NET EFFECTS OF COAL MINING AT A LOCAL LEVEL IN INDIA

by

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Abstract

The theme of my dissertation is natural resources and their impact on the local economies where they are extracted. In doing so, I touch on various sub-themes of education, health and production in the regional set-up and examine the channels through which mining impacts these socio-economic outcomes for individuals and firms in these regions.

In my Ph.D. dissertation titled “Net effects of coal mining at a local level in India”, I make use of three distinguished and unique individual level data sets from India to examine the effects of coal mining on the socio-economic outcomes for individuals and firms in local vicinity of these mines. Presence of coal mines in an Indian region along with the international coal price shock over the time period 1999-2011, is used as an economic shock and instrument in determining the impact on education and health of young children in coal regions as well as on the productivity of firms in these regions.

I discuss below a summary for each of the three research papers that comprise my dissertation;

Children of Black Gold: Local Effects of Coal Mining on Education of Children in India

The geographically concentrated natural resources have been a subject of contentious debate for their nature as a ‘curse’ or a ‘blessing’ to a nation for a decade now. In this paper, I examine the local effects of coal mining on the nearby families within India. International coal price movements strongly impact the labor markets in Indian mining communities. I estimate the trade-offs in household decision making regarding their children’s attendance in school versus at work.

This study merges the geographical location of active coal mines with three National Sample Surveys in India spanning over the period, 1999-2011. With a pooled cross-section of approximately 200,000 children living in rural India, a highly localized analysis allows to evaluate the spillover effects of coal mining.

A difference-in-difference estimation, by exploiting the spatial and temporal variation in mining, reveals that, the probability to attend school for any child in the mining region increases by 4% points when there is doubling of the international coal price. Placebo tests suggest that

these outcomes are valid for children of all ages but limited to those living in coal mining regions only. These positive outcomes can be explained by the higher 'returns to education' owing to economic incentives generated in these regions.

In addition to contributing to the existing literature on the local effects of resource abundance in a region, this study also claims to be the first in addressing this issue in India, which is a prominent emerging economy, having implications for other developing nations.

Local Effects of Coal Mining on Health of Children in India In this paper, I analyze the local effects of international coal price shocks on the health outcomes of children living in coal mining regions of India. The nutritional status of young children is measured through anthropometric measures such as weight-for-age and height-for-age z-scores culminating into the incidence of stunting and underweight tendencies. I estimate how the household decision making regarding the investments in child's health both in terms of time and income is affected when exposed to the coal price shock.

This study merges the geographical location of active coal mines with two survey rounds for the Indian Human Development Survey for the time periods 2004-05 and 2011-12. With a pooled cross-section of approximately 36,500 young children (age<5 years) living across Indian regions sampled in IHDS data, a highly localized analysis allows to evaluate the spillover effects of coal mining.

A difference-in-difference estimation, by exploiting the spatial and temporal variation in mining, reveals that, the probability for a child living in coal districts of India to be 'stunted' reduces by 5% points and to be 'underweight' reduces by 6% points when international coal prices double. Placebo tests suggest that these outcomes are valid only for young children living in coal mining regions of the country. These positive outcomes can be explained by greater time-allocation by mothers towards child rearing in these regions as well as positive income shocks. The study also finds evidence for prevalence of 'son-preference' in household decision making regarding investments in child's health in coal regions of India.

In addition to contributing to the existing literature on the local effects of resource abundance in a region and the effects of aggregate economic shocks on local health outcomes for children, this study also claims to be the first in addressing this issue in India, which is a prominent emerging economy, having implications for other developing nations.

Local Effects of Coal Mining on Firm Productivity in India This paper adds to the existing literature on the net impact of resource abundance on economic outcomes in a region by considering the effect of coal mining on firm productivity in India. The Annual Survey of Industries (ASI) data set at a unit level from India is used to estimate a firm production function across the Indian districts. The study finds that presence of coal mines in a region creates positive spillovers in the form of agglomeration effects, thus enhancing the firm productivity.

Sectoral differences in employment suggest that male workers find work in all sectors in coal regions facing the economic shock, while the female workers are better off only in agricultural and mining sector. Discouraging the theory of mining as an enclave sector, this paper shows that even though firm output improves in all economic sectors due to the increasing local demand for inputs and outputs, it is the manufacturing sector which drives the rising firm productivity in these regions.

In the light of underutilized capacity in coal production in India, the results of the paper can be used to guide policy action and encourage more sustainable mining activity for the welfare of these regions.

Preface

This thesis is an original work by Himani Pandey. No part of this thesis has been previously published.

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Chapter 1

Introduction

Whether natural resources are a 'curse' or a 'blessing' to a nation has been an issue of policy debate for over a decade now. The non-renewable resources which are geographically concentrated are at the center of this debate. The finite nature of such resources makes it imperative to consider the potential costs and benefits of resource extraction, thus identifying the ways for their sustainable use.

