Exploring the Effects of Mining Activities on Welfare and the Labour Market in Peru

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Abstract

This PhD thesis is composed of three chapters that investigate the effects of the mining sector on welfare and labour market outcomes in Peru over the period 2001–2019. The analysis is based on data from the Peruvian National Institute of Statistics and applies a quantitative research approach.

Chapter 2 explores the dynamic effects of the mining sector on welfare at the district level in Peru during the period 2001-2019. Using recent developments in the literature of difference-in-differences, I explore the heterogeneous effects of mineral production on consumption. The findings suggest consumption levels increase up to the third year after districts transition to Producing Districts (PDs). However, these consumption effects diminish thereafter suggesting that ongoing mineral production does not lead to long-term consumption improvements among PDs. These results would favour the implementation of short-term policies for periods of mini-booms during the production stages of mineral production.

Chapter 3 address the research question: To what extent do the effects of extractive industries decay in space and time? This chapter investigates the spatial and temporal diffusion of mining related welfare gains in Peru between 2001 and 2019. I assess the impact of extractive activities on welfare outcomes in both PDs and Non-Producing Districts (NPDs). Leveraging recent advances in difference-in-differences methodology, I find that districts located in close travel time proximity to active mines experience significant and positive improvements in welfare. These persist for up to five years after production begins and are also observed in neighbouring NPDs. These results offer important insights for local and regional policymakers aiming to design effective strategies around local development and migration, resource windfalls, and the spatial distribution of labour and firms.

Chapter 4 explores the effects of mining activities on the Peruvian labour market, with a focus on wages, employment, occupational structure, and informality across PDs and NPDs between 2001 and 2019. It also examines how these labour market outcomes vary across periods of mining booms and busts. Using pooled ordinary least squares and a triple-difference approach, the analysis finds that wages in PDs are strongly procyclical and significantly higher than in NPDs during boom periods. However, the share of employment is counterintuitively lower in PDs, despite a higher concentration of mining-related occupations. This suggests that mining generates a relatively narrow set of high-wage, high-skill jobs concentrated in PDs. In addition, there is evidence that certain mining-linked occupations are located in NPDs, indicating spillover effects and potentially the outsourcing of some support activities may be carried out in NPDs rather than at PDs. Informality rates have also declined more sharply in PDs than in NPDs, likely due to stronger regulatory enforcement in areas under closer institutional oversight. Together, these findings highlight that mining produces spatially concentrated labour market benefits while also generating economic interdependencies with surrounding areas. The results underscore the need for coordinated local and regional development policies that foster economic diversification and formalisation not only within PDs but also in economically linked NPDs.

Access Condition and Agreement

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Chapter 1

Introduction

1.1 Background and Motivation

Mining activities in Peru date back over 4000 years, with evidence of mineral extraction and metalworking found across different regions of the country. Aldenderfer et al. (2008) report that the earliest evidence of gold use can be traced to 2155–1936 B.C., when locally sourced gold nuggets from the eastern Madre de Dios region were used to produce necklaces through rudimentary cold-hammering techniques. More sophisticated gold artifacts and evidence of early metallurgical practices, dating from 1410 to 1000 B.C., have been discovered at sites such as Mina Perdida on the coast and Waywaka in Huancavelica. Over time, pre-colonial societies in the central and southern Andes developed increasingly complex techniques to transform raw minerals into ceremonial and ritual artifacts. Sediment analyses further suggest that Andean civilizations in Peru and Bolivia had already developed smelting technologies by this period. For example, Guédron et al. (2021) find evidence of smelted copper in the Lake Titicaca region dated to 880–1150 A.D., followed by intensified metallurgical activity during the Inca Empire (c. 1500 A.D.), which fostered the transformation of population centres around mining operations, promoted labour specialisation in the central and southern Andes, and expanded regional trade networks. Cooke et al. (2007) argues that the Incas expanded their production beyond gold to include tin and silver, the latter playing a central role in local taxation systems. Following the Spanish conquest, silver production and exploitation were further intensified, combining Inca and European smelting techniques. This colonial period transformed local economies, reorganised labour systems, and reshaped local infrastructure, including roads and cities, to facilitate large-scale mineral exports.

From the 16th century onwards, the extraction of key commodities such as silver and gold played a central role in shaping the export-oriented economies of Peru and other Latin American countries. Brain (2017) estimate that Latin America accounted for roughly 80% of global silver production during this period. Similarly, large quantities of gold and mercury were exported to Europe, fuelling significant economic and financial developments there. Within Peru and the broader Andean region, significant silver deposits were discovered throughout the 16th and 17th centuries, including Castrovirreina (c.1555), Oruro (c.1606), Cailloma (c.1620), Cerro de Pasco (c.1630), San Antonio del Nuevo Mundo (c.1645), and Hualgayoc (c.1771) (Brown 2012). There is also evidence that the Huancavelica mine located in the Andean macro region of Peru served as a main operation based on producing mercury to amalgamate silver from the Potosi mine in Bolivia and other silver miners in the Peruvian Andes, which required a massive transformation of local labour and trading routes across the country. By the early 19th century, however, production at Huancavelica had declined sharply, reaching its lowest point in 1813.[1] According to Quiroz (2013), corruption at multiple levels of colonial administration contributed to this decline, which in turn had significant consequences for local economies dependent on mining activity.

Since the 1990s, the liberalisation of the Peruvian economy has led to significant reforms in the mining sector, triggering a sharp increase in Foreign Direct Investment (FDI) and the expansion of mining projects nationwide. As of 2024, FDI in the mining sector reached USD 64.1 billion, with major contributions from China (21.1%), Canada (20.1%), the United States (15.9%), and Mexico (15.0%) (Ministerio de Energia y Minas 2025).[2] Today, Peru is among the world's leading mineral producers. It ranks second globally in zinc, cadmium, and molybdenum production; third in copper and silver; and fourth in lead and tin. Its mineral reserves are equally significant, with the country holding the world's largest reserves of silver, the second largest of copper, third for molybdenum, fourth for zinc, fifth for lead, seventh for tin, and eighth for gold. These vast reserves suggest that Peru is likely to continue attracting substantial mining investment in the coming years.

[1]The Huancavelica mine was one of the most important sources of mercury for the Spanish crown until Peru's independence (Quiroz 2013).

[2]Additional investment comes from Australia, the United Kingdom, Switzerland, and Japan, accounting for USD 11.2 billion.

Mining activities continue to shape welfare outcomes at multiple levels of the Peruvian economy. The rapid expansion of the mining sector since the 1990s has attracted considerable scholarly attention, with studies examining its effects on rural development (Zegarra et al. 2007), local inequality (Loayza & Rigolini 2016), and case-specific impacts such as those of the Yanacocha mine in Cajamarca (Aragón & Rud 2013, Orihuela et al. 2019).[3] At a broader scale, cross-country and regional studies have also assessed the economic implications of extractive industries, with most focusing on producing areas. Despite this extensive literature, there remains limited evidence on the long-term effects of mining activities on local welfare outcomes in Peru, especially when accounting for spillovers to non producing areas.

This thesis contributes to the literature of natural resource economics, economic geography and labour economics by providing new empirical evidence on the long-term effects of mining activities on district-level welfare outcomes in Peru, using 20 years of data and recent methodological advances in difference-in-differences (DiD) estimation, combined with pooled ordinary least squares (OLS) techniques.

The overall aim of this study is to examine the effects of mining activities on welfare and the labour market in Peru between 2001 and 2019. The central research question is: What are the impacts of mining activities on welfare in producing and non producing districts during the recent two decades of mining expansion? This question is highly relevant given the central role of the mining sector in the Peruvian economy, an influence that is not only well documented in modern times but also evident since pre-colonial periods, when mining shaped various socioeconomic outcomes. Focusing on the first two decades of the 21st century provides a unique opportunity to assess how mining has affected welfare across districts in Peru during a period marked by economic liberalisation, rapid technological change, and a surge in global demand for key minerals.

This thesis makes four main contributions. First, it provides new evidence on the socioeconomic effects of mining during a critical period of Peru's economic development (2001–2019). Second, it works with a binary classification of districts, as either Producing Districts (PDs) or Non Producing Districts (NPDs), allowing to explore the intermittent nature of mining activities in time. This is one of the first studies account for the fact

[3] This list focuses on studies using quantitative methods and data similar to this thesis. See Manrique & Sanborn (2021) for a comprehensive review of research on Peru's mining sector, including environmental and social dimensions.

that mineral production can switch on and off over time, raising questions about the extent of their effects on welfare. It also provides a more realistic view of the sector in terms of its development (i.e., a long term activity that could present periods of standby). Incorporating this feature might help to understand why some mining developments have little to null effects on welfare over time. This same binary classification of districts allow for the separate identification of impacts on PDs and NPDs, with particular attention to the latter, which to the best of my knowledge has been largely overlooked in the existing literature (e.g., spatial spillovers). This is particularly relevant since it not only allows for the implementation of policies at the local level (i.e., PDs) but the need for broader policies at the province or regional level to mitigate dependency to the mining sector. Third, the study contributes to the literature on extractive industries by applying recent DiD methods that account for staggered treatment timing. In this context, treatment corresponds to a district's transition to PDs status, which occurs at different years across mining units (e.g., some districts begin production in 2004, others in 2006 or 2010). Incorporating these methods, which have not previously been applied to this case, allows for the estimation of effects by calendar year, cohort, and time since treatment, yielding results that are both more robust and more informative for policy makers. Finally, the thesis contributes to the literature of labour economics by offering novel evidence on the impacts of mining on Peru's labour market. The analysis focuses on employment, occupational structure, wages, and informality at the district level, providing one of the first long-term, comprehensive assessments of how mining has shaped labour market outcomes in a resource dependent developing economy. A distinctive contribution is the focus on informality, an especially salient feature of Latin American labour markets and highly prevalent in Peru, which makes the results directly relevant for policymakers seeking to address informal employment in resource rich emerging economies.

1.2 Chapter overview

1.2.1 Overview of Chapter 2

Chapter 2 is focused on the effects of mining activities on welfare among PDs during the period 2001-2019. Rather than looking at the implementation of mining activities as fixed in time, it explores the switch on and off dynamics of mining activities during the period of analysis. The analysis relies on secondary data sourced from the Peruvian National Institute of Statistics (INEI), which provides aggregated district-level socioeconomic indicators such as consumption, income, and demographic characteristics, as well as geographic variables (e.g., altitude, surface area, and urbanisation). Mining production data come from the Ministry of Energy and Mines (MINEM), which reports detailed information on all producing mines including production volumes, mineral types, and mining scales (large, medium, small) at the district level for the full period of analysis. Additional sources include the Central Bank of Peru (BCRP) for exchange rates, the International Monetary Fund (IMF) for international mineral prices, and the Peruvian Geographic Institute (IGP) for spatial data and shapefiles.[4]

Given the switch on and off behaviour of mining activities in time, the analysis considers two scenarios. In Scenario A, it is assumed that once mining activities start operations they remain producers for the rest of the sample period. This scenario assumes that, once production begins, treatment effects are fully absorbed and persist over time, even if production status later changes (for instance, some units have switched status of NPDs to PDs up to six times during the period of analysis)[5] across treated units. This assumption mirrors standard DiD practice but may be unrealistic in contexts where production is highly intermittent. To address this concern, Scenario B restricts the sample to districts where mines transition once from NPDs to PDs status and remain under PDs status thereafter. This design isolates welfare effects in districts where mining production remains continuous.

I work with a staggered double difference approach following Callaway & Sant'Anna (2021) (hereafter, CS DID approach) which allow me to explore heterogeneity of treatment in time, which for the case of my research is applied as the change in status of districts that convert to PDs (treatment group). The control group consists of districts that never transition to PDs status during the sample period.[6] The main contribution of Chapter 2 is to bring new empirical evidence of the nature of the mining sector, that can switch on

[4]These additional datasets are used to construct control variables and produce district-level maps.

[5]Standard DiD approaches typically assume that treatment effects are fully absorbed once a unit is treated. However, recent literature challenges this assumption, suggesting that effects may only persist while treatment is active. For example, Roth et al. (2023) illustrate this using minimum wage policies, where effects occur when the policy is implemented, but subsequent wage increases generate new effects. Recent advances in the DiD literature address such "no carryover" scenarios; see De Chaisemartin & d'Haultfoeuille (2020) and De Chaisemartin et al. (2024).

[6]The CS DiD approach also allows the inclusion of not-yet-treated units in the comparison group, i.e., districts that have not been treated at a given time but will become PDs later in the sample.

and off over time and that its effects can vary in time across PDs when considering this dynamic. This is explored using the most recent development in the literature of DiD which in my view brings a more robust approach that consider the nuances of the mining sector over a long period of time.

This chapter builds on the work of previous empirical evidence focused on the mining sector in Peru which have explored the effects on key socioeconomic variables such as income, consumption, poverty, inequality, and labour force (see Loayza & Rigolini (2016), Aragón & Rud (2013), Zegarra et al. (2007), Ticci & Escobal (2015), Del Pozo & Paucarmayta-Tacuri (2015)), using a variety of econometric techniques such as DiD, Propensity Score Matching (PSM), Instrumental Variables (IV). On a more broader scale, this chapter also contributes to empirical evidence on the mining sector and other resource extractive industries where scholars also aim to explore the effects of these industries on welfare at different levels (e.g., see Black et al. (2015) on the effects of coal mining boom in the USA, or Michaels (2011) and Jacobsen & Parker (2016) on oil industry in the USA or Bartik et al. (2019) on hydraulic fracking or Caselli & Michaels (2013) with a focus on oil windfalls in Brasil).

For Scenario A, I find that on aggregate there are no statistical significant effects on consumption levels among PDs for Scenario A. There is also no evidence of significant effects for specific post-treatment years when districts transition to PDs status. In contrast, the results for Scenario B show positive and statistically significant average effects on consumption over the first five years post-treatment. When examining the dynamic effects, the strongest impacts occur in the first, second, and third years after districts switch to PDs status, all significant at conventional levels. There is weaker evidence of positive effects in the fourth year (significant at the 10% level), but I find no effects in the fifth year. These findings suggest that the initiation of mining activities generates short-lived increases in local consumption, resembling "mini economic booms" in PDs. Consumption tends to rise immediately after production begins but the effects diminish after the third year, implying that welfare gains from mining are temporary rather than persistent. As a robustness check, I re-estimate the effects using the Extended Two-Way Fixed Effects (ETWFE) estimator, which also accounts for staggered treatment timing. Results are broadly consistent. Under ETWFE, positive effects on consumption appear from the first year after switching to PDs and persist up to the fifth year. For Scenario A, ETWFE estimates show a positive effect in the second year, but these effects fade over time and become negative in the fourth year, reinforcing the interpretation that PDs experience temporary consumption booms rather than sustained welfare improvements.

I also explore the heterogenous effects of mining activities by mining size and using the same two scenarios for the analysis. I mainly focus on two groups, the first that includes Large and Medium Scale Mining (LMSM) and the second that groups Small and Artisanal Scale Mining (SASM). Similar to previous outcomes I find no statistically significant effects for Scenario A. For the case of Scenario B, I find only positive statistically significant effects at 5% for LMSM in the second year after districts switch to PDs status. There are no statistically significant effects for SASM in Scenario B. I also group regions by clusters considering the average regional GDP growth and average share of mineral exports with respect to total exports (annual). Most statistically significant results arise under Scenario B, where I find positive effects on consumption at the 5% level for Cluster 1 in year 2 and for Cluster 3 in years 3 and 4 following the transition to PDs status. A common feature of both Cluster 1 and Cluster 3 is that they comprise regions with a high dependence on mineral exports relative to total exports.

The main policy implication of Chapter 2 is to provide empirical evidence on the nature of mining activities during the production stage and their effects on consumption levels in PDs. The results suggest that these effects are immediate and short-lived among PDs since these experience welfare improvements in the first years mineral production, however, these effects fade away after four to five years, leaving welfare levels similar to those of NPDs. Short-lived gains may also create high expectations and attract migration from neighbouring areas, but newcomers risk facing bust periods soon after arrival, potentially widening inequality and straining local services. Thus, policy makers should consider that mining-led growth could be short-lived and therefore prioritise policies that diversify local economies away from mining to secure welfare improvements in time. In addition, given that PDs often face brief booms followed by rapid slowdowns, local governments should plan for short-term agglomeration of firms and individuals driven by elevated expectations. The results also also suggest that welfare levels might converge in time, raising the question about spillover effects on surrounding areas. This is explored further in Chapter 3.

1.2.2 Overview of Chapter 3

Chapter 3 aim to address the research question: To what extent the effects of mining activities decay in space and time?. To examine this, I build on the dataset used in Chapter 2, covering welfare, socioeconomic, and geographic variables and incorporating two measures of proximity, these are linear distance and travel distance by car which are estimated using geospatial information from OpenStreetMap. The first measure captures the minimum straight-line distance between a district (PDs or NPDs) to all PDs. The linear distance measure has been used previously in the literature to measure distance decay effects of mining activities in Peru (e.g., see for instance Orihuela & Gamarra-Echenique (2020)). The second of these measures is estimated using the osrm command in Stata and, similarly, it captures the minimum travel distance by car between a district (PDs or NPDs) to all PDs.[7][8]

I use a Pooled Ordinary Least Squared (POLS) model to test both distance variables on welfare in order to explore the extent of effects in space. Then, I use the CS DID approach to explore the heterogeneity of effects in time by testing both linear and travel distances as the main treatment on welfare, this is given that both measures are worked as continuos variables instead of binary. With this approach, the aim is to see whether high or low proximities to mines affect welfare among districts. This is worked as "dosages" and follows recent development in the literature of DiD.[9] The main contribution of this chapter is to provide new evidence on the spatial spillovers of mining activities, showing how their effects on welfare attenuate with distance and evolve over time. By doing so, it extends the analysis beyond PDs and quantifies the reach of mining's impacts into surrounding NPDs.

Chapter 3 is in line to the literature of spatial spillovers and agglomeration economies. With the arrival of mining projects to host areas, it is expected that firms and individuals to concentrate in PDs. The geographic concentration of firms and workers within PDs

[7]Other means of transportation might include, for instance, travel by bus or bicycle, however, only car transportation were considered in the analysis. This is because bus travel might include specific routes to bust stops or bus terminals which might increase the travel distance and time among two units of observation.

[8]Map providers such as Google Maps or HERE can also estimate travel distances using live traffic information. However, using traffic information to estimate travel distances might constraint the replication of results.

[9]See Callaway et al. (2024) for implementation of DiD approach with partially aggregated treatment in dosages

will have implications on the distribution of of labour, wages and consequently on individuals welfare located in the host area and their surroundings. For the case of labour, firms benefit from the same pool of workers and inputs. Other benefits of agglomeration are related to improvements in productivity of firms and the spread of information and knowledge. For the case of wages, this is the result of increased competition for limited labour force, though such effects are often short-lived. Also, these effects are not necessarily confined to PDs but spillovers may extend into neighbouring NPDs. For instance, Aragón & Rud (2013) show that households located within 100 miles of the Yanacocha mine experienced positive effects on real income. Similar spatial effects have been documented in other resource sectors (e.g., oil and gas (Feyrer et al. 2017) and manufacturing (Greenstone et al. 2010) in the US). These evidence suggest that mining activity can generate meaningful spatial heterogeneity in welfare outcomes across PDs and NPDs over time. As part of the theoretical framework, I follow the work of Greenstone et al. (2010) that makes two predictions. Considering mobile labour and homogenous firms, the model predicts that incumbent firms to experience positive effects on its Total Factor Productivity (TFP), with the entry of new firms. The model also predict positive effects on profits in the short term for new entrant firms until the prices of local factors find an equilibrium. Local factors of production are also expected to increase, that is wages and land, this is the result of high pressure on a limited labour force and individuals able to capitalise gains into buying land, that is, higher purchasing power or higher consumption levels in the short term. The second prediction of the model involves heterogenous firms (high-tech and low-tech). The arrival of high-tech firms disproportionately benefits other high-tech firms relative to low-tech firms. This dynamic increases demand for skilled labour, which may be sourced either locally or from outside the district. Consequently, higher consumption gains may accrue to high-skilled workers if they are present in the host district; otherwise, such dynamics risk widening disparities between districts that differ in their endowments of skilled labour.

The first part of the results using the POLS model suggest that PDs have high levels of consumption in comparison to NPDs (these varies between 13.1% to 18.7%). Looking at the effect of distances, I find that effects on mining activities on welfare decay in space where a one standard deviation increase in distance is linked to a drop in consumption from 4.8% for linear distances and up to 7.8% for travel distance. This suggests that linear measures may understate spatial effects, since travel distance incorporates geographic and infrastructure constraints. When looking at the extent of effects in space and time, I find for the case of linear distances that effects on consumption are more likely to be effective in the short term among districts (NPDs and PDs) that are located in closer proximities to PDs. For instance, districts that are located in a linear distance of 50 km to PDs are more likely to evidence some positive effects on consumption levels in the fourth and fifth year after PDs start production (significant at 5%) in comparison to districts that are located 50km farther away.[10]. These results remain robust when reducing the sample and working only with the same measure of linear distances between NPDs to PDs. For the case of travel distances, I find some positive effects on consumption levels for all distance measures (mean, median, 100km and 50km) in the fifth year after PDs start production, but these are only statistically significant at 10% level. Results are consistent when working with the reduced sample. I also test travel time by car finding that districts located in 1hr or 2hr proximity to PDs are more likely to evidence positive effects on consumption levels in the fifth year after PDs start production in comparison to districts located 1hr and 2hr farther away to PDs, respectively.[11] Results are robust to controlling for road quality, where I find that districts located in areas without fully paved roads experience positive effects on consumption levels when they are located 2hr away from PDs (fifth year post production significant at 5%), in comparison to those who are located 2hr away. Additional tests considering regional vehicular density confirm these findings. The difference in consumption levels among PDs and NPDs is larger in both low and high congestion areas (from 13.1% up to 24.6%). Also, there is evidence of distance decay effects in high[12] and low congested areas.[13] Other relevant findings include no evidence of distance decay effects in regions with vehicular density below the median, suggesting these groups of districts might relay in other relevant economic activities rather than mining. Results remain robust for variables of income and real expenditure when working with travel time distances and vehicular densities suggesting that effects to be highly agglomerated to PDs.

[10]I also find some positive effects for the second and third year after PDs start production for the same linear measure but these results are only statistically significant at 10%.

[11]I also find some positive effects on consumption for the first, second and fourth year after PD start production but these coefficients are only significant at 10%.

[12]Where the density index is above 1000 and the median value

[13]With an index value lower than 1000.

Chapter 3 serves for the implementation of policies looking to improve welfare conditions among NPDs, specially those who are located in proximities to PDs. While some positive spillovers on consumption are evident, they are often short-lived and concentrated in peripheral areas around PDs, which risks locking local economies into mining dependence. To mitigate this issue, policies should support diversification by providing credit for firms and entrepreneurs to expand beyond mining related activities, alongside training programs that enhance workers' resilience to sector specific shocks. I also argue that is necessary that policies should continue to invest in road infrastructure, this is essential to facilitate free mobility of individuals and goods thereby reducing welfare gaps between PDs and NPDs.

1.2.3 Overview of Chapter 4

Chapter 4 explores the effects of mining activities on wages, employment and occupations during the period 2001-2019, using data from INEI. I use a POLS model to explore aggregated effects on PDs. I include a travel time variable in the same POLS model to evaluate the extent of the effects to NPDs. I addition to this analysis, and using a tripple difference approach, I also explore whether effects of mining activities on the Peruvian labour market vary between periods of boom and bust. Both periods are defined following previous empirical evidence on mining cycles in Peru. I also explore the informal labour market in the same chapter, this is because this sector accounts for a large share of employment (above 80% on average) in the Peruvian labour market and other emerging economies in Latin America (De Paula & Scheinkman 2010). The goal is to assess whether mining has contributed to the expansion or reduction of informal employment over time. To the best of my knowledge, this is one of the first studies to analyse long-term district-level labour market outcomes of mining in Peru.

In Chapter 4, the literature review relies on the empirical evidence on natural resource economics, economic geography and labour economics. Some of these literature suggest that during boom periods, host areas often experience employment gains that extend beyond the extractive sector. This is found in the empirical case of Black et al. (2015) where during boom years of coal production, an additional two jobs were created in the local service sector with every new coal mining job. But, they also find some evidence of crowding out effects in the local tradable sector. This is the result of labour demand shocks. This manifest primarily through changes in employment and earnings (e.g., see Marchand (2012)) and are typically procyclical, as seen in mining, oil, and gas sectors. Resource shocks can also generate persistent effects across sectors and over time. For instance, mine closures have been shown to alter local labour force composition, with shifts in male-to-female employment shares lasting up to two decades in non-extractive industries (Aragón et al. 2018). More recent evidence by Dallaire-Fortier (2024) finds that the magnitude of closure effects varies across direct, indirect, and induced employment, with the latter two experiencing the most persistent losses, lasting up to ten years. The literature review also links resource shocks to the informal sector. For this purpose, this chapter also draws on the work of Goldberg & Pavcnik (2003),[14] which sheds light on the implications of economic shocks, such as the development of mining projects on the informal sector. Their findings suggest that incumbent firms may face greater competition with the arrival of new firms seeking to capitalise on mining related opportunities. In response, incumbent firms might attempt to reduce costs, for instance by cutting staff or hiring workers informally. On the labour supply side, workers may also respond to these shocks by enrolling into temporary or informal jobs to capitalise on short-term opportunities. Chapter 4 is also guided by the work of Allcott & Keniston (2018) as part of its theoretical framework, which predicts effects on wages and local prices in tradable and non tradable sectors during resource boom shocks. Assuming an economy with two regions (A posses natural resources and B does not), two time periods (boom t=1 and bust t=2), and three economic sectors (tradable, non tradable and natural resources), the model suggest that during t=1 that population and wages increase as a result of the economic boom. Then, the model predicts that local employment and prices in the non-tradable sector increase. Employment in the tradable sector declines. Although similar to the Dutch disease outcomes, this is driven by wages rather than real exchange appreciation. The same model also predicts that migration can attenuate wage increases, limiting effects on the tradable sector. Similarly, Allcott & Keniston (2018) argues that the impact on the tradable sector will depend on the spatial scale of trade, that is, if production is mainly focus to serve the local demand, then it is less likely that manufacturing sector will be crowded out since firms can raise prices to attend the

[14]The seminal work of Goldberg & Pavcnik (2003) is focused on trade liberalisation and the informal labour sector. However, their work helps to understand how economic shocks of similar nature such as the mining sector can shape the informal labour sector, specially for the case of Latin American countries.

demand, but if production is focused externally, then it is likely that the sector will be crowded out. For bust periods, the model predicts that both regions return to parity conditions in terms of wages, employment and productivity. However, in the presence of productivity decline, it is less likely this scenario, suggesting crowding out effects.

The results of Chapter 4 show that PDs experience wages that are 30% higher than NPDs during the period 2001-2019, this is probably the result of high paying wages in the mining sector within PDs and spillovers to other firms within PDs. The share of employment is slightly lower (circa 2.4%) in PDs than NPDs, this result is also confirmed by the level of unemployment which is slightly higher in PDs than NPDs, suggesting a more competitive environment in the former group. This latter result is counterintuitive to some extent, since it would be expected higher levels of employment across of PDs, however, it could be the case that it reflects the nature of the mining activity, of being a capital-intensive rather than labour-intensive activity. Evidence on occupational composition provides further insight, where the share of occupations directly related to mining (Group 1) is higher in PDs than in NPDs (about 1.8%). I also find that the share of employment slightly decays with distance for the 25th and 75th percentiles of travel time between districts (that is PDs and NPDs) and PDs. The analysis on boom (2001-2011) and bust (2012 onwards) years suggest that wages are 17% higher in PDs during boom years. I also find evidence that the share of employment is lower in PDs during boom years (4.1%). This could be the result of lagged economic activity, as a consequence of agglomeration of firms during years of boom and potentially learning by doing spillovers reflected to other industries or neighbouring areas. The share of Group 1 occupations also rose in PDs during booms, pointing to a concentration of skilled mining related jobs. The share of informality is also lower in PDs than NPDs during years 2007, 2013 and 2019. The results remain robust when comparing districts within the same region and province. I argue that this could be the result of higher enforcement activities in PDs than NPDs. For instance, higher enforcement activities have been evidence to reduce unemployment rates and to increase formal employment since the 90s (Meghir et al. 2015). Consequently, a higher number of firms are more likely to be found in NPDs. However, it is likely that this reduction in the share of informality is the result of a combination of factors over time rather than a single specific policy at the district or national level.

The main policy implications is focused at the firm level, where I argue that local firms in PDs and neighbouring areas should have better access to financial support such as access to credit, temporary tax exemptions or subsidies to hire and train young individuals in occupations that are not directly involved in the mining sector. This is because most of the gains seem to be focused during boom times, with high wages concentrated in PDs mainly and among high skilled workers. Training programs to local workers are also key to support their mobility not only across industries once mining enter into bust years but also to foster upward mobility within the occupational structure, enabling local workers to access higher-paying and more stable jobs over time. There is also the need of cooperation beyond PDs to other districts and provinces within producing regions, with the aim to promote diversification strategies to support economic growth and improve welfare in the long term. These diversification strategies could include the support to other relevant economic sectors that are actually benefiting from mining spillovers as well as independent industries that are thriving regardless of the development of the mining sector.

Chapter 2

Exploring the dynamic effects of mining on consumption in Peru

2.1 Introduction

The mining sector represents an important contribution to the Peruvian national economy. According to a recent report by the Peruvian Ministry of Energy and Mines, the mining sector accounts for 8.3% of GDP and 58.9% of all Peruvian exports in year 2022 (Ministerio de Energia y Minas 2023). The country is one of the top producers of key minerals such as copper, gold, silver, zinc, molybdenum, iron and tin, and a preferred destination for mining investors, accounting for 4.1% of the worldwide total budget for mining exploration activities. With a total investment mining portfolio of 47 projects with a value of USD 53,715 million, the mining sector will continue to play a crucial role in shaping the Peruvian economic landscape.

The literature has highlighted that efforts to decarbonise economies will require a substantial increase in the output of key raw materials. For instance, current top producers of copper such as Peru and Chile could see in the upcoming years a sudden raise of mineral production which will require new exploration and exploitation activities and extension of current mining projects, in order to meet the demand for key minerals and metals worldwide.

This research instead of looking to determine whether the extractive sector is a curse or blessing for the Peruvian economy, it explores the dynamism in mineral production at the district level in Peru. It includes long-term data and a novel method approach to study Producing Districts (PDs) and Non-Producing Districts (NPDs). As the literature has highlighted, there is vast empirical evidence that uses econometric techniques, different methods and datasets that, when compared, it could be argued that it is difficult to determine whether resource extraction leads to a dual outcome (curse or blessing). However, one of the remaining gaps in the literature is to explore the dynamism or intermittent nature of mineral production and its effects on consumption among PDs, that is, periods of mineral activity where mining companies operate and are actively producing or exploiting minerals or conversely periods of standby after production starts.

This chapter works with two main sources of data. The National Institute of Statistics and Informatics (INEI) collects household-level data on a yearly basis, with a representative sample at the national level (Aragón et al. 2021). The INEI collects information on various socioeconomic variables, such as income, consumption, level of education, access to public services, and agricultural activities (agriculture, forestry, and livestock). It also records household characteristics such as age, gender, marital status, and occupation. This survey allows for the construction of a pseudo-panel data at the aggregated district level, forming a pseudo-panel with 19 years of consecutive data. The second source of data was obtained from the Peruvian Ministry of Energy and Mines, which host mineral production data on large, medium and small and artisanal mining for all mining projects in Peru. This dataset includes the mineral production of all produced minerals (e.g., copper, zinc, silver, gold, etc) and consolidates information at the district level. The availability of these datasets allows for the exploration of the long-term causal relationship between mining activity and welfare in Peru. It also allows me to observe producing districts across time and have the option to select among various non-producing districts as control units when I use the double difference method approach. One important characteristic of this pseudo-panel is that the sample of districts increases progressively in time, avoiding the common panel data issues such as attrition (Verbeek 2008).

A relevant aspect to consider in the mining sector is the time that takes for a single mining project to reach the production stage. According to Manalo (2023), it takes up to 15 years on average for mines to reach the production phase (within a range of 6 to 32 years).[1] Also, the time to reach full production capacity could be linked to various factors (such as planning, price-driven, external). Although, the literature suggests that most of

[1]Available at: https://www.spglobal.com/marketintelligence/en/news-insights/research/discovery-to-production-averages-15-7-years-for-127-mines

the impact on labour demand occurs during the construction stage, this will depend on the type (e.g., open-pit, underground) and size of mine (large, medium, small and artisanal scale mining), machinery, physical access, approvals, which could actually make fluctuates labour demand during this stage. During the operation stage, mining production also varies over time, and for the case of Peru, it shows a feature of being active/inactive for periods of time (I call this switch on and off). Periods of inactive production could be due to many reasons. For instance, the occurrence of social conflicts across mining projects in Peru is high, according to the Peruvian Ombudsman, two out of three social conflicts in Peru are linked to the mining sector (Defensoría del Pueblo 2024). Other external factors could also impact the continuous production of minerals. According to the Peruvian General Mining Law, mining companies that are in possession of a mining concession are required to produce a mining quantity of minerals per year and hectare (e.g., for large and medium scale mining, mineral production should be not lower than one Tax Unit Value, equivalent to USD 1,369 per year and hectare, for the case of metal mining and 10% of one Tax Unit Value for non-metal mining).[2] Mining companies are obliged to report monthly their mineral production to the Peruvian Ministry of Energy. The lack of production within a window of 10 years after mining companies obtain a concession to exploit minerals is penalised by a fee that will depend to the type and size of the concession. The information on mineral production is relevant to understand how welfare changes across producing districts given the switch on and off behaviour of mining sites during the production stage. Also, given the availability of long-term data, it is possible to observe how welfare changes across time.

Recent developments in the literature on double difference allow for exploration of this topic. For instance, Callaway & Sant'Anna (2021) method is useful to evaluate heterogeneous treatment in time (CS DID, hereafter). This method is different from the canonical double difference approach, where two units of observation are analysed before and after treatment. For the case of this first chapter, the CS DID method is relevant because incorporates the dynamics of the mining sector in the analysis, that is the switch on and off characteristics of PDs that host minining operations. For instance, previous empirical papers use the canonical double-difference approach to evaluate the effects of

[2]A Tax Unit Value (or UIT by its acronym in Spanish) is equivalent to PEN 5,150. One Tax Unit Value in Peru is equivalent to USD 1,369, considering an exchange rate of 0.265921 PEN / USD, 12 July 2024

mining on poverty, inequality and consumption such as Loayza & Rigolini (2016) or Aragón & Rud (2013) studying the Yanacocha mine in Peru using data from INEI.

The main research question that this chapter aim to address is: How do districts perform over time when they enter and exit the mining sector? Therefore, this first chapter aims to bring new empirical evidence using recent developments in the DiD literature which would allow to evidence effects of mining on welfare during the period 2001-2019.

Section 2 presents the literature review, I also discuss some relevant case studies that use INEI data and a quantitative approach in Peru. Section 3 presents the methodology and assumptions for using the CS DID method. Section 4 presents the results and Section 5 the conclusions.

2.2 Literature Review

2.2.1 The social and economic impacts of mining activities in Peru

Over the past five decades, there has been a growing interest among scholars to study the effects of mining activities in Peru, given the relevance of this sector to the whole national economy and due to the various social, health, environmental and governance issues associated with this economic activity. Manrique & Sanborn (2021) argue that most of the research conducted over the past five decades has been focused on conflict studies, economy and development and health and environment. Manrique & Sanborn (2021) also report that there has been a shift in the focus of studies, from research focusing on mining history in the early 70s to studies about economy and development in the early 90s. More recently, there has been a notable increase in research on conflict studies. This shift is likely connected to the expansion of mineral activity and exports and a higher number of social conflicts associated with the mineral activity in the country, the latter recorded and reported by the Peruvian Ombudsman since year 2004 (Triscritti 2013).

Scholars have mainly used secondary sources such as the national census (1993, 2007 and 2017), the national household survey, municipality-level data, poverty map (2007) and a variety of evaluation methods considering the available data e.g., PSM, DiD, Instrumental Variables (IV), at various levels of analysis e.g., district, household, regional level. Another important aspect is the timelines, which are in accordance with the data that scholars used to measure the effect of mining activities, which mainly seem to focus on boom periods. For instance, Zegarra et al. (2007) evaluates the impact of mining on urban and rural households located in the Andes ("Sierra") region (high altitude areas or Peruvian Highlands) for the boom period 1993-2003. The two main reasons for them to focus on these households are because the majority of metal mining activity is located in the "Sierra" region and because this area hosts a high number of social conflicts related to mining activities. Overall, their results suggest positive effects on the mean income and consumption among urban households. Also, rural households seem to have recorded lower levels of poverty during the same period of analysis. However, one interesting finding is related to the difference between an increase in income that is uncoupled with an increase in consumption for the same period of analysis among households located in the southern regions of Peru, which sheds light on the nature of the mining activity, that is short periods of high levels of demand of workers or local procurement which could be linked to early stages of mining operations such as construction phase.

Aragón & Rud (2013) focus on the local economic impacts of the gold mine Yanacocha, located in the northern region of Cajamarca in Peru. They use household-level data for the period of time 1997 to 2006. For the purpose of the analysis, Aragón & Rud (2013) focus on the quantities of goods that were demanded locally by Yanacocha. Other potential ways to find causality between mining activity and local development could be linked to the level of mineral production and using as a proxy the number of local personnel employed by the mine. An important aspect to highlight about Aragón & Rud (2013) work is the use of a general equilibrium framework (see Moretti (2010)) where the authors test whether a shock in the demand of local labour will increase real wages and real income of workers, under a context of low mobility of workers and, also, whether the effects of the latter shock is passed onto local producers and homeowners, thus, benefiting these group. The main results suggest positive impacts on real income due to the high demand for local inputs by Yanacocha. This previous study was years later expanded by Orihuela & Gamarra-Echenique (2020) where they use a longer dataset that covers the period 1997-2017. Their findings suggest that local effects follow a cyclical pattern in line with boom and bust periods of mining activity. Another relevant aspect of Orihuela & Gamarra-Echenique (2020) is related to the discussion about the mechanism in which localised mining effects could be more linked to a short-term income or consumption shock that disappears after boom periods of mineral activity rather than backward linkages (Aragón & Rud 2013).

Another relevant study focused on the effects of mining activities on welfare is the one produced by Ticci & Escobal (2015) where they use a PSM-DD approach finding positive results on education but negligible on poverty reduction for the period 1993-2007. Their results also suggest some spillovers in the non-primary sectors, where the labour share decreases. It is also observed that individuals in rural areas are more engaged in productive activities within mining districts in comparison to non-mining districts.

Loayza & Rigolini (2016) evaluate the impacts of mining on poverty and inequality in Peru. They explore whether the boom of mining activities has benefited local communities, given the growth of mineral exports since the 90s. [3] Loayza & Rigolini (2016) use district-level data and focus on the period 2002-2007. Both scholars acknowledge that their findings might miss some of the effects of mineral activity during the boom years that came after 2007. However, they argue that their results that focus on the period 2002-2007 might capture the effects of mining during the 90s and early 2000s given the continuous growth of mining exports.

Scholars have also studied the effects of mining activities on other important variables such as land, health, and gender. For instance, Del Pozo & Paucarmayta-Tacuri (2015) finds effects on land use and the structure of the labour force within rural areas. Arellano-Yanguas (2011) finds evidence that fiscal transfers push local conflicts at the local level, although these effects might be linked to the cyclical nature of the mining activities, e.g., period of booms (Orihuela et al. 2019).

Over the past 20 years, scholars have extensively studied the effects of mining on welfare and other socioeconomic variables. This first chapter aims to build on existing empirical literature and examine how the dynamics of mineral production influence long-term welfare in Peru.

[3] The latest economic report on mining activity suggests that the level of mining exports accounts for almost 60% of all export products (Ministerio de Energia y Minas (2023)).

2.3 Methodology

2.3.1 Data

Datasets

This chapter works with secondary quantitative data from three Peruvian government institutions, which are the Ministry of Mines and Energy (MEM), the Institute of National Statistics (INEI) and the Central Bank of Peru (BCRP). The MEM dataset incorporates information on mineral production by type of mineral and mine producer at the district level for the period 2001-2019. The INEI dataset includes information about key socioeconomic variables such as consumption, income, poverty, household characteristics and education. This information is processed and analysed at the district level for the period 2001 to 2021. The BCRP dataset includes information on exchange rates and consumer price index for the period 2001-2019. Other relevant sources to obtain information about mineral prices and shapefiles were accessed via the International Monetary Fund (IMF) and the Peruvian Geographic Institute (IGP), respectively. The timeframe for the analysis covers the period 2001 to 2019. I provide further information on the sources of information and how the data was curated and tested prior to use for the analysis of results of this chapter.

The INEI conducts each year a household survey (the ENAHO survey) based on a representative sample at the district level, between urban and rural areas in all 24 regions in Peru. This ENAHO survey collects household data since 1995. The ENAHO survey collects information on housing, household members, education, health, employment, income, consumption, farming, livestock and forestry production, among others. The ENAHO survey has also increased the number of topics and questions asked to households. For instance, recent ENAHO surveys have collected information on topic such as citizen participation, access to justice, governance, democracy and transparency. In the year 2004, the ENAHO survey updated the number of items in the consumption basket, this responded to the consumption of new goods across households. Although these changes in the method to collect data could bias the outputs for consumption, I test the data using a Pooled Ordinary Least Squared (POLS) analysis to differentiate the period 1999-2003 (prior changes to the consumption basket) and 2004 to 2019 (post change in the consumption basket) with the aim to observe whether the two periods of the study are not strictly comparable.

The ENAHO survey is a reputable source of information and has been used by scholars in the field of extractive industries and others to publish in top journals, see for instance Aragón & Rud (2013) and their case study on mining in the region of Cajamarca in Peru, published in American Economic Review. See also Agüero et al. (2021) and their study of the relationship between natural resources and human capital in Peru published in the Journal of Development Economics. Table 2.1 summarises the key variables discussed in this chapter. The main outcome variable is the average individual consumption at the district level (USD/month). The covariates include district-level proportions for gender, rural households, and permanent household members. Additionally, the district's altitude and surface area are included.

