others from the literature. Each dot shows the estimated effect size (%) with 95% confidence intervals. The figure compares the effect of the mining boom exposure on criminal behavior to comparable effect sizes of other resource shocks, such as mining and fracking booms. See Online Appendix E for details on the papers and effect size construction. I distinguish between aggregate- and individual-level studies. 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.9: Directed Acyclic Graph (DAG) of mechanisms linking mining booms to crime



C Appendix: Results for the full sample

Table C.1: Impact of the mining boom on different crime outcomes (full sample), 2000-2015

	(1) First-time convicted	(2) Re-offense	(3) Convicted + no prison	(4) Convicted + in prison	(5) Post-prison reoffense
Post*Treated	-0.0022***	-0.0001	-0.0023***	-0.0007**	0.0006*
	(0.0008)	(0.0004)	(0.0008)	(0.0003)	(0.0004)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes
Nxt	1979481	1979481	1979481	1979481	1979481
N	123718	123718	123718	123718	123718
Mean dep. var (2003)	0.0083	0.0039	0.0103	0.0010	0.0010
Effect relative to the mean (%)	-26.56	-1.79	-21.94	-69.66	60.14
R-squared	0.0951	0.3055	0.1863	0.0937	0.3806
Within R-squared	0.0000	0.0000	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Impact of the mining boom on being convicted by types of crime (full sample), 2000-2015

	(1) Property crime	(2) Violent crime	(3) Drug crime	(4) Traffic crime	(5) Other crimes
Post*Treated	-0.0004	0.0003	0.0006***	-0.0009**	-0.0015***
	(0.0004)	(0.0003)	(0.0002)	(0.0004)	(0.0005)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes
Nxt	1979481	1979481	1979481	1979481	1979481
N	123718	123718	123718	123718	123718
Mean dep. var (2003)	0.0047	0.0021	0.0011	0.0036	0.0042
Effect relative to the mean (%)	-8.68	12.81	52.40	-26.02	-35.51
R-squared	0.2189	0.1507	0.3248	0.2033	0.1532
Within R-squared	0.0000	0.0000	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Impact of the mining boom on being convicted of crime of migrants (full sample), 2000-2015

	(1)	(2)	(3)	(4)	(5)	(6)
Post*Gällivare	-0.0059	-0.0055	-0.0042	-0.0045	-0.0022	
	(0.0056)	(0.0056)	(0.0064)	(0.0064)	(0.0042)	
Post*Control mun.	-0.0015	-0.0005				-0.0022
	(0.0019)	(0.0019)				(0.0018)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	No	No
Nxt	565977	565977	175186	175186	430383	546521
N	35374	35374	10949	10949	26899	34158
Mean dep. var (2003)	0.0965	0.0965	0.0278	0.0278	0.0281	0.0290
Effect relative to the mean, Gällivare (%)	-6.08	-5.65	-15.29	-16.04	-7.83	
Effect relative to the mean, Control mun. (%)	-1.56	-0.48				-7.59
R-squared	0.4946	0.4951	0.3910	0.3911		
Within R-squared	0.0000	0.0009	0.0000	0.0002		

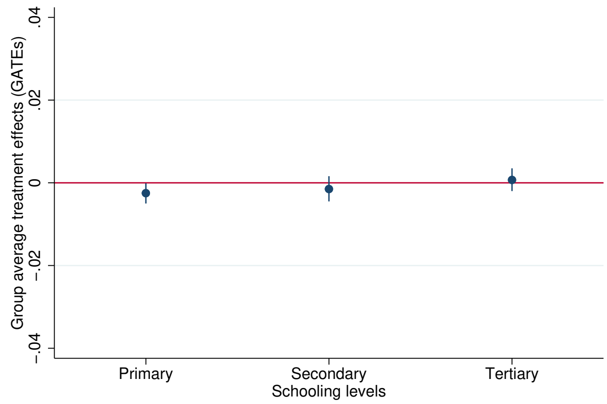
Notes: Two-way fixed effects panel data regression. Migrants before the move are the references. Standard errors (in parentheses) are clustered at the grid level. Columns (1) and (2) compare migrants to Gällivare or the control municipalities to themselves before the migration event. Columns (3) and (4) compare migrants to Gällivare to migrants to the control municipalities. Columns (5) and (6) consider the staggered nature of the migration event and show average treatment effect on the treated (ATT) comparing migrants to Gällivare or the control municipalities to not yet treated migrants. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Mechanisms: impact of the mining boom on different mechanisms (full sample), 2000-2015