The negative impact of resource extraction is an empirical regularity when examined at a macro level. This is more popularly known as the "Resource Curse" phenomenon[1]. Recently, Fleming and Measham [2015] have defined it as "the whole set of unintended consequences that originate from resource extraction activity and trade that can end up negatively affecting the economic development of regions hosting the resource extraction industry or the entire country".

The existing empirical literature on the impact of resource abundance on economic development is motivated by this 'Resource Curse' literature which mainly highlights the various channels of the impact at a macro level [Rosser, 2006]. This literature, however, has had several limitations. Firstly, the causal interpretation of the results is still a concern as much is the consensus on their applicability. These results suffer from omitted variables bias, reverse causality, and measurement errors [Van der Ploeg, 2011]. There has been much work done to address these issues using richer set of covariates, instrumental variables, and panel and time

[1]The term was coined by Richard Auty in 1993 , also earlier referred to as the "Paradox of Plenty" by Terry Lynn Karl in 1997.

series data. However, cross-country variations can still not throw light on the non-uniformity of the differential impacts of resource abundance within a country.

Contrary to earlier theories of resource extraction, where mineral sectors were considered to have enclave effects with minimal or no forward or backward linkages with the rest of the economy [Hirschman, 1958], today we have begun to appreciate the economic importance of the mining sector having socioeconomic effects on the local populations. These linkages are the source of local demand shocks which alter the local equilibrium scenarios through various spillover effects.

Within a country, many spill overs from resource abundance (negative such as pollution and population displacement and positive such as input/output linkages and clustering of economic activity) have a local geographical scope. The impact of an extractive industry can be highly localized and specifically targeted to certain sections of the population only. The resource rents and the institutional quality pertaining to the extractive industry has different implications for its stakeholders. The localized effects of presence of an extractive industry and its expansion will thus shed light onto how these local groups can be targeted to ameliorate the negative effects of resource boom seen mainly at macro level and enhance the potential benefits which might be more applicable at the micro level.

This sets the background of the research undertaken in this work where I would like to examine the effect local demand shocks emanating from mining activity in India on the various socioeconomic characteristics of the local population. This study would add a new dimension to the existing literature on the net impact of resource abundance in a region and at the same time would be one of the first studies to address this issue in the context of India which is an emerging economy having implications for similar developing nations around the world. I would address the research agenda using the case of coal mining in India which is a major source of energy in the country and the world. The research will touch on three dimensions of socioeconomic effects at a local level: i) Education, ii) Health and iii) Labor market outcomes.

1.1 Coal in Indian Economy

Coal is a fossil fuel. It is a combustible, sedimentary, organic rock, which is composed mainly of carbon, hydrogen and oxygen. It is formed from vegetation, which has been consolidated between other rock strata and altered by the combined effects of pressure and heat over millions of years to form coal seams.

Coal is vital for sustainable development. It is the most widely used energy source for electricity generation and an essential input for steel production. Coal is an essential resource for meeting the challenges facing the modern world. India has a long history of commercial coal mining since 1774 and nationalization of coal mines was put to effect in 1973.

Coal provides 55% of commercial energy supply in India currently, and is a dominant source of power production in the country [Ministry of Coal India, 2020]. This is primarily because coal is India's most abundant non-renewable energy source. India has the world's fifth largest recoverable deposits of coal in the world at an estimated 101 billion tonnes, and is also the second largest producer of coal in the world [Coal Controller of India 2019]. Most of India's coal is geographically concentrated in central and eastern parts of the country. Their geographical distribution creates supply challenges owing to separation with the principal areas of consumption requiring substantial infrastructural networks for transportation from mine sites to generators.

Besides playing a crucial role in the energy sector, coal is traditionally considered as an important economic sector in the country. It provides employment to around 366,000 people[2], although there is significant uncertainty around these numbers and the actual number is likely to be somewhat higher (maybe in the order of 500,000 direct jobs).[3]The employment of labor in this sector has been decreasing substantially because of rapid improvements in labor productivity. It can be estimated that the labor productivity of the Indian coal mining sector improved by about 6.6% per year in the period 2000-14, as output grew by 4.9% per year and employment in the sector declined by 1.8% per year.

In terms of value, the coal and lignite sector accounted for about 37% of the nominal value

[2]Statistics of Mines in India [Coal] 2011-12
[3]Coal India Ltd. 2018

of gross output in the Indian mining sector, a figure that has shown a variable trend over the last 15 years, but no absolute decline (it was 37% in 2000). Given that the mining sector made up about 2% of the Indian economy, we can estimate that the coal sector accounted for about 0.7% of the Indian economy as of 2015 (RBI 2018; MOSPI 2018).