Another relevant database that is used for this chapter is the Mineral Production Dataset by the MEM. According to the Peruvian General Mining Law, mining companies are responsible to report monthly mineral production information by type of mineral. This applies to mining companies that have environmental permit approved, and those who might be on standby. For the case of mining sites that are in the construction or exploration stage, these report information on security issues. Where there is mineral exploitation, mining companies report information on mineral production and security. This information is later used by MEM to produce annual statistics reflecting the progress on the mining sector in Peru. This information is also publicly available from year 2001 to 2022. It contains information on mineral production by mine site, owner, type of mineral, quantity produced and location (region, province and district) for all large, medium, small and artisanal mining operations in Peru. Figure 2.1 presents the value of mineral production in USD for key minerals produced by large, medium-scale, small, and artisanal mining companies in Peru from 2001 to 2021. The values are calculated using commodity prices from the International Monetary Fund (IMF) and mineral production data from the Ministry of Energy and Mines (MEM).

I access additional datasets from the Central Bank of Peru (BCRP), INEI and IMF to obtain information on exchange rates and consumer price index, GIS coordinates for all districts in Peru and mineral prices, respectively. The data on exchange rates and

Table 2.1: Summary statistics

Districts	Stats	logexp	pgender	purban	ppmhh	altitude	surface
NPD	Mean	4.667	0.490	0.416	4.808	1,920	808
	se(mean)	0.004	0.001	0.003	0.008	11.054	16.501
	p50	4.657	0.491	0.243	4.748	2,328.00	234.000
	SD	0.584	0.067	0.443	1.097	1,443.42	2154.804
	Min	3	0	0	1	5	2
	Max	7	1	1	11	4,470	24,050
	N	17,072	17,072	17,072	17,072	17,052	17,052
PD	Mean	4.906	0.461	0.470	4.321	2,239	1,362
	se(mean)	0.016	0.004	0.012	0.041	44.082	90.429
	p50	4.950	0.488	0.485	4.470	2,731.00	549.000
	SD	0.524	0.128	0.404	1.383	1,487.74	3,051.89
	Min	3	0	0	0	17	7
	Max	7	1	1	9	4,394	22,219
	N	1,075	1,139	1,139	1,139	1,139	1,139
Total	Mean	4.681	0.488	0.419	4.778	1,941	842
	se(mean)	0.004	0.001	0.003	0.008	10.738	16.501
	p50	4.672	0.490	0.275	4.724	2,355.00	248.00
	SD	0.583	0.073	0.441	1.123	1,448.25	2,225.58
	Min	3	0	0	0	5	2
	Max	7	1	1	11	4,470	24,050
	N	18,147	18,211	18,211	18,211	18,191	18,191

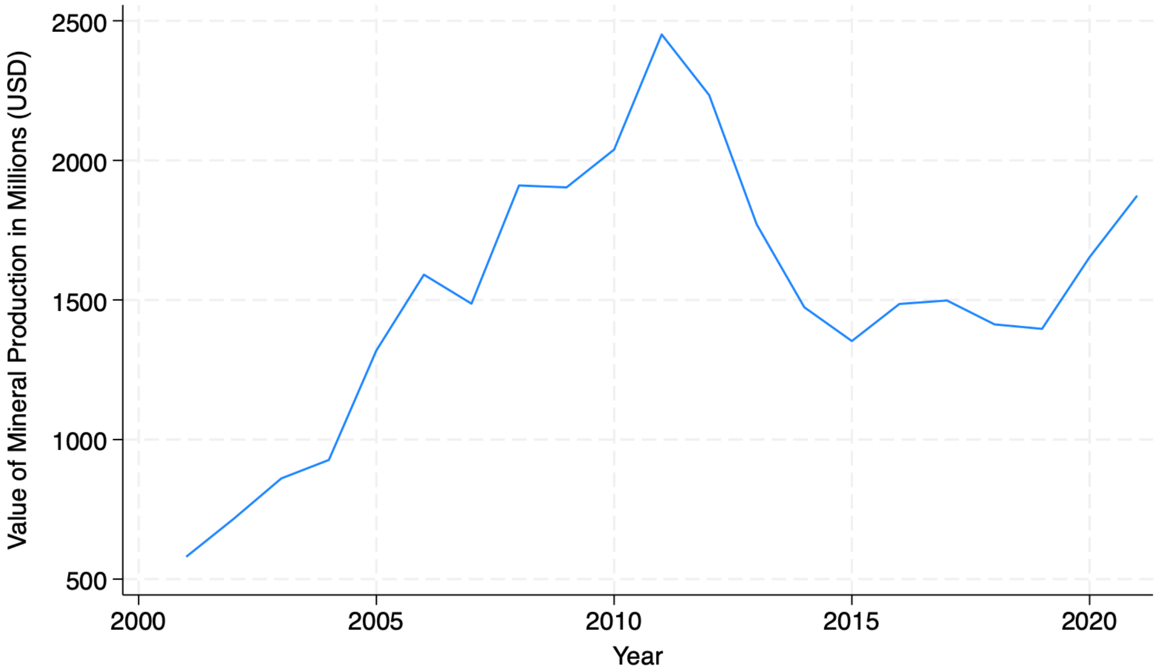
Note: Table 1 presents the summary statistics for PDs and NPDs, including the Mean, standard error, Median (p50), Standard Deviation (SD), Minimum and Maximum values (Min and Max) and Number of Observations (N). Logexp is the Average individual consumption at the district level (USD/month) expressed in log. ppmhh is the proportion of permanent household members at the district level, pgender is the proportion of females at the district level, purban is the proportion of urban households at the district level. Geographic controls include altitude and surface.

consumer price index is used to calculate deflated values to the year 2019. Shapefiles were downloaded from the Peruvian Geographic Institute (IGP) with the aim to produce maps at the national, regional and district levels.

Units of Observation

Peru is divided into three administrative boundaries: regions, provinces, and districts. This study focuses on districts, categorized as either Producing Districts (PD) or Non-Producing Districts (NPD) (see Appendix - Table 2.11 for a summary of PD and NPD). PDs are districts that host mining sites within their geographical boundaries for one or

Figure 2.1: Value of Mineral Production in Millions (USD).



Note: Value of mineral production in millions (USD) for gold, silver, copper, lead, zinc, molybdenum, iron and tin.

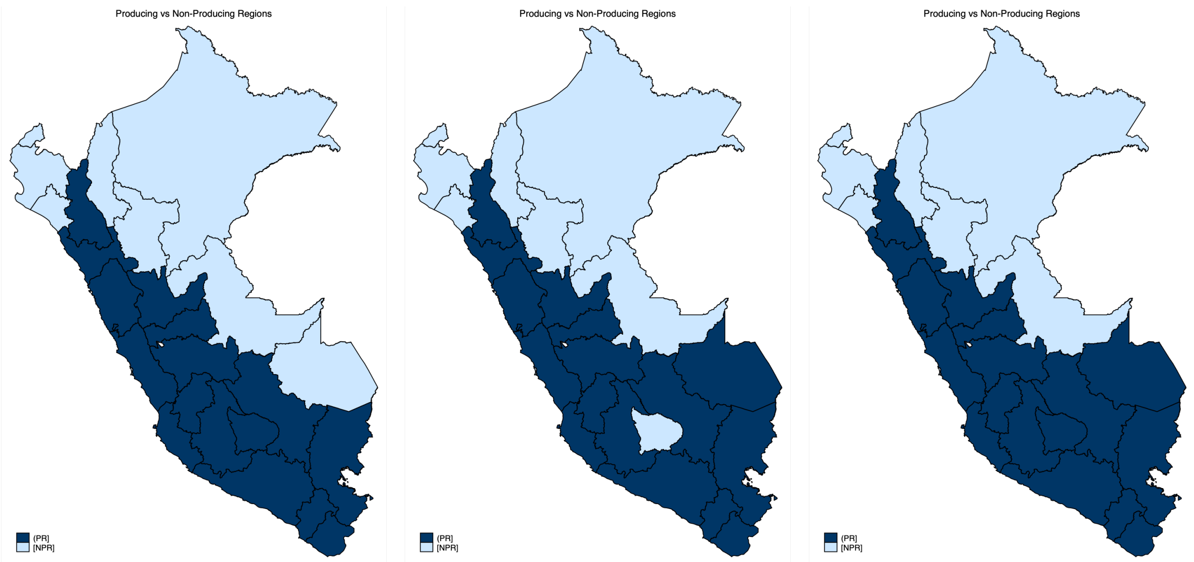
more years. NPDs are districts that do not host any mineral activity during the analysis period. Table 2.11 provides a summary of PDs and NPDs from 2002 to 2019, along with t-tests for the key outcome variable. In 2019, there were a total of 1,874 districts and 24 regions (See Table 2.2). The difference between the total number of districts in 2019 and the number of PDs and NPDs is due to ENAHO collecting data annually on a sample of districts at the national level. Figure 2.2 and Figure 2.3 present the geographical distribution of producing and non-producing regions, as well as PDs and NPDs, for the period 2002-2019.

Table 2.2: Number of Administrative Divisions in Peru

Year	Nº of Departments	Nº of Provinces *	Nº of Districts
1940	22	122	1,064
1961	23	144	1,491
1972	23	150	1,676
1981	24	153	1,680
1993	24	188	1,793
2005	24	195	1,811
2007	24	195	1,834
2014	24	196	1,845
2017	24	196	1,874
2019	24	196	1,874

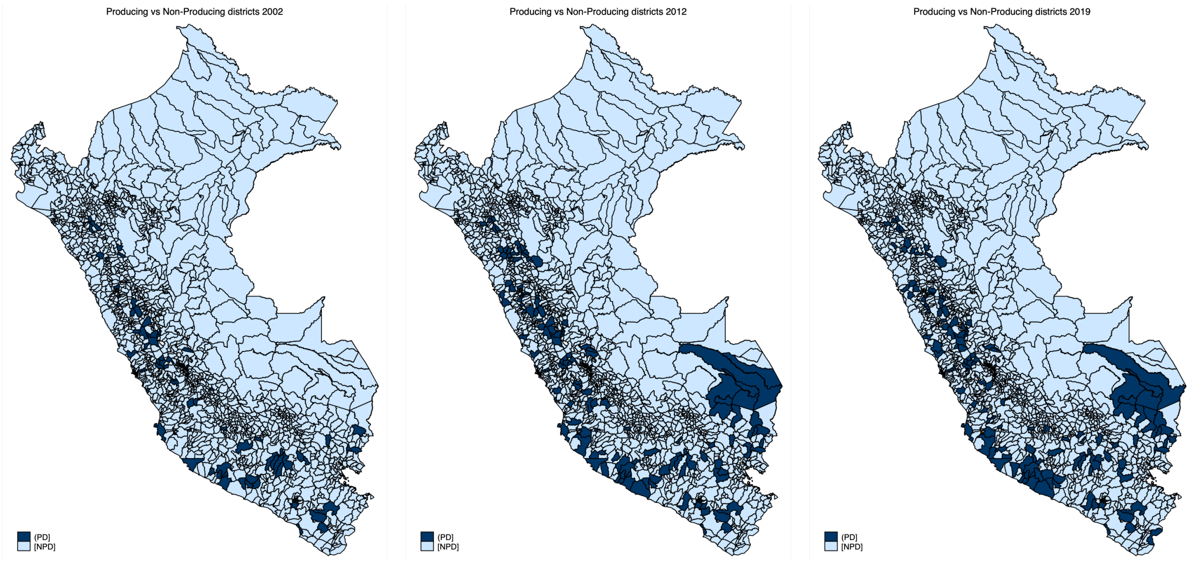
Note: Peru is composed of three administrative divisions: departments which are the largest administrative units, followed by provinces and then districts. The table is sourced from Instituto Nacional de Estadística e Informática (2014) and Instituto Nacional de Estadistica e Informatica (2020).

Figure 2.2: Producing Regions vs Non-Producing Regions in 2002, 2012 and 2019



(a) 2002 (b) 2012 (c) 2019

Figure 2.3: Producing and Non-Producing Districts in 2002, 2012 and 2019



(a) 2002 (b) 2012 (c) 2019

2.3.2 Methods

I explore the dynamic effects of mineral activity across time during the period 2001-2019, one of the main reason for this approach is because mineral production occurs at different times (i.e., production start across mines is staggered in time) and it is not necessarily continuous after the first year of production for various reasons (e.g., social conflicts). The current data allows for the exploration of these dynamic effects at the district level. I consider the following assumptions in order to explore the dynamic effects of mineral activity across time at the district level in Peru:

- PDs are considered treated units when there is evidence of any mineral production for a given year. Then I assume that the effect persists for the remaining period of time. E.g., if a PD is treated for the first time in year 2016, then I expect the effect to remain till the end of the period of analysis. I call this "No exit" strategy.

- I make sure that treated units (PDs) have "observable" data at least two consecutive years before intervention (that is, the start of mineral production). For instance, if a PD starts production in 2014, I make sure that a PD has available information on the two years prior for all key variables (e.g., consumption). In the event that units do not have information two years prior production starts, then the unit is removed from the analysis.

- I explore the dynamic effects for a window of 5 years post intervention. Although this window of study could be increased to a higher number, I observe that increasing time of exposure returns outputs with slightly high standard errors. This might be due to a decrease in the sample size of treated units in time.

- The analysis is conducted using never-treated as control units. These are NPDs that during the period of study do not host any mining development. The outputs using Not-yet treated units (i.e., districts such as NPDs that could become PD and then go back again to NPD status) as part of the comparison group is included in the appendix.

- I remove the districts in the metropolitan city of Lima from the analysis. The main reason for this is because the city of Lima concentrate districts with high income/consumption individuals.

- I use a set of demographic (% of females at the district level, % urban households at the district level, average number of permanent resident members at the district level) and geographic controls (altitude and surface) for the analysis.

Empirical Approach

I use a DiD approach with multiple time periods following the CS DID method by Callaway & Sant'Anna (2021). Previous empirical literature on natural resources have used the canonical double-difference approach where there are two time periods (before and after intervention) and treated and control units. This double difference approach works under the assumption that there are no effects on the treated units before intervention (No Anticipation assumption) and that both treated and control groups outcomes would follow a similar path in the event that there is no intervention (Parallel Trend assumption). One of the main criticisms to the canonical double-difference approach is that in practice, interventions could occur at different times, and the intensity of the treatment/intervention could also vary along time (Roth et al. 2023). There is also the possibility the effects do not absorb over time (see De Chaisemartin et al. (2024)). It is usually assume that treatment effects to absorb on the treated units, but little attention is given to units that one absorb effects on treatment in the given year and that there is "no carryover" onto the next period. The same Roth et al. (2023) provides an insighful example of this event in which, say that changes in employment are subject to increases in minimum wages, but the change in employment in year t will be subject only on changes in minium wage in the same year t and not on previous changes in minimum wages in years t-1, t-2 or other periods t-n.

Recent developments in the literature of DiD have addressed some of above mentioned issues. Callaway & Sant'Anna (2021) address the first of these issues, when treatment occurs in multiple periods. This method facilitates to answer questions such as what are the overall aggregated effects for the period 2001-2019? what are the effects of treatment for an exposition of "n" number of years (event-study / dynamic effects) or what are the effects of treated units by period "t"?.

The canonical double difference set-up estimates the Average Treatment Effect on the Treated units (ATT), where there is a baseline period of no treatment ($t = 1$), the period that follows ($t = 2$) is where units receive treatment. The difference in differences of treated and untreated units in these two periods of time can be understood with the following equation:

$$ATT = \mathbb{E}[Y_{i,t=2} - Y_{i,t=1} \mid D_i = 1] - \mathbb{E}[Y_{i,t=2} - Y_{i,t=1} \mid D_i = 0] \tag{2.1}$$

Where $Y_{i,t}$ is the potential outcome of i unit in t time. $D_i = 1$ is an indicator of treated units and $D_i = 0$ of untreated units.

The CS DID method is built on this latter approach, also considering not anticipation and parallel trends assumptions. The CS DID method estimates the difference in the outcome of cohort g at time t and g-1, and it compares with never-treated units or not-yet treated units. The CS DID method can be arranged as follows (adapted from Callaway & Sant'Anna (2021) and Roth et al. (2023)):

$$ATT_{g,t} = \mathbb{E}[Y_{i,t} - Y_{i,g-1} \mid G_i = g] - \mathbb{E}[Y_{i,t} - Y_{i,g-1} \mid G_i \in \Gamma] \tag{2.2}$$

Where Γ could represent either never-treated units ($\Gamma = \infty$) or not-yet treated units ($\Gamma = g' : g' > t$).

The CS DID method allow to use never-treated units (i.e., districts that are always NPD during the period 2001 to 2019) and not-yet treated units (districts that will become PD eventually during the period 2001 and 2019) as part of the comparison/control group.

Although both groups might behave differently across time, for large sample of treated units it is recommended to work with never-treated units (see Callaway & Sant'Anna (2021) and Roth et al. (2023)). This is also related to the assumption that there is no anticipation in treated units, that is, that districts do not put forward themselves to be considered as part of the intervention given effects on other treated units (PDs).

I use the csdid command in Stata to get the overall aggregated ATT for the full period of study (2001 to 2019) and event-study parameters for a window of exposition of five years. The later parameters are weighted relatively to the size of cohorts that have been exposed to treatment for n number of years (n=5), as per the following equation (adapted from Roth et al. (2023)):

$$ATT_n^w = \sum_g W_g ATT(g, g+n) \tag{2.3}$$

Where W_g is the relative weight of the ATT for cohort g (i.e., group of districts that become PD at time of treatment g, relative to the total number of PDs) and n years after exposition to treatment (n=5). Although it is possible to work with a shorter or larger window of exposition to intervention, after testing the data, I observed that the larger the window of exposition, the higher the standard errors of the coefficients. This might respond to the issue that there are fewer observations that have been exposed to five of more years of treatment. When working with a shorter window of exposition (e.g., n=2 or n=4), sometimes it is not possible to observe how the effects "build up" in time, thus, I work with a conservative window of exposition of five years (n=5).

The outcome variable measures the log of consumption per capita at the district level, aggregated from individual-level data. I work with a set of covariates that capture specific district characteristics, including the percentage of females, percentage of urban households, average number of permanent resident members, altitude, and surface area. These covariates were selected based on prior empirical research on mining in Peru (see, for example, Loayza & Rigolini (2016)). Incorporating covariates into the analysis is crucial as they explain the evolution of the outcome variable over the study period and may exhibit different distributions across groups Callaway & Sant'Anna (2021). The csdid command in Stata also includes time and district fixed effects.

The no anticipation assumption is complied by default since districts (PDs) do not put theirself forward to receive treatment (i.e., to become producer or PDs), but changes in their status will be subject to external factors (e.g., decision of mine operators to start production which at the same time are subject to international commodity prices).

I also work with districts that have at least two years of data before production starts (that is, start of treatment). During the pre-treatment period, these districts report no mineral production. This design allows for the observation of transitions from NPDs to PDs status. Requiring a minimum of two consecutive years of "clean" pre-treatment data (i.e., no mineral production) improves the balance and credibility of the dataset.[4] Districts with continuous mineral production throughout the study period (2001–2019) are also excluded, unless they exhibit at least two consecutive years of non-production prior to treatment.[5]

Robustness Checks

Another possible option is to test the same data with the Extended Two Fixed Effect method (ETWFE) developed by Wooldridge (2021). The ETWFE addresses previous concerns of the former TWFE model. One of the main criticism of the TWFE in the staggered setting is that it might use already treated units, in which already treated units may serve as controls. These sort of comparison between treated and control groups are referred in the literature of causal inference as "forbidden comparisons" (Roth et al. 2023). This approach also works under the assumptions of no anticipation and conditional parallel trends. The expected value of $Y_{i,t}$ given $D_{i,q..T}$ and X_i is obtained as follows:

$$ATT_{g,t} = \mathbb{E}[Y_t(g) - Y_t(\infty)] \tag{2.4}$$

Where $g = q, q+1, \ldots, T$ and $t \geq q$. g is the period of time where a district i converts into a PD (treated/intervened). q is the first year in which district i is a PD and so on. The above expected value relies on the fact that there will be at least one period of no intervention before a district converts to a PD ($q \geq 2$). In order to obtain individual group-time ATTs, the ETWFE relies on the following specification (based on Wooldridge

[4] To ensure PDs have at least two consecutive years of non-production data before treatment (i.e., years $t-2$ and $t-1$), 600 observations were excluded. Additionally, 256 observations were removed because they contain only post-treatment data, starting in the treatment year. A further 101 observations were excluded due to missing data for year $t-1$, despite having data for year $t-2$.

[5] A total of 45 districts report production in every year from 2001 to 2019. These early-producing districts (or "superproducers") were excluded since it is not possible to identify a clear pre-treatment period, making it difficult to determine whether production began before or during the study window. See 2.12 in the Appendix for event time figure on "super producers".

(2021) and Xiao et al. (2023)):

$$Y_{i,t} = \alpha + \sum_{g=q}^{T} \sum_{s=g}^{T} \beta_{g.s}(W_{i,t} \cdot D_{i,g} \cdot f_{S,t} \cdot \dot{X}_{i,g}) + \eta_i + \lambda_t + \epsilon_{i,t} \tag{2.5}$$

Where:

- α is the constant term,
- $\beta_{g,s}$ is the cohort-time specific effect for cohort g and calendar time s, i.e., $\text{ATT}_{g,s}$ (e.g., $\text{ATT}_{2003,2003}$ would be the estimated ATT for a group of districts that start intervention in year 2003 (cohort $g = 2003$) in calendar time 2003 ($s = 2003$)). Therefore, one could obtain ATTs for different combinations of g and s,
- $W_{i,t}$ is a dummy variable that takes the value of one to indicate that district i is treated in year t, and zero otherwise. For the case of "no exit" strategy, this dummy will mark 1 continuously from the moment that district i becomes PD for the remaining time period of analysis. The dummy takes the value of zero otherwise.
- $D_{i,g}$ is a dummy variable that takes the value of one to indicate that district i is treated in year g (i.e., to indicate that belongs to cohort g), and zero otherwise,
- $\dot{X}_{i,g}$ is the demeaned covariate for district i that belongs to cohort g,
- $f_{s,t}$ is a dummy variable that takes the value of one when $s = t$ (to indicate each treated unit by calendar time),
- η_i and λ_t are district and time fixed effects, respectively,
- $\epsilon_{i,t}$ is the error term.

The aggregated ATTs are estimated with the Stata by post-estimation commands for calendar time, window time of exposition or overall ATT or by cohort. I use the jwdid command in Stata to obtained the aggregated ATT for the period 2001-2019 and event-study coefficients for a window of exposition of 5 years. Post-estimation commands include estat_event.

Irreversibility or no exit strategy

The CS DID method operates under the assumption of no reversibility (or no exit), implying that once units are exposed to the intervention, they are considered treated for the remaining time of the study period (see Callaway & Sant'Anna (2021) and Roth et al. (2023)). For the case of this research, there exists two possibilities, the first is that once district become PDs, they remain under this condition till the end of the period of study (i.e., transition from NPD to PD). The CS DID method and the ETWFE are certainly feasible approaches for this condition. I call this "No exit" strategy. A second possibility is where there is more than one transition but always starting as NPD. If that were the case, then I would assume that the effects on the outcome variable would be only specific to the transition to a status of PD at different times during the study period (this is called in the literature as no absorption or no carry over (Roth et al. 2023)). Recent developments in the literature on double difference could address this specific issue (e.g., see De Chaisemartin et al. (2024)). For this chapter, I focus on the first possibility of no exit considering two scenarios. Scenario A where I work under the assumption that no exit happens for districts once they become PDs, in that sense, I work with the full sample and work with a dummy variable that marks 1 when a PD starts its first year of production and zero otherwise. Once they begin production the dummy will mark one for the rest of the years post-intervention (i.e., after they become PD). In scenario B, I work with a subsample of districts that become PD once in their lifetime and remain under the same condition for the remaining years of the period of study (that is, the transition from NPD to PD)[6]. See Table 2.3 for a summary of transitions. Districts also depict more than two transitions e.g., spells 3, 4, 5 and 6 which means that districts have transited from a status of NPD to PD on more than three occasions. Although recent developments in the literature on double difference allow for exploration of effects for these cases of irreversibility (e.g., see De Chaisemartin et al. (2024) and Roth et al. (2023) for further analysis on the case of no carryover effects), this chapter does not address these transitions but the ones mention in scenario A and B.

[6]all PDs will start as NPDs and will have at least two years of data before they become producers

Table 2.3: Descriptive statistics for different spell transitions

Spell number Transition	Stats	Years on standby	Years on production	Scenario
Spells=2 NPD - PD	Mean	0	14	A / B
	p50	0	17	
	Min	0	1	
	Max	0	19	
	N	524	524	
Spells=3 NPD - PD - NPD	Mean	6	5	A
	p50	4	3	
	Min	1	1	
	Max	14	17	
	N	332	332	
Spells=4 NPD - PD - NPD - PD	Mean	3	9	A
	p50	2	10	
	Min	1	2	
	Max	5	15	
	N	158	158	
Spells=5 NPD - PD - NPD - PD - NPD	Mean	7	5	A
	p50	8	5	
	Min	2	2	
	Max	12	7	
	N	78	78	
Spells=6 NPD - PD - NPD - PD - NPD - PD	Mean	5	10	A
	p50	5	7	
	Min	3	6	
	Max	6	14	
	N	47	47	
Total	Mean	3	10	A
	p50	1	10	
	Min	0	1	
	Max	14	19	
	N	1139	1139	

Note: This table summarizes the descriptive statistics for different spell transitions. The last column shows the relation between Scenarios (A/B) and a number of spells and transitions. For instance, in Scenario B, I only consider a subsample of PDs that have transited from NPD to PD. For Scenario A, I consider the full sample of 1,139 observations.

2.4 Results

The results focus on two scenarios, A and B. The first of these assumes that there is no exit of units, which means that once districts become PDs, they will remain under the same condition for the rest of their lifetime within the timeframe of analysis, regardless of how many transitions they have throughout this period of time. For instance, they could transit from NPD to PD and back again to NPD, however, scenario A will assume that there is absorption of effects, regardless of the last transition from PD to NPD. In scenario B, I consider only a subsample of districts that transit from NPD to PD and remain PD for the rest of their lifetime during the timeframe of the data (2001-2019).

Table 2.4 reports the outputs using the CS DID method for Scenario A and B, using never treated units as part of the control group.[7] For the first of these, the group-time ATT[8] is positive but statistically insignificant (post_avg=0.023), meaning that on average consumption among PDs is 2.3% higher than NPDs during the period 2001-2019. Table 2.4 also provides outputs to comply with the parallel trends assumption. In this case, the pre-treatment estimator (pre_avg=0.019) is positive but statistically insignificant, meaning that given the set of covariates included in the model (i.e., the proportion of permanent members at the district level, proportion of females at the district level, proportion of rural households at the district level, surface and altitude),[9] pre-treatment trends for the main outcome variable are the same for PD and NPD before treatment starts. According to Roth et al. (2023), the parallel trend assumption relies on the fact that the mean outcome variable of both treated and untreated (PD and NPD) should be evolved "in parallel" in the absence of the treatment (i.e., districts becoming PDs).

When looking at the coefficients for time period (tp) 1 to 5, the results in Table 2.4 for scenario A suggest positive effects on consumption of PDs from time period 1 to 3 but statistically insignificant. That is, assuming there is no exit of producers, there are no effects on consumption in the next five years after PD start production. For the

[7] In the Appendix, Figures 2.13 and 2.14 include ATTs when using never treated and not yet treated unit as part of the control groups.

[8] Weights are proportional to the size of cohorts and clustered at the district level

[9] I have also included the comparison in ATTs with and without including covariates in the model in Figures2.13 and 2.14 and using never treated and not yet treated units as comparison groups. These outputs also suggest similar ATTs in magnitude of coefficients, size of confidence bands and significance.

same scenario, the aggregate effects are also statistically insignificant, consistent with the earlier findings.

For Scenario B, I found that the group-time ATT is significant for a window of exposition of five years, where consumption among PDs is 11% higher than in NPDs, meaning that there is a positive effect on consumption expenditure among individuals living in PDs in comparison to those in NPDs, when mineral production is continuous for a period of five years. I also found that the ATTs are positive and statistically significant from the first to the fourth year of exposition to mineral production, where consumption improves from 9.9% up to 17.9%. This pattern suggest that the effect grows with the length of exposure (e.g., the period-specific ATT rises from 9.9% in period 1 to 12.1% in period 4, with peaks in periods 2 (17.9%) and 3 (14.0%)). While these results are consistent with the possibility of cumulative impacts, the coefficients themselves capture period-specific effects and are not cumulative measures.

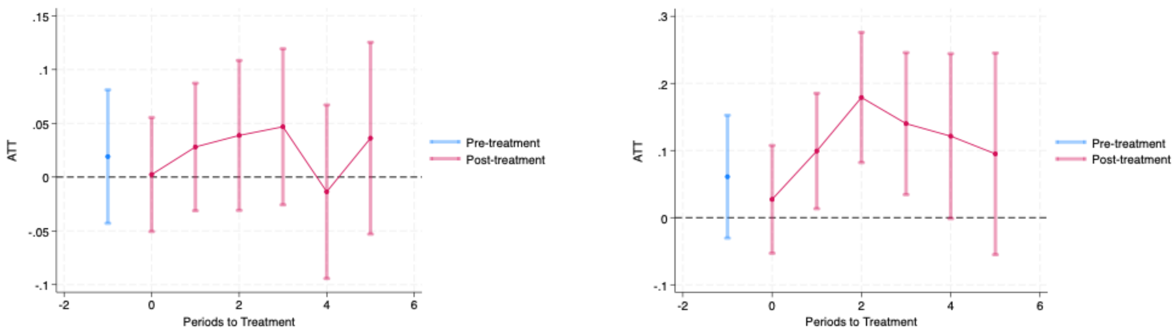
Table 2.4: ATTs for Scenarios A and B

Periods to Treatment	Scenario A		Scenario B	
	Coefficient	P>z	Coefficient	P>z
Pre_avg	0.019	0.546	0.061	0.192
Post_avg	0.023	0.410	0.110***	0.008
Tm1	0.019	0.546	0.061	0.192
Tp0	0.002	0.930	0.027	0.507
Tp1	0.028	0.354	0.099**	0.024
Tp2	0.039	0.276	0.179***	0.000
Tp3	0.047	0.206	0.140***	0.009
Tp4	-0.014	0.741	0.121*	0.053
Tp5	0.036	0.426	0.095	0.215

Note: Pre_avg and Post_avg refer to pre and post-treatment estimates, respectively. Tm1 referees to one period prior treatment year. Tp 1 to Tp5 refer to periods post-treatment. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.4a and Figure 2.4b present the event-study results for a time period of five years of being a PD for Scenario A and B, respectively. Both figures allow to observe the evolution of point estimates presented in Table 2.2 and 95% confidence bands for periods of time before and after districts become PDs. These figures highlight how employing different data approaches (Scenarios A and B) yields varying outputs. Scenario A focuses on districts transitioning from NPD to PD and assumes they maintain this PD status throughout the study period (i.e., effects are carried over into the next stage). Conversely, Scenario B focuses on a subset of districts that transition from NPD to PD and indeed remain in this condition, revealing more pronounced outcomes compared to Scenario A.

Figure 2.4: ATTs for Scenario A and B



(a) **Scenario A** (b) **Scenario B**

Note: Evolution of ATTs-coefficients and 95% confidence bands in blue and red colours for years before and after districts become PDs for a period of five years, respectively.

2.4.1 Analysis by mining size

Following the same approach to work with two scenarios, I explore whether the performance of PDs are different by mining size, grouped into Large and Medium Scale Mining (LMSM) and Small and Artisanal Scale Mining (SASM). When looking at the estimates for pre-treatment years (Pre_avg), the coefficient for Scenario A are negative and insignificant for both LMSM and SASM. This is also similar for Scenario B for the case of LMSM but positive and significant for SASM.[10] The first set of coefficients for Scenario A are negative and insignificant, therefore, these comply with the assumption of parallel trends. The last coefficient that is positive and significant at a level of 10%, it could be argued that, given the set of covariates, there might be other factors to explain the difference in consumption among PDs and NPDs before districts become PDs (see Table 2.5).

For Scenario A, the group-time ATTs for post-treatment periods are positive but statistically insignificant. Considering both LMSM and SASM, there is no evidence that mining activities affect consumption levels once PDs become producers (see Figure 2.5).

For the case of Scenario B, the group-time ATT for pre-treatment period for LMSM is negative and statistically insignificant, which suggests that given the covariates included in the CS DID model, the outcome variable would be the same among PDs and NPDs

[10] Coefficient is statistically significant at 10%, thus, some caution to interpret estimates is required for post treatment effects.

in the event of districts not becoming producers. When looking at the ATTs by time periods, the results for LMSM suggest that the effect increases over time up to two years of becoming PD, with an increase in consumption of 16.3% among PDs in comparison to NPDs, and statistically significant at a 5% confidence level.

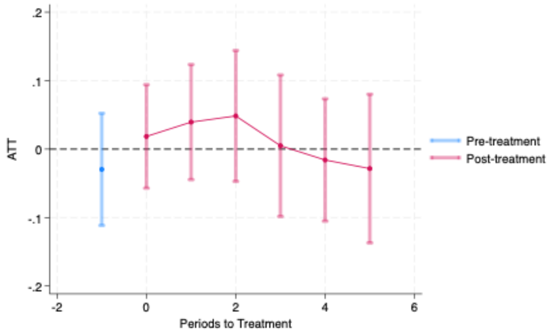
The results vary for the case of SASM in both scenarios. In the first scenario, the group-time ATTs for pre (pre_avg) and post-treatment years (post_avg) are negative but statistically insignificant. For the second scenario, however, the results should be taken with caution since the group-time estimations (Pre_avg) are positive and statistically significant, meaning that pre-trends on the outcome variable for PD and NPD are not the same, thus, other factors might intervene in the evolution of this variable for both PDs and NPDs groups.

Table 2.5: ATTs by Mining Size

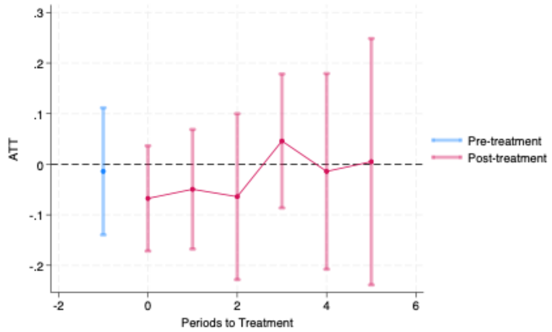
	Scenario A				Scenario B			
	LMSM		SASM		LMSM		SASM	
P.T.	Coeff	P>z	Coeff	P>z	Coeff	P>z	Coeff	P>z
Pre_avg	-0.030	0.478	-0.014	0.826	-0.023	0.712	0.141*	0.069
Post_avg	0.011	0.759	-0.024	0.703	0.067	0.209	0.042	0.499
Tm1	-0.030	0.478	-0.014	0.826	-0.023	0.712	0.141*	0.069
Tp0	0.019	0.631	-0.068	0.203	-0.009	0.892	0.020	0.814
Tp1	0.039	0.358	-0.050	0.412	0.082	0.183	-0.026	0.728
Tp2	0.048	0.320	-0.064	0.444	0.163**	0.018	0.128	0.184
Tp3	0.005	0.925	0.046	0.497	0.089	0.164	0.071	0.186
Tp4	-0.016	0.727	-0.014	0.886	0.107	0.117	0.030	0.788
Tp5	-0.028	0.608	0.005	0.968	-0.032	0.742	0.029	0.293

Note: ATTs for Scenario A for Large and Medium Scale Mining (LMSM) and Small and Artisanal Scale Mining (SASM). Pre_avg and Post_avg refer to pre and post-treatment estimates, respectively. Tm1 refers to one period prior treatment year. Tp 1 to Tp5 refers to periods post-treatment. P.T. stands for Periods to Treatment. Significant levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

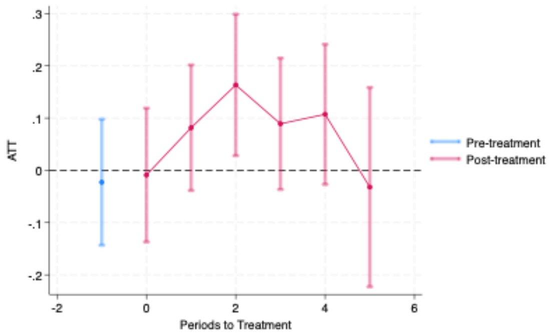
Figure 2.5: ATTs for Scenario A and B by Mining Size



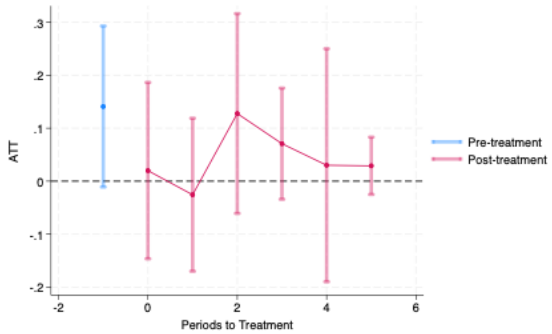
(a) **Scenario A - LMSM**



(b) **Scenario A - SASM**



(c) **Scenario B - LMSM**



(d) **Scenario B - SASM**

Note: ATTs point estimates and 95% confidence bands for Scenario A and B for Large and Medium Scale Mining (LMSM) and Small and Artisanal Scale Mining (SASM) for pre and post-treatment years up to five years after districts become producers (PDs)

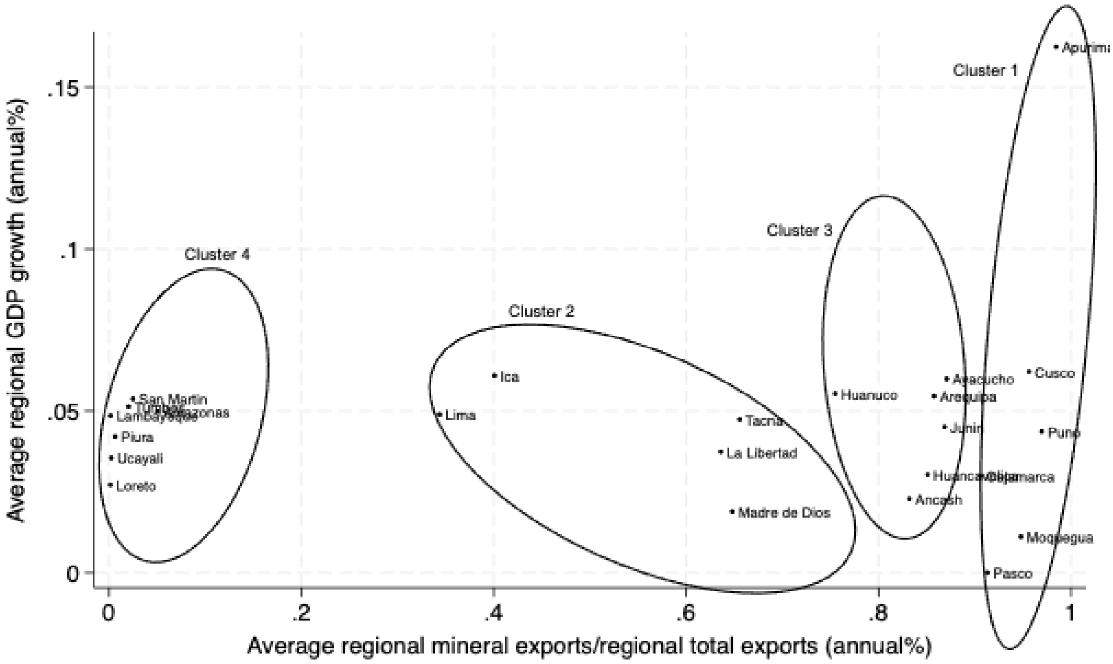
2.4.2 Analysis by clusters

I follow Orihuela & Gamarra-Echenique (2019) macroeconomic volatile hypothesis to perform an analysis by cluster, which considers the relationship between the level of mineral exports at the regional level and the average annual GDP growth of the same regions for the period 2007 - 2019, given the availability of secondary data[11]. Since regional consumption data are unavailable, both variables serves as a proxy for the identification regional clusters relevant to the analysis. I use k-means clusters approach and 100 iterations in Stata 18 to classify the 24 Peruvian regions by the macroeconomic variables, obtaining as a result four clusters (see Figure 2.6). Although the sample is reduced when working by clusters, one of the benefits is that the comparison groups for the PDs will be obtained within the same cluster. For instance, a PD in Cluster 1 will be compared

[11] I use macroeconomic information from the Central Bank of Peru to obtain export data and GDP at the regional level for the period 2007-2019

to a NPD within the same cluster using the CS DID method.

Figure 2.6: Clusters at the Regional Level for Mineral Exports and Economic Growth



Note: This figure shows the clustering of regions based on their mineral exports and annual economic growth for the period 2007-2019.

Table 2.6 presents the results for Scenario A. These results suggest that regions in Cluster 1 experience an increase in consumption levels from the time when districts become PDs up to three years post-intervention. Regions grouped in cluster 1 have as a common feature that they have a high level of specialisation in mining activity (average mineral exports is more than 90% of their total export basket) and have seen on average an annual increase in regional GDP growth from 1% to circa 6%.[12] The results for Cluster 1 also show that consumption among PDs are 15.3% higher in comparison to NPDs in the second year after they become producers, these results are statistically significant at a 5% significance level. For the case of regions in Cluster 2, the results suggest that consumption among PDs increase up to 14.2% at the time when they become producers, this positive increase is also statistically significance at 10%. Group-time ATTs for pre-treatment years are positive for clusters 1 and 2 but insignificant suggesting compliance

[12]Within the same cluster, the region of Apurimac is the only one with an annual increase in regional GDP growth of circa 15%.

with parallel trends assumptions, given the set of covariates included in the CS DID model.

For Cluster 3, the group-time ATT for post-treatment years is negative but statistically insignificant. This means that, on average, PDs in Cluster 3 have seen a decrease in consumption in comparison to NPDs in the same cluster during the timeframe of analysis. The effects on consumption among NPDs seem to deteriorate in time when districts become producers, up to 13.6% in comparison to NPDs in time period 4. Regions grouped within Clusters 4 show lower levels of export specialisation of minerals, although the annual GDP growth varies in the same range as per Cluster 2 and 3 (circa 1% to 10%). However, the group-time ATT for pre-treatment years used to test parallel trends assumption is negative and statistically significant (equal to 14.8%). This outcome suggests that consumption is different among PD and NPD prior districts become producers.