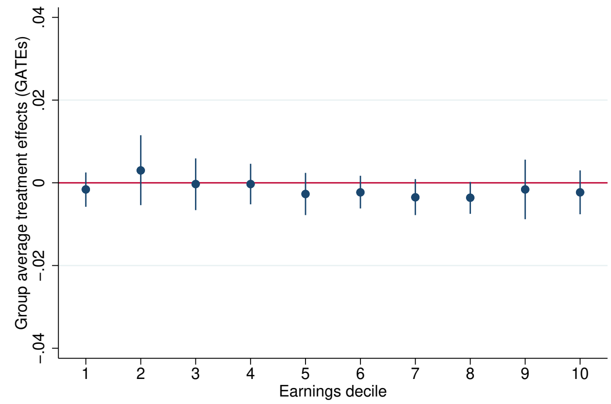
	(1) Disposable income	(2) Labor income	(3) Employment	(4) Employment mining	(5) Police occupation	(6) Police industry	(7) Top earning tercile	(8) Secondary educ. (18-24)
Post*Treated	83.0050***	138.6666***	-0.0017	0.0181***	-0.0005	-0.0010**	-0.0034***	0.1233***
	(10.7283)	(12.7474)	(0.0036)	(0.0023)	(0.0004)	(0.0005)	(0.0011)	(0.0149)
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	1979481	1979481	1979481	1979481	1629705	1979481	1770546	173701
N	123718	123718	123718	123718	125362	123718	110659	10856
Mean dep. var (2003)	1534.6901	1498.8355	0.7164	0.0213	0.0033	0.0066	0.0658	0.5816
Effect relative to the mean (%)	5.41	9.25	-0.24	84.95	-15.57	-15.76	-5.20	21.20
R-squared	0.3398	0.7567	0.5897	0.7858	0.7193	0.7212	0.9706	0.7113
Within R-squared	0.0000	0.0005	0.0000	0.0012	0.0000	0.0000	0.0000	0.0022

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

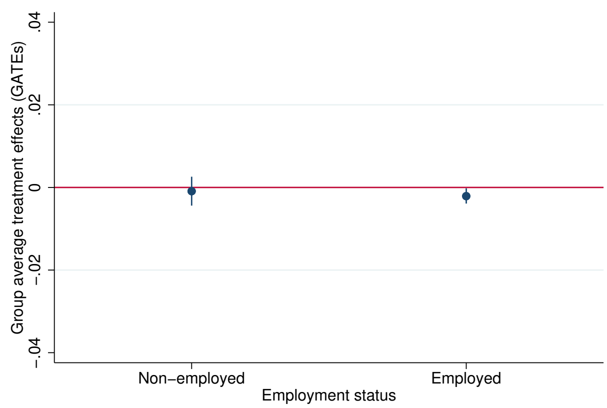
Figure C.1: Group average treatment effects (GATEs) by characteristics (full sample), 2000-2015



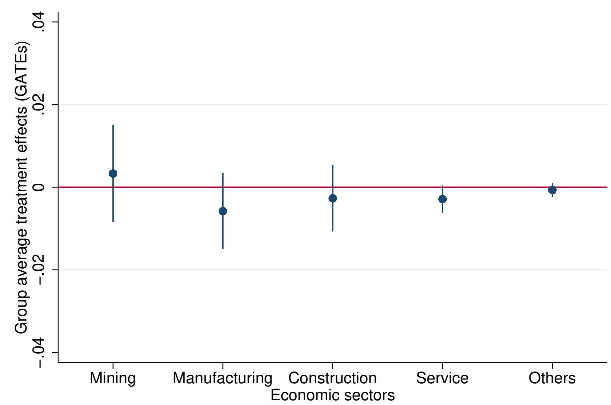
(a) Schooling levels



(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.

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).[34] 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. To ensure sufficient within-leaf variation and maintain treatment–control balance under the honest-splitting procedure, I estimate the causal forest using the full sample. In the case of the young-male subsample, the combination of honest sample splitting, a high-dimensional covariate space, and a relatively sparse treatment assignment substantially reduces the effective sample size (Wager and Athey, 2018; Athey et al., 2019). For this reason, the model is trained on the full population. 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

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

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

In my specific case, the main outcome is the probability of criminal conviction. 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 (Gällivare), 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.8.

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]).

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