Between 2000 and 2014, nominal wages for coal mining grew from 204.82 Rupees/day to 416.74 Rupees/ day.[4] Adjusted for inflation, this amounts to a real wage growth of some 42% across the period. However, in the same period, the labor productivity of coal mining (tons/ job) grew, as noted above, by 131%. This indicates that real wages grew at a significantly slower rate than labor productivity. This gap between labor productivity growth and real wage growth was relatively smaller in the coal mining sector: 11 out of the 17 sectors had a gap between labor productivity growth and wage growth that was larger than that of coal [Spencer et al., 2018].

The above analysis shows that despite being dangerous and dirty, coal mining is a source of relatively "good" employment in India, with positive real wage growth; a delta between real wage growth versus labor productivity growth that is large but still smaller than most other industrial sectors; and a relatively high level of remuneration relative to other sectors. Nonetheless, the coal sector accounts for a small section of the overall Indian economy and labor market (in the order of 0.8% of total employment, consistent with the coal mining sector contributing 0.7% to the total Indian economy).

1.2 Political Economy of Coal in India

India's domestic coal industry is primarily government owned and coordinated. The Ministry of Coal at the apex formulates and implements all policies pertaining to exploration, project approvals, and other issues relating to production, supply of coal and pricing of coal [MOC 2019]. The Coal Controller is a subordinate office of the Ministry of Coal which sets standards for assessing coal quality and works as an arbitrator in event of conflicts, disputes, collects excise duties and manages coal related statistics [Coal Controller of India 2019].

Coal India Limited was formed as the holding company for coal mining in 1975 following

[4] 1 USD = 44.94 Indian Rupees (2000); 1 USD = 59.44 Indian Rupees (2014)

the nationalization of India's coal assets. It accounts for 80% of all the coal production in India. It's targets and performance indicators are directed by the Ministry of Coal itself. Aside from the Central government, the state governments can retain some influence over coal sector through approval of mining leases and licenses and setting royalty rates. The state governments also own coal mining companies either as subsidiaries of CIL or in partnership with the central government. Captive producers are also present which account for 8% of the Indian production. These are the privately-owned-end users (electricity, steel, cement etc.) who produce their own coal through auction of coal blocks. These producers are referred to as 'captive' as their production can't be exported and can be used for approved activities only. They can, however, sell to Coal India any amount that is surplus.

This political structure affects the pricing of coal in India. The coal intended for power generation is priced lower to subsidize electricity in the country. Around 80-90% of domestically produced coal in India is allocated through long term agreements called fuel supply agreements [Philalay et al., 2019]. These prices are fixed by the government, with the remaining coal not intended for power generation is sold via e-auctions. This creates disparity in the international and domestic prices of coal. It is expected that an increase in domestic prices to the market-clearing prices would significantly increase coal production in the country [Zhang, 2018].

1.3 Import Penetration of Coal in India

In spite of sufficient coal reserve, India is not able to meet demand from own production. Moreover, the supply of high quality coal (low-ash coal) in the country has been more limited than the low quality coal. Therefore, to bridge the demand-supply gap as well as sweeten indigenous production, there is dependency on imported coal, especially low-ash coal [Coal Directory of India 2012-13]. In 2012-13, import of coal by India was 145.785 MT (value USD 11658 billion) against import of 102.853 MT (value USD 10853 Billion) registered in 2011-12 [Coal Directory of India 2012-13][5]. This shows an increase of 41.74% in quantity and 10.16% in value over the previous year. The leading suppliers of coal to India in 2011-12 were

[5] Value converted from INR to USD as per exchange rate in 2021.

Indonesia (56.52%), Australia (20.89%) and South Africa (13.92%). Although, there is short supply of coal in India compared to its demand and therefore imports dominate the exports of coal in India, India does export some quantity of coal to its neighboring countries. In the year 2012-13, the total export was 2.443 MT, where Bangladesh accounted for (66.35%) of export followed by Nepal (25.67%) and Bhutan (3.93%) [Coal Directory of India 2012-13].

The net energy imports in India have roughly averaged around 4% of the GDP since 1995, with various spurts in 2008,2011,2012,2013 when it reached 7-8% of the GDP [Tongia and Gross, 2019]. Coal has also contributed significantly to this current account deficit, with coal imports contributing 14% to trade deficit in India in 2017-18 compared to crude oil imports which contributed 65% to the deficit. Most of the coal imports constitute steam coal (for power generation) and coking coal (for steel production). Therefore, half of coal imports in India can be considered structural given that steel production is expected to be higher in coming years and the scope of import substitution of coking coal is small enough [Tongia and Gross, 2019]. In order to account for other users of imported coal in India, the Annual Survey of Industries database can be used. According to ASI 2010-11, the industries that import coal include those that manufacture or process copper, aluminum and iron & steel. A close look at the input output tables could reveal the exact implication of international coal prices on the industries importing coal. However, since the power producing and metallurgical industries which are spread all over India (especially in regions with no active coal mines) are at the major importers of coal in 2010-11 (useful for analysis in this paper), it can be concluded that international coal prices do impact the livelihoods of individuals living in non-coal regions attached to such industries in that manner.