Table 2.6: ATTs by Clusters at the Regional Level for Scenario A

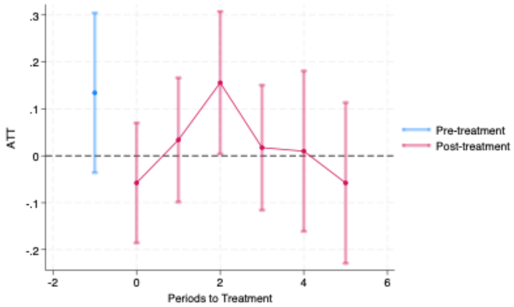
	Cluster 1		Cluster 2		Cluster 3		Cluster 4	
P. T.	Coeff	P > z	Coeff	P > z	Coeff	P > z	Coeff	P > z
Pre_avg	0.134	0.122	0.022	0.793	0.032	0.532	-0.148***	0.000
Post_avg	0.017	0.755	0.084*	0.076	-0.066	0.178	0.216***	0.000
Tm1	0.134	0.122	0.022	0.793	0.032	0.532	-0.148***	0.000
Tp0	-0.058	0.375	0.142*	0.063	-0.066	0.156	0.186***	0.001
Tp1	0.034	0.617	0.104*	0.053	-0.036	0.477	0.039	0.485
Tp2	0.156**	0.045	0.075	0.247	-0.072	0.256	0.339***	0.000
Tp3	0.017	0.799	0.033	0.621	0.015	0.823	0.231***	0.000
Tp4	0.010	0.910	0.026	0.664	-0.136*	0.086	0.314***	0.000
Tp5	-0.058	0.507	0.121*	0.051	-0.103	0.188	0.190***	0.001

Note: P.T. related to Periods to Treatment. This table shows coefficients and p-values for different periods to treatment in clusters 1 to 4. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

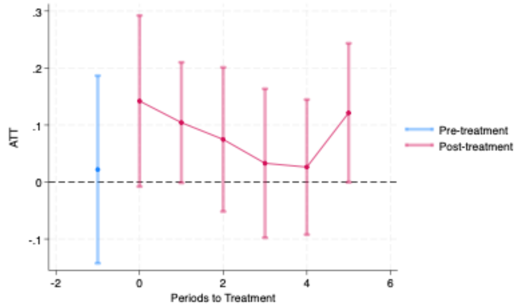
Figure 2.7 presents the point estimates and 95% confidence bands for Scenario A where it is shown the evolution of consumption PDs before and after these become producers. Changes in the point estimates for Clusters 1 and 3 follow a similar trend, which could be linked to the fact that regions within these clusters have high levels of export specialisation and their annual GDP growth varies similarly from circa 2% to 12%. Cluster 2 presents a different pattern in the evolution of consumption within the same timeframe, suggesting a deterioration of consumption among districts that become producers in time up to 4 years, although the ATTs are not statistically significant. For regions in Cluster

4, the group-time ATT for pre-treatment years is negative and statistically significant, thus, there is reason to believe that the changes in consumption among districts after they become producers could be due to other factors rather than the mere condition of becoming a PD.

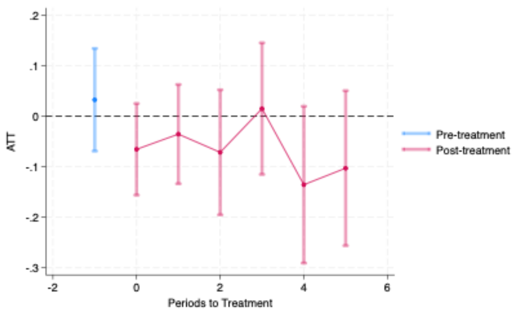
Figure 2.7: ATTS by Clusters at the Regional Level for Scenario A



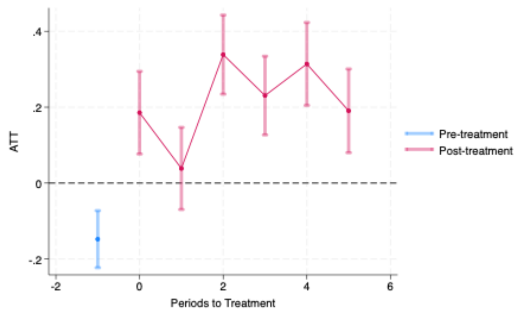
(a) Cluster 1



(b) Cluster 2



(c) Cluster 3



(d) Cluster 4

Note: Bar in blue colour represent the 95% confidence band for pre-treatment years. Bars in red represent the 95% confidence band for post-treatment years up to five years after a district become PD. The dots within the 95% confidence bands represent the point estimates.

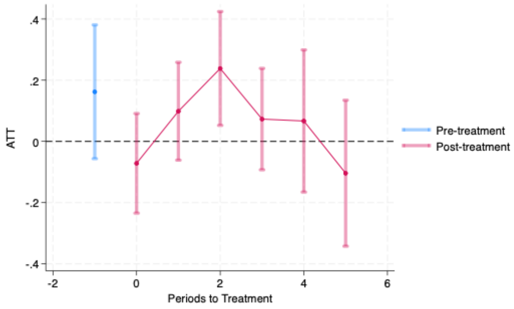
The set of results for Scenario B follows a similar pattern in the evolution of the outcome variable for districts after they become PDs for the case of Clusters 1 and 3. In Cluster 1, I find that consumption increases up to 23.8% among PDs in comparison to NPDs. In Cluster 3, the increase in consumption is higher, being 28% more in PDs in comparison to NPDs in time period 3. Similar to Scenario A, the positive effects on consumption among PDs could be due to the fact that these districts are located within regions that are highly specialised in mineral exports and that have evidenced at the same time changes in their annual GDP growth up to 12%. PDs that belong to Cluster 2 also show positive point estimates but these seem to decrease in time, being statistically significant for the timeframe of analysis. Post-treatment evolution of consumption for districts after they become PDs can be seen in Figure 2.8.

Table 2.7: ATTs by clusters at the regional level for Scenario B

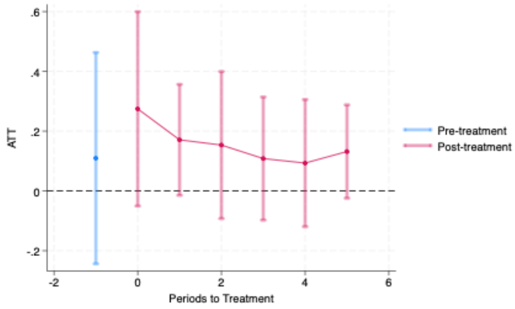
	Cluster 1		Cluster 2		Cluster 3	
P.T.	Coeff	P > z	Coeff	P > z	Coeff	P > z
Pre_avg	0.162	0.146	0.110	0.543	0.138*	0.082
Post_avg	0.050	0.489	0.155*	0.066	0.141**	0.018
Tm1	0.162	0.146	0.110	0.543	0.138*	0.082
Tp0	-0.072	0.388	0.275*	0.098	0.006	0.909
Tp1	0.099	0.227	0.171*	0.071	0.039	0.687
Tp2	0.238**	0.012	0.153	0.222	0.190**	0.018
Tp3	0.073	0.389	0.108	0.303	0.285**	0.017
Tp4	0.067	0.574	0.093	0.391	0.221***	0.006
Tp5	-0.104	0.393	0.132*	0.098	0.105	0.241

Note: This table shows coefficients and p-values for different periods to treatment (P.T.) in various clusters. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. There are not enough treated observations for cluster 4 that fall within the category of spells 1 and 2 (Scenario B).

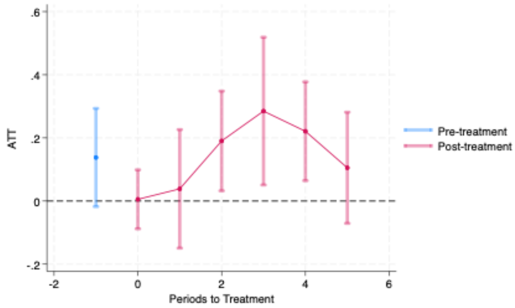
Figure 2.8: ATTS by Clusters at the Regional Level for Scenario B



(a) Cluster 1



(b) Cluster 2



(c) Cluster 3

Note: Bar in blue colour represent the 95% confidence band for pre-treatment years. Bars in red represent the 95% confidence band for post-treatment years up to five years after a district become PD. The dots within the 95% confidence bands represent the point estimates. Results for Cluster 4 were omitted since the number of observations is too small to conduct CS DID method.

2.4.3 Analysis by macroregion

I also explore the evolution of consumption by ecological macroregions of Coast, Andes and Amazon. Although mineral exploitation is spatially distributed across the country, it is also assumed that most of the mineral activity occurs in the Andes. Also, it is believed that most gold mining occurs in the ecological region of the Amazon (Orihuela & Gamarra-Echenique 2019).

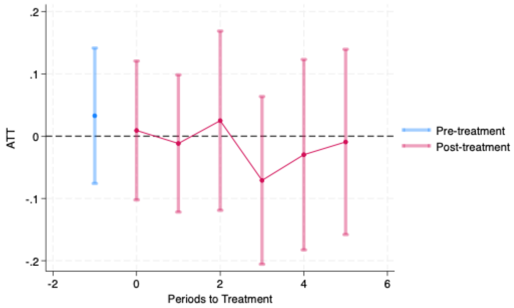
I follow the same strategy to assess the effects on consumption over time using the CS DID method between Scenario A and B. For the case of Scneario A, Table 2.8 reveals that group-time ATT for post-treatment years for districts within the Andes macroregions is positive but statistically insignificant. This means that, overall consumption among PDs has positively increased by 2% in comparison to NPDs within the Andean macroregion, although the coefficient is statistically insignificant. The group-time ATT for post-treatment years for the case of Coastal PDs is negative and statistically insignificant, suggesting that the consumption among PDs have deteriorated by 1.5% in comparison to NPDs. The group-time ATTs for post-treatment years for the Amazon macroregion is positive and highly significant. This can also be seen in the coefficients for time period 1 to 4, with an increase in consumption up to 23.9% up to the first period after districts in the Amazon macroregion become producers. The positive effects on consumption among PDs remain up to the third year after districts become PDs (see the evolution of effects on consumption among PDs in Figure 2.9). These results suggest positive effects in consumption levels in the subsequent years after PD start producing and that the effects in regions that are located within the Amazonian macroregion are most likely to evidence such positive effects. However, these results should be treated with caution since confidence intervals seem to be wider (similar to the Coast macroregion) than the Andean macroregion, one possibly explanation is due to sample size reduction for such analysis. However, these results shed some light into the possible effects on consumption under scenario A for the Amazon macroregion.

Table 2.8: ATTs by macroregions for Scenario A

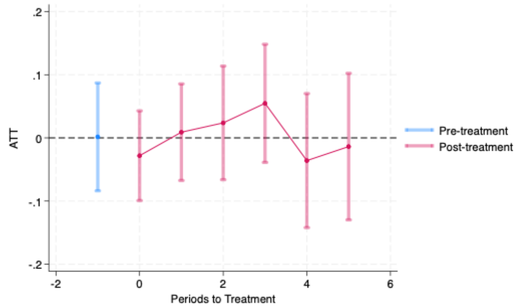
	Coast		Andes		Amazon	
P.T.	Coefficient	P > z	Coefficient	P > z	Coefficient	P > z
Pre_avg	0.033	0.555	0.002	0.970	0.052	0.559
Post_avg	-0.015	0.813	0.002	0.961	0.225***	0.006
Tm1	0.033	0.555	0.002	0.970	0.052	0.559
Tp0	0.009	0.873	-0.028	0.437	0.182***	0.010
Tp1	-0.012	0.835	0.009	0.817	0.239***	0.002
Tp2	0.025	0.735	0.024	0.605	0.191**	0.032
Tp3	-0.071	0.301	0.055	0.252	0.281**	0.020
Tp4	-0.030	0.703	-0.036	0.507	0.163	0.174
Tp5	-0.009	0.902	-0.014	0.816	0.298**	0.021

Note: This table shows coefficients and p-values for different periods to treatment in various regions. P.T. refers to Periods to Treatment. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

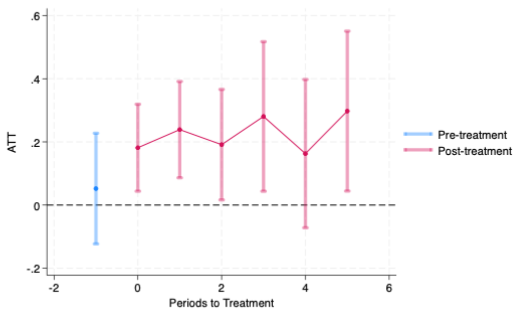
Figure 2.9: ATTS by Macroregions for Scenario A



(a) Coast



(b) Andes



(c) Amazon

Note: Bar in blue colour represents the 95% confidence band for pre-treatment years. Bars in red represent the 95% confidence band for post-treatment years up to five years after a district becomes PD. The dots within the 95% confidence bands represent the point estimates.

For the case of Scenario B and conducting the analysis by macroregions, the results in Table 2.9 suggest similar positive effects on consumption for PDs in comparison to NPDs in the Amazon macroregion. For PDs located in the Andes, the results of the group-time ATT for post-treatment years is positive, meaning that overall PDs have experienced an increase in consumption of 6.7% in comparison to NPDs, although the coefficient is statistically insignificant. However, the results also suggest that consumption increases among PDs in the Andes macroregion up to 16.1% after they become producers in time period 3, being statistically significant at 5%. The evolution of consumption for PDs for all macroregions is presented in Figure 2.10. The latter figure also suggests that the positive effect on consumption among PDs located in the Amazon macroregion remains positive (increase in consumption in 32.1% in comparison to NPDs) and statistically significant up to the third year after they become producers.

Table 2.9: ATTs by macroregions for Scenario B

	Coast		Andes		Amazon	
P.T.	Coefficient	P > z	Coefficient	P > z	Coefficient	P > z
Pre_avg	0.054	0.460	0.076	0.307	0.021	0.846
Post_avg	0.090	0.102	0.067	0.286	0.261***	0.007
Tm1	0.054	0.460	0.076	0.307	0.021	0.846
Tp0	0.092	0.137	-0.088	0.175	0.249***	0.000
Tp1	0.027	0.691	0.076	0.269	0.273***	0.004
Tp2	0.182***	0.010	0.166*	0.055	0.251**	0.014
Tp3	0.034	0.675	0.161**	0.038	0.321**	0.033
Tp4	0.116	0.156	0.141	0.156	0.170	0.248
Tp5	0.089	0.283	-0.056	0.639	0.304**	0.037

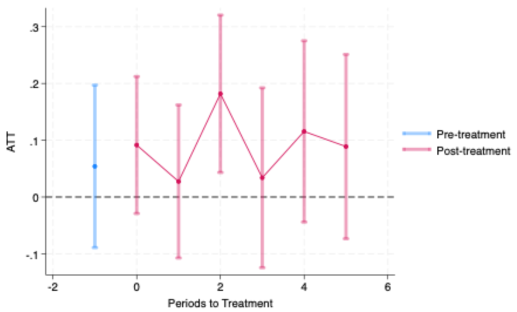
Note: This table shows coefficients and p-values for different periods to treatment in various regions. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.4.4 Robustness Checks

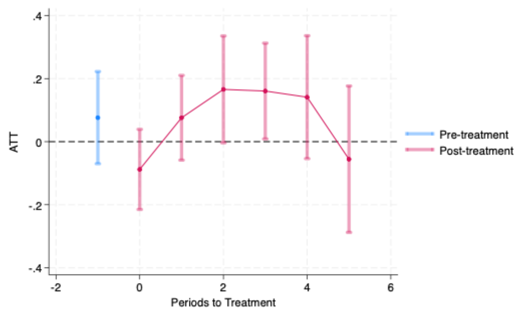
As a robustness check, I implement the ETWFE approach with the original outcome variable and the same control group of never treated units. The ETWFE works with a set of dummy variables (see equation 2.5) allowing to assess heterogeneity of treated units (i.e, districts becoming PDs) across cohorts and time. I also focus on the full sample (Scenrio A) and a subset of the sample (Scenario B) for this analysis.

The results of the ETWFE suggest that the dynamism of mineral activity influence

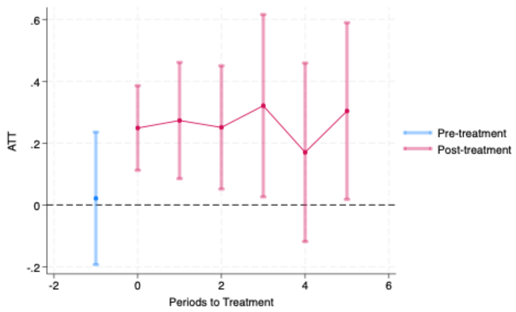
Figure 2.10: ATTs by Macroregions for Scenario B



(a) Coast



(b) Andes



(c) Amazon

Note: Bar in blue colour represents the 95% confidence band for pre-treatment years. Bars in red represent the 95% confidence band for post-treatment years up to five years after a district becomes PD. The dots within the 95% confidence bands represent the point estimates.

consumption among PDs. This means that, when considering Scenario B, where PDs do actually remain producers [13], there is a positive effect on consumption up to 14.4% among PDs in comparison to NPDs. These results are statistically significant for all time periods after districts become producers (see outputs in Table 2.10 and Figure 2.11). When working under Scenario A, there are positive effects on consumption up to the third period after districts become producers, being statistically significant in time period 2, where consumption increases at 4.5% across PDs in comparison to NPDs. Under the same scenario, there is also a fall in consumption in time period 4, where consumption decreases in 3.3% among PDs, these results suggest that, when working within a short timeframe (i.e., 5 years), there seem to be "mini" periods of boom and bust across PDs (see Figure 2.11).

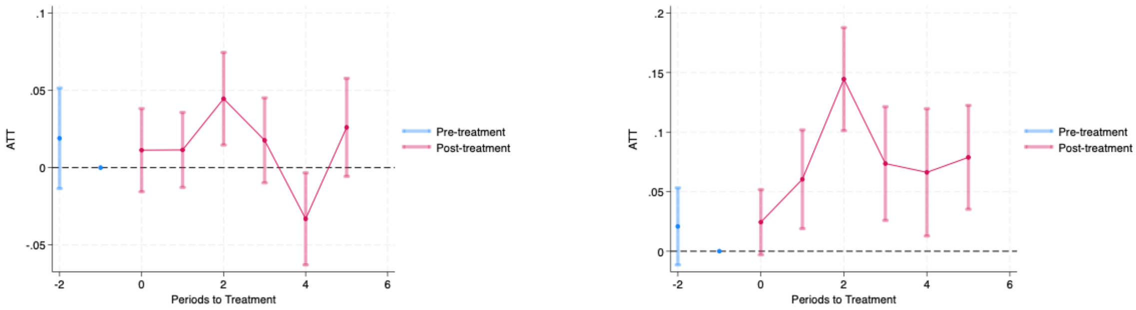
Table 2.10: ATTs for Scenario A and B

	Scenario A		Scenario B	
P.T.	Coefficient	P > z	Coefficient	P > z
-2	0.019	0.252	0.021	0.206
0	0.011	0.410	0.024*	0.081
1	0.011	0.354	0.060***	0.004
2	0.045***	0.004	0.144***	0.000
3	0.018	0.208	0.074***	0.003
4	-0.033**	0.029	0.066**	0.015
5	0.026	0.107	0.079***	0.000

Note: ATTs and p-values for pre and post-treatment periods for Scenario A and B. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[13] i.e., I can observe in the data that mineral activity is reported in the host district via mineral production

Figure 2.11: ATTS for Scenario A and B with ETWFE



(a) Scenario A

(b) Scenario B

Note: ATTs for Scenario A and B. Blue and Red lines show 95% confidence bands for pre and post-treatment years, respectively. Both figures also include point estimates up to year five after districts become producers.

2.5 Conclusion

This chapter explores the dynamic effects of the mining sector on welfare at the district level in Peru during the period 2001-2019. I mainly focus on the variable consumption expenditure and use a set of covariates related to socioeconomic and geographic variables. Recent developments in the literature of DiD allow for the exploration of heterogeneous effects in time. I follow Callaway & Sant'Anna (2021) and work with a dataset that comprises the period 2001-2019 and focus on two main groups, PDs and NPDs, where these are considered as treated and control units.

The CS DID method allow for the exploration of the dynamism of the mining sector in Peru. I focus on two scenarios, the first one (Scenario A) uses the full sample and considers that effects are carried over to the next period, being this a common approach in the literature of DiD. However, the dataset allows for the exploration of districts when these transit from NPD to PD. For this case, I consider Scenario B, where I work with a sample of districts that transition from NPDs to PDs and remain PDs thereafter.

I also explore the effects on consumption by mining size, clusters (by mineral exports and regional GDP growth) and ecological macroregions. Robustness checks were also performed using the ETWFE, developed by Wooldridge (2021).

The results highlight the differences between the two approaches (Scenario A and Scenario B). The outcomes are more pronounced in Scenario B, where periods of mini-booms and busts are evident after districts become producers, typically more noticeable in the second or third-year post-intervention (i.e., after districts become PDs). Similar patterns are observed when analysing the data by mining size (e.g., LMSM), clusters (e.g., Cluster 1 and 3), and ecological macroregions (e.g., Andes).

These results would support the implementation of short-term policies from both private sectors and local stakeholders. Where it is believed that most of the mining effects are absorbed during the construction phase, when looking at the production stage, it is possible to observe that mining does have some effects on consumption for short periods of time, post-intervention, that is, PDs consumption improve after they become producers but effects decay in time passing the third or fourth year after they transition to PDs. Since welfare effects appear short-lived, policies should prioritise diversification programs that target both PDs and NPDs, as the short booms following a transition to PD status often raise expectations and attract firms and individuals. While this agglomeration may generate some local benefits, it also risks widening disparities between PDs and NPDs if not accompanied by broader regional policies.

2.6 Appendix

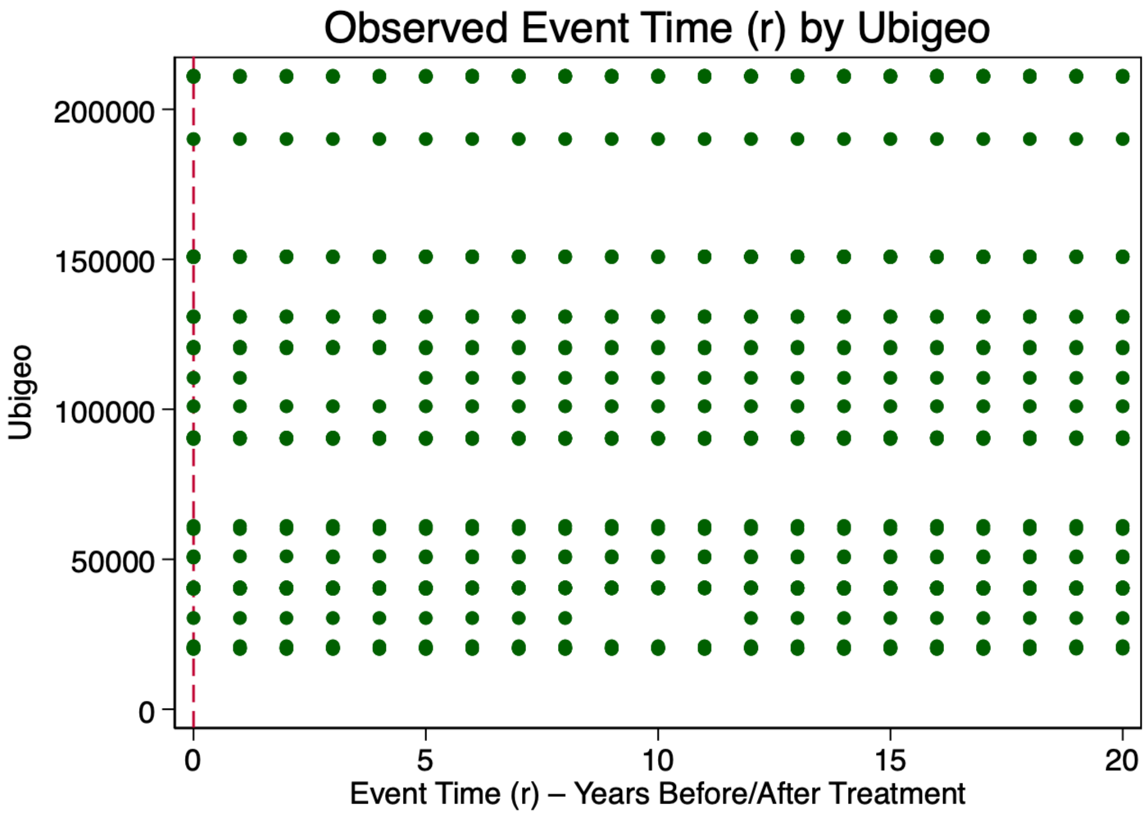
2.6.1 T tests

Table 2.11: District-level individual consumption and income data from 2002 to 2019.

District	Descriptive	2002-2012		2012-2019		2002-2019	
		(1)	(2)	(1)	(2)	(1)	(2)
PD	**Year**	2002	2012	2002	2012	2012	2019
	Mean	87.9	99.3	175.9	245.5	87.9	99.3
	N	111	111	137	137	111	111
	Year	2012	2019	2019	2019	2019	2019
	Mean	175.9	245.5	149.6	191.8	149.6	191.8
	N	137	137	170	170	170	170
	Dif	87.9	146.2	-26.2	-53.7	-61.7	-92.4
	St Err	10.7	22	9.7	19.1	7.6	12
	t value	8.2	6.7	-2.7	-2.8	-8.2	-7.7
	p value	0.000	0.000	0.007	0.005	0.000	0.000
NPD	**Year**	2002	2012	2002	2012	2012	2019
	Mean	87.9	97.5	159.7	195.1	87.9	97.5
	N	741	741	891	891	741	741
	Year	2012	2019	2019	2019	2019	2019
	Mean	159.7	195.1	143.4	175.2	1082	1082
	N	891	891	1082	1082	143.4	175.2
	Dif	71.9	97.7	-16.3	-20	-55.5	-77.7
	St Err	4.6	6.9	4.1	6	3.7	5.5
	t value	15.8	14.1	-4	-3.3	-15.2	-14.2
	p value	0.000	0.000	0.000	0.001	0.000	0.000

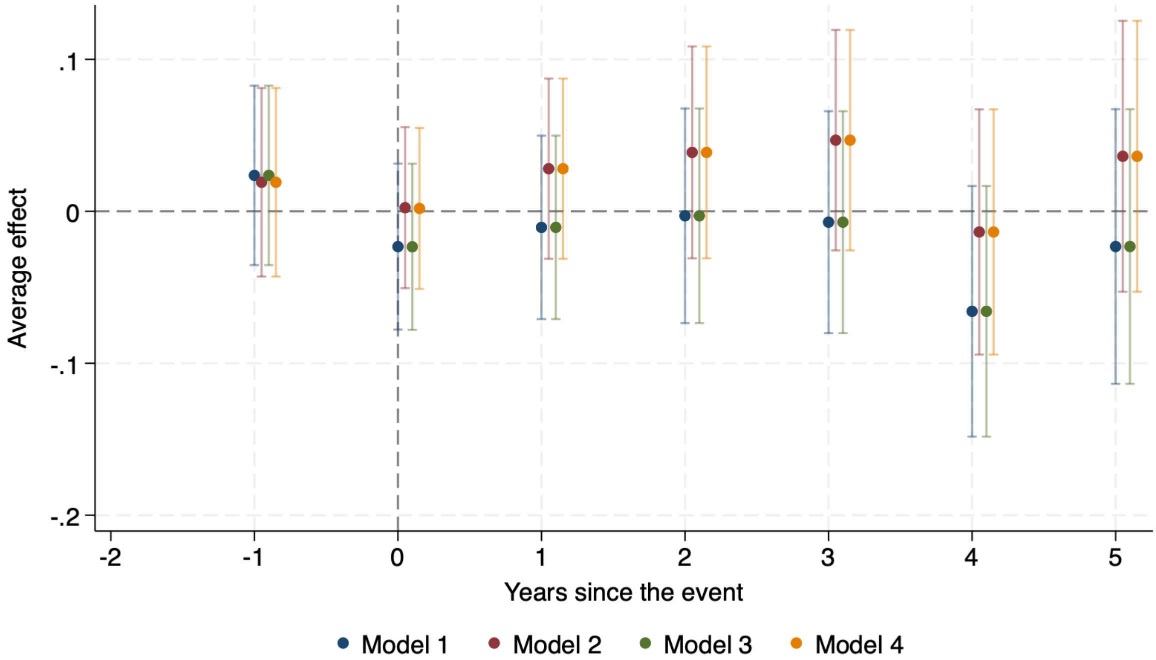
Note: (1) Average individual consumption at the district level (USD/month). (2) Average individual income at the district level (USD/month). The table shows the district-level individual consumption and income data from 2002 to 2019, including means, sample sizes (N), differences in means, standard errors, t-values, and p-values.

Figure 2.12: Distribution of "Super producers" by Time of Event 2001



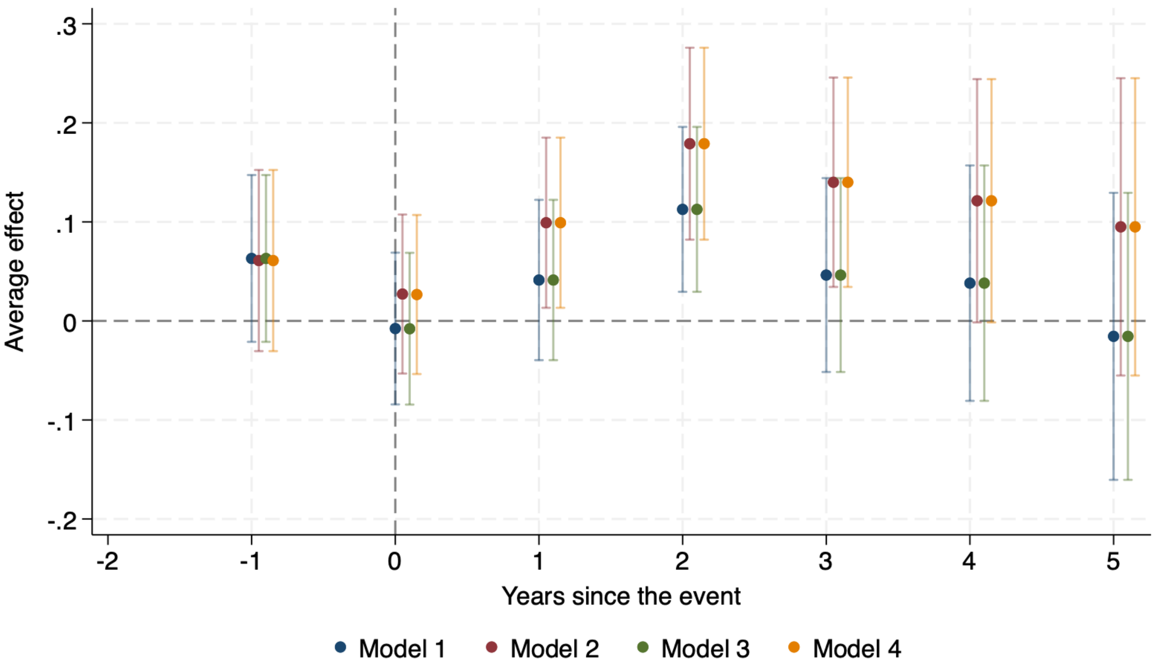
Note: This figure shows the distribution of PDs with a treatment year of 2001 ($r = 0$). The corresponding *ubigeo* codes range from 010101 to 250401, indicating that these early-producing districts (or "superproducers") are geographically dispersed across the country rather than concentrated in a single region.

Figure 2.13: ATTs for Scenario A with and without Covariates



Note: Outcomes on PDs using never treated and not-yet treated comparison groups. Model 1 accounts for ATTS without including covariates in the model and never treated units as control group. Model 2 accounts for ATTs including covariates in the model and never treated units as a control group. Model 3 and 4 account for ATTs without and with covariates but using not yet treated units as control group, respectively. Bars represent confidence intervals at 95% level for each colour code model. Dots represent coefficients estimates.

Figure 2.14: ATTs for Scenario B with and without Covariates



Note: Outcomes on PDs using never treated and not-yet treated comparison groups. Model 1 and 2 accounts for ATTs also without and with covariates in the model and never treated units as a control group. Model 3 and 4 account for ATTs without and with covariates but using not yet treated units as control group, respectively. Bars represent confidence intervals at 95% level for each colour code model. Dots represent coefficients estimates.

Chapter 3

Mining and welfare in Peru: The role of spatial distance

3.1 Introduction

This chapter explores how welfare changes in space and time due to the implementation of mining activities in Peru. When new mining projects start production in a host district, they tend to attract individuals and firms to the area. Once these large developments start operations, the empirical evidence suggest that some of the effects on welfare or other economic indicators (e.g., productivity, employment, wages) remain mostly localised, with some spillover effects on firms (e.g., increase in productivity) and individuals (e.g., increase in wages). However, there are a number of factors that influence the extent of the effects in space (e.g., from social to geographical factors, to firm level decisions, [1] and labour mobility [2]). The empirical evidence suggest that some of the economic effects could be observed farther away from the host area of the main development. This has a major effect on local PDs and neighbouring areas NPDs and could explain some of the differences in welfare among these.

Most of the empirical evidence works with linear distance to asses the extent of decay,

[1]In the context of firm-level decision-making, Kalnins & Lafontaine (2013) finds that the distance between a firm's headquarters and its subsidiaries significantly influences subsidiary survival. This is relevant in the context of the mining sector, since the arrival of a new mining projects, it is expected that firms to concentrate in PD, including both newly established firms and those relocating from neighbouring areas.

[2]For the case of labour mobility, Perez-Trujillo (2024) finds that most of non core mining services are outsourced to areas that are located farther away from the main development, meaning that spillover effects are unlikely to remain localised

this is mainly in research papers that focus on the manufacturing sector where most of the empirical literature is centred (e.g., see Greenstone et al. (2010)), but also observed in the mining sector (e.g., see Aragón & Rud (2013)). However, for mining activities in Peru, a linear measure might not account for the geographic characteristic of districts and availability of road infrastructure that influence individuals and firms decision to agglomerate within and around host areas. For this reason, I use linear and travel distance measures in the analysis. The latter accounts for road travel distance by car using data from OpenStreetMap (OSM) to calculate fixed travel distances from NPD to PD and PD to PD[3].

In the first part of this paper, I use a Pooled Ordinary Least Square Model (POLS) to test both measures (linear and travel distances) using a pseudo panel data that includes socioeconomic information sourced from the Peruvian National Institute of Statistics and mining information at the district level, from the Ministry of Energy and Mines. I also use a double difference approach to explore the extent of mining activities on welfare in time. For this purpose, I use the Callaway & Sant'Anna (2021) approach (also named CSDID in this paper) that implements the double difference approach considering that mining activities have started operations in different years across districts (i.e., treatment is heterogenous in time). I test both measures of linear and travel distance using the CSDID approach and also include a third measure of travel time considering 1hr and 2hr travel time to PD (i.e., travel time from NPD to PD and PD to PD), this is tested with the same method. Although travel time is a function of distance, it more realistically reflects proximity because it incorporates transport infrastructure. In the last part of this paper, I also include road infrastructure and vehicle flow information to test whether these factors explain the extent of the effects in space.

The results of the POLS approach are mainly aligned with the empirical literature in the fields of economic geography and agglomeration economies, that is, that effects of mining activities on welfare are mainly localised to host areas (i.e., PDs), with some of the effects on welfare extending in space among districts located within 50km linear distance to PDs. The results also suggest that individuals living in close proximities of 1hr or 2hr travel time to PD experience positive and significant effects from the first up to the fifth year after PDs start production. These results hold when exploring the effects of

[3]Other map service providers such as Google Maps or HERE are able to estimate dynamic distances using live traffic information. However, this might constraint the replication of results.

mining activities on income and real expenditure, as part of the robustness checks. I also use data on road infrastructure in order to assess whether this is a factor that constraint the extent of the effects. Even when national roads are not fully paved, districts that are located within 2hr travel time distance to PDs experience on aggregate a positive and significant effect on their consumption levels. These effect are also discernable in the mid and long term (these are observable in the second, fourth and fifth year after PDs start production). In the last subsection of the results, I include vehicular flows in the analysis by constructing a density index, this is measured as the density of vehicle flow per length of national paved road at the regional level. I assume that more congested areas will experience higher economic dynamism and connectivity among districts, suggesting more availability of transport and road infrastructure to access PDs and more agglomeration economies. I find that welfare decays in space up to 18.3% in areas with high vehicular density[4]. However, areas with lower vehicular density might experience improvement in their welfare levels the more distant districts are to PDs, suggesting remoteness from PDs might not necessarily diminish economic development, but implies that these districts may be more reliant in other economic activities that are potentially more profitable than the formal mining sector (e.g., this could be related to the participation in the informal sector or engagement in informal mining activities, among others).

These findings have implications for policy design in the mining sector for host and neighbouring areas. Current policies are mainly focus on the implementation of windfall taxes or local content policies, administered by regional and local governments and mining companies in host areas, respectively. However, the extent of mining activities in space and time could suggest that local host areas benefit at the expense of neighbouring areas (NPDs). Whilst welfare increase in the former areas (e.g., one standard deviation increase in distance is linked to a drop in consumption from 4.8% up to 7.8% for linear and travel distances, respectively)[5], this chapter provides empirical evidence to suggest that neighbouring areas (NPD) see lower improvements in their welfare the more distant these are to producing areas. These finding helps to understanding the extent of the effects in space and time among NPDs, rather than focusing mainly on producing areas, where more of the literature relies. These findings could be used to promote policies to level

[4]I find that, with an increase in 1 Standard Deviation (SD) in the travel distance between districts and PD, welfare decays from 13.08% up to 18.3%.

[5]These results are also confirmed with the CSDID approach, where on aggregate, NPDs in close proximity of 50km to PD experience positive and significant effects

up these areas (NPDs) by using current windfall taxes or other local or regional mining related resources. Similarly, neighbouring areas that attract firms and workers could continue to prosper after mining operations enter into closure stage or bust years. For instance, short term income shocks in non producing areas that host mining workforce are reflected into higher local spending and the development of local businesses. Once mining operation closes, these non producing areas also serve as long term destinations to migrant workforce as well as established firms from other neighbouring areas (Haslam McKenzie & Hoath 2014).

The next section presents the literature review, including empirical evidence and a theoretical framework based on the theory of agglomeration economies, following Greenstone et al. (2010). Section 3 outlines the methodology, including a summary of the data, and an analysis of distance measures used in the paper, as well as the proposed POLS model and double difference approach following Callaway & Sant'Anna (2021). Section 4 presents the results of the POLS and double difference approach, along with the robustness checks. Section 5 concludes this paper.

3.2 Literature Review

3.2.1 Firm Concentration, Labour Mobility, and Spatial Inequalities

Mining activities restrict production to specific locations due to the geographic concentration of natural resources, which in turn fosters the agglomeration of diverse industries and firms (Rosenthal & Strange 2020). As a result, some employment and procurement opportunities arise which are then reflected into changes in the labour dynamics, wages, and consequently in the welfare of individuals living in the area that host the main development (e.g., this could be a mining project, a large manufacturing plant) and other areas proximate to this (e.g., neighbouring areas, cities or districts within the region where the main development is established). From a consumer point of view, agglomeration of firms within a specific area promotes the diversification of goods and services. Due to firm agglomeration, firms are expected to face higher competition, primarily through product differentiation based on price and quality(Leonardi & Moretti 2023). This is beneficial for local consumers that have access to a wide range of goods and services.

Firms benefit from the agglomeration of industries and businesses into one single area, since they can share the same pool of labour with different skill levels, or inputs for the production of goods and services. They also enjoy better infraestructure and connectivity which minimise transportation costs. Firms benefit as well from the spread of information and knowledge that is concentrated in one single area(Rosenthal & Strange 2020)[6]. These benefits are reflected into improvements in productivity levels of firms, and they seem to extent to miles away from the host local area. For instance, Giroud et al. (2022) finds that the concentration of large plants within counties in the US facilitate knowledge transfer to subsidiaries located miles away, with no significant spatial decay in productivity spillovers. This suggests that firms can have substantial benefits from agglomeration, even over extended geographic distances.

[6]The literature on agglomeration economies largely builds on the seminal work of Marshall (1890), which emphasises that firms experience productivity gains when they share a localised labour market, benefit from input sharing, often linked to available infrastructure, and engage in knowledge spillovers. The latter, in particular, plays a crucial role, as firms concentrated in a single geographic area can more easily exchange information and best practices.

Some of these benefits come with implications to the spatial distribution of labour[7]. and firms, and, by default, this is reflected in the welfare of workers and individuals living in host and other areas beyond. For instance, with the implementation of a new significant development (e.g., see empirical evidence by Greenstone et al. (2010) on Large Plant Opennings in the US), it is expected the arrival of newcomers from nearby areas looking for employment opportunities, changing the distribution of labour market in the host and neighbouring areas. Although, labour's mobility from nearby areas to the host areas could be constrained by travel distances[8], in some cases, individuals may find that the premium associated with working in the host area outweighs the cost savings of remaining in their original location, thereby reinforcing spatial inequalities between the host district and neighbouring areas.

A similar trade-off exists for firms, where these are attracted to host areas[9], looking to profit not only from procurement opportunities generated by the main development (e.g., mining project or large plant development) but due to the agglomerations of firms, such as hotels or restaurants. The main goal for these firms is to relocate closer to the demand, they do these by installing subsidiaries or even moving the headquarters to the host area, further contributing to firm agglomeration and spatial inequalities. Some of these firms also incur in higher transportation costs in order to attend the final demand in host areas[10]. As firms move closer to demand centres, increased competition for labour exerts upward pressure on wages in the host area, widening wage differentials between the host and neighbouring areas or more distant regions. To some extent, these allocation

[7]This includes the arrival of mining companies to the host district, alongside existing firms and new entrants attracted by expectations of higher profits.

[8]As distances increase, individuals face higher transportation costs in terms of both monetary expenses and time commitments, including the effort required to use multiple modes of transport.