Some points in consideration in understanding the need for imported coal include the limited availability of land for developing new coal mines in India, transportation bottlenecks, regulatory requirements which potentially make domestic coal expensive to purchase outside Fuel Supply Agreements for local users in India. For comparison, coal costs for Indian power plants are about 50 percent higher than the United States on a per kilowatt-hour electricity basis, which is partly due to the higher energy content of U.S. coal, but levies and transport costs in the Indian coal supply chain are also an important component [Tongia and Gross, 2019].

Therefore, even though international coal prices could directly impact regions which do not produce coal due to the import penetration of coal, the intensity of these effects are reduced as volume of imports for coal is still less than total production of coal in India (601.878 MT) [Statistics of Mines Vol. I Coal 2011-12]. Therefore, the major effects of international coal price shock are felt in regions with active coal mines through its pass-through effect on domestic coal prices and production.

1.4 Coal in State and Regional Economies

While coal may not be a significant economic sector for the country as a whole, it is highly significant for certain states, and more particularly for certain districts within those states. Coal is a major source of revenue and employment generation in resource rich states like Jharkhand, Chhattisgarh and Odisha. In India, it is seen that a handful of states dominate the production of coal, notably Jharkhand, Madhya Pradesh, Chhattisgarh, Andhra Pradesh, Odisha, and Maharashtra. In Table 1, the estimated importance of coal mining in the economy of these states is calculated. From Column (3) in Table 1, it can be seen that these 6 states have a major proportion of their mining sector devoted to coal mining. Finally, in Column (4), the share of coal mining in the state's overall economy shows that coal mining contributes approximately 3-10% in the economy of these coal rich states.

Coal mining is further concentrated within certain specific districts of these major coal producing states. Estimating the share of coal mining in the district's economy is tough owing to data limitations, but an example of Dhanbad - a district in Jharkhand which is also referred to as the coal capital in the country shows promising estimates. Dhanbad's share in Jharkhand's state value added is 41%, where coal mining contributes 26% to Dhanbad's economy [Districts of India, 2018]. Due to presence of the coal mining sector, Dhanbad's GDP/capita is 46% higher than that of Jharkhand as a whole on an average, which is in itself a relatively poor state. This goes on to show that the coal sector has a relatively higher level of value added and wages compared to other sectors [Spencer et al., 2018].

Table 1.1 – Importance of Coal in State Economy

State	State-share in All India Value of Coal Output (1)	State-share of coal output in state's mining sector (2)	Share of mining in state's economy (3)	Estimated share of coal mining in state's economy (4)
Jharkhand	22%	91%	11%	10%
Madhya Pradesh	16%	78%	4%	3%
Chhattisgarh	15%	66%	13%	9%
Andhra Pradesh	13%	43%	4%	2%
Odisha	11%	38%	12%	4%
Maharashtra	10%	83%	5%	4%

Note: Calculations and estimations are used from [Spencer et al., 2018]. Based on data from 2009-10 (relevant to period of study in the thesis); data sourced from RBI(2018) and Indiastat(2018).

1.5 Coal in India - Way ahead

Coal is intrinsically linked to economic growth of India. It has become indispensable for fueling the growth through the increasing need for energy[6]. Approximately half a million people in the country are employed directly and indirectly via the coal sector (coal mining, coal fired power plants, transportation etc.). Coal mining companies such as CIL and its subsidiaries are also known to provide roads, schools and other infrastructure in the vicinity of the mines for the benefit of the local population [Tongia and Gross, 2019]. Levies on coal are an important source of revenue for the central government and also for the coal-producing states which are relatively poorer than other states in the country. For example, coal levies in Jharkhand are as much as 7% of the state's budget even before accounting the employment and other local economy effects[7]. India is thus, not only an important producer of coal but also an important consumer of it. This implies that all supply chain impacts related to coal mining, production, transportation and use are felt in the same country.

There is enough scientific evidence to show that there are negative externalities associated

[6]India is the third largest energy consumer and approximately 35% of the coal consumption is for non-energy purposes such as cement and steel.[Philalay et al., 2019].

[7]Ministry of Finance Government of Jharkhand, "Budget Highlights 2017-2018," 2018, https://finance-jharkhand.gov.in/pdf/budget2017_18/Budget_Highlights201718.pdf.

with mining, transportation and usage of coal. However, as a developing nation, India has to lift a majority of population out of poverty, build infrastructure and provide for growth in general. Energy consumption is therefore expected to be at a continual high pace in the decade ahead. India's energy policy aims at providing affordable electricity to all homes. While, renewable energy is gearing up in the country and it's capacity is being enhanced significantly, coal still serves as an affordable and reliable form of energy and will continue to do so at least until 2030 and beyond [Tongia and Gross, 2019]. A recent report by Niti Aayog, Government of India and Institute of Energy Economics, Japan highlighted that while penetration of renewable energy in India will increase from 3.7% in 2012 to 11-14% in 2047, the reliance on coal will persist even in 2047 with an envisaged share of 42-50% in the energy mix for the country, given its abundant resources and easy accessibility making it a cheap source of energy security for the nation [Aayog and Japan, 2017].

Considering, India's reliance on coal for energy and development purposes for the near future, sustainable mining practices need to be adopted such that this extractive industry is used beneficially for the people while considering and monitoring the negative impacts of coal mining on environment and local people. There is a need for responsible supply chain to mitigate the negative impacts of coal mining and accentuate its benefits.

In light of the strategic importance of coal, it is rather useful to analyze the socio-economic impact of this extractive industry at a local level in the country. Such an analysis would highlight the areas where coal has touched the lives of people in its nearby vicinity understanding its net effects at a local level in India. This could essentially guide the sustainable mining practices and advance the knowledge with regards to the impact of resource abundance in general and non-renewable resource extraction in particular on the local economy of a developing nation.

1.6 Thesis Outline

In this thesis, I make use of three distinguished and unique individual level data sets from India to examine the effects of coal mining on the socio-economic outcomes for individuals and firms in the local vicinity of these mines. Presence of coal mines in an Indian region along with the international coal price shock over the time period 1999-2011, is used as an economic shock and instrument in determining the impact on education and health of young children in coal regions as well as on the productivity of firms in these regions.

In the first paper, I examine the local effects of coal mining on schooling attendance of children in the age-group of 5-14 years (school-going age) living in the nearby coal mining regions of India during the period 1999-2011. A difference-in-difference estimation, by exploiting the spatial and temporal variation in mining, reveals that, the probability to attend school for any child in the mining region increases by 4% points when exposed to a doubling in the international coal price. On evaluating the different mechanism through which these effects are transmitted, the positive income shocks resulting in higher 'returns to education' and positive 'wealth effects' dominate the negative substitution effects emanating from rising wages and prices.

In the second paper, I analyze how the international coal price shocks affect the nutritional status of young children (age <5 years) in coal mining regions of India. Prevalence of 'stunting' and 'underweight' tendencies in these children is evaluated with focus on the channels through which these effects are transmitted. The paper highlights that prevalence of stunting and underweight reduces significantly in children living in these regions owing to strong 'income effects' through greater time and monetary investments in child's health. The study also finds evidence for the prevalence of 'son-preference' in household decision making regarding investments in child's health in coal regions of India.

In the third paper, I make use of firm level data in India to evaluate the impact of coal mining on firm productivity in the treated regions. Firm production is enhanced significantly in these regions owing to greater demand of local inputs especially labor. Firm productivity is enhanced specifically for firms in the manufacturing sector due to benefits of agglomeration effects as well technological advancements.

These analysis highlight the socio-economic benefits that can derived be from this extractive industry at a local level, thus stressing on further utilizing the unused capacity for mining in a sustainable manner for the overall development in the nation.

Chapter 2

Children of Black Gold: Local Effects of Coal Mining on Education of Children in India

Coal is an important energy source for India, as it is for other nations in the world. For a resource industry as strategic and of as much national importance as this one, the policy implications hold relevance in understanding the socioeconomic effects associated with natural resource extraction at a local level.

Human capital outcomes due to resource extraction are at the core of welfare effects that need attention especially in a developing country like India where child labor and poor educational outcomes are a major impediment to development, thus generating long-term effects. As such, the literature on the educational effects of natural resources is scarce and inconclusive, making it an area ripe for more research [Marchand and Weber, 2018b], with recent works by Marchand and Weber [2020] and Gradstein and Ishak [2020] being among the few contributing in this area.

India like other developing nations is also plagued with high incidence of child labor and low levels of child school attendance. As per Census 2011, out of the total child population in India (age group 5-14 years) of 259.6 million, 10.1 million (3.9% of total child population) were working, either as 'main worker' or as 'marginal worker'. In addition, more than 42.7 million children in India were out of school (ILO 2017). Thus, it becomes imperative to devise policies to improve child schooling and reduce child labor and understand their linkages.

This paper, therefore, probes into the educational impacts of the economically attractive resource – coal. In doing so, it also contributes to the literature on the channels for educational attainment of children which are mainly linked to the household decision making models. Following the traditional theory for household decision making by Becker [1964, 1965], an individual's educational attainment at equilibrium is a result of the balance between the opportunity costs of acquiring further education and it's expected returns. The expected returns from education are governed by several factors in general such as cognitive skills of child, family and religious background, age of school entry, school characteristics and government policies [Ahlerup et al., 2016] while the opportunity costs are determined by the labor market opportunities and wages. For a nation with a growing regional extractive-industry sector such as coal mining, rising wages in coal mining sector can be a potential substitution-effect in place, driving the children towards work, even though the higher incomes in these regions can also allow for greater investments in child's education by the households.