[9]The motivation for firms to enter the local host market is not only driven by the opportunity to procure goods and services to mining operations but also by the potential benefits from the agglomeration externalities (e.g., cost efficiencies, knowledge spillovers, and labour market pooling), all of which can enhance firms productivity and profits in the short and long term. Other specific characteristics related to the host area, such as available infrastructure and rental prices, may play a crucial role in firms' decision to enter the local market. However, there is a lack of empirical evidence specific to the mining sector to argue about the influence of these factors on firms' entry into local host markets. Overall, the competition of firms will result in an uneven distribution of firms in space in the local host area and neighbouring districts. There is empirical evidence suggesting that, because of increase in labour mobility, these neighbouring areas experience changes in their socioeconomic settings(see for instance Haslam McKenzie & Hoath (2014))

[10]According to Evans & Harrigan (2005), firms typically seek to minimize transportation costs e.g., firms in the US opt for land or maritime shipping over air transport. However, firms are also willing to pay a premium for faster market access when the benefits of reduced delivery time outweigh the additional costs.

of firms closer to the demand centres has an effect over the factors of production (e.g., labour and capital) for incumbent firms in the host and neighbouring areas[11]. These dynamics also contribute to differences in industrial specialisation between host areas and their surrounding localities (Evans & Harrigan 2005), which also seem to follow the procyclical nature of extractive activities (i.e., periods of boom and bust), making both host and neighbouring areas highly vulnerable to external economic shocks (see for instance Feyrer et al. (2017), Aragón & Rud (2013), and Orihuela & Gamarra-Echenique (2020), these studies highlight the procyclical nature of resource extractive sector and their wider spatial and welfare implications. These studies are discussed in the next subsection).

With the concentration of firms, labour and potential spillovers in the host and neighbouring areas, it is expected that local host areas of mining projects to experience some localised benefits such as increased employment and procurement opportunities, leading to improved welfare conditions. However, these benefits may come at the expense of other localities, either in neighbouring areas or more distant ones to the host district that source labour, goods and services to the host area. Therefore, on aggregate, it should be expected that the net effect cancels out. Empirically, this is find in the case of the manufacturing sector in the US, where policies are designed to attract large manufacturing plants as a means of promoting regional development. These policies typically target specific locations, often yielding positive effects on local welfare. However, Kline & Moretti (2014) argue that such benefits come at the expense of welfare declines in other areas. Unlike targeted policies aimed at attracting firms, the implementation of mining projects is not designed to improve welfare in a specific area but it is subject to the geographical distribution of natural resources. However, the economic impact of these projects can, to some extent, be compared to some of the empirical evidence on the manufacturing sector, specifically, for the case of large plant openings that concentrate high level of resources,

[11]In the retail sector, Evans & Harrigan (2005) investigate the tendency of firms to agglomerate near areas of final demand in the US. The study finds that firms in close proximity to these demand centres tend to specialise in goods that consumers require within the shortest possible time frame. Firms are more inclined to relocate their production facilities to nearby locations to gain a competitive advantage by being closer to their target market. This phenomenon is particularly evident in firms that have relocated or improved their profitability by establishing operations in Mexico or Canada to better serve the U.S. market. While these firms cannot directly compete on labour costs with manufacturers in Eastern and Southern Asia, certain industries (e.g., apparel sector), demonstrate a distinct comparative advantage due to the importance of timely product availability. In that sense, for firms in the retail sector, proximity to consumer markets is a key factor, allowing firms located near the core market to capitalise on shorter delivery times and greater responsiveness to consumer demand.

such as labour, land and capital.

With recent changes in technology and industry processes (e.g., outsourcing of non-core activities), the traditional mechanisms of agglomeration economies, including labour market pooling, input sharing, and knowledge spillovers, could be questioned to fully explain the dynamics of spatial economic concentration. For instance, recent changes in work patterns (e.g., Work From Home) have altered labour's mobility and spatial distribution of workers and firms, meaning that these do not necessarily need to be located within the host area or even neighbouring districts but in other areas beyond (e.g., capital or metropolitan cities) to perform work directly or indirectly related to the main development (e.g., workers that perform some core and non core mining activities such as consultancy services could be located in metropolitan cities) [12]. These recent changes have implications to the spatial distribution of labour and firms in the host and neighbouring areas, as well as implications for their welfare (e.g., remote workers are expected to consume goods and services in the locations where they live). Other similar phenomena is the increase of long distance commuting workers which is more linked to the specific case of the mining sector, where the empirical evidence highlight that this behaviour could explain some of the spatial differences in welfare around host areas and more distant locations (see for instance Haslam McKenzie & Hoath (2014))

In the next subsection, I analyse empirical evidence related to agglomeration economies, and why it matters to take into account the spatial distribution of firms and workers to explain distance decay effects on welfare in the mining sector. Similarly, I present empirical evidence that highlight the extent of these effects in space.

3.2.2 Empirical evidence

The literature on economic geography highlights that firms, localities, or individuals close to a core economic areas tend to experience greater economic benefits (e.g., higher welfare levels), than those located in peripheral regions. This phenomena has been empirically tested in social science, the implications could be diverse for firms, individuals, cities in

[12]Bick et al. (2023) examine changes in work-from-home (WFH) patterns in the United States during the late stages of the COVID-19 pandemic. Their findings indicate that not only did the number of WFH days increase post-pandemic compared to pre-pandemic years, but structural conditions, such as work arrangements, also facilitated the persistence of remote work. This shift, in turn, has altered commuting patterns and may have implications for knowledge spillovers. For instance, reduced in-office hours could diminish informal knowledge exchange, a key driver of agglomeration economies at the micro-level.

both areas. In some cases, proximity to economic hubs foster specialisation and comparative advantage, leading to productivity gains and differentiated welfare outcomes across space.

In this subsection, I explore the empirical evidence on the extractive sector and how the implementation of these projects have lead to spatial differences in welfare. I also explore empirical evidence for other relevant economic sectors that experience the development of large investments (e.g., large manufacturing plants). There is a lack of empirical evidence addressing the effects of mining activities on welfare indicators in space, particularly, how NPDs are impacted when mining projects in PD become fully operational. While the mining and other relevant sectors (e.g., manufacturing) differ significantly in nature, for instance, there is vast empirical evidence that documents social and environmental externalities, the effects of large-scale industrial investments on regional economic dynamics offer valuable insights. For instance, studies on the opening of large manufacturing plants (e.g., billion-dollar investments in the U.S., see Greenstone et al. (2010)) provide useful empirical evidence, demonstrating how such developments influence key socioeconomic indicators, including wages, firm productivity, and employment. These effects, in turn, shape welfare outcomes in both host and neighbouring areas.

Empirical evidence in the extractive sector

The empirical evidence suggest that effects of resource booms on welfare are procyclical (i.e., welfare increases during periods of boom, and it decreases on bust years), and that these effects could be extended in space and time to other sectors. For instance, Allcott & Keniston (2018) find that wages increase up to 3% with one SD increase in county resource endowment. They argue that, with the presence of agglomerative effects and and limited crowd-out effects on manufacturing, resource booms may generate net welfare gains. They also find that the manufacturing sector follows the same prociclycal behaviour to resource booms, arguing that on aggregate there are no crowding-out effects effects on this sector. This trend is likely driven by the presence of locally traded goods and linkages between upstream and downstream industries. However, the extent to which the manufacturing sector is affected depends on its composition. Specifically, their results suggest that highly tradable manufacturing industries are more susceptible to negative impacts during resource booms.

Aside from this cycles of resource booms, new changes in technology in the extractive industry sector can have vast spatial implication on socioeconomic outcomes, influencing labour markets, regional development and economic inequalities across space. For instance, Feyrer et al. (2017) explores the oil and gas sector in the US during the period 2005 - 2012, due to implementation of new technologies for fracking and drilling, and explore the effects in time and space of new production of oil and gas projects. They find positive effects on wages and jobs locally, these effects also extend up to a 100 mile radius of the producing county. The effects remain positive in time up to two years post start of production. They also measure effects across industries, finding that the effects persists beyond the two initial years for other industries different from oil and gas sector, suggesting spillover effects in time.

The expansion of current mining projects also have implications on welfare in space. This is study by Aragón & Rud (2013) who focus on the Yanacocha mine located in the northern Region of Cajamarca in Peru. They evaluate the effects of the expansion of Yanacocha mining site on real income and other welfare indicators at the household level for the period 1997-2006. They find a positive significant effects on real income among households located within 100 km linear distance to the city of Cajarmarca. Orihuela & Gamarra-Echenique (2020) extend on the previous analysis using a longer period of time from 1997 to 2017 to include boom and bust years. They also find positive effects on welfare during boom years and a fall in both income and consumption among households during bust years, the effects are present within 100 km distance to the city. These both studies highlight how relevant is the expansion of this mining projects to explain changes in welfare in housholds that are located in proximity to mining projects. The changes in welfare during boom years suggest that wages and income of individuals were linked to the mining sector to some extent. It has also implication for the local labour market (e.g., different levels of specialisation) and the concentration of firms (e.g., focusing on goods and services targeting directly and indirectly the mining sector) within the 100 km threshold. It also highlight how economic agents are vulnerable to external shocks in the price of commodities, since welfare indicators were developing in line to boom and bust years of mineral production.

The empirical evidence in the extractive sector also highlight labour's mobility as an important factor to explain spatial effects to non producing areas. Haslam McKenzie & Hoath (2014) focus on the implications of Long-Distance Commuting (LDC) for non-producing areas that supply labour to mining regions in Australia[13]. They highlight that most of the attention has been given to the local host areas but little to non producing areas, despite their distance, they serve as key labour supply hubs. These areas accommodate a significant portion of the mining workforce due to common labour arrangements in the sector (e.g., rotational work schedules such as seven days on-site followed by seven days of furlough). Some of the LDC employment effects include income shocks, which are often reflected in the growth of small businesses benefiting from increased local spending. Furthermore, they find that once individuals complete their contracts in the mining sector, they tend to remain in these non-producing areas, suggesting that these locations serve as long-term destinations for migrants from other parts of the country rather than just temporary residences. Social, economic and psychological challenges were also identified as some of the negative effects (e.g., social tensions, lack of engagement with community activities).

Other relevant studies examining the spatial effects of the mining sector include Atienzaa et al. (2021), who focus on the Chilean copper industry and highlight the high concentration of procurement firms in the Metropolitan Region of Santiago, rather than in the mining regions themselves. A more specific case study in Antofagasta, a key mining region in northern Chile, is provided by Perez-Trujillo (2024). Their findings indicate that structural changes in the extractive sector have had profound effects on the labour market (e.g., outsourcing of non core mining activities), particularly in how workers from both the host area and neighbouring regions compete for mining-related employment. Many individuals from outside the host area commute long distances, as they do not necessarily reside in the immediate vicinity of mining operations. As a result, the welfare gains associated with mining employment may accrue more significantly to these commuting workers and their home regions, rather than to the host areas themselves. They also highlight the emergence of new firms largely driven by outsourcing trends that have accelerated since the 1990s. This has led to an increase in small and locally based firms providing goods and services to the mining sector, though these firms are not nec-

[13]For example, the city of Mandurah (located south of Perth) serves as a non-producing area that supplies part of the workforce to distant mines in Boddington and other mining sites in the southwest, located 90 km or more away. Workers typically commute through Fly-In Fly-Out (FIFO) or Drive-In Drive-Out (DIDO) arrangements to access employment in these producing areas.

essarily located within the host area itself, leading to a fragmented spatial distribution of labour and economic activity. Similar to the Australian case, the outsourcing of non-key mining activities has led to the introduction of long distance commuters (LDC), which emphasises the implications for the labour market in the local host areas and their surrounding regions and how these are exposed to external shocks, such as fluctuations in global commodity prices.

Empirical evidence in other relevant economic sectors

Greenstone et al. (2010) explore the arrival of new large manufacturing plants at the county level in the United States. Using a DiD approach, they find that counties hosting large new plants experience an increase in the Total-Factor Productivity (TPF) of incumbent firms by up to 12%. Moreover, these productivity gains are particularly pronounced in counties that share a common labour pool and technological base with the newly established plant. On a similar approach, Giroud et al. (2022) find positive effects on productivity on existing plants, with effects persisting miles beyond the immediate host area for plants of the same firm. However, effects remain localised for other firms, with effects decaying in a 50 miles radius around the large plant and insignificant beyond 100 miles threshold. Hornbeck & Moretti (2024) also focuses on the manufacturing sector at the city level in the US and explore how differences in productivity growth among firms affect workers' earnings and housing costs. They find, as part of the direct effects of productivity growth, positive impacts on local workers' earnings, along with increases in house rents and home values within the local cities. Additionally, they investigate the indirect effects of productivity growth on earnings and housing costs in other cities, particularly those connected to the city of origin of the newcomers. They find that wages increase in these other cities, while housing rents decline, highlighting positive spatial effects.

Agglomeration economies can also occur at more disaggregated levels. For instance, rather than looking at a regional or county level, Rosenthal & Strange (2020) explore the effects of agglomeration economies not only at the metropolitan and neighbourhood levels but also at finer spatial scales, including individual buildings. Their findings indicate positive labour market effects of agglomeration, though these effects diminish with increasing distance from the core (or host) area. One of their results concerns knowledge spillovers, which are more pronounced at lower spatial scales. These findings of agglomeration at multiple levels shed light on why some neighbourhoods attract more firms than others (e.g., why some clusters of restaurants and firms emerge in specific areas, or even at a more disaggregated level, why some firms locate within the same building). At these most finer spatial scales, the effects of agglomeration seem to remain (i.e., positive spillovers to firms, individuals). For instance, it is expected then that at smaller spatial scales, interactions between individuals become more frequent, facilitating communication, knowledge exchange, and information sharing. This is evidence in the work of Mas & Moretti (2009) where they demonstrate that, at the individual level, productivity spillovers occur among peers when highly productive workers are introduced into the same shift within a supermarket company. These effects are particularly evident when productive workers are in close proximity to their peers[14]. This is also the case for firms, where with the arrival of most productive firms to a dense area, these have positive spillover overs on the productivity of other incumbent firms in the host area. Gaubert (2018) finds that approximately 50% of the productivity advantage in denser areas can be attributed to this natural sorting of firms (i.e., arrival of productive firms)[15]. Gaubert (2018) also find that subsidies incentivising entry of firm to these areas have negative aggregated effects on productivity, since it most of the cases this could be attributed to the arrival of less productive firms to the host areas.

The spatial allocation of firms plays a crucial role in regional development. Some studies argue that effects of agglomeration effects decay with distance, then, it is expected that the effects remain locally where more denser areas[16] are expected to evidence higher levels of productivity in firms and workers in comparison to surrounding localities (Comber & Gobillon 2015). However, in most of the cases, agglomeration effects are most likely to extent up to a certain threshold (e.g., this could 50km, 100km, and usually measured in linear terms). This decision of firms to locate in more dense areas are based due to the presence of a thick labour pool market and knowledge spillovers, which contributes to increasing spatial inequalities (Gaubert 2018). In some cases, this decision to locate in

[14]Mas & Moretti (2009) argue that workers improve their productivity when they located within the "line of vision" of more productive workers (p. 114)

[15]This could be also compared to the arrival of new firms to host areas in PD, such as in the case of mining projects, where these do not necessarily are implemented due to agglomeration economies but the geographic distribution of natural resources.

[16]i.e., Areas with high levels of population and employment.

denser areas will play a role into determining the survival of firms. For instance, Kalnins & Lafontaine (2013) findings on the retail sector in the US suggest that that more distant firms to their HQ are more likely to exit the market than those who are in close proximity. They find similar effects for the lodging industry (e.g., hotels), where distance play a role in the revenues that firm obtain per room. These findings address an important issue that relates to the effects of distance decay on inter-firm effects, particularly for small-scale small scale firms. In the context of the mining sector, the arrival of firms to the local host district would imply at least two scenarios. First, the establishment of new firms within the local district and which their HQ belong the same area. Second, the arrival of subsidiary firms from already established businesses in neighbouring or more distant areas (e.g., small firms in the hotel and restaurant industries). The future revenue prospects of firms supplying goods and services to mining projects in the host area will likely be influenced by their distance from their headquarters, with implications for firm survival and regional economic development.

The allocation of firms in more dense areas will also play an important role for the spatial distribution of labour and and, it will consequently have implications on individuals' welfare. Fajgelbaum & Gaubert (2020) argue that a high concentration of individuals in high-wage areas is more likely to exacerbate regional disparities and reduce spillovers, whereas the presence of high-skill individuals in low-wage areas may foster greater spillover effects. These findings are relevant in the context of mining industry, since most of policies focus on income redistribution, ranging from national programs such as canon minero to local content policies aimed at improving rents among local populations. However, there is a lack of evidence of policies that seek to optimise the spatial allocation of individuals working in mining projects, both within the host area and in surrounding regions. Beyond the immediate context of mining camps and worker housing in neighbouring areas to PD, little attention has been given to how the natural distribution of skilled and unskilled labour for mining activities influences spillover effects in proximate locations. These natural allocation of individuals with high and low skills might be one of the answers of why some effects are more or less visible in host and neighbouring areas to PD. The findings of Fajgelbaum & Gaubert (2020) suggest that inefficient sorting of individuals by skill levels (high skill, low skill) might derive in higher welfare costs and inequality, compared to more balanced allocations. In the context of mining projects, this implies that a high concentration of skilled workers in host districts may limit spillovers to adjacent areas, particularly if low skill workers remain under-represented in those regions. However, this natural allocation of workers across spaces will be also determined by availability of infrastructure and connectivity to the host area. Thus, travel distances and travel times will also play a role on individuals decision to take a job within the host area. At the individual level, longer commuting distances and travel times act as disincentives for job applications, unless the expected utility of the job outweighs the costs associated with commuting. Empirical evidence suggests that unemployed individuals exhibit a strong preference for local employment opportunities, with the probability of choosing a local job being nearly 20% higher than that of selecting a job located 5 km away (Manning & Petrongolo (2017))[17]. In the context of PD, understanding labour market dynamics requires moving beyond the assumption that individuals are purely driven by rent-seeking behaviour to capitalise on employment and procurement opportunities. Instead, spatial disparities between PD and neighbouring or more distant areas are likely influenced by a combination of these frictions, which then should be reflected in their welfare conditions.

3.2.3 Theoretical Framework

This chapter uses the theory of agglomeration economies as a main framework to understand the extent of the effects of mining activities in space. For this purpose, I follow Greenstone et al. (2010). The model suggest two scenarios, the first where all existing firms in the host district are similar and a second with heterogenous firms.

The first scenario assumes homogenous existing N firms in the host district, with a given labour (L), capital (K) and Land (T), and technology (A)[18] that maximises profits ϕ, and considering the optimal levels of L, K and T given wages (w), costs of capital(r) and land(q)[19], it is assumed that labour to be mobile across districts with a fixed quantity of labour hours per worker c. In a local host economy with a total of

[17] Individuals are also less likely to apply for jobs in areas with high expected competition, further constraining their job search radius. The findings by Manning & Petrongolo (2017) highlight the importance of spatial frictions in labour market dynamics. The decision of individuals to seek for a job or accept it will not be solely based on future profit gains but labour market competition, commuting costs, job accessibility.

[18] This could be defined as well as other relevant factors that influence capital, land and labour, which are related to increases in firms productivity

[19] Cost of capital is fixed, cost of labour and land are subject to local prices

N firms (where $A = A(N)$), it is expected that as the number of firms increases and technology improves, positive spillovers from agglomeration will emerge. These spillovers are reflected in the relationship $\frac{\partial A}{\partial N} > 0$, indicating that an increase in the number of firms leads to greater overall productivity or efficiency. In contrast, if there are no spillovers from agglomeration, we have $\frac{\partial A}{\partial N} = 0$. [20] As the number of firms in the host district changes (e.g., through new entrants), the model predicts the following dynamics:

$$\frac{d(\phi)}{dN} = \left(\frac{d}{dA} \cdot \frac{dA}{dN}\right) - \left(\frac{dw}{dN} \cdot L + \frac{dq}{dN} \cdot T\right)$$

Where ϕ is the firms profit. There first part of the equation predicts a positive effect where with the entrants of new firms is expected that incumbent firms in the host district to experience a positive effect in their Total Factor Productivity (TFP). The second term of the equation suggest a negative effect on incumbent firms linked to an increase in the cost of factors of production wages(w) (assuming $\frac{\partial w}{\partial N} > 0$) and land (q)$\frac{\partial q}{\partial N} > 0$), since with the entrant of new firms these will compete for the same pool of resources, increasing the prices of both of these.[21] The prices of capital are unaffected, these prices are determined at international level. In that sense, firms can increase level of capital used for production. According to the same model, in the short term, there are some positive effect on profits for new entrants whilst prices of local factors accommodate. In the long run, an equilibrium of these factors is expected to a point where workers are indifferent to move across locations. Prices of land will increase since higher productivity and wages will make individuals more likely to capitalise gains into land buying.

Empirically, the model predicts that, with the entry of a large firm and positive spillovers in the host district, more firms to enter the same host district to get the benefits of these spillovers. Second, it is expected that the price of the local factors of production to increase, since new firms will compete for these resources (Greenstone et al. 2010).

In the second scenario, the model considers two types of existing firms in the host district: high-tech firms that require L_H workers and low-tech firms that demand L_L workers. The model predicts that with the entry of a large new high-tech firm, existing high-tech firms will benefit more than low-tech firms. This is expressed as:

[20] Agglomeration spillovers are assumed to be evenly distributed across the three factors of production—labor, capital, and technology.

[21] The magnitude of the effects will depend on the elasticity these resources which is limited and marginally decreases the more entrant firms.

$$\frac{\delta f_H}{\delta A_H} \cdot \frac{\delta A_H}{\delta N_H} > \frac{\delta f_L}{\delta A_L} \cdot \frac{\delta A_L}{\delta N_H}.$$

Similar to the first scenario, the cost of the factor of production—in this case, wages for high-tech workers (ω_H)—is expected to increase for existing firms in the host district. This occurs because firms compete within the same labour market, driving up wages for high-tech workers.

In the first scenario, assuming homogeneous firms in the host district, the entry of mining companies generates positive spillovers that enhance the profitability of existing firms (i.e., non mining companies). In the short term, this increase in profitability incentivise additional firms to enter the district, leading to greater demand for both labour and services. Consequently, individual consumption levels are also expected to rise.

As new firms enter the district, competition for labour among firms in both traded and non-traded sectors intensifies. This increased competition places upward pressure on wages, attracting additional workers to the district who seek to capitalize on the economic opportunities created by the arrival of the mining project. While firms benefit from productivity and technological spillovers associated with the mining project's presence, rising wages and land costs impose constraints on their profit margins. Nevertheless, sustained demand for labour continues to drive positive effects on consumption within the district.

Beyond the model's immediate implications, if the local labour supply is insufficient to meet rising demand, it is expected that workers from neighbouring areas will migrate to the host district. This labour influx, in turn, may exert upward pressure on wages and consumption levels in both the host district and surrounding areas, though the effects are likely to be more pronounced within the host district itself. In the long run, as production factors move toward equilibrium, higher wages may lead individuals to capitalise on their earnings by investing in land within the host district or in nearby areas. Additionally, increased wages enhance individuals' purchasing power, driving higher consumption of goods and services both within the host and neighbouring districts. Consequently, a positive long-term impact on consumption is anticipated.

In the second scenario, assuming differences in technology levels among existing firms in the host district, the arrival of mining projects, characterised by high levels of automation and a demand for fewer high skilled workers, is expected to generate stronger positive effects among technologically advanced firms compared to low-tech firms. At the same time, wages for high-tech labour are anticipated to rise as demand for specialised skills increases. This dynamic may incentivise the entry of new high-tech firms seeking to capitalize on these benefits, further driving up wages for highly skilled workers and potentially widening income disparities within the host district.

Higher levels of consumption could thus be linked to the technological heterogeneity of existing firms, particularly in the presence of large mining companies, suggesting a more concentrated economic effect. While low-skilled workers are also expected to benefit from the arrival of new firms, the magnitude of these benefits is likely to be lower compared to those experienced by high-skilled workers.

In the absence of high-tech firms within the host district, two possible scenarios emerge. First, new firms may enter the market to take advantage of the spillovers generated by the arrival of a large mining company, with some implications on individual's welfare (e.g., widening the gap between high skilled and low skilled workers). Alternatively, the economic benefits may be captured primarily by high tech firms located outside the host district rather than within it.

3.3 Methodology

3.3.1 Data

I work with secondary household level data sourced from the Peruvian National Institute of Statistics. The latter organisation perform household surveys on an annual basis at national level. This survey collects information on household characteristics such income, consumption, access to public services, dwelling characteristics, employment, among other socioeconomic indicators. The information on consumption and income is presented in USD and deflated to 2021 values. I access price index data from the Central Bank of Peru in order to deflate consumption and income values.

Information about mineral activity per mine and at the district level in Peru is sourced from the Ministry of Energy and Mines. This information is published on an annual basis by this government entity and includes detailed information on mineral production by size of mine (e.g., small, medium or large scale mining), year, type of minerals being produced and geographic location (region, province and district). Because mineral level data are available on a yearly basis, it is possible to construct a panel that tracks the operational status of individual mining sites over time.

Geospatial data on public road infrastructure and administrative boundaries at the district, provincial, and national levels were obtained from OpenStreetMap (OSM). The latter source is used in combination with the command OSRM to estimate road travel distances by car in Stata, following Huber & Rust (2016). The information downloaded from the OSRM website was tested using GIS software, however, all maps and distances estimations were performed using Stata software to ensure consistency and facilitate reproducibility via do-files. As an additional validation step, both linear and route-based distance estimates were randomly cross-checked using Google Maps and Google Earth.

The data is merged using the district identifier of geographic location. This is a six level digit number where the two first digits locates the region, the next two the province and the last two the district.

Table 3.1 presents a summary statistics for the main outcome variable, along with key socioeconomic, geographic, and distance-related covariates, over the period 2001–2019. Average individual consumption and income are calculated at the district level. Socioeconomic indicators are expressed as district-level proportions (i.e., gender, the share of urban households, literacy rates, and the proportion of permanent residents). The sample spans the years 2001 to 2019.

Table 3.1: Summary Statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Average individual consumption p/m (USD)	17,647	128.03	85.84	13.17	1397.25
Average individual income p/m (USD)	17,647	154.28	131.35	10.23	2857.84
Poverty Line (USD)	17,647	100.15	17.78	66.68	181.13
Proportion poverty level (district level)	17,711	0.29	0.21	0.00	1.00
Proportion extreme poverty (district level)	17,711	0.17	0.23	0.00	1.00
Proportion gender (district level)	17,711	0.49	0.07	0.00	0.89
Proportion urban (district level)	17,711	0.41	0.44	0.00	1.00
Proportion literacy (district level)	17,711	0.21	0.09	0.00	0.71
Average permanent members p/hh	17,711	4.76	1.12	0.00	11.45
Producer (dummy)	17,711	0.04	0.20	0.00	1.00
Altitude(masl)	17,694	1957.04	1446.25	5.00	4470.00
Surface (sq. km.)	17,694	847.52	2239.33	2.00	24050.00
Minimum Linear Distance (km)	17,694	67.29	102.56	0.82	878.28
Dynamic Minimum Linear Distance (km)	17,694	123.96	121.11	1.60	955.72
Minimum Travelling Distance (km)	17,637	151.82	245.27	1.34	1929.21
Dynamic Minimum Travelling Distance (km)	17,637	251.65	261.51	2.48	1964.54

Note: Monthly per capita consumption and income are measured in U.S. dollars at the aggregated district level and are deflated to constant 2021 values. Proportional variables such as demographic and socioeconomic indicators are also computed at the district level. Both linear and travel based distances are measured in kilometres.

3.3.2 Methods

In order to explore the extent of decay of mining activities on welfare in space, I work with linear and travel distances. The first of these is one of the most common measures used in the empirical papers. The second of these offers a more realistic approximation that accounts for the geography and transport road infrastructure of the country. Both measures are estimated in kilometres and calculated using the Stata Software.

Linear and travelling distances

Linear distances are calculated using the longitude and latitude coordinates between two districts, based on the standard coordinate system World Geodetic System 84 (WGS 84). The linear distance calculates the shortest linear distance between two districts using the command geonear in Stata Software.[22] Each district (NPD or PD) is measured against all PD in the database generating a total of 354,000 combinations for distances between NPD to PD and 57,600 combinations for PD to PD. The first group aims to capture the spatial spillovers from PD to NPD, where I work under the hypothesis that welfare effects from mining activities are more likely to be observed in NPDs located closer to PDs. The second set examines spillovers among PDs themselves, assessing whether mining activities in one PD influence welfare outcomes in neighbouring PDs.

Unlike previous case studies that mainly work with linear distances for the case of mining (for instances, see Aragón & Rud (2013), Orihuela & Gamarra-Echenique (2020), Chuhan-Pole et al. (2015)), I include in my estimations road travel distances by car (as the preferred mode of transportation). The reasons behind this choice respond to the use of the command Open Source Routing Machine (OSRM) in Stata and the public data available in OpenStreetMap, following Huber & Rust (2016). Other sources of transportation such as public transportation rely on real time data, however, this might also be a disadvantage if the estimations for travel distances are to be replicated[23]. These other modes of transportation could be included in a more depth analysis (e.g., using public transport, by foot or bicycle). However, this will require more powerful computations and potential the use of more than one software to validate calculations.[24]

Both linear and travel distances are estimated using the minimum distance between two points. Other measures such as the mean and median are also explored in this chapter. Table 3.2 present a brief analysis on these measures, these are used in the POLS

[22]I also use the command geodist as a robustness check, which works similarly to geonear. The command geodist estimates linear distances using a geodetic method, in this case by default assumes the earth as an elipsoid. The command geonear calculates distance to the nearest neighbour. Distance calculations using geodist and geonear are comparable for the purpose of this research

[23]The estimations rely on the Stata command "osrmtime", developed by Huber & Rust (2016). From experience running the command, it is recommended to perform the calculations with latest operating system (whether this is performed in Windows or Mac OS) and latest Stata software. Calculations using a Windows 10 system using Stata 17 took between 1 to 2 hours to perform (other previous versions took around 6 hours e.g., using Windows 7 and Stata 15). Calculations with a Mac OS were not possible to perform because of the incompatibility of the software (Mac OS Ventura) and the command.

[24]This sort of calculations are also performed by mapping services such as Google, HERE among others. This last map tools include their approach additional features such as time of departure/arrival or consider traffic conditions to estimate travel time and distance for different transportation modes (e.g., travel by car, public transport, bicycle or by foot). Depending on the conditions of the data, the travel calculations could be different for day/night travelling, thus, travel routes will change accordingly as well as the travel calculations. These mapping tools (such as Google or HERE) provide services for calculation of large batches of data. Approximate costs to estimate travel distances using real-time data with both mapping tools were priced between USD 500 to USD 2000. Therefore, the latter approach was discarded from the analysis.

and DiD approach.

Table 3.2: Summary of Distance Measures Between Districts and PDs

Unit	**Approach**	**Evaluation**	**Pros/Cons**
Minimum	Estimates the minimum distance between a district (either NPD or PD) and all 240 PDs.	For NPDs to PDs, minimum distances are always > 0. For PDs to PDs, minimum distance is > 0, capturing effects from neighbouring PDs.	**Pros**: Captures effects of nearby or closest PDs. **Cons**: May miss effects of other nearby PDs within the same province or region, especially when the number of PDs is relatively high.
Mean	Estimates the mean distance from a district (NPD or PD) to all PDs.	Mean distances are always > 0, allowing assessment of how closely districts are surrounded by PDs. Lower mean values indicate proximity to several PDs; higher values suggest isolation.	**Pros**: Provides an approximation of overall proximity of PDs to NPDs. **Cons**: Includes mean distance from all PDs nationwide, potentially missing localised effects.
Median	Estimates the median distance from a district (NPD or PD) to all PDs.	Median distances are always > 0, offering an alternative summary measure to assess proximity to PDs.	**Pros**: Often better than mean for representing typical distances between PDs and NPDs. **Cons**: Like the mean, includes distances from all PDs regardless of location, possibly giving a lower importance to localised effects.

Static vs dynamic distances

I work with two approaches, the first considers a "fixed" or "static" distance and a second one focused on "dynamic" distances. In the first of these, it is assumed that the minimum distance between two points will be same regardless of time. For instance, assume the shortest linear distance between a NPD(x) and PD (y) is 100km. If PD(y) has information available[25] for "m" number of years but is only active during "n" number of years (where m>n), then linear distance between NPD(x) and PD(y) during "m" number of years will be 100km. However, considering how dynamic is the sector where

[25] For instance, this could be socioeconomic information such as proportions of gender composition, literacy rates or degree of urbanisation at the district level.

mining projects switch on and off in time, the second approach weights in the distance calculations the actual period of time in which PD are active. Using the same example, assume during "m" number of years, the distance calculations from NPD(x) to PD(y) during "n" number of years is 100km. However, there are also "l" number of years where PD(y) was inactive (where n+l=m). For the case of "l" number of years of being inactive, the software would estimate a new distance to the next nearest PD, which for the case of the example would be NPD(x) to PD (z) is now say 120 km for "l" years. Therefore, distances between NPD (x) to the nearest PD (that is PD(x) and PD(y)) during "m" years of time would vary accordingly to active years of production of the given nearest PD. This new approach would account for the dynamics that are existent in the mining sector, and would might reflect more accurately how mining activities vary in time, for instance, periods of inactivity could be linked to exogenous factors such as commodities prices (Fernandez 2019).

3.3.3 Model

Pooled Ordinary Least Squares

I work with a Pooled Ordinary Least Squares (POLS) regression in order to test the main variables of interest, in this case, both linear and travel distances against welfare variables, combine with a set of social and geographic variables. The POLS regression is based on Aragón & Rud (2013) and the extended study by Orihuela & Gamarra-Echenique (2020) where they work with a 100km linear distance measure to assess the effects of the mining project Yanacocha on welfare in Peru, and Greenstone et al. (2010) where they include a variable of economic proximity to asses agglomeration effects of large plant openings on productivity in the US. Considering these approaches, I propose the following POLS model:

$$Y_{i,t} = \alpha + \beta_1 Producing_{dt} + \beta_2 Distance_{it} + \beta_3 X_{it} + \beta_4 DCH_i + \beta_5 T_{it} + \epsilon_{it} \quad (3.1)$$

Where $Y_{i,t}$ is the potential outcome of i district in t time, measured by consumption, log income, or real expenditure.[26] $Producing_{dt} = 1$ is a dummy variable that indicates

[26] Average individual consumption is estimated in monthly USD and aggregated at the district level.

whether district i is a Producing District in time t and zero otherwise. $Distance_{it}$ is a measure of proximity (i.e., linear or travel distance) between two i districts in a given time (e.g., these could be the distance from a NPD to a PD or the distance from a PD to another PD except itself). This variable is measured in km using the minimum (linear or travel) distance. The variable X_{it} accounts for a set of socioeconomic characteristics measured at the district level (e.g., % of females at the district level, % urban households at the district level, average number of permanent resident household members at the district level). The POLS regression also incorporates the geographic characteristics of districts, such as altitude and surface area, denoted as DCH_{it}. The model further includes time-fixed effects (T_i).

When using "static" distances, the minimum linear or travel distance measure is estimated under the assumption that PDs maintain their status throughout the years covered by the dataset. This assumption similarly applies to NPDs. However, considering the availability of mineral activity data for districts in Peru, I also estimate "dynamic" distances. These account for temporal changes in districts status, such as instances where a NPD transitions to a PD or reverts to NPD status. Therefore, the minimum linear or travel distance will vary in accordance with the evolving status of the districts under consideration.

I use the POLS regression to test the four types of distance measures, these are minimum linear static distance, minimum linear dynamic distance, minimum travel static distance, and minimum travel dynamic distance. The analysis of these distance measures is explored by examining the parameter β_2.

Difference in Difference Approach

This second approach works with distance measures as the main treatment. The variable distance is measured as a continuous variable instead of a binary given the availability of data related to minimum linear and travel distance for the analysis. When considering distance variables as the main treatment, I aim to evaluate high and low proximities or "dosages". This helps to understand how proximity (or dosage) to a mine affects the development of certain NPD.

Considering that treatment is heterogenous in time and that the same variable is

Log income and real expenditure are constructed in the same manner.

continuous, I work with Callaway et al. (2024) which considers event-study application where treatment is "partially" aggregated. The latter could be presented in the form of two values (e.g., high or low dose) and related to values determined by the researcher (e.g., this could be the minimum, mean, median or other relevant related to the scope of the research).

The event-study specification suggested by Callaway et al. (2024) works as follows:

$$ATT^{evst}(e) = \mathbb{E}\left[ATT^{obs}(G, G+e) \mid G+e \in [2,T], D>0\right] \tag{3.2}$$

The model above estimates the average treatment effect (ATT) in an event-study design ($evst$) by considering the observed ATT (ATT^{obs}) for groups G that were treated at time t within the timeframe T. Here, the letter e denotes the number of periods after exposure to treatment D.

When considering at least two dosages (e.g., d_1 and d_2), the specification adapts as follows:

$$ATT^{evst}_{d1,d2}(e) = \mathbb{E}\left[ATT^{obs}_{d_1,d_2}(G, G+e) \mid d_1 \leq D \leq d_2, G+e \in [2,T], D>0\right] \tag{3.3}$$

In this updated model, it accounts for partial aggregated dosage levels d_1 and d_2, which represent lower and higher doses, respectively, within the range of D. As shown in this specification, the observed ATT now accounts for the relationship between two dosages, d_1 and d_2. According to Callaway et al. (2024), dosages can be categorised in relation to the median or mean. However, when working with a number of dosages, one of the main challenges is that the sample may get reduced. For instance, in the same paper, Callaway et al. (2024) replicate the results by Bartik et al. (2019) and look at the effects of fracking on employment in the USA using a continuous variable which is the cost of fracking (or prospectivity score). They work with two dosages (high and low) that respond to minimum and median prospectivity scores (i.e., counties in the US that were expose to fracking) and compare these treated groups with counties with a prospectivity score of zero (i.e., no exposition to fracking). Since there is a range for the prospectivity score, there could be more than two dosages that could be tested but would be subject to new threshold levels different to the minimum and median values.

The above model assumes parallel trends (i.e., in the absence of treatment, groups receiving different dosages would evolve similarly), no anticipation of the treatment, a continuous treatment, and that the data follows a panel structure with staggered treatment deployment.

In a similar way, my research look at the heterogeneous treatment effects of distances from NPD to PD on welfare in Peru by looking at a single dosage which could be measure by the median or mean values for linear and travel distances. The benefit to work with one single dosage allow my research to divide the sample in two groups. A first group of districts where the linear or travel distance is below the median value (treatment group) and a group of districts which the linear or travel distance is above the median value (control group). A second group of district where the treatment group is selected in relation to the mean value (i.e., treated group linear and travel distance is below the mean vs control group where the linear and travel distance is above the mean). I work with the following even-study specification, following Callaway et al. (2024) and Johansson et al. (2024). The coefficients for the event-study specification are estimated using the `csdid` command in Stata:

$$Y_{i,t} = \alpha + \beta_1 D_{dt} W_{it} + \beta_2 X_{it} + \beta_3 DCH_i + \beta_4 T_{it} + \beta_5 DFE_{it} + \epsilon_{it} \tag{3.4}$$

In this model, D_{it} is a continuous variable representing the minimum linear or travel distance (in kilometres) between the NPD and PD for district i at time t. W_{it} is a dummy variable that takes the value of one if the distance is below the median or mean value, and zero otherwise. The coefficient β_1 captures the effect of distance on the outcome variable $Y_{i,t}$. The other terms in the model control for the same characteristics as in the previous Pooled Ordinary Least Squares (POLS) specification.

3.4 Results

3.4.1 POLS

In Table 3.3, when looking at the static minimum linear distance, the difference in consumption between PD and NPDs varies between 13.1% to 18.7%, holding all other variables constant.[27] These differences are significant at 5% level, suggesting that during the period of analysis (2001 to 2019), PDs have higher consumption levels than NPDs in Peru. Another interesting finding is that, regardless of the measure used for the analysis (e.g., static or dynamic approach) with linear and travel distances, coefficients are quite proximate, with differences ranging within a 5.1% and 4.3%, [28] respectively.

When looking at proximities to PD, I find that one standard deviation increase in distance is linked to a drop in consumption from 4.8% up to 7.8% for linear and travel distances, respectively (e.g., dynamic linear distance S.D. 121.11 km*(-0.0004) or dynamic travel distance S.D. 261.51km * (-0.0003)). These coefficients are also significant at 5% level for both measures of distance. These results suggest that when districts are more distant to PDs, consumption levels are lower in the former group, with effects more pronounced when using travel distances.

The difference in approach for static and dynamic seems relatively higher for travel than linear distances.[29] The difference for linear distance is 0.3% [30] whilst the difference for travel distance of 2.9%.[31]

These results highlight the possibility that consumption levels might decay the further NPDs are to PD, but when the two measures are compared in the analysis, the estimates based on travel distances (using a dynamic approach) indicate that the drop in consumption levels could be higher (around 3%) than when using linear distances. This measure would also account for factors linked to geography (e.g., altitude and surface) or lack of availability of road infrastructure which could be overlooked when using linear distances in the analysis. However, the drop in consumption levels among NPD that

[27]This includes socioeconomic and geographic variables as controls. The full regression including the coefficient for the latter variables is presented in the Appendix

[28]i.e., difference between static and dynamic distances

[29]Using SD for static and dynamic distance in both linear and travel distances and their corresponding coefficients for their calculations, equal to -0.0005 for static linear, -0.0004 for dynamic linear, -0.0002 for static travel and -0.0003 for dynamic travel distances.

[30]It accounts for 5.1% for static and 4.8% for dynamic.

[31]It accounts for 4.9% for static and 7.8% for dynamic.

are in proximities to PD have decayed over the period of analysis, regardless of the used measure. This opens the possibility to explore the extent of this decay in space (what are the effects among NPDs that are closer and farther away to PD?) and time (e.g., to explore the extent of effects after a number of years after districts become host of mining projects). That is, to evaluate whether closer districts (e.g., located at 50km or 100Km of distance to PD) have retain some of the benefits of being located near producing mines during the period of analysis. These issues are examined in the next subsection. The Appendix includes the full tables including control variables.

Table 3.3: POLS Results for Linear and Travel Distances

Dependent	Min. Linear Distance		Travel Distance	
Variables	Static (1)	Dynamic (2)	Static (3)	Dynamic (4)
Producing	0.136***	0.187***	0.131***	0.174***
	(0.032)	(0.037)	(0.032)	(0.038)
Distance	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	5.035***	5.084***	5.038***	5.087***
	(0.043)	(0.044)	(0.043)	(0.044)
Observations	16,868	16,868	16,811	16,811
R-squared	0.636	0.638	0.636	0.642
Demographic controls	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

3.4.2 Difference in difference approach

Linear distances

The results in Table 3.4 suggest that on aggregate there is a positive effect at 10% significance level across NPD that are located below the mean or median distance to PDs during a window of five years after PD start production (see columns 1 and 2).[32] The results remain positive and significant when comparing NPDs that are 100 km or less located to PDs in comparison to NPD located away from this measure (see column 3). The coefficient becomes significant to a 5% level when the measure is changed to 50 km (see column 4). The above results include all districts in the analysis (i.e., incorporate

[32]Results without covariates are shown in the Appendix, Table A5.

distances from NPDs to PDs and PDs to other PDs). I also explore whether these effects hold when reducing the sample to NPDs (i.e., distances from NPDs to PDs). The results in columns 5 to 8 are similar to the former group (i.e., that includes all districts), where post average treatment effects are positive and significant at 10% level when comparing NPDs by the mean and median. Similarly, when the comparison measure is reduced to 50km, the post average treatment effect becomes highly significant at 5% level. For the case of NPDs, these results confirm that on aggregate, NPDs that are located in close proximities to PDs experience a positive effect on consumption in comparison to NPDs that are located 50 or 100 km away to PDs, as well as those who are located above the mean or median linear distance to this latter group of districts.

Table 3.4 also suggest pre-treatment effects are not significant. These coefficients evidence that comparison groups defined by distance-based measures (e.g., mean or median linear distance or 100 km or 50 km linear distance) are comparable prior to the start of production among PDs.

The effects on consumption's district are positive but lack significance for the first three years after PD start production.[33] The effects are positive and highly significant (1% level) in the fifth year after PDs start production when comparing districts[34] located within 100 km linear distance to PDs to those situated farther from this measure. This means that once PDs start production, it will not have any difference on the district's consumption levels being located below 100 km linear distance or farther away than this. However, there is evidence of a positive and significant effect on consumption levels on districts that are located within a linear distance of 100 km five years after PDs starts production, in comparison to those that are farther away from this linear distance. When I explore if these results hold for districts located in 50 km linear distance to PDs, I find positive and significant effects in the second and fourth at 10% significance level and the fifth year at 5% significance level after PDs start production. This result reinforce previous evidence that districts located in close linear proximity to PDs will experience positive effects in their consumption levels from two to five years after PDs start production, in comparison to those that are located 50km farther away from these. These results suggest that the closer districts are to PDs, the more likely they will see

[33]The effective distance from districts to PD is determined by the start of production of the given nearest PD

[34]This could be NPD or PD.

positive effects in their consumption levels in the short term, to those that are located farther away.

These latter effects are also visible when reducing the sample to NPDs (i.e., distance from NPDs to PDs). The effects on consumption levels among NPDs located in 50 km linear distance from PDs lack significance during the first two years post start of production of PDs. However, the effects on consumption on these same districts are positive and significant from 10% up to 5% level during the second to the fifth year after PDs start production (see column 8). This means that NPDs that are located in close proximities to PDs such as 50 km linear distance are likely to experience positive effects in their consumption levels in the short term, being these effective from the second year of production and more significantly in the subsequent years. Other tested distance measures, such as the mean, median, and 100 km liner distances, also show positive and significant effects on consumption from the fourth year after PDs start production (see columns 5 to 7), these outputs also suggest that positive effects on consumption are more likely to occur four to five years after PDs start production.[35]

[35] In column 6, when using the distance measure of the median, the effects on consumption are positive and significant in the second year after PD start production at a 10%.

Table 3.4: Outputs for Linear Distances

	All districts				Only NPDs			
	Mean (1)	Median (2)	100 km (3)	50 km (4)	Mean (5)	Median (6)	100 km (7)	50 km (8)
Pre_avg	0.012	0.001	0.001	0.009	0.011	-0.001	-0.000	0.008
	(0.011)	(0.013)	(0.015)	(0.011)	(0.011)	(0.014)	(0.016)	(0.012)
Post_avg	0.039*	0.047*	0.045*	0.050**	0.041*	0.055*	0.044	0.054**
	(0.017)	(0.020)	(0.022)	(0.018)	(0.018)	(0.022)	(0.023)	(0.019)
Tm2	0.033	0.025	0.028	0.020	0.035	0.029	0.031	0.023
	(0.018)	(0.022)	(0.023)	(0.019)	(0.019)	(0.023)	(0.024)	(0.020)
Tm1	-0.008	-0.022	-0.027	-0.002	-0.013	-0.032	-0.031	-0.007
	(0.017)	(0.021)	(0.020)	(0.018)	(0.018)	(0.022)	(0.022)	(0.019)
Tp0	0.024	0.033	0.032	0.028	0.020	0.033	0.030	0.024
	(0.017)	(0.018)	(0.020)	(0.017)	(0.018)	(0.019)	(0.021)	(0.018)
Tp1	0.024	0.029	0.019	0.031	0.023	0.030	0.014	0.030
	(0.018)	(0.020)	(0.024)	(0.018)	(0.019)	(0.021)	(0.026)	(0.019)
Tp2	0.035	0.044	0.004	0.046*	0.043	0.056*	0.003	0.056*
	(0.021)	(0.024)	(0.029)	(0.022)	(0.022)	(0.026)	(0.030)	(0.023)
Tp3	0.021	0.034	0.015	0.045	0.024	0.047	0.015	0.051*
	(0.023)	(0.027)	(0.029)	(0.024)	(0.024)	(0.029)	(0.030)	(0.025)
Tp4	0.043	0.051	0.071*	0.059*	0.051*	0.068*	0.076*	0.072**
	(0.024)	(0.030)	(0.035)	(0.026)	(0.025)	(0.031)	(0.036)	(0.027)
Tp5	0.085**	0.089**	0.130***	0.090**	0.084**	0.094*	0.124***	0.088**
	(0.026)	(0.034)	(0.036)	(0.029)	(0.028)	(0.037)	(0.036)	(0.031)

Notes: tm refers to "time minus" 1 and 2 years before PDs start production. tp refers to time period from 1 to 5 years after PDs start production. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Travel distances

For the case of travel distances, Table 3.5 suggest that, on aggregate, effects on consumption levels are positive and significant for districts located below the mean or median travel distance to PDs, this effect is positive and significant at a 10% level for both measures (see columns 1 and 2).[36] The same occurs when the sample is reduced to only NPDs. This means that, on aggregate, NPDs located in close travel distance by car to PDs, experience positive and significant effects in consumption at a 10% level in comparison to those NPDs living farther than the mean, median or 100 km travel distance to PDs. However, when looking at the results for travel distances of 50 km in column 4 (for all districts) and column 8 (for only NPDs), the coefficients lack significance. It might be the case that there is a higher concentration of PDs and NPDs located in proximities

[36] Results without covariates are shown in the Appendix

within the range of 50 to 100km (or more) travel distance to PDs, than those located in a very close proximity such as those below the 50km travel distance to PD.[37] This result could be also linked to the higher standard deviation observed for travel distances in Table 3.1 e.g., SD for minimum travel distance is 245 km, which is higher in comparison to the SD for minimum linear distance of 102km.

The coefficients for the pre-treatment years lack significance for all travel distance measures, this means that the cohorts (treated and control ones) are comparable before PDs start production. This is the case when working with all districts and also when reducing the sample to NPDs.

All distance measures (mean, median, 100km and 50km travel distance) present positive coefficients and some level of significance for the fifth year after PD start production in both samples (all districts and only NPDs). There are also no significant effects during the first to the fourth year after production starts except for the case of the mean travel distance in column 5. These results suggest that on average, there are no discernable effects in the short term on consumption levels across districts (PD and NPD) located in proximities to PDs (e.g., located 100 km or 50 km travel distance to PDs), in comparison to those districts situated farther away (e.g., 100 km or more away from PDs). This is also the case for the reduced sample of NPDs, where the effects on consumption are positive and significant only on the fifth year after PDs start production, and highly significant for the case of NPDs located in a proximity of 100km travel distance by car to PDs, in comparison to NPDs located farther away. When the distance measure is reduced to 50km, in both cases (sample for all districts and only NPDs), the effects on consumption are positive and significant up to 10% level, suggesting that is more likely to evidence some positive effects in consumption levels in the long rung across districts located in a 50km travel distance to PDs, in comparison to those locate farther to this measure. However, at the same time standard errors increase for both samples and for all distance measures tested at the fifth year post production, which could suggest a drop in the number of cohorts that are compared the more the window post production is extended (e.g., six to ten years).

[37]I also observe higher standard errors for the 50 km travel distance measure, suggesting that the number of cohorts below the 50 km threshold decrease

Table 3.5: Outputs for Travel Distances

	All districts				Only NPDs			
	Mean (1)	Median (2)	100 km (3)	50 km (4)	Mean (5)	Median (6)	100 km (7)	50 km (8)
Pre_avg	0.008	-0.003	0.008	-0.004	0.004	-0.010	0.003	-0.013
	(0.011)	(0.013)	(0.011)	(0.016)	(0.011)	(0.014)	(0.012)	(0.018)
Post_avg	0.043*	0.048*	0.033	0.044	0.048**	0.052*	0.040*	0.052
	(0.017)	(0.021)	(0.018)	(0.024)	(0.018)	(0.023)	(0.019)	(0.027)
Tm2	0.020	0.012	0.021	0.018	0.018	0.007	0.019	0.011
	(0.017)	(0.021)	(0.018)	(0.025)	(0.019)	(0.022)	(0.019)	(0.027)
Tm1	-0.003	-0.018	-0.005	-0.026	-0.010	-0.027	-0.013	-0.037
	(0.017)	(0.020)	(0.018)	(0.024)	(0.018)	(0.022)	(0.019)	(0.026)
Tp0	0.018	0.025	0.011	0.037	0.021	0.025	0.015	0.036
	(0.017)	(0.019)	(0.018)	(0.023)	(0.018)	(0.021)	(0.019)	(0.025)
Tp1	0.021	0.032	0.011	0.031	0.022	0.036	0.012	0.035
	(0.019)	(0.022)	(0.020)	(0.025)	(0.020)	(0.024)	(0.021)	(0.027)
Tp2	0.033	0.042	0.028	0.039	0.043	0.053	0.038	0.053
	(0.022)	(0.027)	(0.023)	(0.031)	(0.023)	(0.030)	(0.025)	(0.036)
Tp3	0.032	0.044	0.019	0.032	0.040	0.053	0.030	0.051
	(0.023)	(0.027)	(0.024)	(0.032)	(0.023)	(0.029)	(0.025)	(0.034)
Tp4	0.045	0.049	0.035	0.037	0.053*	0.055	0.045	0.043
	(0.024)	(0.031)	(0.025)	(0.036)	(0.025)	(0.034)	(0.026)	(0.042)
Tp5	0.108***	0.093**	0.097***	0.089*	0.110***	0.093*	0.100***	0.094*
	(0.026)	(0.034)	(0.028)	(0.040)	(0.027)	(0.037)	(0.029)	(0.046)

Notes: tm refers to "time minus" 1 and 2 years before PDs start production. tp refers to time period from 1 to 5 years after PDs start production. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Travel time

In addition to travel distance measures, I calculate travel time to PDs but limited to 1 to 2 hr travel time distances by car, using the OSRM command in Stata. Other travel times could be tested in the analysis, but the main purpose to explore these two new measures of travel distance is to explore again whether welfare decays with proximities to PDs. Although these two measures are linked (travel distance and travel time), this measures of travel time by car could be more effective than the previous measures (i.e., travel distance) since it could reflect more realistic the proximity to PDs, for instance, individuals living in districts located 1 or 2hr away from PDs would be more willing to commute to PDs for employment or business opportunities rather than those located farther away.

The results in Table 3.6 show positive and significant effects at 5% level on consumption on aggregate for both samples (all districts and only NPDs).[38] These results suggest that on average, there is a positive effect on consumption among districts located in close travel time of 1hr and 2hr to PDs in comparison to those located farther away. Some level of significance is also observed in the coefficients in columns 1 and 3 from the first year after PDs start production. This could be interpreted as the positive effect on consumption level among districts located in a proximity of 1hr of travel distance by car from PDs, than those located farther away (e.g., more than one hour of travel distance by car). The results seems to hold when the distance measure is extended to two hours (see coefficients in column 2 and 4) and are consistent during the second, up to the fifth year post start of production of PDs. For the case of NPDs, these results indicate that NPDs located in a proximity of 2hr travel distance from PDs have seen positive and significant effects on consumption at 10% level from the second up to the fourth year after PDs districts start production, being highly significant in the fifth year.[39]

[38]Results without covariates are shown in the Appendix.

[39]In the same table, standard errors increase the more the post years after PDs start production for all distant measures. This is similar to the previous analysis on travel distance, hence, the higher the window of exposure (e.g., six to ten years), the more likely will be to find higher standard errors, suggesting that sample is small for the analysis.

Table 3.6: Outputs for Travel Time

	All districts		Only NPDs	
	1h	2h	1h	2h
	(1)	(2)	(3)	(4)
Pre_avg	-0.025	0.007	-0.024	0.010
	(0.017)	(0.012)	(0.017)	(0.012)
Post_avg	0.072**	0.050**	0.071**	0.051**
	(0.026)	(0.018)	(0.026)	(0.019)
Tm2	-0.009	0.020	-0.009	0.021
	(0.027)	(0.019)	(0.027)	(0.019)
Tm1	-0.042	-0.006	-0.040	-0.000
	(0.025)	(0.018)	(0.025)	(0.019)
Tp0	0.037	0.016	0.036	0.019
	(0.024)	(0.018)	(0.025)	(0.018)
Tp1	0.056*	0.023	0.055*	0.027
	(0.026)	(0.020)	(0.027)	(0.021)
Tp2	0.077*	0.046*	0.077*	0.048*
	(0.034)	(0.023)	(0.034)	(0.024)
Tp3	0.058	0.052*	0.055	0.052*
	(0.033)	(0.023)	(0.033)	(0.024)
Tp4	0.076*	0.048*	0.075*	0.049
	(0.038)	(0.024)	(0.038)	(0.025)
Tp5	0.131**	0.114***	0.129**	0.113***
	(0.042)	(0.028)	(0.043)	(0.029)

Notes: tm refers to "time minus" 1 and 2 years before PDs start production. tp refers to time period from 1 to 5 years after PDs start production. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Effects by vehicle flow and density

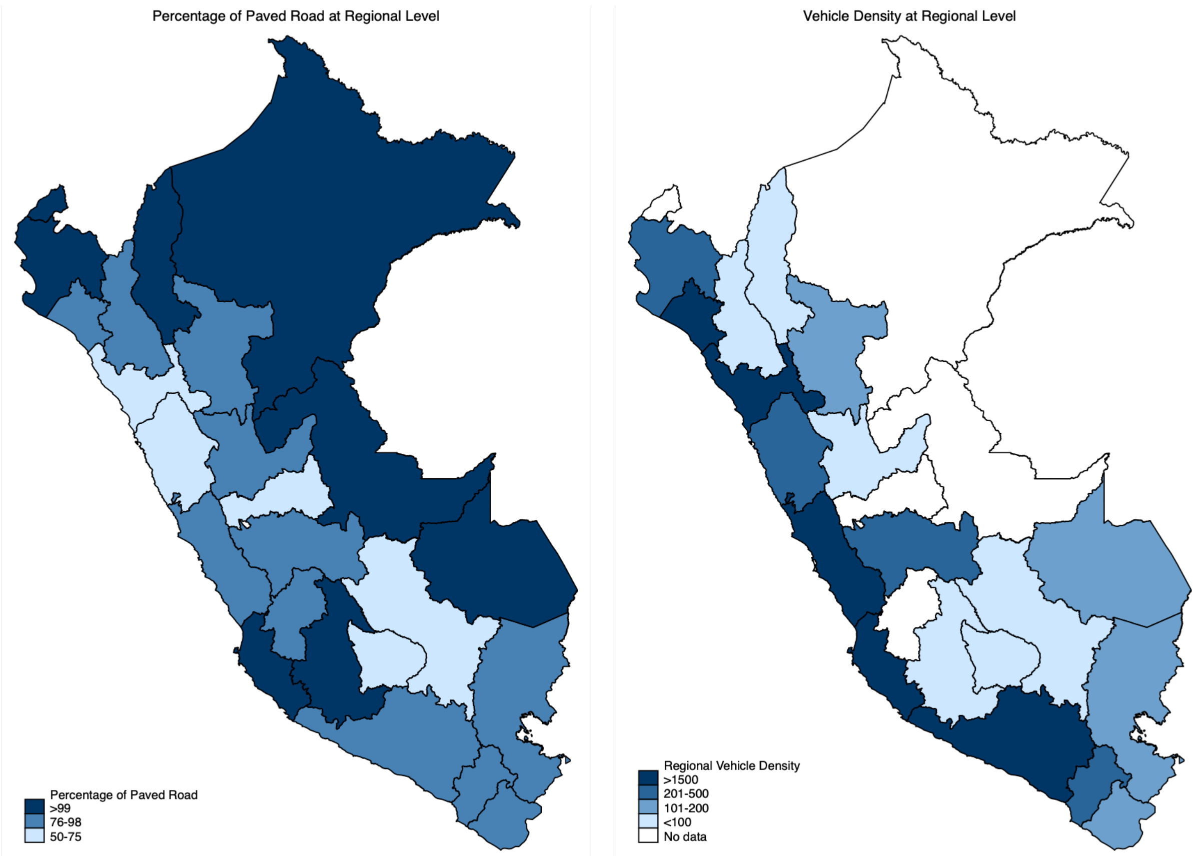
Following previous results in subsection 3.4.2, where effects on consumption levels among districts are more likely to be seen with shorter travel time distances, in this new subsection I explore whether these results hold considering vehicle flows and road infrastructure. These two factors play an important role in individuals' access to PDs and labour mobility across districts.

In Peru, roads are categorised as National, Regional and Local roads. The construction and maintenance of these are responsibly of the national and regional governments. Information on the state of National Roads is available via the Peruvian Ministry of Transport and Communications (MTC). I mainly focus in districts that are located in regions where the percentage of the National paved roads is lower than 100%.[40] As of 2016, the Peruvian MTC records that eight regions in the country have paved 100% of their national road networks. I mainly focus on regions where the percentage of paved national roads is below 100%. This is because, first, it is expected that regions with more than 99% of national paved roads will more likely have lower travel times among districts to PDs in comparison to regions with lower percentages of national paved road. However, districts that face restrictions in transport infrastructure such as lack of national paved roads would more likely to see higher travel times. The second reason to work wih a reduced sample of regions (<100% national paved roads) is related to the number of units available for the analysis. With a reduced number of regions, I obtained standard errors that increase in the event study set up using the CSDID approach (e.g., higher standard errors in time period 3, 4 and 5 post production). I use the Callaway et al. (2024) method to explore districts that fall within regions with <99% national paved road and use the same two thresholds (1hr and 2hr) for the analysis. For instance, I look at the effects on consumption levels among districts that are located within 1hr travel distance to PDs (treated group) and compare this group to districts located beyond 1hr travel distance to PDs (control group). The same applies for the 2hr travel distance threshold.

I also estimate the density of vehicle flow per length of national paved road at the regional level. In this test, I assume that regions with high density will have higher vehicle flow with respect to the length of the national paved road. The higher this density index, the more likely it is that individuals travel across districts (i.e., available

[40]Data on regional and local paved roads is not available.

transport), potentially suggesting more economic dynamism in comparison to regions with low density index. In Figure3.1b, most of the coastal regions located in the western areas of Peru host major capital cities and therefore are important population clusters with high levels of vehicle flows. With such clusters, then, this index could serve as a proxy to observe more congested areas, potentially, making travel times across districts higher in comparison to areas with lower vehicle density (i.e., proxy for congestion). In that sense, I cluster regions into four groups based on the median vehicular density and a fix threshold density of 1000 vehicles per lenght of paved road, this latter measure helps isolate the capital city of Lima in the analysis (with high density) as well as La Libertad region with same density as Lima. I use a POLS specification as per model 3.1.



(a) Percentage of National Paved Roads (b) Vehicle Density

Figure 3.1: Paved Roads and Vehicle Density at the Regional Level
Note: Paved roads are estimated only for the case of National Roads. Other roads such as Regional or Local roads are not included due to lack of data. Source: (a) Ministry of Transport and Communications (2016) (b) INEI (2024)

The results in Table 3.7 are based on 17 regions where the length of national paved roads is below 100%. The lack of a fully paved national road mean that districts would face limitations to connect to other districts within the same or other regions, making travel times to destinations longer and potentially restricting mobility across districts.

In Table 3.7, I test two thresholds for travel times of 1hr and 2hr. Districts are compared based on these travel times, for instance, in column 1, I compare districts that are located within 1hr travel time to PDs (treated group) against districts located more than 1hr to PDs (control group). The same logic applies for the second threshold of 2hr travel time distance. The sample is divided into two groups to explore the effects across districts (All districts, this includes PDs and NPDs, in columns 1 and 2) and only NPDs (columns 3 and 4).

On aggregate, the results for the pre-treatment years (that is, two years before PDs start production) present a negative and significant coefficient at 10% level for the first threshold of 1hr travel time in both samples (all districts and Only NPDs). These results could suggest that comparison groups are not similar before PDs start production. For instance, in column 1, consumption level among districts located within 1hr travel time to PDs are different to districts located more than 1hr travel time to PDs, this difference in consumption levels is significant at a 10% level. However, for the case of the second threshold of 2hr, there are no significant differences across comparison groups for both samples (columns 2 and 4) before PDs starts. The average treatment effect for post production years is positive and significant for both samples at a 5% (column 2) and 10%level (column 4), suggesting that on average, there are positive effects on consumption levels across districts located within 2hr travel distance to PDs.

The results in Table 3.7 also suggest positive and significant effects in consumption levels across districts located within 2hr travel time to PDs in the second, fourth and fifth year after PDs start production. This is also the case when the sample is reduce to NPDs, meaning that these latter districts located within 2hr travel time to PDs see positive effects in consumption levels in the mid and long term in comparison to NPDs located 2hr away from PDs.

Overall, these results suggest that, on average, districts located within regions where national roads are not fully paved and where these are located within 2hr travel time proximity to PDs should see a positive effects on their consumption levels in the mid and long term, in comparison to those located farther away than 2hr travel time to PDs. This means that, although some of these districts might face limitations in terms of access to a fully paved national road, these still see positive effects in their consumption levels after

PDs starts production.

Table 3.7: Outputs for Length of Paved Road

	All districts		Only NPDs	
	1h	2h	1h	2h
	(1)	(2)	(3)	(4)
Pre_avg	-0.040*	-0.003	-0.040*	-0.002
	(0.018)	(0.013)	(0.018)	(0.013)
Post_avg	0.074**	0.058**	0.079**	0.052*
	(0.028)	(0.020)	(0.028)	(0.021)
Tm2	-0.016	0.011	-0.016	0.012
	(0.029)	(0.022)	(0.029)	(0.022)
Tm1	-0.065*	-0.016	-0.064*	-0.015
	(0.026)	(0.020)	(0.026)	(0.021)
Tp0	0.037	0.027	0.039	0.025
	(0.026)	(0.019)	(0.025)	(0.020)
Tp1	0.066*	0.032	0.068**	0.028
	(0.027)	(0.021)	(0.026)	(0.022)
Tp2	0.078*	0.060*	0.082*	0.057*
	(0.038)	(0.026)	(0.038)	(0.026)
Tp3	0.056	0.051	0.062	0.045
	(0.037)	(0.027)	(0.037)	(0.028)
Tp4	0.077*	0.055*	0.083*	0.050
	(0.039)	(0.027)	(0.039)	(0.028)
Tp5	0.132**	0.121***	0.141**	0.108**
	(0.044)	(0.032)	(0.044)	(0.033)
N	9,253	7,597	10,151	6,699

Notes: tm refers to "time minus" 1 and 2 years before PDs start production. tp refers to time period from 1 to 5 years after PDs start production. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

In Table 3.8, I compare four groups of regions based on their vehicular density. For the case of Group 1[41] and 3, the difference in consumption levels among PDs and NPDs is positive but lack significance. The effects of distance decay among districts (proximity to PDs) is negative and significant at a 10% level and 1% level, in group 1 and 3, respectively. There is also drop in consumption levels from 13.1% to 18.3% among districts when its travel distance to PDs increase in 1 S.D (S.D. 261.51 km). This means that more congested areas with "high vehicular densities" (e.g, above median density) will see significant differences in consumption levels the more the travel distance in km is from

[41] Contains the regions of Lima and La Libertad.

districts to PDs.

The coefficients for Group 2 and 4 show differences in consumption levels among PDs and NPDs of 17.5% and 24.6%, respectively, these differences are significant at 1% level. The effect of travel distance on consumption in Group 2 aligns with previous results observed in Groups 1 and 3, where a 1 SD increase in travel distance to a PDs is linked with a decline in consumption levels up to 10.5%.

The coefficient for travel distance in column 4 are different to previous estimates, with a positive and significant value at 5% level. This suggests that in areas characterised by lower vehicular density, greater distance from a PDs is associated with higher consumption levels. Specifically, a 1 SD increase in travel distance from a PDs corresponds to an increase in consumption levels of 2.6%. This result implies that in less congested or accessible areas (e.g., due to lack of full paved road), remoteness from PDs may not necessarily hinder economic activity and could, in some cases, be linked to higher consumption levels in comparison to districts located in close proximity to PDs. For the case of Group 4, districts that are not in close proximity show no evidence of distance decay effect, these results suggest that these districts might rely on other important economic activities that could be more profitable than the mining sector among regions that are not very well connected.

Table 3.8: Vehicular Density by Groups

	Group 1	Group 2	Group 3	Group 4
	D > 1000	D < 1000	D > Median	D < Median
	(1)	(2)	(3)	(4)
Producing	0.057	0.175***	0.053	0.246***
	(0.060)	(0.050)	(0.054)	(0.082)
Distance	-0.0005*	-0.0004***	-0.0007***	0.0001**
	(0.0003)	(0.0000)	(0.0001)	(0.0001)
Constant	5.433***	5.134***	5.264***	4.734***
	(0.130)	(0.051)	(0.065)	(0.069)
Observations	1,510	13,202	6,832	7,880
R-squared	0.669	0.637	0.645	0.586
Demographic controls	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Robustness Checks

I test two aggregated variables at the district level, log income (measured as the monthly average income per capita at the district level in USD deflated to 2021 values) and real expenditure (also measured at the district level in USD and deflated to 2021 values) on two travel time distances of 1hr and 2 hr using the CSDID approach. I compare travel time distances that are below (treated group) and above (control group) the given measure (this could be 1hr or 2hr travel time distance threshold). I also work with the same window of years prior and post treatment, the latter being linked to the year in which PD start production.

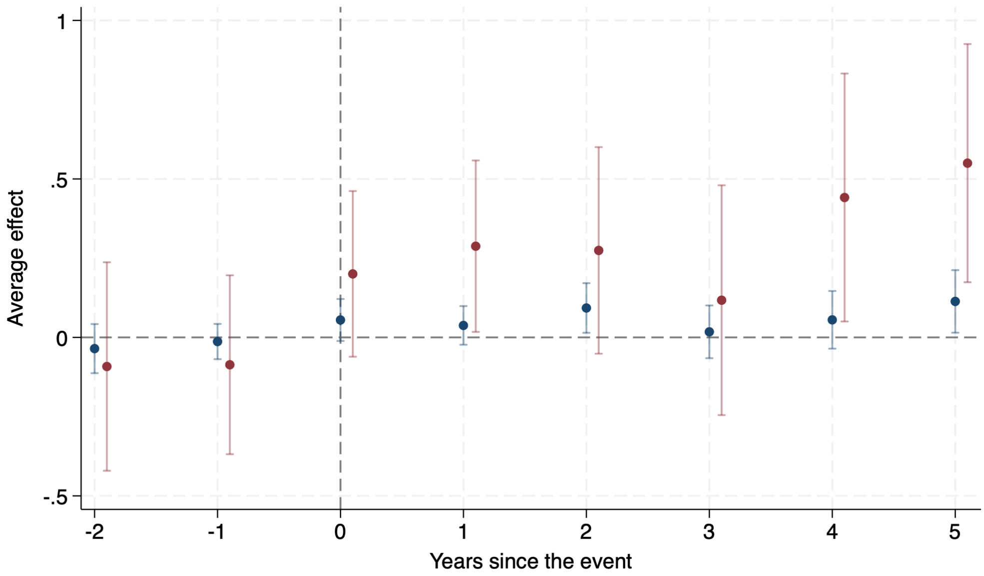
The figures below present the coefficients (as dots) and confidence intervals for the two variables of interest, log income in blue and real expenditure in red.[42] Figure 3.2 present the outputs for 1hr and 2hr travel time distance threshold. These results follow a similar pattern to previous outputs on consumption levels, where the majority of effects are positive and significant towards the fifth year post PDs start production (see Appendix 3.17). Also, most of the aggregated effects are positive and significant at a 10% level on income for the 2hr and 1hr travel time threshold and at a 5% level on real expenditure for 1hr threshold (see Appendix 3.17)[43]. These results suggest that, on aggregate, districts that are below 1hr and 2 hr travel time distance by car to PDs have seen positive effects on their income levels in comparison to districts located 1hr and 2 hr farther away to PDs. Also, districts that are in close proximities to PDs (i.e., 1hr travel time distance to PD), have seen their real expenditure increase (results significant at 5% level) in comparison to districts located 1hr away in travel distance to PDs. The closer is the travel time distance from districts to PDs, the more likely to see that both income and real expenditure to increase in the former group.

There are some positive effects (at 10% significance level) on income in the second year after PD start production, among districts located in 2hr and 1hr travel time to PD (see confidence intervals in blue in Figure 3.2a and Figure 3.2b). There are also some positive effects on real expenditure after PD start production (at a 10% significance level), this specially for the case of districts located in close proximity to PD (1hr travel time

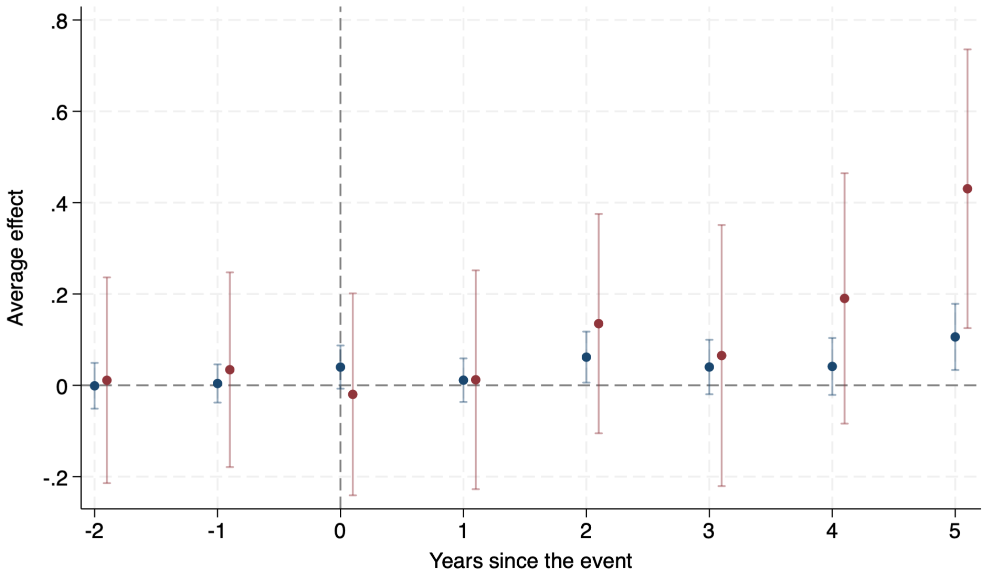
[42] Although confidence intervals are wider for real expenditure, suggesting more uncertainty in their estimates than for the case of income, the evidence suggest a similar trend in terms of results being positive and significant after four or five years post PDs start production

[43] There are no significant effects on real expenditure for the 2hr travel time threshold.

distance), since there are positive effects on real expenditure among districts located 1hr travel time to PD after the first and fourth year after PD start production (see confidence intervals in red in Figure 3.2a). The effects are more significant (5% level) during the fifth year post PD start production for the case of both variables at 1hr and 2hr travel time distances. Overall, these results suggest, on aggregate, some positive effects on income and real expenditure, and more likely to occur in the short term in the real expenditure of districts located within 1hr travel time distance to PD. District located 1hr or 2hr away from PD share in common a positive effect after five years after PD starts production, suggesting more positive effects in the long-run than in the short-run.



(a) ATT by Periods for 1hr Travel Distance for Log Income (confidence intervals in blue) and Real Expenditure (confidence intervals in red).



(b) ATT by Periods for 2hr Travel Distance for Log Income (confidence intervals in blue) and Real expenditure (confidence intervals in red).

Figure 3.2: ATET for Log Income and Real Expenditure for 1hr and 2hr Travel Distance

I also analyse the effects of distances to PDs on income and real expenditure, similarly to subsection 3.4.2 I divide the sample into four groups where the first two host regions with a vehicular density above and below 1000 vehicle per kilometre of national paved road (Group 1: $D > 1000$; Group 2: $D < 1000$). This threshold helps to observe the effects in regions with high levels of vehicle flow per length of national paved road (e.g., capital city Lima with a regional vehicle density of c. 1400 vehicles per km of national paved road). The second threshold is related to the median, the sample is split between regions that have a vehicular density above (more congested areas) and below (less congested areas) the median vehicular density.

The results for Group 2 in Table 3.9 suggest a distance decay effect for income and real expenditure in all regions but Lima and La Libertad, since for each increase in travel distance to PD in 1 SD (261.51KM), the levels of income and real expenditure decay from 15.7% up to 54.9%, respectively (both are statistically significant at 5% level). More congested areas where the vehicular density is above the regional median, the differences in income and real expenditure among districts that are closer and farther away is significant. For instance, for an increase in 1 SD in travel distance to PDs, income levels decrease 20.9% and real expenditure up to 96.8% (both are statistically significant at 1% level). Although these regions have more connectivity (due to available length of paved road) and vehicle availability (due to high vehicle flow), these results seem to suggest less economic spillovers, and effects to be highly agglomerated to PDs. For less congested areas (where the regional vehicular density is below the median), there are some positive effects on real expenditure (at 10% statistical significance),[44] suggesting that with increase travel distance (in terms of SD), the real expenditure increase up to 18.3%. This result means that the more the travel distance to PDs, the more likely to see districts with higher real expenditure than those located in close proximity. This results is similar to the one found in subsection 3.4.2 on consumption, where I argue that not being closer to a PDs might actually not hinder economic activity, but make districts to profit from other relevant economic sectors different from the mining sector.

[44]The effects on income are positive but lack statistically significance.

Table 3.9: Log Income and Real Expenditure by Groups

	Log Income				Real Expenditure			
	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
	$D > 1000$	$D < 1000$	$D > Median$	$D < Median$	$D > 1000$	$D < 1000$	$D > Median$	$D < Median$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Producing	0.115*	0.225***	0.091	0.320***	0.116	1.127***	0.430	1.162**
	(0.065)	(0.070)	(0.072)	(0.112)	(0.293)	(0.417)	(0.462)	(0.518)
Distance	-0.0004	-0.0006***	-0.0008***	0.0000	-0.0029*	-0.0021***	-0.0037***	0.0007*
	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0016)	(0.0003)	(0.0003)	(0.0003)
Constant	5.583***	5.425***	5.616***	4.919***	3.942***	3.360***	3.456***	1.836***
	(0.158)	(0.063)	(0.082)	(0.079)	(0.640)	(0.278)	(0.389)	(0.331)
Observations	1,510	13,202	6,832	7,880	1,510	13,202	6,832	7,880
R-squared	0.634	0.613	0.599	0.575	0.463	0.405	0.377	0.382
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.5 Conclusion

The first set of results using the POLS model suggest that PDs have higher consumption levels than NPD during the period of analysis 2001 to 2019. This difference in welfare between PDs and NPDs is consistent with both linear and travel distances, with differences in consumption levels ranging from 13.1% (static travel distance) to 18.7% (dynamic linear distance). However, the difference between PDs and NPDs seem slightly higher when using linear than travel distances. For instance, the difference in consumption levels between PDs and NPDs using the static approach is 13.6% for linear and 13.1% for travel distances.

The POLS results also reveals distance decay effects on welfare, where consumption levels are lower among NPDs that are farther away from PDs. Also, the drop in consumption levels seem to be higher when using travel distances rather than linear distances. An increase in one standard deviation in the linear and travel distances is linked to a drop in welfare from 4.8% up to 7.8%, respectively.

The outputs of the double difference approach suggest that, on aggregate, district's welfare decay with distance to PDs (that is, distance from NPDs to PDs and PDs to PDs) but these results are not as significant as when the sample is reduced to account for only NPDs, where on aggregate distance decay effects on welfare are significant at 5% level for 50km linear distance. That is, NPDs that are 50km in linear distance to PDs have shown that, on aggregate, their welfare levels increase during the period of analysis. The level of significance is lower when the linear measure is 100km or mean or median, suggesting distance decay effects on welfare. When looking at the effects in time, the results of the CSDID approach suggest that effects on welfare are more likely to be effective among NPDs located within 50km proximity to PDs, from the fourth year after PDs start production. [45] However, when using travel distances in the analysis, on aggregate there are some positive effects on welfare for the mean, median and 100 km measures but not for 50km travel distance measure, suggesting that distance decay effects on welfare are visible from higher thresholds, such as NPDs that are located within 100 km travel distance to PDs, as well as for NPDs located within the mean travel distance to PDs. There are no effects on aggregate for NPD located within 50km travel distance

[45] Some effects are evident from the second year after PD start production but these are only significant at 10%

to PDs. Therefore, the measure used in the analysis will help to understand how deep are the effects of mining activities on welfare. Whilst the linear distance seem to present more localised effects on welfare (e.g., positive effects on welfare within 50 km distance to PDs), using travel distances might suggest that the extent of effects in space are higher and up to 100 km, although not as significant as when using linear distances. When using travel time, distance decay effects on welfare are visible among NPDs in close travel time proximity to PDs, where, on aggregate, effects are positive and significant at 5% level. For the case of NPDs located in 1hr travel time proximity, effects on welfare are positive and significant at 10% from the first year after PDs start production.

I also consider the availability of road infrastructure, and evaluate whether the lack of access to a fully paved road is a constraint to connect among districts, and potentially having an impact in the mobility of individuals across districts. I find that in regions with lack of fully paved roads, welfare effects are only significant at 10% for 2hr travel time distances. The results are also highly significant in the fifth year after PDs start production. These results suggest that effects on welfare might be highly localised to PDs when districts belong to regions that lack access to fully paved roads and some effects on welfare might be visible among NPD located within 2hr travel time by car to PDs.

In areas of high vehicular density, there is a lack of significant difference between PDs and NPDs consumption levels, which could be in line to the high economic dynamism of other sectors rather that mining. This difference in welfare between PD and NPD is more noticeable in areas of low vehicle density, which suggest that, in more remote areas where districts have less available transports (i.e., less vehicle density), there seems to be a difference in consumption levels among PDs and NPDs. In areas where the vehicular density is below the median density, the results suggest that welfare levels do not decay, but improve with distance, meaning that remoteness from PDs in areas of low vehicle density might rely on other profitable economic activities that compete with the mining sector.

Overall, the difference in welfare levels between PDs and NPDs is confirmed with these results during the period of analysis. This also suggest that the main benefits from mining development are highly localised to PDs. There is a difference in welfare when using linear and travel distance in the analysis which would over-or-under-estimate effects in welfare among districts (PDs and NPDs) that are in proximity to PDs. However, the second of these measures seems to more accurately reflect individuals' efforts to move between PDs and NPDs. Although geography may constrain labour mobility, the benefits of living or working in the host area often outweigh the associated travel costs.

The results of the DiD approach confirm distance decay effects on welfare, which have several implication for the spatial distribution of labour and firms. For instance, distance decay effects in welfare could be linked to differences in the availability of high skilled and low skilled workers between host and neighbouring areas (e.g., see Greenstone et al. (2010)). This also has implications on the differences in firms and industrial specialisation (e.g., see Evans & Harrigan (2005)), as well as in firm's decision to settle in PDs or neighbouring areas, in order to attend the demand that derives from related mining activities (e.g., see Giroud et al. (2022) on the case of HQ and subsidiaries). However, in some instances where there is lack of significant effects (such as when using travel distances), it might be the case that, on aggregate, the net effect is insignificant where improvements in some areas are cancel out due to poor performance in other neighbouring areas to PD. That is, benefits among PDs or some NPDs in close proximity to NPDs, come at the expense of decline of welfare in other areas that source labour and firms to the host area (PDs). In other instances, where there is evidence of improvement on welfare in time, it could be the case that these neighbouring areas or NPD convert into long term destinations to newcomers and firms, changing the socioeconomic landscape of these areas (e.g., see Kline & Moretti (2014). Other relevant explanation might be related to the change in nature of the activity, where more tasks or non core mining activities could be performed in locations farther away from the PDs or NPDs in close proximities, thus, mining activities have had a null impact in these areas during the period of analysis. It might be also the case that longer travel distances and travel times act as a disincentive to individuals to mobilise to PD, therefore, changes in welfare might be constraint to districts in close travel distance and time to PDs. Similarly, the lack of road infrastructure or vehicular availability for transportation might deepen the differences in welfare among PD and NPD.

The findings of this paper could serve for the implementation of regional or local mining policies looking to improve welfare levels among NPDs. One of these policies could be that NPDs serves as a long-term destination for the mining workforce. The changing nature of the mining sector demands some activities to be outsourced, where these could be performed from NPDs within the province or region where the main development occurs. Similarly, firms settled within NPDs could enter into a loan system and training (e.g., diversification, resilience to economic shocks), with the aim to keep these alive throughout the mine's lifetime. Investment in road infrastructure is also necessary to provide more access to individuals and firms to districts in close proximity to PDs. This will reduce the welfare gap between PDs and NPDs and give more opportunities to individuals to thrive in other economic sectors.