This study will estimate the child schooling outcomes in the coal mining districts of India. In doing so, the study would exploit the temporal variation via international coal prices and the spatial variation via the presence of coal mines in a district. The schooling probability for younger and older children in coal mining regions of India would throw light on the child schooling (time-allocation) decisions of households in these regions[1]. This paper thus, contributes to the literature on the local effects of resource abundance in a region as well as the household decision-making models for education in developing countries. This study claims to be the first study addressing this issue in India at a local level, having implications for similar developing nations around the world.

2.1 Related Literature

This paper is related to at least two strands of literature on the socio-economic impact of natural resource abundance in developing countries. Firstly, it discusses the famous but inconclusive

[1]Young children belong to the age group 5-9 years; Old children belong to age group 10-14 years

’natural resource-curse’ phenomenon at a local level. The literature on ’resource-curse’ so far has greatly advanced our knowledge on the various channels of transmission of this impact at the macro level [Sachs and Warner, 1995, Gylfason, 2006, Ross, 2004, Rosser, 2006, Mehlum et al., 2006]. Recently, this literature has evolved to discuss these mechanisms at a local level in a region [Van der Ploeg, 2011, Aragón et al., 2015, Fleming and Measham, 2015, Marchand and Weber, 2018b]. These studies allow for greater dis aggregation of economic responses and exogenous identification of impacts [Cust and Poelhekke, 2015].

Secondly, this paper explores the educational impact of natural resource abundance at a local level. The impact of natural resources on educational outcomes have been discussed at a broad macro level across countries as well [Gylfason, 2001, Stijns, 2006]. While Gylfason [2001] finds that natural capital tends to crowd out the human capital, showing a negative correlation between natural capital share in total capital and public expenditure on education relative to national income, expected years of schooling for girls, and gross secondary-school enrollment across countries, Stijns [2006] on the other hand argues that these relations are not robust to the different measurements of resource abundance and there is a positive correlation between subsoil wealth per capita and educational outcomes and expenditures. Within country analysis are few, for example, using a panel of 48 U.S. States spanning over the years 1970-2008, James [2017] finds that resource-rich governments spend more on education than their resource-scarce counterparts and this effect is more pronounced during periods of energy booms. Such analysis at a local level within a country have still not been explored. Very recently, Gradstein and Ishak [2020] have shown how income shocks emerging from oil price fluctuations in Africa have affected the educational attainment of children depending on the age of child when exposed to the shock. They find that income shocks in early childhood (age 0-4 years) has a positive effect on educational attainment and household wealth for both boys and girls, while for older children (age 10-14 years), the impact on educational attainment is positive only for boys, with the girls in Africa experiencing a significant decline in education as their age progresses when exposed to the income shocks through oil price fluctuations around the world. Marchand and Weber [2020] have exploited the Texas boom in shale oil and gas drilling to examine the student performance. They find that despite the revenue windfall and tripling tax base during the boom, the student performance declined due to declining teacher quality with higher gap between teacher wages and private sector wages.

As discussed above, there has been an initiation of studies that discuss the socio-economic effects of natural resources at a local level within a country. The local living standards in Peru are improved for the households that live in close proximity to the Yanacocha gold mine through a positive effect on real incomes and poverty reduction among the population not directly linked to mining [Aragón and Rud, 2013, Loayza et al., 2013]. With respect to the employment spillovers through natural resource extraction, Black et al. [2005] show a modest increase in non-coal jobs in north-eastern United States during a boom and a reversal during the bust which seems more persistent in the long-run. The asymmetry of this effect is also reflected by a recent study on coal mine closures in the United Kingdom [Aragón et al., 2018] and by Kotsadam and Tolonen [2015] in Sub-Saharan Africa for gender differentiated effects of mine openings and closings. In general, these studies highlight the labor market shift in favor of men on closures of mines, with employment in manufacturing and services rising for men and decreasing for women. The structural shifts seem persistent and permanent even after the boom-bust situation ends especially for women. Aragón and Rud [2016] show the effects of gold-mining related pollution on the agricultural productivity and rural poverty in Ghana. They find robust evidence that cumulative gold production indicative of higher pollution levels is associated with a significant reduction in agricultural productivity and increase in rural poverty. These effects are concentrated within 20 km of mine sites and decline with distance.

The socio-economic outcomes for children have however been explored using the price shocks for agricultural commodities such as Rice in Vietnam [Edmonds and Pavcnik, 2005b], Cocoa in Cote d' Ivoire [Cogneau and Jedwab, 2012] and Coffee in Brazil [Kruger, 2007]. These commodity price shocks for rice, cocoa and coffee have socio-economic effects for children through changes in household income. In Vietnam, rice prices rise by 30% between 1993 and 1998, bringing about income effects at a community level and resulting in lower levels of child labor by 9% points especially in households who are net producers of rice. In Cote d' Ivoire, a drastic cut in the administered price of Cocoa in 1990 negatively affects the human capital (health and education) of cocoa producer's children when compared to children of non-cocoa producers, across time and within same geographical area for several dimensions such as school enrollment, child labor, height, incidence of illness. In Brazil, rise in coffee prices and production between 1992-1999, leads to rise in child labor among middle-income boys and girls, poorer children being withdrawn from school while richer children being unaffected in terms of schooling.

In light of the emerging literature on the two broad strands of discussion highlighted above, this paper would contribute to the analysis of the socio-economic effects of natural resource abundance at a local level within a country through the effects on the educational outcomes for children. This study also contributes to such literature on developing nations particularly India, where such studies are available at a sub-national level thus far [Asher and Novosad, 2014a,b].[2]

2.2 India's Coal Sector

India has a long history of commercial coal mining covering nearly 220 years starting from 1774 by M/s Summer and Heatly of East India Company in the Raniganj Coalfield along the Western bank of river Damodar (MOC 2017). Today, India's domestic coal industry is primarily government owned and co-ordinated. The central government plays a key role in India's coal policy development. The Ministry of Coal (MOC) has the overall responsibility of determining policies and strategies in respect of exploration and development of coal and lignite reserves. These key functions are exercised through its public- sector undertakings, namely Coal India Limited (CIL) and Neyveli Lignite Corporation Limited (NLC) and Singareni Collieries Company Limited (SCCL), a joint sector undertaking of the State Government of Telangana and Government of India with equity capital in the ratio of 51:49 (Annual Report, MOC, 2015).

In general, resources in India are jointly managed by central and state governments. The proprietary title vests in the federating states while the center has jurisdiction over mines and minerals development. With regards to coal, Mines and Minerals (Regulation and Development) Act (MMRDA) was enacted in 1957 where in coal is listed as a schedule one mineral. This implies that while ownership of coal resources vests with state, prospecting and mining

[2] Asher and Novosad [2014a] show that exogenous increases in mineral resource wealth result in broad-based economic growth in nearby towns, increasing employment across all manufacturing and service sectors.

are controlled by the central government [Khanna, 2013]. Coal prices in India are determined by the level of domestic supply and demand. However, the response of overall demand and supply to price variations is slow due to the structure of the coal industry as well as the nature of the user industries. Therefore, coal prices in India are low and stabilized compared to the international prices (Appendix Figure 2.4) (ICC Report on Coal 2012).

Coal as the most important and abundant fossil fuel in India accounts for 55% of the country's energy need. 65% of the raw coal is used by electricity industry in the country followed by five other industries such as steel, paper, textiles and fertilizers. India has the world's fifth largest proved recoverable reserves of coal & lignite (60.6 billion tonnes) after the United States, Russia, China and Australia (IEA 2014). However, there have been recent concerns over accessibility of these reserves given the current technologies being deployed (IEA 2012). Overestimation of reserves could be a problem for production planning over the medium to longer term. Most of India's coal reserves are present in the eastern part, with Jharkhand, Odisha, Chhattisgarh and West Bengal accounting for around 78 per cent of total proved reserves. The distribution of India's coal reserves creates a supply challenge for electricity generators in India owing to transportation problems [Cully, 2015].

In terms of production, India is the world's third largest producer of thermal coal, well behind China and the United States. Despite large reserves, production growth has been below the growth in consumption since a few years. In response to the widening gap between India's coal consumption and production, imports of thermal coal have grown from 12 million tonnes in 2004 to 142 million tonnes in 2013 [Cully, 2015]. Present import policy allows coal to be freely imported under Open General License by the consumers themselves considering their needs. Coking coal is imported by Steel sector and Coke manufacturers mainly on availability and quality consideration. Coast based power stations and cement plants are also importing non-coking coal on consideration of transport logistics and commercial prudence. Despite hardening prices of both coking and non-coking coal internationally and increase in ocean freight, large amount of coal continues to be imported by India (Coal Directory of India, 2016).

2.2.1 Revenue Sharing

Major minerals in India such as iron and coal are jointly regulated by national and state governments, while the minor minerals such as limestone, zinc etc. are controlled directly by state governments.

Fiscal revenues from minerals which in general form an important route for regional development in mineral economies can be eliminated as a potential channel in evaluating local welfare effects in this study. Despite the state governments being the sole recipients of the royalties on minerals in their respective regions in India, there is a lack of a formal distribution rule to various sectors or districts. Since, the within-region variation will be considered in this paper, I avoid this channel for the time being.