3.6 Appendix

Table 3.10: Linear distance - static

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	FE	RE
producing	0.277***	0.269***	0.270***	0.209***	0.197***	0.137***	0.136***	0.114***	0.176***
	(0.051)	(0.051)	(0.051)	(0.041)	(0.036)	(0.032)	(0.032)	(0.031)	(0.031)
distance		-0.000	-0.000	-0.000*	0.000***	-0.000***	-0.000***	-0.001***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pgender			0.009	-0.274***	-0.259***	-0.153***	-0.153***	-0.204***	0.036
			(0.082)	(0.074)	(0.070)	(0.054)	(0.054)	(0.038)	(0.042)
purban				0.626***	0.602***	0.532***	0.533***	0.319***	0.352***
				(0.020)	(0.019)	(0.019)	(0.019)	(0.014)	(0.010)
ppmhh					-0.182***	-0.118***	-0.118***	-0.089***	-0.188***
					(0.006)	(0.005)	(0.005)	(0.003)	(0.003)
altitude						-0.000***	-0.000***	-0.000***	-0.000***
						(0.000)	(0.000)	(0.000)	(0.000)
surface							0.000	-0.000	0.000
							(0.000)	(0.000)	(0.000)
Constant	4.620***	4.630***	4.626***	4.524***	5.360***	5.035***	5.035***	4.964***	5.715***
	(0.012)	(0.015)	(0.041)	(0.039)	(0.044)	(0.043)	(0.043)	(0.033)	(0.030)
Observations	16,885	16,868	16,868	16,868	16,868	16,868	16,868	16,868	17,630
R-squared	0.015	0.015	0.015	0.257	0.378	0.636	0.636		
Demographic controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes	Yes	Yes	No
District FE	No	No	No	No	No	No	No	Yes	No
R-sq Within								0.627	0.222
R-sq Between								0.593	0.567
R-sq Overall								0.608	0.479

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.11: Linear distance - Dynamic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	FE	RE
producing	0.356***	0.328***	0.328***	0.246***	0.236***	0.185***	0.187***	0.064***	0.068***
	(0.055)	(0.056)	(0.056)	(0.049)	(0.044)	(0.036)	(0.037)	(0.020)	(0.023)
distance		-0.000***	-0.000***	-0.000***	0.000	-0.000***	-0.000***	-0.000***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pgender			-0.041	-0.340***	-0.326***	-0.151***	-0.152***	-0.205***	0.003
			(0.081)	(0.073)	(0.069)	(0.054)	(0.054)	(0.038)	(0.041)
purban				0.629***	0.602***	0.534***	0.533***	0.322***	0.344***
				(0.020)	(0.019)	(0.019)	(0.019)	(0.014)	(0.009)
ppmhh					-0.173***	-0.119***	-0.118***	-0.089***	-0.172***
					(0.006)	(0.005)	(0.005)	(0.003)	(0.003)
altitude						-0.000***	-0.000***	-0.000***	-0.000***
						(0.000)	(0.000)	(0.000)	(0.000)
surface							-0.000	-0.000*	0.000***
							(0.000)	(0.000)	(0.000)
Constant	4.623***	4.668***	4.688***	4.600***	5.373***	5.085***	5.084***	4.987***	5.922***
	(0.012)	(0.018)	(0.042)	(0.039)	(0.044)	(0.044)	(0.044)	(0.034)	(0.029)
Observations	16,885	16,868	16,868	16,868	16,868	16,868	16,868	16,868	17,630
R-squared	0.015	0.021	0.021	0.264	0.373	0.638	0.638		
Demographic controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes	Yes	Yes	No
District FE	No	No	No	No	No	No	No	Yes	No
R-sq Within								0.627	0.279
R-sq Between								0.597	0.527
R-sq Overall								0.608	0.457

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.12: Travel distance - Static

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	FE	RE
producing	0.277***	0.260***	0.260***	0.203***	0.191***	0.132***	0.131***	0.109***	0.171***
	(0.051)	(0.052)	(0.052)	(0.041)	(0.037)	(0.032)	(0.032)	(0.031)	(0.031)
distance		-0.000*	-0.000*	-0.000**	0.000***	-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pgender			-0.005	-0.280***	-0.266***	-0.159***	-0.159***	-0.203***	0.036
			(0.082)	(0.074)	(0.070)	(0.054)	(0.054)	(0.038)	(0.042)
purban				0.625***	0.604***	0.530***	0.530***	0.318***	0.349***
				(0.020)	(0.019)	(0.019)	(0.019)	(0.014)	(0.010)
ppmhh					-0.181***	-0.117***	-0.118***	-0.088***	-0.188***
					(0.006)	(0.005)	(0.005)	(0.003)	(0.003)
altitude						-0.000***	-0.000***	-0.000***	-0.000***
						(0.000)	(0.000)	(0.000)	(0.000)
surface							0.000	-0.000	0.000
							(0.000)	(0.000)	(0.000)
Constant	4.620***	4.635***	4.637***	4.528***	5.361***	5.038***	5.038***	4.967***	5.723***
	(0.012)	(0.015)	(0.041)	(0.039)	(0.044)	(0.043)	(0.043)	(0.033)	(0.030)
Observations	16,885	16,811	16,811	16,811	16,811	16,811	16,811	16,811	17,573
R-squared	0.015	0.015	0.015	0.256	0.376	0.636	0.636		
Demographic controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes	Yes	Yes	No
District FE	No	No	No	No	No	No	No	Yes	No
R-sq Within								0.628	0.222
R-sq Between								0.596	0.569
R-sq Overall								0.609	0.481

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.13: Travel distance - Dynamic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	FE	RE
producing	0.356***	0.308***	0.308***	0.236***	0.226***	0.175***	0.174***	0.056***	0.067***
	(0.055)	(0.057)	(0.057)	(0.050)	(0.045)	(0.037)	(0.038)	(0.019)	(0.023)
distance		-0.000***	-0.000***	-0.000***	0.000	-0.000***	-0.000***	-0.000***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pgender			-0.079	-0.355***	-0.333***	-0.168***	-0.168***	-0.205***	0.000
			(0.081)	(0.073)	(0.070)	(0.053)	(0.053)	(0.038)	(0.041)
purban				0.624***	0.603***	0.526***	0.527***	0.320***	0.337***
				(0.020)	(0.019)	(0.019)	(0.019)	(0.014)	(0.010)
ppmhh					-0.172***	-0.114***	-0.115***	-0.088***	-0.174***
					(0.006)	(0.005)	(0.005)	(0.003)	(0.003)
altitude						-0.000***	-0.000***	-0.000***	-0.000***
						(0.000)	(0.000)	(0.000)	(0.000)
surface							0.000	-0.000	0.000***
							(0.000)	(0.000)	(0.000)
Constant	4.623***	4.682***	4.721***	4.612***	5.379***	5.087***	5.087***	5.014***	5.925***
	(0.012)	(0.017)	(0.042)	(0.039)	(0.044)	(0.044)	(0.044)	(0.034)	(0.029)
Observations	16,885	16,811	16,811	16,811	16,811	16,811	16,811	16,811	17,573
R-squared	0.015	0.025	0.025	0.265	0.372	0.642	0.642		
Demographic controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes	Yes	Yes	No
District FE	No	No	No	No	No	No	No	Yes	No
R-sq Within								0.627	0.272
R-sq Between								0.608	0.537
R-sq Overall								0.614	0.461

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.14: Outputs for linear distances - no covariates

	Mean	Median	100 km	50 km
Pre_avg	0.00885	-0.00221	0.0108	0.00423
	(0.0102)	(0.0126)	(0.00989)	(0.0109)
Post_avg	0.0376*	0.0439*	0.0352*	0.0402*
	(0.0171)	(0.0216)	(0.0171)	(0.0185)
Tm2	0.0369*	0.0254	0.0482**	0.0236
	(0.0178)	(0.0226)	(0.0169)	(0.0197)
Tm1	-0.0192	-0.0298	-0.0267	-0.0152
	(0.0166)	(0.0206)	(0.0160)	(0.0178)
Tp0	0.00997	0.0270	0.0108	0.0149
	(0.0155)	(0.0182)	(0.0148)	(0.0162)
Tp1	0.0159	0.0266	0.0168	0.0221
	(0.0167)	(0.0189)	(0.0169)	(0.0170)
Tp2	0.0277	0.0347	0.0154	0.0324
	(0.0201)	(0.0248)	(0.0202)	(0.0217)
Tp3	0.0236	0.0303	0.0242	0.0358
	(0.0228)	(0.0289)	(0.0220)	(0.0249)
Tp4	0.0492*	0.0529	0.0379	0.0524
	(0.0241)	(0.0321)	(0.0240)	(0.0272)
Tp5	0.0994***	0.0918*	0.106***	0.0833**
	(0.0274)	(0.0357)	(0.0278)	(0.0306)

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.15: Outputs Travel Distance - No Covariates

Variable	Mean	Median	100 km	50 km
Pre_avg	-0.00390	-0.0157	-0.00334	-0.0174
	(0.0103)	(0.0132)	(0.0108)	(0.0158)
Post_avg	0.0431*	0.0437*	0.0305	0.0360
	(0.0172)	(0.0221)	(0.0184)	(0.0258)
Tm2	0.0139	-0.00184	0.0136	0.00497
	(0.0176)	(0.0212)	(0.0187)	(0.0249)
Tm1	-0.0217	-0.0296	-0.0203	-0.0398
	(0.0165)	(0.0199)	(0.0173)	(0.0238)
Tp0	0.0130	0.0260	0.0101	0.0335
	(0.0160)	(0.0191)	(0.0170)	(0.0226)
Tp1	0.0173	0.0284	0.00822	0.0279
	(0.0177)	(0.0218)	(0.0186)	(0.0247)
Tp2	0.0340	0.0347	0.0273	0.0298
	(0.0210)	(0.0276)	(0.0228)	(0.0330)
Tp3	0.0372	0.0362	0.0168	0.0202
	(0.0227)	(0.0286)	(0.0244)	(0.0338)
Tp4	0.0476*	0.0494	0.0339	0.0301
	(0.0237)	(0.0316)	(0.0257)	(0.0385)
Tp5	0.109***	0.0876*	0.0866**	0.0745
	(0.0266)	(0.0350)	(0.0283)	(0.0421)

Notes: Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.16: Outputs Travel Time - No Covariates

Variable	1h	2h
Pre_avg	-0.0408*	-0.00169
	(0.0173)	(0.0115)
Post_avg	0.0768**	0.0441*
	(0.0280)	(0.0185)
Tm2	-0.0220	0.0146
	(0.0277)	(0.0198)
Tm1	-0.0596*	-0.0180
	(0.0249)	(0.0182)
Tp0	0.0364	0.0136
	(0.0244)	(0.0174)
Tp1	0.0571*	0.0159
	(0.0267)	(0.0194)
Tp2	0.0828*	0.0419
	(0.0358)	(0.0233)
Tp3	0.0613	0.0449
	(0.0354)	(0.0245)
Tp4	0.0861*	0.0452
	(0.0405)	(0.0251)
Tp5	0.137**	0.103***
	(0.0458)	(0.0297)

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.17: Log Income and Real Expenditure Over Time

	2 Hours		1 Hour	
	Log Income (1)	Real Expenditure (2)	Log Income (3)	Real Expenditure (4)
Pre_avg	0.001	0.023	-0.024	-0.089
	(0.014)	(0.061)	(0.021)	(0.083)
Post_avg	0.050*	0.136	0.062*	0.312**
	(0.022)	(0.100)	(0.028)	(0.116)
Tm2	-0.001	0.011	-0.035	-0.092
	(0.026)	(0.115)	(0.040)	(0.168)
Tm1	0.004	0.034	-0.013	-0.086
	(0.021)	(0.109)	(0.028)	(0.144)
Tp0	0.040	-0.020	0.055	0.200
	(0.024)	(0.113)	(0.034)	(0.133)
Tp1	0.011	0.012	0.038	0.288*
	(0.024)	(0.122)	(0.031)	(0.138)
Tp2	0.062*	0.135	0.093*	0.274
	(0.029)	(0.123)	(0.040)	(0.166)
Tp3	0.040	0.065	0.018	0.117
	(0.030)	(0.146)	(0.042)	(0.185)
Tp4	0.041	0.190	0.055	0.441*
	(0.032)	(0.140)	(0.046)	(0.200)
Tp5	0.106**	0.430**	0.114*	0.550**
	(0.037)	(0.156)	(0.050)	(0.192)
N	9,479	9,479	12,706	12,706

Notes: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Chapter 4

The Labour Market Effects of Mining: Wages, Employment, and Informality in Peru

4.1 Introduction

This chapter examines the impact of the mining sector on wages, employment, and occupational structure in Peru during the period 2001-2019. The motivation for this study stems from the substantial expansion of the Peruvian mining sector over the past two decades, driven by rising global prices for key minerals such as copper, gold, and silver (Ministerio de Energia y Minas 2023). As a resource-rich country with the infrastructure and labour capacity to exploit these resources, Peru experienced a surge in mining investment (Ministerio de Energia y Minas 2023), leading to labour demand shocks in local markets and potentially altering wage structures and employment patterns (Marchand 2012). Thus, this chapter aim to address the following research questions: What are the aggregate effects of mining activity on the employment share? and how does mining influence wages and occupational outcomes? The analysis is based on district-level panel data from 2001 to 2019, sourced from the Peruvian National Institute of Statistics (INEI). Given that external shocks in the mining sector can generate cyclical fluctuations in activity, it is important to account for both boom and bust periods when assessing long-term labour market effects. Rather than focusing solely on average impacts over the full period (2001–2019), this paper also examines whether the effects of mining differ across phases of the commodity cycle. I distinguish between boom years (2001–2012) and bust years (2013 onward), based on established empirical evidence on mining cycles in Peru. This leads to the third core research question: How do the effects of mining on wages, employment, and occupational structure vary between boom and bust periods?. The motivation for this disaggregated approach lies in the potential heterogeneity of mining's labour market effects over time.

In addition to analysing formal labour market outcomes, I also examine the dynamics of the informal sector, which plays a central role in the Peruvian economy and in many emerging Latin American countries (De Paula & Scheinkman 2010). Informality is particularly relevant for small firms, which may choose to operate outside the formal system to avoid regulatory costs or during downturns when formal employment contracts are scarce. Some scholars argue that informality acts as a safety net during economic contractions (Loayza & Rigolini 2011), while others view it as a form of implicit subsidy, as informal firms often avoid paying local taxes and social contributions (Meghir et al. 2015). Despite these perceived advantages, informal employment is typically associated with significant disadvantages, including the absence of labour protections, health insurance, and pension coverage (Bacchetta et al. 2009). Nevertheless, informality remains widespread, and many workers transition repeatedly between formal and informal jobs, often due to short-term contracts or unstable employment, highlighting its role in sustaining household income in the absence of consistent formal opportunities (Bacchetta et al. 2009). Given the magnitude of the informal sector, which accounts for over 80% of total employment on average in my sample, I ask: How has the informal labour market responded to the expansion of mining activities in Peru over the past two decades?

This research adopts the theoretical framework developed by Allcott & Keniston (2018), which models the dynamic local impacts of resource shocks on wages, employment, and productivity. Their model yields four key predictions. Predictions 1 and 2 describe the short-term effects during a boom, namely, that wages and employment rise in response to the local economic shocks. These effects are procyclical to the resource extraction, and may reverse during busts. The wage increase attracts migrants, raising the local population, even though the model assumes imperfect labour mobility. However, the extent of wage increases is moderated by the level of migration, that is, the more elastic migration is, the smaller the wage increase.[1] Allcott & Keniston (2018) also argues that the boom simultaneously raises employment in the local non-tradable sector (e.g., housing, food, and services) due to increased demand. Predictions 3 and 4 concern long-term productivity and welfare outcomes. In the absence of productivity spillovers, the two counties return to parity after the boom, with equal wages, population, and productivity and the boom unambiguously increases cumulative welfare. However, if productivity spillovers exist through learning-by-doing or agglomeration effects, then, productivity in the local sector increases, while the direction and magnitude of effects on the tradable sector will depend on the relative strength of agglomeration versus learning-by-doing spillovers. Although the third and fourth predictions are not tested in this chapter, they are important to understand the potential long-run productivity and welfare consequences of resource booms.

I use a quantitative approach to address the above research questions on the Peruvian labour market. For the analysis on aggregated results, I use a Pooled Ordinary Least Squared (POLS) model. This is then slightly adapted to explore the spatial heterogeneity on NPD by including a travel time variable in the model. Then, in order to explore effects of the mining sector by periods of boom and bust, I use a triple difference approach, following Olden & Møen (2022) and using the same set of outcome and control variables. In order to test for parallel trends, I work with an event study specification following Sun & Abraham (2020) and Callaway & Sant'Anna (2021). This allows me to assess the pre-treatment dynamics of treated and control groups. Specifically, I include two pre-treatment periods and five post-treatment periods in the specification.[2]

This paper makes three main contributions. First, it is one the first papers to examine the Peruvian labour market including informality considering an extended period of analysis. A second contribution is related to the spatial spillovers of mining activities on NPDs. Using fixed travel time distances between districts and NPDs, I test whether

[1] The model also predicts that the tradable sector (e.g., manufacturing) is crowded out during a boom due to rising wages that increase production costs. Yet this effect depends on the degree to which goods are traded externally or locally. If goods are primarily exported, manufacturers face higher input costs but cannot adjust prices, leading to crowding-out effects. In contrast, if goods are sold locally, price increases are possible due to higher local purchasing power, which may result in crowding-in effects for the tradable sector.

[2] The main assumption is that both comparison units (e.g., PDs and NPDs) do not show different trends before treatment starts. The no anticipation assumption is comply by default due to the exogenous timing of mining operations, which depends on factors such as international commodity prices and firm-level decisions.

proximity to PDs influences wages, employment, and occupational composition in NPDs. This measure also works as a proxy to determine the role of NPDs such as whether they host commuting or subcontracted workers connected to the mining sector. This approach build on empirical evidence such as Tano et al. (2016) who finds negligible effects on local employment due to presence of outsourcing of mining activities and fly-in-fly-out practices. The third contribution is related to the analysis by periods of boom and bust, where the model captures the effect of becoming a PD during boom years, using as comparison PDs that have become producer during bust years, NPDs and all districts before treatment starts (i.e., start of mining production).

As part of the results, I find differences in wages between PDs and NPDs for the period of analysis 2001-2019 equivalent to 30%. This difference also remains when comparing districts within the same region and provinces. The levels of employment (measured by the share of individual employed at the district level) is on average 2.4% lower in PDs than NPDs. Similarly, the levels of unemployment for individuals actively looking for jobs is 0.3% higher for PD than NPD, suggesting a slightly larger number of job seekers during the period of analysis. The effects on occupations are mainly present on Group 1 (occupations directly related to the mining sector) which are also slightly higher for PDs (1.8%). No significant differences are found in Group 2 (indirectly related) or Group 3 (economically dependent) occupations. Distance decay effects are also observed in the results, where employment levels within NPDs located 1.7 hours away to PDs are marginally lower (equal to 0.03%), this effects increases for NPD located 5.8 hours away to PDs (equal to 0.11%). The share of unemployment for those not actively looking for a jobs also decays in space for both measures (1.7 hours and 5.8 hours), which might suggest that apart from the lack of employment opportunities, there might be other reasons for individuals to not join the labour force (e.g., other reasons could be linked to a competitive labour market). I also find negligible effects on wages. However, some positive effects on the share of groups of occupations 2 and 3 are also found with increasing distance, which would suggest that some of these occupations which are indirectly related or economically dependent are performed from NPDs, possibly due to cost savings on housing and local amenities. I later present the results on the boom and bust years. I observe that wages are higher during boom periods of mining activity and mainly concentrated to PDs (these are 17% higher than bust years), suggesting that boom periods of time lead to concentration of jobs that are high on wages within PDs. The share of employment is lower in boom years in comparison to bust years. This outcome is counterintuitive to what it would be expected but it becomes clearer when looking at the results in occupations, where Group 1 occupations is 1.4% higher in PDs during boom years, suggesting that the concentration of high wages was on directly related occupations. No significant effects are observed for groups 2 and 3, which suggest that the most benefits were concentrated among high skilled individuals performing occupations in Group 1. The final part of the analysis focuses on informality in the Peruvian labour market. I find that PDs exhibit lower levels of informal employment compared to NPDs over the study period. Moreover, the share of informal employment in PDs has declined by half between 2007 and 2019. One possible explanation for this decline is the presence of stronger enforcement mechanisms in PDs relative to NPDs. Additionally, small firms aiming to integrate into the mining supply chain may be incentivised to formalise in order to comply with contractual requirements set by mining companies. However, formal sector linkage is unlikely to be the only factor at play. Many firms operate formally while still hiring workers informally, particularly during bust periods using informality as a buffer against uncertainty such as periods of bust years (Loayza & Rigolini 2011). Finally, displacement effects may also contribute to some extent where some informal firms may relocate from PDs to nearby NPDs, where regulatory enforcement is weaker and informality offers a strategy for survival.

This paper builds on previous contributions on the empirical evidence of mining effects on socioeconomic outcomes in Peru, see for instance, previous studies by Aragón & Rud (2013), Loayza & Rigolini (2016), Orihuela et al. (2019) which use a quantitative approach and work with long-term data sourced from INEI. To the best of my knowledge, this is one of the first research papers that focus on the Peruvian labour market including the informal sector and that uses data from the period 2001-2019. It also incorporates an analysis on spatial spillovers to estimate the effects on NPDs. This paper also proposes a novel approach to estimates the effects of mining activities for both periods of boom and bust, which allow to assess the extent of effects on the labour market in the long-term. This approach allows for a more nuance analysis of whether central and local governmental efforts to promote mining activities have yield results in the labour market, not only during periods of boom but also for the aftermath years. These last outputs are particular of interest because most of outcomes are predominantly observed during boom periods.

This paper is structured as follows. The next section presents the literature review which covers empirical papers in various extractive industries of similar shock sized to the mining sector and a theoretical model based on Allcott & Keniston (2018). Section 3 introduces the data, summary statistics and regression models included in the analysis. Section 4 presents the main outcomes and section 5 concludes the paper.

4.2 Literature Review

This literature review examines empirical evidence on the aggregate effects of extractive industries and similar sectors that generate local economic shocks on wages, employment, and occupations among host producing and neighbouring areas. It also includes a brief discussion of informality, a key feature of the Peruvian labour market. The literature reviewed lies at the intersection of natural resource economics, economic geography, and labour economics. While some studies investigate the long-run impacts of extractive activity on local economies, this review also place emphasis on the distinct effects of boom and bust periods. The objective is to disentangle both periods of time and assess their separate impacts on local labour markets, with a focus on wages, employment, and occupations.

4.2.1 Empirical evidence on wages, employment and occupations

The literature generally finds that wages, employment, and occupational outcomes in regions dependent on extractive industries are procyclical, expanding during boom periods and contracting during busts. Several empirical studies support this pattern. While the extractive sector typically experiences direct gains during booms, some of the most significant effects are observed in non-extractive sectors. These sectors often face rising wage pressures due to increased labour demand from the mining industry. As local firms compete for a limited labour supply, they may be forced to raise wages, which can reduce output and lead to long-term declines in employment outside the extractive sector. For example, Black et al. (2015) conduct a sectoral analysis of the coal boom of the 1970s and the subsequent bust of the 1980s across four U.S. states. During the boom, they find modest positive spillovers to local non-tradable sectors such as construction and retail, estimating that every ten coal mining jobs created fewer than two additional jobs in local service sectors. However, they find no spillovers to the tradable sector and some evidence of crowding out (e.g., for every ten mining jobs, approximately three jobs were lost in the local tradable sector). During the bust period, employment in non-mining sectors declined, further illustrating the procyclical nature of labour market effects in extractive regions.[3] Using a similar boom-bust framework in a different extractive context, Jacobsen & Parker (2016) studies oil-producing regions in the US during the 1970s and 1980s. He finds strong procyclical patterns in employment and income, with significant gains during the boom period followed by declines during the bust. In particular, income per capita falls, and unemployment compensation claims rise significantly during downturns, suggesting that the local labour market deteriorates markedly when resource activity contracts.

These pro cyclical effects are also noted in other resource extractive sectors. For instance, Bartik et al. (2019) focuses on the shale gas industry covering data from 1990s to 2013, specifically on areas that have implemented new fracking techniques in the US. The identification strategy relies on a differences in differences approach that compare counties that share shale formation and also considering the time when fracking initiates, therefore, they assume that treatment is also staggered in time. The results evidence that resource booms have positive impacts on income, employment and salaries (from 3% up to 11%), as well as increase in consumption expenditure (12.9%) and in house prices and rent (5,7 and 2.9%, respectively). Using a shorter time frame (2001-2013) for analysis and working in the same industry, Weinstein et al. (2018) focus on the growth of the shale industry in the US and its sector and spatial effects, with focus on earnings and employment multipliers finding that effects of the extractive sector are modest and of similar magnitude. The paper also argues that the estimated multipliers are of equal size to other shocks occurring in the economy, this suggest that other economic sectors that implement big development in host areas can have the same effect on the local economy. Weinstein et al. (2018) also finds "leakages" of the effects of earnings, highlighting that the effects instead of remain locally, they are observed outside the assigned county that host the main development.

Black et al. (2015) also address this last feature on shocks, in which it is argued that the extractive sector can have the similar effects in direction and magnitude to other type of similar large scale operations (LSO). For instance, Black et al. (2015) highlight the impact of external shocks on the local economy from LSO such as the Trans-Alaskan Pipeline System (TAPS), the closure of military bases in the US and the opening of

[3] These employment effects are also shaped by population migration dynamics. Booms tend to attract new migrants and return migration (particularly among prime-age males), which can temporarily inflate local employment figures. Conversely, bust periods often trigger higher out-migration, leading to reductions in the local labour force and employment.

enterprise zones (EZ). For the case of the TAPS, the number of created jobs was more than half of the available jobs that the local economy could host during boom years, therefore, it was expected a negative impact during bust years. For the case of the closure of the military base, they find an increase in local spending, suggesting that such phenomena is more likely to be attributed to retirees military individuals. Contrary to what it should be expected (a decrease in spending), the results suggest that the the host city was resilient to the closure of the military base. Similarly, the opening of enterprise zones, which were expected to stimulate significant economic growth, produced negligible and even some crowding-out effects.[4]

Another relevant study is the one produced by Marchand (2012) who analyses the impact of the energy sector (i.e., oil and natural gas) during boom and bust times in western Canada (period 1971 to 2006 that contain two boom periods of 1971-1981 and 1996 to 2006). Once again, they find effects on the local economy that are pro cyclical nature of the extractive sector, Marchand (2012) argues that a labour demand shocks has a positive impact on earnings and employment in the resource extractive sector and also might have some spillovers in other sectors such as construction and services. It is also expected that during bust times that a negative shock in the labour demand of workers to have negative effects on earnings and employment in the resource energy sector and other associated sectors. Therefore, according to Marchand (2012), the generation of employment and spillover effects could be linked to the periods of boom and bust where generation and closure of jobs are expected, respectively.

Ouedraogo (2016) explores the spatial and sectorial effects of shocks in the extractive sector in the US during the period 1970 to 2012. Using a DiD approach, Ouedraogo (2016) finds that during boom times, employment within the extractive sector grew faster but slow down during periods of bust. Ouedraogo (2016) also finds that earnings grew during boom times at a slow rate but these earnings per worker grew faster during the bust period. The paper also argues about negative spillovers on the labour market of neighbouring areas to host ones of mineral resources (slower grow on non-primary sector

[4]According to Allcott & Keniston (2018), crowding-out effects are expected when high wages in resource-rich areas increase production costs, making it difficult for tradable sectors such as manufacturing to remain competitive. The extent of this effect, however, depends on the nature of the tradable sector. If the sector primarily serves local markets, it may be able to raise prices and avoid displacement. In contrast, if it produces goods for external markets, it is less able to adjust prices and more likely to be crowded out. This mechanism resembles a Dutch disease effect, but instead of being driven by real exchange rate appreciation, it arises from wage-induced cost pressures.

employment during boom but faster grow during bust). These last result might be linked to the variations in earnings presented lines above. The paper also reports that sectorial effects are null on the manufacturing sector, positive in the construction sector and negative in the service sector labour market among counties that are dependent of producing areas.

Overall, these empirical evidence suggests that labour market impacts are strongest during periods of resource booms, indicating that these effects are largely procyclical to the resource extractive sector. Also, sectoral shifts may generate spillovers into other parts of the economy, including potential crowding-out effects in tradable industries. Moreover, the consequences of the extractive sector are not confined to the producing areas themselves but some effects spill over into neighbouring areas, where they may be negative in the short run but potentially reverse and turn positive over the longer term.

4.2.2 Heterogenous effects of resource booms and busts

Other implications of resource booms and bust years can be found at the individual level (e.g., effects by gender) or in changes human capital, or by its extent in space (i.e., effects that can be perceived in areas beyond the local host producing areas) and time which affect the composition of the labour market (high skilled or low skilled workers or by changes in the share of occupations),[5] or that have rippled effects to other sectors as well. To mention a couple of examples, for instance, Aragón et al. (2021) research on the effects of closure of UK coal industry in the UK on the non-primary sector, more specifically, the look at the effects by gender highlighting that mining activities such as the coal industry mostly hire males than females. Using a double difference approach,

[5]Changes in the share of employment and occupations are likely to have an effect on wages. The shift-share analysis is a relevant tool to understand this mechanism, in which is possible to isolate between and within components, the first of this captures changes in employment composition and the later captures changes in sectoral wages (e.g., see Tschopp (2015) for further analysis). Although, the current paper holds data on employment shares at the district level, it lacks information on wages across sectors. However, the shift-share analysis still provides a framework for the analysis. However, this method of estimation has been criticised in the literature since it does not account for spillover effects (see Tschopp (2015) and Beaudry et al. (2013))(e.g., workers moving into high paying jobs and therefore leaving options open in the same and other industries, pushing wages up, even in sectors that are not directly related or seen employment changes directly). Still, according to the literature, the shift-share method has been widely used in the literature of labour economics to measure changes in the share of employment across industries and its effects on wages (Beaudry et al. (2013). Beaudry et al. (2013) presents a relevant example related to how calculate the impact of compositional shifts, for instance, say a high wage industry that pays a premium of 30% wages higher than the rest of industries closes, this same industry employs 50% of employment in the given districts. The impact is estimated by multiplying both the wage premium and share of employment, resulting in 15% decline in the districts wage.

their findings suggest that once coal mine closed in the UK, the labour market share of males to females in the manufacturing sector increase and effects seem to last beyond 20 years after closure of coal mines. These effects seem to persist in other non tradable industries (e.g., services), thus, their implications are wide for the composition of the labour market (e.g., differences not only by gender, but age or years of experience). On a similar line of research, Dallaire-Fortier (2024) focus on the ripple effects of mining closure on the labour market across industries during the 1980s in Canada. Rather than looking at an overall effect in employment in mining regions, Dallaire-Fortier (2024) provides a disaggregated analysis into direct, indirect and induced employment. After closure, the results suggest direct negative effects on employment that are immediate (circa 9% decline in mining employment at the regional level) and observable over the next two years after the mine closes. The indirect effects on employment are also negative (related the forward and backward linkages on firms) and perceived up to five years after closure. Negative induced effects on employment are also present up to 10 years after closure, this is related to industries that are driven by consumption demand.

In Ecuador, Mosquera (2022) explores the effects of resources oil boom during the 1970s and how it affected human capital accumulation. The study of Mosquera (2022) also argues that during the boom time, low skilled employment increased. There was limited growth of high skilled jobs. Using a DiD approach, Mosquera (2022) finds that oil resource boom decrease educational attainment at college level (circa 2.9%). One of the most interesting findings of this study is the long term effects on the labour market, where Mosquera (2022) argues that there is evidence of a labour market that has inclined to low-skilled occupations. The paper also seem to suggest that young labour (i.e., those who are before turning 18) are more likely to join the informal sector. On a similar line of research, Emery et al. (2012) raises the argument whether a lower skill premium might have an effect on educational attainment, given that wages in the extractive sector are expected to be higher, then, the opportunity cost to remain in school increases. That means that in the short term, individuals employed in the extractive sector prioritise wages and employment, but consequences during bust could be that the same individuals to struggle to find employment and compete in the labour market due to lack of for instance secondary or college education, a stage that was postponed due to individuals decision to accrue earnings in the short term. However, Emery et al. (2012) also argues that the same group of individuals could use the earnings gained during boom times to support future education, to then later catching up with their peers in the same cohort (e.g., birth year).

In Canada, the effects of boom mineral resources had implications for areas that host commuters, this case is analysed by Green et al. (2019), where they find spillover effects on wages on non resource sectors. Green et al. (2019) also find that effects can be different among areas that host a higher number of commuters, for instance, Toronto having lower number of individuals commuting to host producing areas in comparison to Cape Breton in east Canada, that host a large number of workforce working in the oil sector. Considering as well the local effects on host areas and demand induced effects to other non resources sector, the paper by Green et al. (2019) suggest that the boom period of resource extractive can account for 49% of the increase in wages after year 2000.

Empirical evidence on the informal labour market

Albrecht et al. (2009) highlight key characteristics of the informal labour market, which emphasis that informality is a widespread social phenomenon in many Latin American economies, where it accounts for over 50% of the workforce. They also argue that the informal sector can, at the micro level, be seen as an entrepreneurial domain, encompassing both self-employed individuals and small-scale employers. There are some difference however in the composition of high and low skill workers distributed in the informal sector. Although formal employment remains much more likely among high-skilled workers (e.g., Bacchetta et al. (2009) estimates that such workers are up to five times more likely to be found in the formal rather than the informal sector), still, there is substantial evidence of labour mobility between the two sectors (e.g., see Goldberg & Pavcnik (2003)). Beyond its unregulated nature and implications for tax evasion (Brockmeyer et al. 2019), the informal sector poses challenges for overall economic efficiency where informal firms compete with formal ones, including in labour markets, but their presence tends to reduce total factor productivity (TFP) (Ulyssea 2018). This productivity gap could also be attributed to the small size of informal firms and their limited access to finance, regulatory protections, and government support such as labour market reforms or formalisation incentives (De Paula & Scheinkman 2010).

Most of the literature of informality seem focused on the mechanism of these phenomena, explained through theoretical models (e.g., Bosch & Esteban-Pretel (2012) model's allow firms to choose whether to hire formal or informal workers explaining cyclical pattern in workers allocation)[6] and empirical applications such as the case studies of Costa Rica (e.g., see Brockmeyer et al. (2019) with empirical evidence on policy of tax enforcement) or Brasil (e.g., see Meghir et al. (2015) which examine the effects of enforcement on unemployment and wages) (both case studies also incorporate a theoretical model on informality as part of their framework for analysis) or for a group of countries (e.g., see Loayza & Rigolini (2011) that provides empirical evidence of the effects of informality in the labour market). Most of the literature also coincides that informality is deeply rooted in the labour market of developing countries. However, it seems to be a lack of studies in the literature that linked specifically the informal labour market and the extractive sector. Apart from studies looking at the informal mining operations (which is also part of the informal economy - e.g., see case study in Colombia by Lara-Rodríguez (2021) with a qualitative approach which examine the role of institutions to promote formalisation among Artisanal and Small Mining (ASM) firms or see Goetz (2022) with a mixed methods approach who examines the composition of the informal labour market in the ASM in Tanzania, finding transitions among waged and self-employment activities (i.e., processing activities vs diggers, respectively)), which is not the focus of this paper, there is no clear evidence on the effects of main developments such as mining operations and the informal labour market (e.g., does extractive industries increase the share of informal workers in local labour market?).

If the start of mining operations are treated as a local demand labour shocks, then the study of Goldberg & Pavcnik (2003) can shed some light on the implications of the mining sector on the informal sector. Their research examines how the informal sector responded to trade liberalisation in two Latin American economies, Brasil and Colombia. In their framework, firms facing trade shocks attempt to lower production costs by reducing staff, cutting employment benefits, and hiring workers on more flexible and often informal terms. This includes subcontracting without benefits and sourcing inputs from small informal firms operating at lower cost. Goldberg & Pavcnik (2003) find no significant relationship between trade liberalisation and informality in Brasil, and only a

[6] Bosch & Esteban-Pretel (2015) also studies the effects of unemployment benefits on informality using a search and matching model finding that such policy would reduce informality, in combination to other policies such as tax benefits.

modest increase in Colombia, limited to a period preceding the implementation of labour reforms. Translating these findings to the context of mining, one could hypothesize that the opening of mining projects creates labour market pressures as firms (in the tradable and non tradable sector) compete for local workers, driving up wages. In response, incumbent firms might seek to lower labour costs by hiring workers informally (e.g., offering pre-boom wage conditions), or turning to subcontracting, particularly if there is an influx of competing firms due to agglomeration effects. This could lead to an increase in informal employment. However, the same Goldberg & Pavcnik (2003) also raise an important counterargument to the latter position, arguing that if informality offers cost savings, why don't firms adopt informal labour practices before the shock?. They point to several confounding factors on the relationship between trade liberalisation and informality, including growth in non-tradable sectors, which typically have high informal employment shares, and concurrent labour policy reforms. These limitations suggest caution in drawing a direct parallel, and they highlight the need for further empirical work.

4.2.3 Theoretical Framework

I follow the model proposed by Allcott & Keniston (2018), which builds upon the seminal work of Moretti (2010) on local multipliers. These frameworks identify the effects of resource boom shocks on wages and local prices across tradable and non-tradable sectors. The model by Allcott & Keniston (2018) predicts increases in wages, employment, and local welfare during resource booms, but it also shed light on the implications on local productivity and welfare for bust years. For the long-term effects, the model also distinguishes between outcomes with and without productivity spillovers from learning by doing activities (i.e., experience gained by workers over time, becoming more efficient and reducing costs, therefore increasing productivity) and agglomeration effects (i.e., which arises from spatial concentration of firms, workers and industries within the host producing area or PDs).

The model considers an economy with two regions, where regions A and B belongs to $reg \in \{a, b\}$, and three sectors: tradable (tr), non-tradable (ntr), and natural resources (nr), where each sector belongs to $j \in \{tr, ntr, nr\}$. Sectoral revenue productivity is denoted by X_{jreg}. Region A possesses natural resources, while region B does not (i.e., $X_{nrb} = 0$). The model also assumes that labour is imperfectly mobile. Time is divided into three periods: $t = 0$ (pre-boom), $t = 1$ (boom), and $t = 2$ (post-boom). In the pre-boom period, it is assumed that $X_{nra} = X_{nrb} = 0$, and during the boom, $X_{nra} > 0$. If the boom is temporary i.e., if it has a switch-on/switch-off behaviour, then by $t = 2$, we have $X_{nra} = X_{nrb} = 0$ again, otherwise it would be expected that $X_{nra} > 0$ for periods beyond t=1.[7] Revenue productivity in the nr sector, X_{nr}, is exogenous. For the tr and ntr sectors, productivity is defined as:

$$X_{j,\text{reg}} = P_{j,\text{reg}} \cdot \Omega_{j,\text{reg}}$$

where $P_{j,\text{reg}}$ is the sectoral price and $\Omega_{j,\text{reg}}$ denotes physical productivity. The model assumes $P_{tr,\text{reg}} = 1$ (exogenously determined for tradables), while $P_{ntr,\text{reg}}$ is endogenously determined in the non-tradable sector.

[7]Imposing $X_{nra} = X_{nrb} = 0$ after $t = 1$ is a strong assumption, as it implies parity across regions with no mineral extraction in either. While this may approximate the intermittent behaviour of individual mining sites, aggregate production data for PDs typically exhibit gradual slowdowns rather than abrupt cessations (see Ali et al. (2017); Orihuela & Gamarra-Echenique 2020). The assumption is therefore better suited to individual dynamics of mining operations but remains a useful conceptual simplification.

During a resource boom in region A at time $t = 1$ (i.e., $X_{nr,\text{rega}} > 0$), the model yields two main predictions. The first is that population and wage increases in $t = 1$ as a direct response to the boom (Prediction 1). The second is that local employment and non-tradable prices rise, while employment in the tradable sector declines (this is without considering productivity spillovers). This outcome is reminiscent of the Dutch disease, but one of the differences is that for the latter case this is driven by real exchange rate appreciation and the case of the model due to wages. The model also notes that migration is one key factor that can attenuate wage increases, therefore, limiting Dutch disease effects. Allcott & Keniston (2018) also argues that the impact on the tradable sector (e.g., manufacturing) depends on the spatial scale of trade, that is, if production serves mainly local demand, manufacturing may be crowded in. This is because the firms are able to raise prices, given increase in production costs (i.e., due to high wages). However, if the manufacturing sector mainly serves external markets, then, it is likely to be crowded out.

The third and fourth prediction of the model is related to productivities in the local and tradable sector and welfare overtime, which by $t = 2$, without considering productivity spillovers, they are expected to increase. However, it is important to acknowledge that these last two predictions of the model are not tested in this research paper but are relevant to guide the overall analysis. In the absence of productivity spillovers (e.g., no agglomeration of firms, workers or industries), the model predicts parity conditions across regions during post-boom years, that is, equal wages, employment and productivity and an increase in cumulative welfare over time.

Allcott & Keniston (2018) argues that with productivity spillovers, welfare outcomes become ambiguous. The productivity in the local sector increases in t=2 due to increases in population and local employment (this is for the case of region A in time t=1). The productivity in the tradable sector and welfare is subject to the magnitude of the agglomeration and learning by doing activities spillovers. For instance, if productivity declines, the tradable sector is crowded out, potentially reducing cumulative welfare (i.e., knowledge gained overtime within sector is difficult to extrapolate to other sectors). However, strong agglomeration economies may counteract this, resulting in welfare gains (i.e., individuals that gained experience in the extractive sector are able to transfer skills and experience to other firms and industries within the host producing area).

The model also predict some outcomes for periods beyond t=2, where population may concentrate in one of the two regions (a or b) and potentially remain in the resource-producing region after the boom ends (i.e., during the bust years). This has been evidence, for instance, in the empirical case of closure of military bases by Black et al. (2015), and also for the Australian case of fly-in-fly-out workers, where, once their contract ends, Haslam McKenzie & Hoath (2014) argues that individuals remain in mining regions, suggesting these areas are long term destinations for migrant workers. The result of productivity differences between regions could increase the gap between them in time. However, the model also argues that if the magnitude of such effects (productivity and spillovers) are small, then it is more likely that both regions return to parity conditions after the resource boom ends.

4.3 Methodology

4.3.1 Data

I use data from three secondary sources. The first of these is the Peruvian National Household Survey which collects socioeconomic information at the household level across districts in Peru on a year basis. This household information for socioeconomic characteristics is then aggregated at the district level, which allow to produce a pseudo panel where districts (with a unique identifier) can be tracked in time. The first set of socioeconomic variables included for this analysis are related to the monthly total and net wages obtained by individuals in their primary occupation, which are presented in USD and deflated to 2021 values. Also, these values are aggregated at the district level. Table 4.1 shows that monthly average wages at the district level is USD 699.35 (this is an aggregated value considering the whole period of analysis 2001-2019). Other important socioeconomic variables sourced from ENAHO and that are included in this analysis are related to the level of education by the head of the household (HHH), literacy, gender, age (within two ranges of 14 to 65 and 18 to 65), these information is presented as well as proportions at the district level (e.g., at the district level, 74% of individuals are aged between 18 to 65 during the period of study) (see Table 4.1). From the same survey, I source information about the number of individuals that belong to the economically active population (including employed and unemployed) and economically inactive population, these variables are also calculated as proportions at the district level. Overall, the proportion of individuals employed (76 %) is higher that those unemployed (circa 3%) and who are economically inactive (21%) for the period 2001-2019. The data also allows to distinguish between two types of unemployed individuals, where we can identify a first group that are unemployed and actively looking for a job (this is regarded in the dataset as % of individuals unemployed (open))[8] and those who are unemployed but are not looking for a job and therefore not doing anything to find one (this group is regarded

[8]This category of unemployment (open) refers to former workers as well as first-time job seekers who, during the week prior to the survey, were unemployed but actively seeking either self-employment or paid employment (INEI 2000). The economically active population consists of individuals who were employed and those actively looking for a job (open unemployed) during the survey reference period. In the UK, this group corresponds to the Office for National Statistics (ONS) category of Economically Active: Unemployed (Office for National Statistics 2022).

as the % of unemployed individuals (close)).[9] Both groups together form the number of unemployed individuals at the district level. These statistics could suggest that on aggregate, the country has faced high levels of employment in comparison to unemployment for the period of analysis, regardless of the type of districts. However, in the next analysis I present the difference in employment and unemployment levels between PD and NPD and its evolution in time.

The ENAHO household survey also includes information related to the occupations that individuals perform, these are classified by the Peruvian National Institute of Statistics (INEI-CNO 2015 heareafter) (see INEI (2016)), in line to the International Standard Classification of Occupations 2008 (ILO (n.d.)), prepared by the International Labour Organisation (ILO). The INEI-CNO 2015 classifies occupations at 4 digit level code. Each code of these numbers within the 4 digit level code classifies occupations from a "global group" (first digit that contain 10 groups of occupations) to a "specific or primary group (fourth digit that contain 8 groups of occupations). For instance, an occupation of airline steward (5111), belongs to the "global group" of Service workers and Vendors in Commerce and Markets (code 5), and principal subgroup of Personal Service workers (code 51), and subgroup of direct personal service for passengers (code 511) and primary group that contains the airline steward (5111). However, the ENAHO household data only allow to identify occupations up to 3 digit level, from left to right, to subgroups of occupations. This information at three digit level is still very valuable for the analysis on occupational shifts in time at a subgroup level. A more granular analysis could be conducted using panel data at individual level where occupation shifts could be explored within the mining sector (e.g., changes in occupations due to start of mining operations among rural areas in Peru), however, this will part of a more detailed analysis in a subsequent research. Given the available information on occupation at ENAHO survey, I look for occupations that are linked to some extent to the mining sector and cluster these occupations into three main groups, which are occupations directly related to the mining sector (Group 1), indirectly related (Group 2) and economically dependent (Group

[9]This category of unemployment (close), also referred to as hidden unemployment (or *desempleo oculto* in Spanish), refers to individuals who do not have an occupation and may have the desire to work but are not actively seeking employment. This situation may arise due to a lack of opportunities, low motivation, or job requirements that are difficult to meet. This group is classified within the economically inactive population, which also includes fully inactive individuals (INEI 2000). In the UK, this group corresponds to the Office for National Statistics (ONS) category of Economically Inactive (Office for National Statistics 2022).

Table 4.1: Summary statistics for key variables, 2001–2019

Variable	Obs	Mean	Std. Dev.	Min	Max
Outcome Variables					
Average total wage (monthly)	16,235	699.35	521.43	5.00	14,503.33
Average net wage (monthly)	16,239	122.43	245.14	0.00	10,846.00
% Economically active: in employment	17,628	0.76	0.12	0.14	1.00
% Economically active: unemployed (open)	17,628	0.01	0.02	0.00	0.24
% Economically active: unemployed (close)	17,628	0.01	0.03	0.00	0.50
% Economically inactive	17,628	0.21	0.11	0.00	0.78
% Occup. directly related (Group 1)	17,628	0.00	0.02	0.00	0.54
% Occup. indirectly related (Group 2)	17,628	0.01	0.02	0.00	0.33
% Occup. economic. dependent (Group 3)	17,628	0.00	0.01	0.00	0.36
Socioeconomic Variables					
% Literacy	17,628	0.21	0.09	0.00	0.71
% Household heads with primary education	17,628	0.13	0.07	0.00	0.71
% Household heads with secondary education	17,628	0.12	0.08	0.00	1.00
% Males	17,080	0.49	0.07	0.09	1.00
% Females	17,080	0.51	0.07	0.00	0.91
% Individuals aged 14–65	17,080	0.86	0.11	0.00	1.00
% Individuals aged 18–65	17,080	0.74	0.10	0.00	1.00
% Informal employment (since 2007)	13,299	0.89	0.15	0.00	1.00
% Formal employment (since 2007)	13,299	0.11	0.15	0.00	1.00
% Secondary employment – informal sector	13,297	0.89	0.13	0.00	1.00
% Secondary employment – formal sector	13,297	0.11	0.13	0.00	1.00
Members per household (permanent residents)	17,628	4.78	1.08	1.00	11.45
Distance Variables					
Minimum travel time in hours (NPD to PD)	17,554	7.19	22.98	0.05	252.72
Geographic Variables					
Altitude (meters above sea level)	17,611	1,954.99	1,446.07	5.00	4,470.00
Surface area (km^2)	17,611	848.73	2,244.12	2.00	24,050.00
Mining Variables					
Producer (PD=1/NPD=0)	17,628	0.037	0.189	0	1
Total mineral investment in USD (regional level)	17,628	186,000,000	318,000,000	0	1,960,000,000

Note: Calculations are at the district level. Aggregated values for consumption and income are monthly averages and expressed in USD. Wage and income values are deflated to 2021 and converted to USD. Informal and formal employment data are available from 2007 onward. Occupation categories follow INEI – CNO 2015 classification.

3). These together make circa 1% of total occupations available at the ENAHO survey. However, the total number of occupations related to the mining sectors (from Group 1 to Group 3) allow to track in time whether individuals have specialised in occupations related to the mining sector, by looking at changes in the proportion of occupations in these three groups at the district level in time.

This approach differs from previous studies in the mining sector and extractive industries where effects on employment or occupations could be looked as part of the multiplier effect in the local economies or sectorial effects (e.g., tradable and non tradable sectors) (e.g., see Moretti (2010), Aragón & Rud (2013), Fleming & Measham (2014)). Looking at changes in occupations can help to understand whether individuals tend to specialise into some mining related occupations (rather than looking at the whole set of occupations, which could be performed in more detail by doing an analysis at the individual level), specially if long-term data is available to assess this change. However, the same literature on the extractive sector highlights that mining activities are usually capital intensive in nature, meaning that it is expected that these development does not rely on high levels of direct employment with some indirect employment generated which could be measured by the local multiplier. Table 4.2 presents a summary of occupations that could be linked to the mining sector, as well a brief justification for its inclusion under each category. I work these information at the district level, for instance, for individuals in Group 1, the information in Table 4.1 presents that the maximum proportion of individuals at the district level that have an occupation that fall within Group 1 is 54% for the period of analysis. These clusters of occupations by groups is constructed using the ILO (n.d.) classification, by reviewing information on the definition and tasks included by occupation. Group 1 of occupations follows the classifications provided by INEI and the ILO. For example, code 132 ("Directors and managers in mining, construction, transport, oil, and gas") is explicitly defined as belonging to the mining sector and is therefore included in Group 1. Group 2 is more challenging to delineate, since these occupations are not explicitly identified as mining related. To construct this group, I reviewed the task descriptions in the ISCO classification (see ILO (n.d.)) and considered the types of services commonly contracted by mining firms. For instance, large and medium mining companies outsource some activities to consultancy firms that provide environmental permitting, GIS analysis, financial advice, engineering design, and other similar services. While this list does not capture the full spectrum of professional services linked to mining, it provides a an attempt to group occupations that contribute indirectly to mining activity. Group 3 encompasses occupations that, while not directly or indirectly classified as mining related, are economically dependent on the mining sector by providing specialised on site services. These three groups do not exhaust the universe of occupations related to mining. Additional groups could be constructed, but doing so would require more granular worker-level data within the sector.

The same survey identifies whether individuals form part of the informal or formal labour market. This information is available from year 2007 and is presented aggregated at the district level. On average, a high proportion of individuals fall within the informal labour market (circa 89% for the period of analysis). According to Van Doornik et al. (2023), informal labour markets provide an alternative to formal market, in the sense that individuals can rely on the informal sector to trade goods and services, avoiding to pay taxes but working under conditions that do not guarantee them work stability (e.g., being laid off without notice), pension, health insurance, or other benefits that workers usually receive when working in the formal sector. This phenomena is not particularly to the case study of Peru, although it has one of the highest levels of informality in the South American region (see Chong et al. (2008)), but it is also a phenomena occurring in other mid income countries such as Brasil (see Van Doornik et al. (2023)). Given that the informal labour market is significantly high for the case study, I also source from the same ENAHO survey information regarding where does this informal employment is located, whether in the informal or formal sector. This is presented in Table 4.1 as % secondary employment in the informal or formal sector.

Other relevant variables included in the analysis are related to distance variables, which measured the travel time distance by car in hours from NPDs to PDs, this is to explore the extent of effects in space (i.e., effects on NPD). This information is calculated using the command OSRM and geodist in Stata (see Huber & Rust (2016) for further information on implementation of the OSRM command). Travel time in km were calculated using fixed distances, that is, it does not include live information on traffic to determine the travel distance in KM. This is to support the replicability of results. Geographic information for the travel distance calculations where sourced from Open Street Map. I also work with geographic controls and mining variables, the first is a dummy to identify PD and NPD. The second of these variables is related to the mineral investment, this information is sourced from the Peruvian Ministry of Energy and Mines (Ministerio de Energia y Minas (2023)), and it is only available at the regional level.

Table 4.2: List of occupations by group

Code	Occupations	Explanation to group allocation
Group 1		
132	Directors and managers in mining, construction, transport, oil and gas sectors	Oversee mining business development
214	Engineers (e.g., mining, metallurgists, civil, environmental)	Involved in various aspects of mining activities (e.g., design, planning, processes)
311	Technicians in physical science and engineering	Involved in specific tasks related to mining development
711	Construction workers (e.g., Miners and Quarriers)	Involved in phases of mine life (construction, operation, closure)
811	Operators of mining, extraction, and mineral processing facilities	Operate equipment that processes mined materials
834	Mining machine operators of mobile machinery	Operate mobile equipment (operational roles)
Group 2		
121	Human resources and business management directors	Oversee staffing for mine, produce HR policies
211	Physicists, chemists and related professionals	Involved in design and planning from a consulting level
213	Professionals in biological sciences	Involved in environmental permitting
216	Architects, urban planners, surveyors and designers	Involved in permitting, design, and mine planning
226	Occupational health professionals	Health and safety professionals throughout mine's life
241	Finance specialists (e.g., accountants)	Involved in accounting and company finance
242	Organisation and management specialists (e.g., analysts)	Administrative and technical support

Code	Occupations	Explanation to group allocation
251	Information system analysts and developers	GIS specialists involved in cartography
261	Lawyers	Involved in all legal aspects
311	Technicians in physical science and engineering	As above; cross-listed role
432	Transport and stock clerks	Support staff
441	Administrative support staff	Assistants in admin, accounting, law, etc.
721	Welders, molders, assemblers of metal structures	Specific to mine infrastructure
723	Machinery mechanics and repairers	Specific to mine infrastructure
741	Electrical equipment installers and repairers	Specific to mine infrastructure
833	Heavy truck and bus drivers	Activities vary by mine stage (e.g., transport during operation)
834	Machine operators of mobile machinery	Operate mobile equipment (operational roles)
Group 3		
422	Customer information service employees (e.g., receptionists)	Provide services to mine camp or nearby area
512	Cooks	Provide services to mine camp or nearby area
911	Cleaners and domestic assistants	Provide services as contractors to the mine

Note: List of occupations is prepared using information from ENAHO household surveys. Information on occupation codes is available at 3-digit level.

Analysis on the evolution of key variables in time

When looking at the differences between PDs and NPDs in time (see Figure 4.1), average wages are higher for the former group during the period of analysis. This could be linked to various factors, such as higher wages for skilled and unskilled workers in PDs in comparison to NPDs, or the difference in wages across sectors (e.g., differences in wages between mining, agriculture, etc). Although wages are higher in the mining sector, the level of employment is not as high as in NPDs, where employment levels are high for the entire period in comparison to PDs (circa

75% of individuals in employment/self-employment). The gap between NPDs and PDs in terms of employment seems to reduce from year 2010 onwards, raising various questions from: is this change a response to migration of individuals coming from NPDs within the same region? or is the gap reducing due to more intensive mining activity? is it the case that more individuals are getting employed in the mining sector or related firms? or is it the case that more individuals are getting self employed in other sectors and profiting from associated activities? In any case, the next variable provides more evidence of the decline in unemployment in PDs (unemployment - close i.e., those who are actively looking for a job). These decline in unemployment levels also reach to a similar point to NPDs, where 2% to 3% of individuals at the district levels are unemployed from year 2010 to 2019. The levels of unemployment (close) (i.e., individuals unemployed that are not looking for a job) for both PDs and NPDs seem to fall since year 2005 to year 2019, suggesting changes in the composition of the labour market (e.g., it could be the simple case that individuals are entering the labour market, as well as those looking to profit from a better economic outlook among PDs and NPDs). The economic inactive population seem to remain within a range of 2% to 3% since year 2003 up to 2019.

There last three variables on occupations related to the mining sector (Group 1, 2 and 3) show important differences for PDs and NPDs. The first group shows a sharp decline in occupations from years 2001 to 2009, and then keeping stable on a range from 1% to 2% from year 2010 onwards. These again raises some questions such as, is this drop linked to the nature of the same activity where initial stages required more skilled individuals?. However, the same should apply for unskilled individuals (e.g., high demand of construction workers for construction stage of mines, which would also require a higher demand for other similar jobs such as cooks, camp staff to support workforce but this is expected to decline once mines start operation). The other two groups show a similar decline trend for PDs, and more noticeable for Group 3 (e.g., occupations such as cooks, clerks), which could be in line to the previous argument, where the decline in demand for workers in Group 3 starts in year 2003 up to year 2010 and then fluctuating from 0.5% to 1% from year 2011 onwards. Changes in Group 2 also show decline in the proportion of individuals at the district level but remains stable in a range of 0.5% to 2% from year 2003 onwards, suggesting constant demand of these workers regardless of the operational stage of mines or, looking at a more macro scale, periods of booms and bust. In all three groups, PDs have higher proportion levels than NPDs, also there is less fluctuation of proportions of these groups across years but low demand for these occupations (e.g., in group 1, they fluctuate below 1%, in group 2, from 1.5% to 1% and group 3, from 1% to 0.4%).

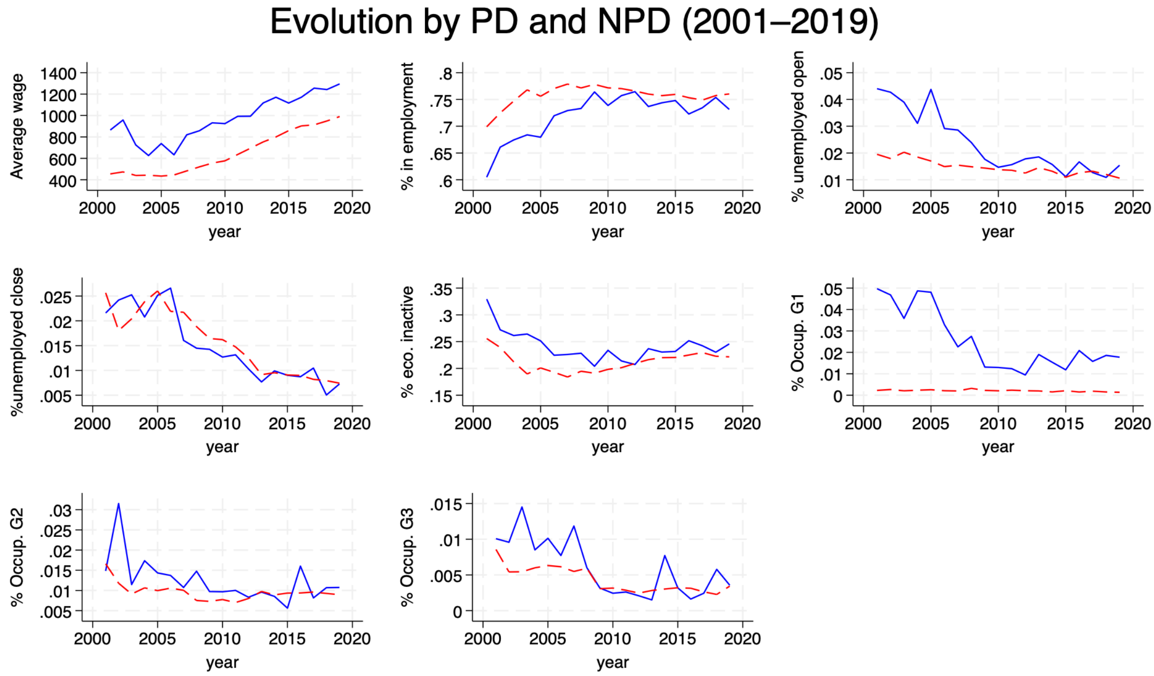


Figure 4.1: Evolution of Outcome Variable: 2001-2019
Note: Line in blue is related to PD. Dotted line in red is related to NPD. Information is sourced from ENAHO - INEI. The share of occupations in Group 1 is related to occupations directly related to the mining sector, Group 2 is related to occupations indirectly related to the mining sector and Group 3 is related to occupations economically dependent to the mining sector.

4.3.2 Methods

POLS model

I start the analysis working on a POLS model focused at the district level, the aim is to first see the difference between PDs and NPDs by looking at the proposed dummy variable "prod" in the model, where 1 accounts for PDs and zero otherwise. I test this linear model using a set of socioeconomic characteristics (previously analysed) on wages, employment and occupations. The proposed POLS models is stated as:

$$\mathrm{Y}_{it} = \beta_0 + \beta_1 \mathrm{Prod}_{it} + \boldsymbol{\gamma}' \mathbf{X}_{it} + \delta_t + \varepsilon_{it} \tag{4.1}$$

where:

- Y_{it} is the outcome variable (log(wages), employment (open, close) and occupations (Group 1, Group 2, Group 3 independently, and share of informality) in district i at time t.
- Prod_{it} is a dummy that takes the value of 1 for PD and cero otherwise for district i at time t.
- $\mathbf{X}_{it}$ is a vector of control variables measured at the district level i at time t, including: proportion of males, proportion of population between 18 to 65 years old, proportion of urban households, proportion of literacy, proportion HHH with completed primary education, proportion HHH with completed secondary occupation, average number of permament members.
- δ_t represents year fixed effects.[10]
- ε_{it} is the error term clustered at the district level.

The latter equation is useful to see the difference in the outcome variables between both PDs and NPDs. This is a common approach in the literature of extractive industries, where scholars aim to see how better or worse perform host districts of mining activities (that is PDs) with respect to non host districts (that is NPDs) in time. However, when including a dynamic variable such as travel time in the linear regression model, I am able to observe changes in NPDs with respect to the distance they have to PDs. This approach allow to see the extent of the effects in space and how, for instance, districts in short travel proximity have been influenced

[10]District fixed effects were incorporated in preliminary tests of this model, however, most of coefficients drop. Therefore, it was removed from model 1 and subsequent POLS models. This drop in coefficients is potentially due to lack of variability in districts status overtime.

by the mining sector during the period of study. In this way, I will be able to address changes in the labour market of the mining sector, where it has been highlighted that the outsourcing of some activities or long distance commuting of workers might diminish the local impacts of mining activities. For instance, Tano et al. (2016) argues that outsourcing of some mining activities and Fly-in-flight-out could answer why the demand of local workers during boom and bust periods is low, and therefore, might explain some of the negligible effects on local workers, as well as changes in consumption on local economies (e.g., low purchasing power).

For this purpose, I add the variable "Distance_{it}" that accounts for the minimum travel time distance by car from NPDs to PDs. The outcome and control variables remaining the same as per model 1. The POLS model is adjusted as per follows:

$$\mathrm{Y}_{it} = \beta_0 + \beta_1 \mathrm{Prod}_{it} + \beta_2 \mathrm{Distance}_{it} + \boldsymbol{\gamma}' \mathbf{X}_{it} + \delta_t + \varepsilon_{it} \tag{4.2}$$

The coefficients of interest in the adjusted POLS model are β_1 and β_2. The coefficient β_1 captures the average difference in the outcome variable between PDs and NPDs. In contrast, β_2 measures the marginal effect of distance from NPDs to PDs on the outcome variable, thereby identifying the extent to which proximity to a PDs influences outcomes in District_i.

Triple difference approach

I use a triple-difference (DDD) approach to estimate the differential effect of becoming a producer during the boom period, relative to those who became producers later (during the bust) and to non-producers, on wages, employment, and occupations. The DDD estimator can be expressed as the difference between two difference-in-differences (DiD) estimators (Olden & Møen 2022). As with any DiD design, identification relies on the assumptions of parallel trends and no anticipation (Baker et al. 2025). However, the DDD framework helps mitigate violations of parallel trends by differencing out biases that could distort a simple DiD comparison (see Olden & Møen (2022) for details on how these biases are removed in the coefficients). Later in this subsection, I also examine pre-trends using an event-study specification to assess whether the treatment and control groups evolved similarly prior to treatment.

Recent literature has discussed the implications of implementing DDD as the difference of two DiD estimators, especially when covariates are important for identification or when treatment is staggered over time, where the main concern is to use not-yet-treated units as a comparison group in the analysis (Baker et al. 2025). These issues can be addressed in the following ways. For instance, Olden & Møen (2022) argues that the inclusion of covariates can improve precision in the estimates by reducing residual variance and may be necessary if observable characteristics influence treatment selection. For this paper, however, treatment selection is driven by exogenous shocks (e.g., mineral production is triggered by commodity shocks), so covariates are unlikely to bias estimates but can still enhance precision. For the case of staggered treatment, one solution is to included alternative comparison groups or by applying regression adjustment or inverse probability weighting to recover ATT estimates (Baker et al. 2025). The main comparison groups in this analysis are PDs during bust, NPDs during boom and NPDs during bust. Not yet treated units are not considered for the analysis. Finally, the no-anticipation assumption is likely to hold because producers had no incentive or ability to bring production forward since it responds to global price shocks rather than endogenous expectations (Ali et al. 2017). I follow Olden & Møen (2022) in estimating the following DDD model:

$$
\begin{aligned}
Y_{it} = \beta_0 &+ \beta_1 \text{Producing}_i + \beta_2 \text{Post}_{it} + \beta_3 \text{BoomPD}_i \\
&+ \beta_4 (\text{Producing}_i \times \text{Post}_{it}) + \beta_5 (\text{Producing}_i \times \text{BoomPD}_i) \\
&+ \beta_6 (\text{Post}_{it} \times \text{BoomPD}_i) + \beta_7 (\text{Producing}_i \times \text{Post}_{it} \times \text{BoomPD}_i) \\
&+ \mathbf{X}'_{it}\gamma + \delta_t + \epsilon_{it}
\end{aligned}
$$

where:

- Y_{it} is a district-level labour outcome (i.e., log(average wage$_{it}$), share of individuals employed, share of individuals unemployed (open), share of individuals unemployed (close), share of individuals in occupation group 1, share of individuals in occupation group 2, share of individuals in occupation group 3).
- Producing_i is a binary indicator equal to 1 for districts that ever become producers.
- Post_{it} is a binary variable equal to 1 for years after the district starts producing.
- BoomPD_i is a binary variable equal to 1 if the district started producing during the mineral boom (2001–2012).
- $\mathbf{X}_{it}$ includes district-level demographic (proportions of males, working-age, urban, literacy, primary and secondary education completion, permanent residence) and geographic (altitude, and surface area) controls.
- δ_t are year fixed effects.
- ϵ_{it} is the error term clustered at the district level.

The main coefficient of interest is β_7 that captures the effect of becoming a producer during the boom period, after production begins (measured by Post_{it}), relative to other districts and periods, these would be NPDs during boom and bust (i.e., Producing_i equal to zero) and PDs during bust (i.e., BoomPD_i*Producing_i equal to zero).

I also test the parallel trends assumption using an event study specification following Sun & Abraham (2020) and Callaway & Sant'Anna (2021). This approach examines the coefficients for the pre-treatment and post-treatment periods to ensure that treated and control units (i.e., PDs and NPDs) do not exhibit differential trends prior to the event, which is a key condition for the validity of the DiD design. Furthermore, the event study specification allows exploration of the dynamic effects of treatment on the outcome variable over time. The model is estimated using high-dimensional fixed effects, with robust standard errors clustered by district. The specification includes two leads and ten lags of the treatment indicator.[11] I work with the following specification model:

$$Y_{it} = \beta_0 + \sum_{k=-2}^{10} \beta_k \cdot \mathbf{1}\{r_{it} = k\} + \gamma \mathbf{X}_{it} + \delta_t + \varepsilon_{it} \tag{4.3}$$

where:

- Y_{it} denotes a labour market outcome in district i and year t, including: log(wage), employment rate, open unemployment rate, closed unemployment rate, and shares of workers in occupation groups 1, 2, and 3.

- r_{it} is the event-time variable (time relative to treatment), and $\mathbf{1}\{r_{it} = k\}$ are event-time dummies for each lead ($k < 0$) and lag ($k \geq 0$), with $k = -1$ omitted as the reference category.

- $\mathbf{X}_{it}$ is a vector of time-varying district-level covariates, including: the proportion male, the share of the population aged 18–65, the share of urban households, the literacy rate, the shares of household heads with completed primary and secondary education, and average household size (measured by number of permanent members).

- δ_t are year fixed effects.

- ε_{it} is the idiosyncratic error term, clustered at the district level.

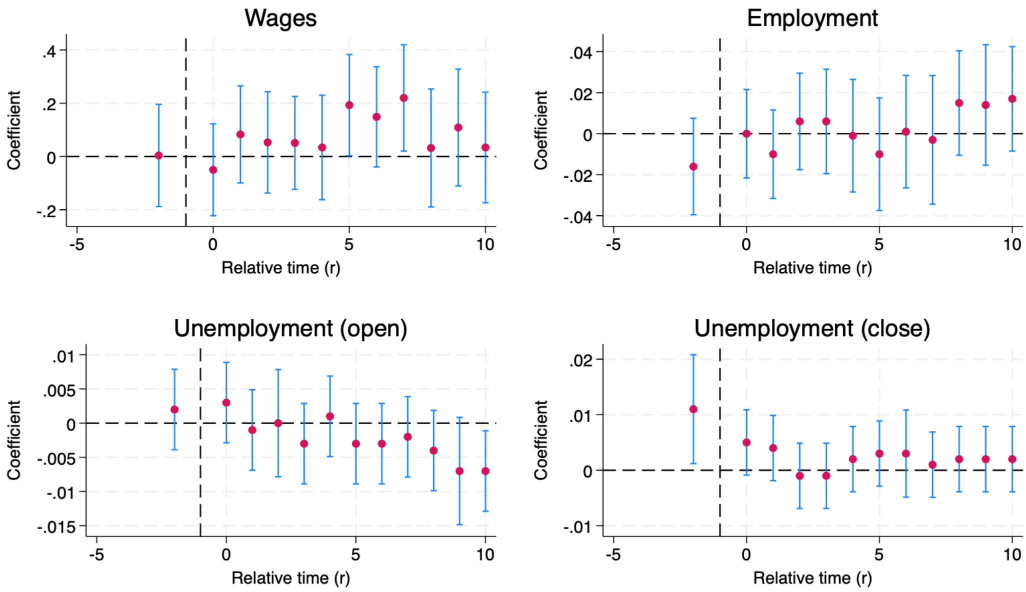
Figure 4.2 presents the results from the event study specification, which includes two pre-treatment periods and ten post-treatment periods. Treatment is defined as district i becoming

[11] District fixed effects are excluded in this specification to avoid the loss of many event-time coefficients

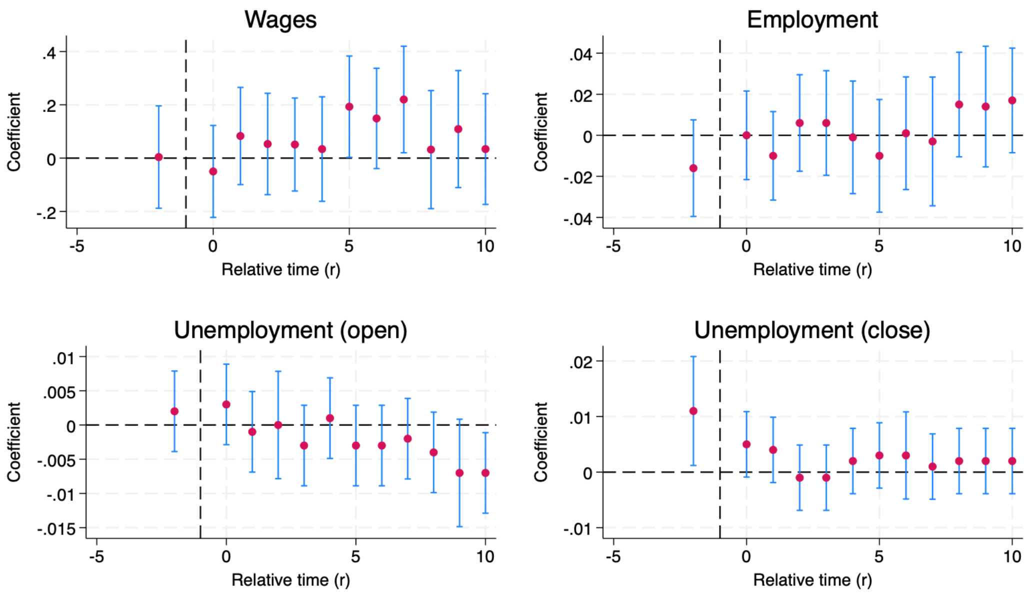
a PD in year t. The choice to include only two pre-treatment periods ensures that all treated districts have sufficient data prior to treatment, specifically, at least two years of recorded mineral production, which is the criterion for PD status. Districts with fewer than two pre-treatment observations were excluded from the analysis. There is no restriction on the number of post-treatment periods; however, as the window expands, standard errors tend to increase. After testing various specifications, I find that including up to ten years post-treatment yields reliable estimates without excessively inflating standard errors.

For all outcomes except unemployment (close), I find no statistically significant differences in the two years preceding treatment. While coefficients for variables such as log wages, unemployment (open), and employment in Group 1 and Group 3 occupations vary in sign, none are statistically significant at conventional levels. An exception is unemployment (close), where PDs exhibit a statistically significant higher rate equal to 1.1 % relative to NPDs in the second year before treatment ($r = -2$), significant at the 5% level. This suggests a slightly larger share of individuals not actively seeking employment in PDs prior to treatment and warrants caution when interpreting post-treatment effects for this variable.[12]

[12]The event study specification also sheds light on the dynamic post-treatment effects of obtaining PD status. The full results including coefficients and standard errors is included in the Appendix in Table 4.8.



(a) Coefficients and 95% Confidence Intervals for Log Wages, Employment, Unemployment (open), and Unemployment (close).



(b) Coefficients and 95% Confidence Intervals for Groups 1, 2, and 3 of Occupations. Group 1 includes occupations directly related to the mining sector, Group 2 indirectly related, and Group 3 economically dependent occupations.

Figure 4.2: Event-Study Estimates with 95% Confidence Intervals

4.4 Results

4.4.1 Effects on wages, employment and occupation

The first set of results in Table 4.3 suggest that wages are 30% higher in PDs than NPDs for the period 2001-2019. This difference account for demographic, geographic controls and year fixed effects to address time-varying factors. The results are robust when restricting the comparison to PDs and NPDs within the same region (22% wage gap) or within the same province (20% wage gap). All estimates are statistically significant at the 1% level.

These wage differentials suggest that mining activity may have contributed to local wage increases, potentially through the high wages paid in the mining sector itself and spillovers to other firms in PDs. This result is in line to the first prediction of the model proposed by Allcott & Keniston (2018), where, a resource shock will likely results in the generation of new jobs and high wages, however, since the pool of workers remain low in the short term, it is expected that wages to increase in the tradable sector and other related ones. It also highlights the possibility that wages have remained higher for PDs than NPDs for the period of analysis, suggesting a lower chance for NPDs to catch up with PDs (i.e., there is no evidence to suggest that wages return to parity conditions among PD and NPD over time). High wages in PDs may also reflect the presence of local multiplier effects, whereby the creation of jobs in the extractive or tradable sector stimulates additional employment in non-tradable sectors. For example, in manufacturing, each new tradable-sector job is estimated to generate 1.6 jobs in the non-tradable sector, with even larger effects (2.5 jobs) when the employment is skilled (Moretti 2010).[13]

Similar wage effects from extractive activity have been documented elsewhere. In Chile, Chavez & Rodriguez-Puello (2022) find that mining development raises wages in exposed areas. In Sweden, Tano et al. (2016) documents income gains for both mining and non-mining workers, suggesting local and regional spillovers. Likewise, Rehner & Rodrigues (2021) find spillovers to other industries, with evidence of higher wages in construction and real estate.

[13]Moretti (2010) also note that multiplier effects vary by industry; for instance, technology industries appear to generate even larger local spillovers.

Table 4.3: Effects on wages

	(1) Across/within regions	(2) Within region	(3) Within province
Producing	0.306***	0.225***	0.202***
	(0.051)	(0.042)	(0.042)
Constant	5.626***	5.575***	5.480***
	(0.110)	(0.121)	(0.192)
Observations	14,979	14,979	14,979
R-squared	0.397	0.413	0.436
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

When looking at the difference among PDs and NPDs in terms of economic activity status, the share of individuals in employment is slightly lower in PDs than NPDs (circa 2.4%), this difference is statistically significant at a 5% level. It also seems that the share of individuals unemployed and actively looking for jobs in PDs is slightly higher (circa 0.3%) that NPDs. This result is significant at 10% level. On one hand, this result suggest that more individuals are unemployed in PDs than NPDs during the period of analysis, but, it also highlights that the share of individuals unemployed and actively looking for a job in PDs is slightly higher than in NPDs, suggesting a more competitive or dynamic labour market in PDs relative to NPDs. The last column present outputs for the share of unemployed individuals who are not actively looking for a job. The coefficient estimate is statistically insignificant, suggesting no meaningful difference between PDs and NPDs in this dimension.

I also examine the differences among PDs and NPDs within regions and provinces across the three outcome variables. The results show that the share of employed individuals is consistently lower in PDs compared to NPDs. Within-region comparisons indicate a difference of approximately 2.3%, statistically significant at the 5% level. At the province level, the difference is smaller (about 1%) but still statistically significant at the 10% level. These findings suggest that even when comparing districts within the same geographic unit, PDs tend to have lower employment levels relative to NPDs. There are no significant difference among PDs and NPDs within regions and provinces for the share of unemployed individuals actively looking for a job and unemployed individuals not actively looking for job, except at the province level, where the difference (approximately -0.2%) is statistically significant at the 10% level.[14] The regional and

[14]This result suggests a marginally lower share of inactive unemployed individuals in PDs compared

province outputs are included in the Appendix 4.9 to 4.11.

Lower employment levels are somewhat counterintuitive, as the theory predicts that resource booms are typically followed by an expansion in local employment (Allcott & Keniston 2018). The same theoretical model also argue about wages and employment to return to parity conditions in the long-term, although it is subject to agglomeration and learning by doing spillovers. Yet, when examining the average effects for 2001–2019, the employment gap persists even when comparing districts within the same region or province. One possible explanation is the migration of individuals to production districts (Allcott & Keniston 2018), which increases competition for a limited number of jobs. Mining activities are generally capital-intensive rather than labour-intensive, meaning that the surge in labour demand during booms is modest relative to the influx of workers. A second mechanism may involve displacement in other industries. Large projects can raise input costs (e.g., cost of rents) forcing some non-mining firms that cannot absorb these costs to exit the market or relocate to nearby areas with lower operating costs. This channel is more difficult to document empirically, as it would require detailed industry and firm level data. However, the subsequent analyses on occupations and spatial effects shed further light on these employment dynamics.

Table 4.4: Effects on employment

	(1) In employment	(2) Unemployed (open)	(3) Unemployed (close)
Producing	-0.024^{**}	0.003^{*}	-0.002
	(0.010)	(0.002)	(0.001)
Constant	0.615^{***}	0.004	0.009^{***}
	(0.016)	(0.003)	(0.003)
Observations	16,355	16,355	16,355
R-squared	0.311	0.198	0.090
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	No	No
Province FE	No	No	No

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Regarding the effects by groups of occupation, the share of individuals in Group 1 (i.e., occupations directly related to the mining sector) is slightly higher in PDs than NPDs (circa 1.8%), the coefficient is statistically significant at 5% (see Table 4.5). There are no significant differences in the share of occupations for groups 2 and 3 during the period of analysis. For Group 1, the slight difference in the share of occupations between PDs and NPDs may suggest

to NPDs, although the effect is relatively small.

that these occupations are more likely to be found in PDs, but given the small difference, it could also imply that some of these occupations are performed not necessarily within PDs but in neighbouring areas within the same region or even across regions. When looking at the differences within regions and provinces, the difference in the shared of population for Group 1 of occupations is smaller and up to 1.6% and 1.3%, for differences within regions and provinces, respectively. The lack of significant results for Groups 2 and 3 suggests that mining activities do not generate large quantities of employment in occupations such as lawyers, technicians, clerks, or cooks (see Table 4.2 for the full list of occupations). If mining activities were generating significant employment in these fields, we would expect the share of individuals in these occupations to show a statistically significant difference between PDs and NPDs (i.e., spillover effects across industries and occupations). However, that is not the case for the mining sector. These results further suggest that employment opportunities are more likely to be found in occupations directly related to the mining sector, such as directors, engineers, operators of mining extraction, or mining machine operators (see Table 4.2 for the full list of occupations), potentially suggesting very few spillovers across industries[15] and occupations.

Table 4.5: Effects by Groups of Occupations

	(1) Group 1 Directly related	(2) Group 2 Indirectly related	(3) Group 3 Eco. Dependent
Producing	0.018***	-0.000	0.000
	(0.005)	(0.001)	(0.001)
Constant	-0.012*	0.017***	0.002
	(0.006)	(0.003)	(0.002)
Observations	16,355	16,355	16,355
R-squared	0.062	0.137	0.034
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	No	No
Province FE	No	No	No

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[15]Although this is not part of the focus of this chapter, there is still scope for analysis the extent of the effects across sectors using more granulated data. This is a topic that could potentially be researched in a future academic paper.

4.4.2 Effects on NPD using travel time distances

In order to explore the extent of effects of mining activities in space, I use a continuous variable of distance which measure the minimum travel time by car from districts (PDs and NPDs) to NPDs. I use the POLS model in equation 2, and explore the effects of mining activities on the same set of outcome variables related to wages, employment and occupations. The level of analysis remains the same at the district level. Calculations for the travel time distance are fixed (i.e., they do not consider live traffic information), which are useful for replication purposes. The POLS model also uses demographic and geographic controls variables to account for time-varying factors.

I use the Interquartile Range (IQR) to get estimates of the 25th and 75th percentiles of travel time distances from districts to PDs.[16] The IQR spans from approximately 1.7 to 5.8 hours (i.e., 4.04 hours)(See IQR values on Figure 4.3). The results suggest that when the travel time distance by car to PDs increases in 1.7 hours, there is a marginal decline in employment of about 0.03%. This implies that districts located in close proximity of 1.7 hours away from PDs are more likely to have slightly lower levels of employment on aggregate during the period 2001-2019. Similarly, for districts with travel time distance in the 75th centile, it is expected that the share of employed individuals to drop up to 0.11%. These outputs suggest distance decay effects, where longer travel distances to PDs might show that the shared of employed individuals to decay marginally. These results is statistical significant at 1% level.

Another interesting finding is related to the extent of mining effects on the share of population who is unemployed and not actively looking to incorporate into the workforce. The results show that districts located in a travel time distance of 1.7hrs away from PDs are more likely to present a slightly higher shared of individuals unemployed and not actively looking for a job (equal to 0.02% and statistical significant at 1% level). This value increases marginally up to 0.06% for districts located farther away, for those based approximately 5.8hrs to PD (75th centile). Overall, these results suggest districts located in proximity to PDs might not only be having less employment opportunities but these seem to decay the farther these districts are to PDs. Also, the shared of individuals that are unemployed at district level and not actively looking to enter the workforce seems to increase the farther the distance is from districts to

[16] I also estimate other descriptive statistics such as the standard deviation which is approximately 22.98hrs, the mean is 7.19hrs, minimum and maximum values are 0.05 and 252.72. The median is 3.08 hrs, this value is below the mean due to extreme outliers that are above the 95 percentile (10.45hrs). At the 99% centile, it shows that the minimum travelling time by car is 152.38 hrs. This high values might distort the standard deviation. For this reason, I work with IQR values of the 25th and 75th centiles. Log values are also useful for the same purpose and to avoid outliers in the data, however, I use IQR since interpretation of values are more straightforward for policy implementation.

PDs, suggesting that the lack of employment opportunities might be pushing individuals out of the labour market. However, other possible reasons might be due to a labour market that is too competitive or crowded with specific requirements for type of labour, as well as individuals choices to join the labour market. I find negligible effects on wages and some effects statistically significant at 10% level in groups 2 and 3 of occupations,[17] where an increase in the median distance to PDs (circa 3 hrs) have a marginally effect in the shared of occupations for groups 2 and 3 of approximately 0.012% and 0.006%, respectively, meaning that some indirectly and economically dependent occupations might be performed from areas that are not necessarily within the PDs that host mining activities. There are no statistical significant effects on group 1, suggesting that these groups of occupations might be performed strictly within PDs.

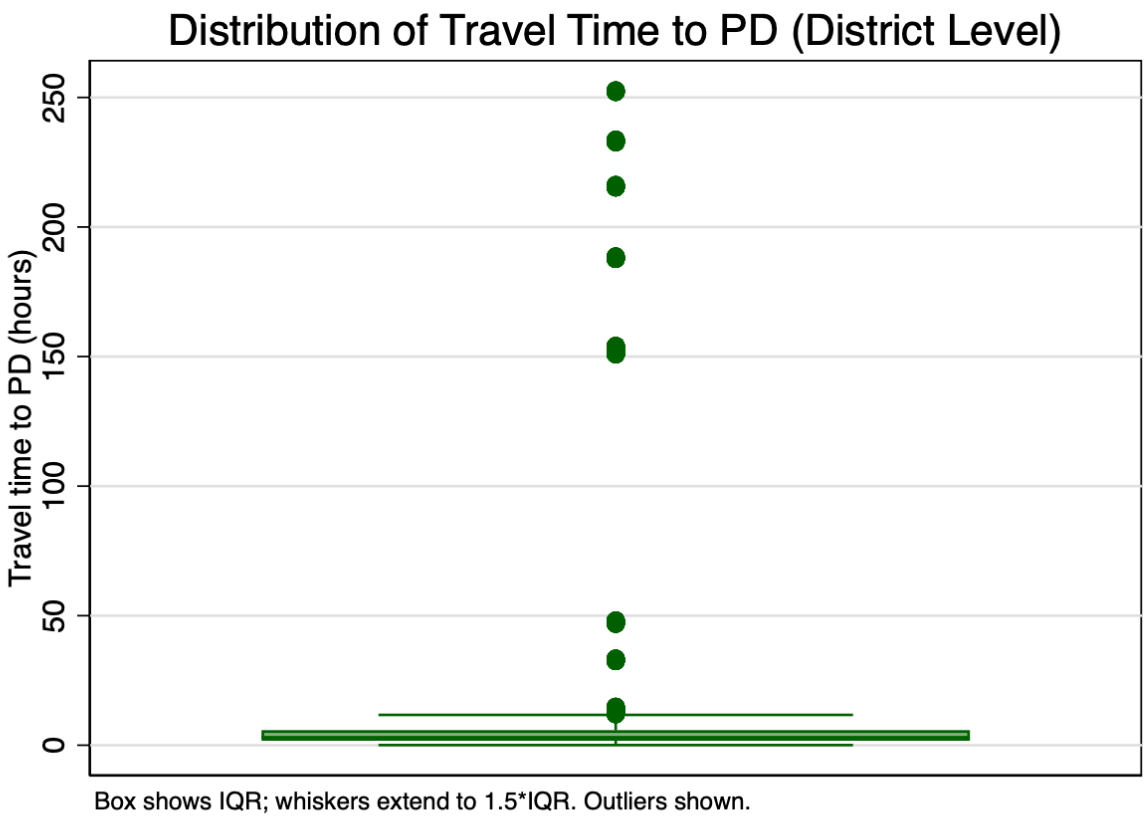


Figure 4.3: Boxplot Travel Time by Car to PD: 2001-2019
Note: Values for median=3.08, upper quartile=5.77, lower quartile=1.73, upper whisker=10.45, lower whisker=0.18.

[17]Coefficients equal to .0000173 with p-value 0.097 and .0000202 with p-value 0.058, for groups 2 and 3, respectively.

Table 4.6: Effects on NPD on Wages, Employment, and Occupations

	(1) Wages	(2) In employment	(3) Unemployment (open)	(4) Unemployment (close)	(5) Group 1 (Directly related)	(6) Group 2 (Indirectly related)	(7) Group 3 (Eco. dependent)
Producing	0.307***	-0.028***	0.003**	-0.001	0.016***	0.000	0.001
	(0.053)	(0.010)	(0.002)	(0.001)	(0.005)	(0.001)	(0.001)
Distance	0.000	-0.000***	-0.000*	0.000***	-0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	5.632***	0.612***	0.004	0.009***	-0.012*	0.017***	0.002
	(0.110)	(0.016)	(0.003)	(0.003)	(0.006)	(0.003)	(0.002)
Observations	14,931	16,299	16,299	16,299	16,299	16,299	16,299
R-squared	0.396	0.314	0.198	0.093	0.056	0.137	0.035
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Analysis during boom and bust years

I explore whether the effects on wages, employment and occupations hold during the years of boom and bust. In order to define both periods, I analyse data on the level of mineral investment for the period of analysis (data is sourced from Ministerio de Energia y Minas (2023)). During the first decade of 2000, the level of mineral investment (this includes investment in development and preparation, mining equipment, exploration, infrastructure, mining processing plant).[18] sharply increases reaching up to USD 426 millions in 2013. It is also observed an upward trend from years 2003 to 2004 up to years 2012 to 2013. After this, the level of total mineral investment show a decline up to year 2019. There seem to be another positive trend since year 2016 but this is relatively lower in comparison to the first positive trend. Figure 4.4 show the total level of mineral investment and mining investment by category regardless of the stage of the mines life. However, the component "Exploration" is more likely to reflect the initial investment to the first stages of mineral activity. When looking at the level of investment in exploration, this follow the same trend per other components (e.g., infrastructure, or processing plant). This could be understood as mine owners decision to continue exploration activities in current or new mines in Peru which seem to peak in year 2012 with approximately USD 46 millions and then dropping down to USD 18 million in year 2019. These trend reinforces the previous timeline in which boom activities in the mining sector seem to peak up to year 2013 and then following a decline in activities (bust years).

[18]Some of these categories could be linked to different stages in the life of a mine (i.e., stages of discovery/exploration, construction, operation, closure). According to Manalo (2023) the first stages of discovery, exploration and construction could last on average 15 years. The total level of mineral investment comprise all these stages.

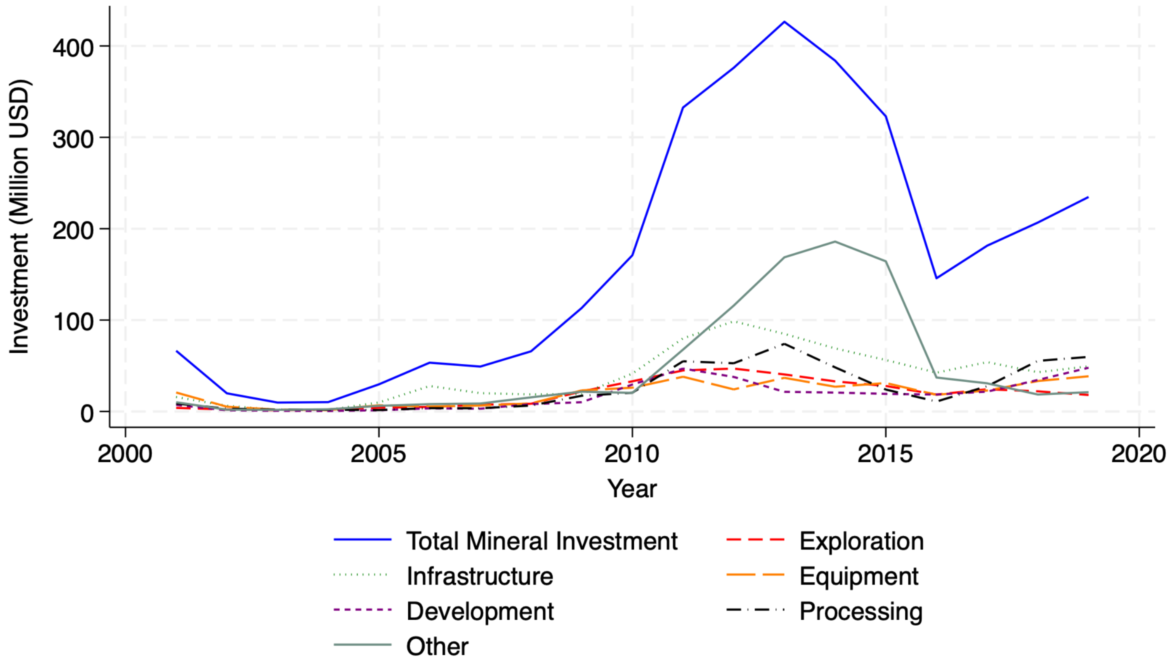


Figure 4.4: Total Mineral Investment by Component for the Period 2001-2019
Note: Sourced from Ministerio de Energia y Minas (2023).[19]

Both periods of boom and bust are also defined following empirical evidence of mining effects on socioeconomic indicators for the same period of study. The period of time considered boom years of mining activity comprise the period of time after year 2002. For instance, Dargent et al. (2017) focuses on institutional development in Peru during the period of boom years (also called commodity boom cycle) and addresses the most recent commodity boom in Peru as the period 2004 to 2012. Other scholar such as Loayza & Rigolini (2016) or Orihuela & Gamarra-Echenique (2020) address the period of mining boom years from 1993 up to 2007. Periods of bust are highlighted from years 2012 onwards, for instance, Ali et al. (2017) shows that investment in exploration decays after this year, which is likely to be correlated with a fall in the prices of commodities in international markets.

In table 4.7, I present the outputs of the DDD approach, the coefficient of interest is presented in the first row which estimates the effects of being a PD during post-treatment years (i.e., once PD start production) during boom years. The results from the DDD estimation indicate that wages in PD areas during boom years are 17% higher than in bust years. This difference is statistically significant at 5% level. This result suggests that economic booms lead to a spatial concentration of higher-wage jobs in PD areas, potentially due to increased firm clustering and competition for a limited local labour supply. Consistent with Moretti (2010), this wage premium may reflect a demand-driven effect, where intensified labour market competition during booms drives up wages in these areas. In contrast, the share of employed individuals appears to be lower in PD areas during boom years compared to bust years, as reported in Column 2. This result is counterintuitive, as one might expect economic expansion of mining activity to increase employment shares. During the boom of mining activities, the employment rate in PD areas was 4.1% lower than during bust periods. Moreover, unemployment rates were slightly higher in PD areas during booms, by approximately 0.6%. However, results in Column 5 show a positive and statistically significant effect at the 1% for Group 1 of occupations; the share of individuals employed in these occupations rose by approximately 1.4% during boom years. This suggests that wage gains in PD areas are concentrated among specific high-skilled occupational groups. No significant effects are observed for occupations in Groups 2 and 3.

According to the model in Allcott & Keniston (2018), production districts PDs should experience higher employment during boom years, with employment levels converging toward those of NPDs in the longer term (i.e., during bust periods). However, the evidence points to the opposite pattern, that PDs exhibit lower employment levels during boom years relative to both bust years and NPDs. This finding suggests that employment may not expand as strongly during the boom itself, but instead grows more during the bust period, potentially reflecting lagged economic activity from mining development, such as firm agglomeration that raises output and employment after the boom has ended. Alternatively, "learning-by-doing" spillovers from the mining sector may accrue to other industries or even to neighbouring areas rather than remaining concentrated within PDs.

The second row of Table 4.7 reports estimates for PDs under the "no switch-off" assumption, which treats mines as continuously producing even during years when production is inactive (e.g., temporarily inactive after production starts). In this specification, the share of employment in PDs is approximately 1.6% higher than in non-production districts (NPDs), and this coefficient is statistically significant at the 5% level. No statistically significant effects are observed for the other outcome variables. It is important to note that this estimate reflects the entire study period (2001–2019) rather than explicitly distinguishing between boom and bust phases. Given the DDD results, the 1.6% employment gap may largely reflect patterns from the later bust decade, rather than contemporaneous effects of the boom.

Table 4.7: Triple Interaction Effects on Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Wages	In employment	Unemployment (open)	Unemployment (close)	Group 1 (Directly related)	Group 2 (Indirectly related)	Group 3 (Eco. dependent)
`Producing × W × Boom`	0.171**	-0.041***	0.006**	0.000	0.014***	0.002	0.000
	(0.077)	(0.012)	(0.003)	(0.002)	(0.005)	(0.002)	(0.001)
`Producing × W`	0.092	0.016**	-0.002	-0.002	0.002	-0.002	0.000
	(0.058)	(0.008)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Constant	5.891***	0.595***	0.007***	0.006**	-0.012*	0.022***	0.000
	(0.125)	(0.016)	(0.003)	(0.003)	(0.006)	(0.003)	(0.002)
Observations	15,688	17,064	17,064	17,064	17,064	17,064	17,064
R-squared	0.421	0.343	0.225	0.086	0.057	0.151	0.033
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	No	No	No
Province FE	No	No	No	No	No	No	No

Notes: Robust standard errors in parentheses. The variable `producing × w × boomPD` captures the triple interaction between being a producing district, the dummy for the number of years in which a district is PD (no switch off), and the boom period indicator.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

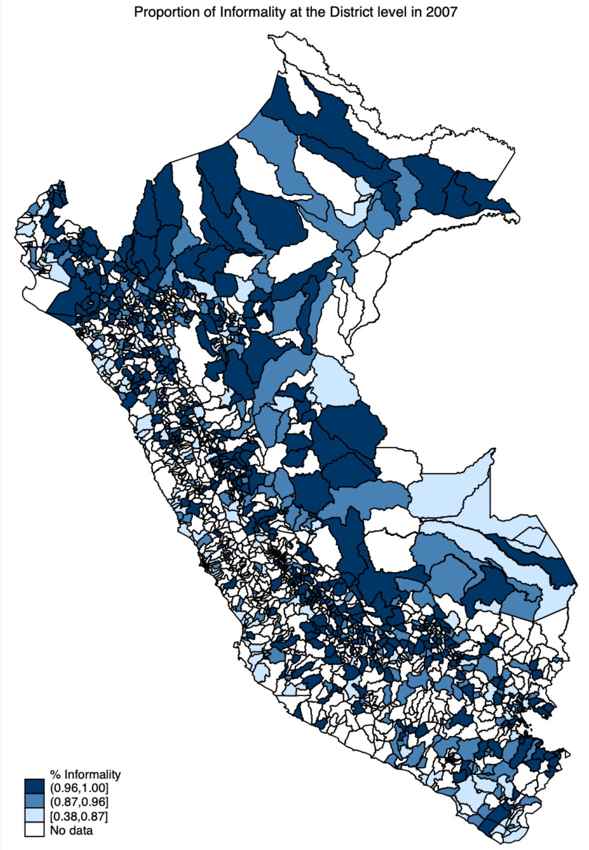
Analysis on the informal market

I next examine the effects of PDs status on the share of individuals employed in the informal labour market. Figure 4.5 shows that informality is widespread across both PDs and NPDs over the period of analysis, with more than 80% of individuals working informally. This share is consistently higher in NPDs, exceeding 85% throughout the study period. While the overall trend in both PDs and NPDs show a gradual decline in informality over time, the levels remain persistently high and seem to be evenly spread across districts. Figure 4.6 further illustrates this pattern, where informality rates remain elevated even during periods of mining expansion (2007–2013) and subsequent downturns (post-2013). Specifically, Figures 4.6a through 4.6c show that the majority of districts, both PDs and NPDs, maintain informality levels above 75%, as indicated by the prevalence of darker blue shading in both figures.

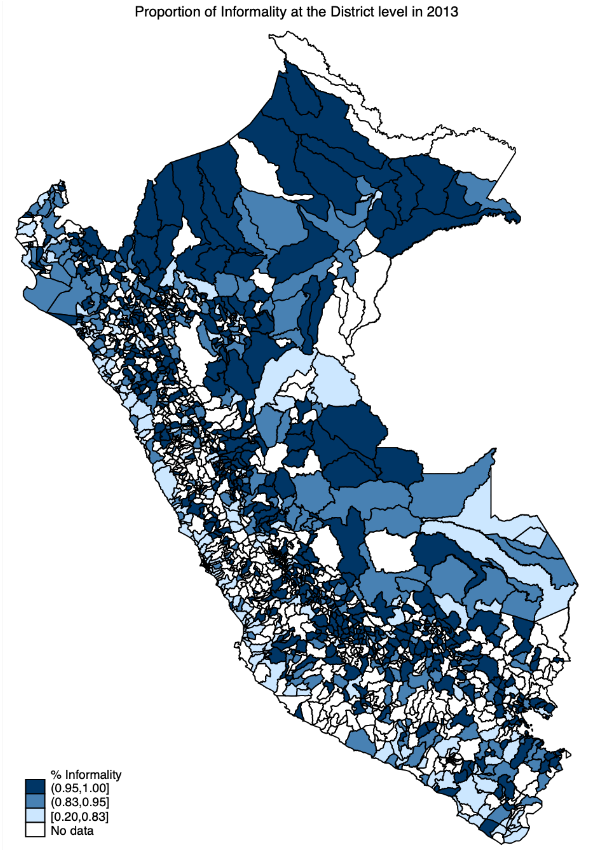
Informal employment is a persistent policy concern in developing countries. Although periods of economic expansion can increase labour market dynamism, including job creation, the informal sector often continues to absorb a substantial share of the workforce. Individuals may enter informal employment for various reasons. For instance, formal sector workers may transition to informal jobs to increase income, while unemployed individuals may view informal work as a short-term opportunity due to its lower entry barriers, such as fewer formal requirements or the availability of temporary contracts. These informal markets are typically characterised by the absence of formal contracts, social protections (e.g., pensions or health insurance), and access to benefits (Bacchetta et al. 2009). Given the scale and persistence of informality in the Peruvian labour market, this subsection investigates whether mining activity has contributed to either an increase or reduction in the share of individuals employed informally.

Figure 4.5: Evolution of the Share of the Informal Labour Market During the Period 2007-2019

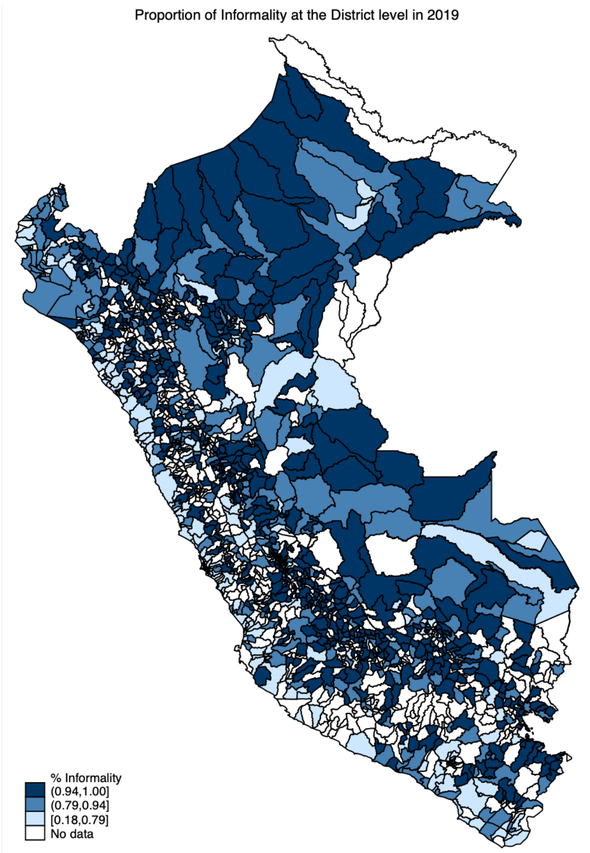
Note: Data on the informal labour market is only available from year 2007 onwards. PDs are presented in blue line, and NPDs in red dotted line.



(a) Share of Informality in year 2007



(b) Share of Informality in year 2013



(c) Share of Informality in year 2019

Figure 4.6: Share of Informality at the District Level
Note: First year of data available for informality is 2007.

Using the same empirical specification as in Regression Model 1, I find that PDs exhibit lower levels of informality than NPDs in the years 2007, 2013, and 2019. These differences are statistically significant at the 5%. Over this period, the share of informal employment in PDs declined by nearly half, from 2007 to 2019 (Figure 4.7).

These effects remain robust when comparing districts within the same region and province. In 2007 and 2019, informality rates in PDs were 5.5% and 3.7% lower than in NPDs, respectively, with both differences statistically significant at the 5% level. No statistically significant difference is observed for 2013, which marks the beginning of the bust period (Appendix Tables 4.15–4.17).

The observed reduction in informality in PDs relative to NPDs may reflect several mechanisms. First, firms located near or linked to mining projects may face higher levels of regulatory enforcement, which disproportionately affects smaller firms.[20] In such contexts, informality may function as an implicit subsidy for small firms, allowing them to remain profitable by avoiding taxes and social security contributions.[21] Higher levels of enforcement in PDs may also arise from stronger regulatory presence due to the visibility of large-scale mining operations. Additionally, small firms that supply goods or services to mining projects, either directly or through intermediaries, may be incentivised to formalise in order to participate in mining-related value chains. If so, the presence of mining could generate formalisation spillovers among local firms through increased demand and compliance pressures.

Broader policy efforts to reduce informality, such as targeted subsidies or local formalisation programs, may also have contributed to the observed decline in informality across both PDs and NPDs areas. However, a sustained reduction in informality likely reflects a combination of factors over time rather than the effect of any single policy. For example, periods of mineral booms may generate stronger economic spillovers, encouraging the movement of labour into the formal sector, while bust periods may have the opposite effect due to overall economic contraction. As shown in Figure 4.5, informality levels exhibit a downward trend over time in both PDs and NPDs, although they remain persistently high. At a broader level, evidence suggests that increasing enforcement efforts since the 1990s have led to higher unemployment rates but also to an increase in formal employment, as firms respond to tighter regulatory environments (Meghir et al. (2015)).

Another potential explanation is that formal firms, particularly those operating in PDs,

[20] De Paula & Scheinkman (2010) argue that small firms are more likely to operate informally due to barriers such as limited access to credit.

[21] Meghir et al. (2015) suggest that small firms often adopt informality as a strategy to reduce costs in low-enforcement environments.

may displace informal competitors, pushing them to neighbouring areas with weaker regulatory enforcement. This displacement could raise the share of formal employment in PDs. At the same time, displaced firms (primarily informal, but also some small formal ones) may revert to informality as a way to maintain earnings, especially during bust periods. As Loayza & Rigolini (2011) notes, informality can serve as a safety net during bust years, while in boom periods it may provide a source of economic dynamism for small firms.

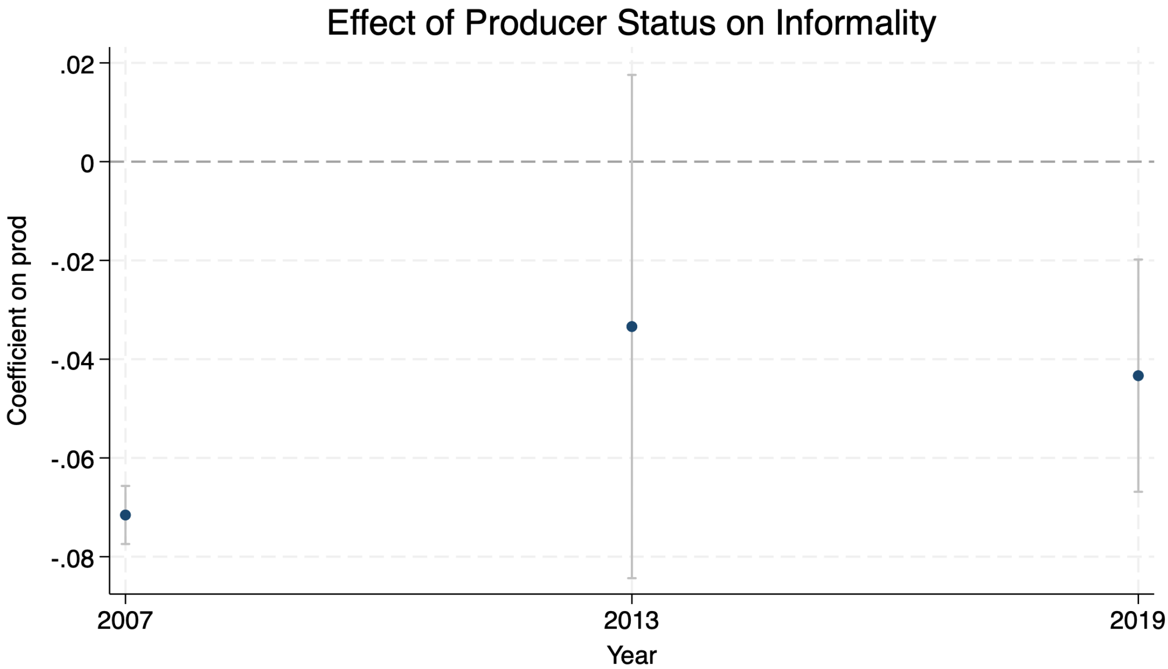


Figure 4.7: Outputs on Informality for years 2007, 2013, and 2019
Note: Blue dots show coefficients and brackets are confidence intervals (measured at 95% level).

4.5 Conclusion

This paper provides empirical evidence on the effects of mining activities on the Peruvian labour sector during the period 2001-2019, it also distinguish the effects by periods of boom and bust and examines the spatial spillover effects of mining activities on the labour market among NPD. A final contribution relates to the informal labour sector, which remains significant in Peru and other emerging economies in Latin America (Albrecht et al. 2009).

The main results of this paper suggest that, on aggregate, wages are higher in PDs than NPDs (difference of 30%). This wage gap persists even when comparing districts within the same regions and provinces, indicating that PDs tend to concentrate high-paying jobs. These higher wages likely attract both workers and firms, contributing to agglomeration in PDs. The results on employment are somewhat conterintuitive since PDs seem to have slightly lower levels of employment than NPD with an average difference of 2.4% over the study period. This results could suggest that during this period of analysis the number of jobs created in the local economy were more concentrated to high paying jobs. This is confirmed with the next set of results on occupations where the results evidence that Group 1 of occupations in PDs is higher than NPDs (difference of 1.8%). Although this is a slight difference, it could be argued that most of jobs created which were high wage jobs, were mainly targeted to occupations that are directly related to the mining sector. When looking at the extent of effects in space, for instance, employment levels decay for NPDs located 1.7 hours and 5.8 hours (up to 0.1%) away from PDs. A similar outcome is found for the levels of unemployment, specifically for the group of individuals who are not actively looking to enter the workforce. The results suggest that the more distant districts are to PDs, the more likely is that this share marginally increases with distance (circa 0.02% to 0.06%). I also find negligible effects on wages, therefore, there are no significant difference in wages across PDs and districts (these could be PDs and NPDs) in areas that are in their proximities. I find some effects on groups 2 and 3 of occupations (significant at 10% level) which might suggest that some occupations that are indirectly related or economically dependent to the mining sector are being performed from NPDs, potentially confirming presence of outsourcing of some activities. Another interesting finding that this paper reveal is related to the periods of boom and bust, where I find concentration of high wages in PDs, this is 17% than in PDs or NPDs during boom years. This result is predicted in the model of Allcott & Keniston (2018). However, I find counterintuitive results regarding effects on the share of employment, where this is lower for PDs (4.1%) during boom years (in comparison to PDs in bust years, and NPDs). As suggested by Moretti (2010), higher wages might be the result of a demand-driven effect due to concentration of firms (which is a result of the arrival of a mining project to a host area, and with that, the agglomeration of new firms in the area). This concentration should be expected to increase the levels of employment in PDs (as suggested in the Allcott & Keniston (2018) model). However, the results on occupations provide some answer to the previous findings, where the share of individuals in group 1 of occupations is higher for PDs (1.4%) than NPDs, confirming that high wages during boom times were mainly concentrated into these occupations. I find negligible effects for Group 2 and 3. Finally, the last part of the results on informality suggest that PDs concentrate lower levels of informality than NPDs, these results are also consistent when looking at the difference in districts within regions and provinces for years 2007 and 2019 (5.5% and 3.7%, respectively). Some of the reasons behind these differences could be related to higher levels of enforcement activities within PDs, specifically targeted to small firms (De Paula & Scheinkman 2010). It could be also the case that higher levels of enforcement are expected within the host area, due to presence of large scale operations. Another reasons might be related to high competition in PD, which by default displace small informal firms to other areas (e.g., NPDs).

The contribution of this paper is threefold. First, mining activities substantially raise local wages, but the gains are concentrated in occupations linked to the extractive sector. When disaggregating by time, the wage effects do not dissipate in the long run, thus, there is no evidence of a "catch-up" effect for NPDs, which may contribute to persistent inequality between PDs and NPDs. Second, the spatial analysis shows that employment effects decay only slightly beyond PD boundaries, and that some occupations might be outsourced to NPDs. This outsourcing provides not only an economic boost to NPDs but also an opportunity for local governments to leverage spillovers to foster growth in other industries. Finally, the paper documents important dynamics in the informal labour market, which seem to be higher in NPDs than PDs, suggesting among various reasons that concentration of informality remains a key issue to be solved among policy makers, with specific focus on NPDs. Although informality can act as a survival safety net, it also perpetuates risks, such as widening inequality and the exclusion of workers from pensions and health insurance. These factors could slow progress toward more inclusive and sustainable regional growth.

Several policy measures could be considered to enhance the local labour market benefits of mining activities. First, targeted support could be provided to local firms to expand their capacity to hire formal workers, such support might include improved access to credit, temporary tax exemptions, or subsidies linked to youth employment programs. These policies should also extend to NPDs located near PDs, which often host workers or firms indirectly linked to mining operations. For these nearby NPDs, a key objective should be to foster upward mobility among individuals employed in occupations indirectly related or economically dependent on the mining sector. This could be achieved through training programs in complementary industries such as construction, manufacturing, or services, with a particular focus on preparing workers for transitions during bust periods. Finally, the observed concentration of high wages within a specific group of occupations should serve as evidence to local policy makers that the benefits derived from extractive industries might be to focalised to specific group of occupations and that some of the core activities could be performed from outside the host area (e.g., to NPDs in proximities). These findings reinforce the need for local and regional governments to coordinate economic diversification strategies and working beyond district boundaries to promote broader, province or region wide development.

4.6 Appendix

Table 4.8 presents the full event-study estimates used to assess pre-trends for each outcome variable. While the main analysis relies on a triple-difference specification and does not focus on post-treatment dynamics, the table indicates statistically significant positive effects on log wages in PDs relative to NPDs at event times $r + 5$ and $r + 7$, both significant at the 5 percent level. These results suggest moderately higher wage levels in PDs in the medium term following the initiation of mineral production. Similarly, the share of individuals employed in occupations categorised under Group 2 increases significantly in post-treatment years $r + 3$, $r + 4$, $r + 5$, and $r + 7$, at the 10% and 5% significance levels. These findings are consistent with positive medium-term labour market adjustments in occupational structure following mining expansion. Conversely, the results indicate negative long-run effects on unemployment (open) and occupations categorised under Group 3 in years $r + 8$ and $r + 9$, with coefficients significant at the 5% level. Additionally, negative effects on Group 1 occupations emerge in years $r + 8$ and $r + 9$, though these are marginally significant at the 10% level.

Table 4.8: Effects by Relative Time from Start of Treatment (r)

	(1) Log Wages	(2) Employment	(3) Unemployment (open)	(4) Unemployment (close)	(5) Group 1	(6) Group 2	(7) Group 3
$r-2$	0.004	-0.016	0.002	0.011**	0.001	0.000	-0.001
	(0.098)	(0.012)	(0.003)	(0.005)	(0.005)	(0.001)	(0.003)
r	-0.050	0.000	0.003	0.005*	-0.003	-0.002	-0.004*
	(0.088)	(0.011)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
$r+1$	0.083	-0.010	-0.001	0.004	0.006	0.004	-0.003
	(0.093)	(0.011)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
$r+2$	0.053	0.006	0.000	-0.001	0.000	0.004	-0.001
	(0.097)	(0.012)	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)
$r+3$	0.051	0.006	-0.003	-0.001	-0.005	0.005*	-0.002
	(0.089)	(0.013)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)
$r+4$	0.034	-0.001	0.001	0.002	-0.002	0.005*	0.000
	(0.100)	(0.014)	(0.003)	(0.003)	(0.007)	(0.003)	(0.004)
$r+5$	0.193**	-0.010	-0.003	0.003	0.004	0.007**	-0.003
	(0.097)	(0.014)	(0.003)	(0.003)	(0.008)	(0.003)	(0.002)
$r+6$	0.149	0.001	-0.003	0.003	-0.004	0.005	-0.004
	(0.096)	(0.014)	(0.003)	(0.004)	(0.008)	(0.003)	(0.003)
$r+7$	0.220**	-0.003	-0.002	0.001	-0.003	0.007*	-0.003
	(0.102)	(0.016)	(0.003)	(0.003)	(0.009)	(0.004)	(0.003)
$r+8$	0.032	0.015	-0.004	0.002	-0.012*	0.003	-0.006**
	(0.113)	(0.013)	(0.003)	(0.003)	(0.007)	(0.002)	(0.003)
$r+9$	0.109	0.014	-0.007*	0.002	-0.014*	0.003	-0.006**
	(0.112)	(0.015)	(0.004)	(0.003)	(0.008)	(0.002)	(0.003)
$r+10$	0.034	0.017	-0.007**	0.002	-0.010	0.001	-0.007**
	(0.106)	(0.013)	(0.003)	(0.003)	(0.013)	(0.002)	(0.003)
Constant	5.495***	0.600***	0.005*	0.008**	-0.002	0.014***	0.002
	(0.103)	(0.014)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
Observations	15,653	17,036	17,036	17,036	17,036	17,036	17,036
R-squared	0.580	0.545	0.374	0.218	0.479	0.358	0.214
Controls							
Demographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.9: Effects on employment within Regions and Provinces

	(1) Across/within regions	(2) Within region	(3) Within province
Producing	-0.024**	-0.023***	-0.010*
	(0.010)	(0.008)	(0.006)
Constant	0.615***	0.595***	0.573***
	(0.016)	(0.017)	(0.024)
Observations	16,355	16,355	16,355
R-squared	0.311	0.349	0.394
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.10: Effects on unemployment (Open) within Regions and Provinces

	(1) Across/within regions	(2) Within region	(3) Within province
Producing	0.003*	0.002	-0.001
	(0.002)	(0.001)	(0.001)
Constant	0.004	-0.001	0.003
	(0.003)	(0.003)	(0.003)
Observations	16,355	16,355	16,355
R-squared	0.198	0.219	0.247
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.11: Effects on Unemployment (Close) within Regions and Provinces

	(1) Across/within regions	(2) Within region	(3) Within province
Producing	-0.002	-0.001	-0.002*
	(0.001)	(0.001)	(0.001)
Constant	0.009***	0.006*	0.007*
	(0.003)	(0.004)	(0.004)
Observations	16,355	16,355	16,355
R-squared	0.090	0.115	0.133
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.12: Effects on Group 1 within Regions and Provinces

	(1) Across/within regions	(2) Within region	(3) Within province
Producing	0.018***	0.016***	0.013***
	(0.005)	(0.005)	(0.004)
Constant	-0.012*	-0.012**	-0.012**
	(0.006)	(0.006)	(0.005)
Observations	16,355	16,355	16,355
R-squared	0.062	0.080	0.162
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.13: Effects on Group 2 within Regions and Provinces

	(1) Across/within regions	(2) Within region	(3) Within province
Producing	-0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)
Constant	0.017***	0.020***	0.020***
	(0.003)	(0.004)	(0.004)
Observations	16,355	16,355	16,355
R-squared	0.137	0.143	0.177
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.14: Effects on Group 3 within Regions and Provinces

	(1) Across/within regions	(2) Within region	(3) Within province
Producing	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)
Constant	0.002	0.002	0.004**
	(0.002)	(0.002)	(0.002)
Observations	16,355	16,355	16,355
R-squared	0.034	0.044	0.074
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.15: Effects on informality for year 2007

	(1) Across and within regions	(2) Within region	(3) Within province
Producing	-0.072***	-0.055**	-0.054**
	(0.025)	(0.025)	(0.025)
Constant	0.925***	0.945***	0.852***
	(0.031)	(0.032)	(0.056)
Observations	822	822	822
R-squared	0.515	0.559	0.692
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	No	No	No
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.16: Effects on Informality for Year 2013

	(1) Across and within regions	(2) Within region	(3) Within province
Producing	-0.039**	-0.013	-0.026
	(0.015)	(0.016)	(0.017)
Constant	0.878***	0.903***	0.903***
	(0.041)	(0.041)	(0.053)
Observations	995	995	995
R-squared	0.503	0.545	0.679
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	No	No	No
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.17: Effects on Informality for Year 2019

	(1) Across and within regions	(2) Within region	(3) Within province
Producing	-0.048***	-0.039**	-0.035*
	(0.018)	(0.017)	(0.021)
Constant	0.831***	0.851***	0.756***
	(0.040)	(0.044)	(0.063)
Observations	1,130	1,130	1,130
R-squared	0.538	0.579	0.676
Demographic controls	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes
Year FE	No	No	No
Region FE	No	Yes	No
Province FE	No	No	Yes

Notes: Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Chapter 5

Conclusion

This PhD thesis examines the effects of mining activities on welfare in Peru over the period 2001–2019, using secondary data from INEI, the Ministry of Energy and Mines, the Central Bank of Peru, and other official sources. Across three chapters, it applies quantitative approaches to explore differences between PDs and NPDs. Chapter 2 focuses on PDs, providing new empirical evidence on welfare effects while accounting for the intermittent nature of mining activity over time. Chapter 3 extends the analysis to NPDs, testing linear and travel distance measures to assess the spatial and temporal extent of mining's impacts. Chapter 4 turns to the labour market, analysing wages, occupations, and employment dynamics during boom and bust cycles, as well as the role of the informal sector. Taken together, these chapters contribute to the literature on natural resource economics, economic geography, and labour economics by providing a long-term, district-level perspective on how mining shapes welfare and labour outcomes in Peru.

5.1 Summary of results

Chapter 2 brings new empirical evidence on the effects of mining activities on welfare across PDs, highlighting the intermittent nature of mining activities over time. This is performed by working with two scenarios. The first assumes that welfare effects are absorbed even when mining activities are temporarily on hold. The second considers only districts that transition once from NPD to PD status. It is in this second scenario where I find short term effects, resembling periods of mini economic booms for PDs. However, there is no indication that these effects persist over time.

When looking specifically at the results by mining size, I find positive short-term effects for districts hosting large and medium-scale operations, which vanish quickly thereafter, and no significant effects for small-scale or artisanal operations. Finally, districts located in mining-dependent regions are more likely to experience positive welfare effects, which can persist for up to four years after transitioning to PD status.

In Chapter 3, I find that the effects of mining activities on welfare decay with distance, and that these effects are larger when using travel distance rather than linear distance. This highlights the importance of distance measures for analysing spatial spillovers. Over time, districts located within 50 km of PDs show positive welfare effects four to five years after production begins, while districts within one to two hours of travel time experience similar gains in the fifth year, suggesting lagged spillovers to NPDs.

These results remain consistent when accounting for road quality, with effects again concentrated in districts located closer to PDs. Considering regional vehicular density, I find that welfare effects continue to decay with distance even in congested areas, where longer travel times would normally be expected. Finally, robustness checks using income and real expenditure confirm that positive mining effects are spatially concentrated around PDs.

Chapter 4 examines the effects of mining on the Peruvian labour market, including informality, across both PDs and NPDs. I find that PDs exhibit higher wages than NPDs, likely reflecting the availability of high-paying jobs in the mining sector. At the same time, overall employment levels are lower in PDs, consistent with mining being capital intensive rather than labour intensive. These patterns suggest that wage gains are concentrated among a narrow group of workers directly employed in mining, a result confirmed by the higher share of mining-specific occupations in PDs.

Spatial analysis shows that employment opportunities decay with distance, indicating that job concentration is largely confined to PDs. The boom–bust analysis further reveals that wages rise during boom years, while employment remains lower in comparison to bust years, perhaps reflecting lagged economic effects. Finally, I find that informality is lower in PDs than in NPDs, which may reflect not only stronger enforcement activities within PDs but complementary regional or local policies over time.

5.2 Policy Implications and future Research

The findings suggest that mining projects often generate immediate but short-lived welfare gains, resembling "mini booms". Local authorities should anticipate these dynamics, since short-term improvements are frequently accompanied by rising prices, inequality, and pressure on public services. The costs of accommodating such surges may outweigh the temporary benefits, particularly in contexts where production is intermittent.

This does not imply that mining projects should be discouraged, but rather that their development requires careful planning and complementary policies. For instance, programs to diversify local economies, and investments in infrastructure and skills can help transform temporary gains into longer-term improvements in welfare. Without such measures, mining-led growth risks remaining volatile and a source of inequality.

The results also suggest that mining generates short-lived positive spillovers into nearby NPDs. However, these effects risk creating dependence on mining and exposing peripheral areas to similar pressures as PDs, including price increases and inflows of workers. This highlights the importance of extending diversification and resilience policies beyond host districts to their surrounding areas.

Credit programs for local firms, entrepreneurship support, and training initiatives that promote upward mobility can help mitigate vulnerability to sector-specific shocks. Since spillovers extend 50 km or around 2 hours of travel time from PDs, policies should be designed at the provincial or regional level rather than narrowly at the district level. Investment in transport infrastructure also remains critical, not only to connect NPDs with PDs but also to facilitate linkages with more diversified local economies.

The findings on informality suggest that stricter enforcement within PDs may have helped reduce informal employment, but similar efforts are needed in surrounding NPDs, where firms often emerge to capitalise on short-term mining booms. Enforcement alone, however, is unlikely to be sufficient. Complementary policies such as targeted tax incentives, small grants, and training programs can support firms in formalising and diversifying beyond mining related activities, thereby reducing vulnerability to sector-specific shocks.

This thesis also raises new questions about the longer-term dynamics of labour markets in mining regions. The evidence of wage concentration in PDs during boom periods suggests that workers may increasingly specialise in mining related occupations, but it remains unclear how such specialisation evolves once production slows or resource booms come to an end. Future research should investigate whether mining specific skills are transferable to other extractive and non-extractive sectors, and how the reallocation of specialised labour shapes local and regional economies. Similarly, further work is needed to understand how firms that provide mining related services adjust during downturns, and whether they diversify, relocate, or exit. Addressing these questions would require more granular data on workers and firms, including longitudinal information on occupational transitions to the formal and informal sector, firm dynamics, and sectoral linkages.

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