However, there is spending on local communities which is done by private and public mining firms and the state also spends on various development sectors. Moreover, there has been a recent implementation of MMDR Bill 2015 which provides for the creation of a District Mineral Foundation (DMF) and a National Mineral Exploration Trust (NMET). The DMF is to be established by the state government for the benefit of persons in districts affected by mining related operations. The NMET shall be established by the central government for regional and detailed mine exploration. Licensees and lease holders shall pay the DMF an amount not more than one-third of the royalty prescribed by the central government, and the NMET two percent of royalty. Since, the implementation of the bill by several states has been an ongoing process, continuing still in present, I am unable to capture this in the analysis in this paper.

2.3 The Effect of Coal Mining on Education

A cursory glance at statistics across the Indian districts reveals that mineral wealth is not always leading to better development outcomes for children especially in the districts that are more dependent on mining. In such districts, more than 10% of the children were found not attending school and having lower literacy levels compared to national averages two decades earlier, according to the Census 2001 [Mundoli, 2010]. According to Census 2011, an average of 4% of the total child population is still found working as laborers in the coal-rich regions of India.

[3]

It is worth noting that ancillary work related to coal mining can be assumed by both men and women (including children). Mining sector despite it's strenuous requirement of physical labor is not solely dominated by men [Tolonen, 2015]. Therefore, given that coal mining is notorious for attracting men and women alike along with children (in many cases) for unskilled jobs, creating adverse incentives for child education, the benefits of agglomeration, spillovers and rising family incomes on child education if any are examined in this paper.

The benefits and costs associated with mining are diffuse. Coal which is a primary source of energy in the country has been mined for centuries deep underground. The intention of coal extraction is to remove coal as efficiently as possible. The trend of opencast and surface mining too has become prominent in the country making use of heavy machinery and explosives for opencast mountain coal removal. The technical advancements in coal mining is a potential source of spillovers on other sectors (particularly infrastructure and industry) causing the demand for educated and skilled workforce to rise. This paves the way for rising income effects owing to rising coal prices as better income opportunities get generated. Considering such dominating income effects, returns to education are expected to rise favoring greater school attendance among children in these regions. Higher returns to education are also expected when schooling infrastructure gets uplifted. Mining companies in India are required to allocate a designated amount out of their profits for infrastructural development in the mining region (MMDR Bill 2015). These can create positive incentives for families to send their children to school.

Child schooling can be understood as an absolute alternative to child labor. There is evidence to show that child labor declines in scenarios where there is improvement in living standards of the family, therefore even with greater work opportunities for children in wake of the rising prices, child labor can decline [Edmonds and Pavcnik, 2005a]. Rising family standards can lead to declining child labor and improved school attendance if child labor is considered a 'bad' in the household welfare function and children need to work only when the family is not able to meet the subsistence needs [Basu and Van, 1998]. Secondly, with increasing family

[3]This study focuses on the schooling outcomes for the children living in coal regions of India for the time period 1999-2011.

incomes, the marginal contribution of children in the family income reduces and, moreover with high family incomes the returns to child labor also reduces as the substitutes of child labor become more viable and affordable, and lastly, greater incomes can enhance child schooling productivity with greater affordability for text books, school fees etc. [Edmonds and Pavcnik, 2005a].

The technical advancements in mining have however also been documented to cause widespread environmental, social and health related externalities around the world [Von der Goltz and Barnwal, 2014, Rau et al., 2013, Aragón et al., 2015]. Coal mining related activities cause severe loss to the surrounding environment including the forests and water bodies which are a major source of subsistence for the local population especially the natives or tribal communities of the region. The changing environmental landscape can substantially affect the costs of schooling owing to poor quality of educational supply and poor health conditions [Currie, 2013, Rau et al., 2013]. With inadequate educational infrastructural set up being provided to by the mining companies, the higher returns to education will not be able to compensate the adverse household conditions (in terms of the educational preferences for their children). Households with low income and assets (wealth) prefer their children to work for supporting the family income. In such scenarios, the rising prices (of coal and other commodities) lead to a dominating substitution effect in household decision making.

Apart from the costs of education and returns to education serving as major determinants of child schooling in such regions, another factor that plays an important role is the presence of well-functioning credit markets. There are studies to show that if credit markets allow families to borrow against future earnings then child schooling would not be affected by educational costs [Baland and Robinson, 2000]. Credit markets in rural India are not perfect and rely heavily on local money lenders [Rosenzweig and Wolpin, 1993], therefore Indian households are forced to make decisions regarding sending their children to school versus to work primarily on the trade off between the costs and returns to education.

Together these substitution and income effects in decision making by the households living in coal mining regions determines the net effect of coal mining on schooling outcomes for children in these regions.

2.3.1 Conceptual Framework

The landscape of mining sector has evolved over the years in India, and in that light, the effect of rising international coal prices on the schooling outcomes of children living in districts with active coal mines in India adds a further dimension to the effects of resource extraction as they had been perceived in the literature previously.

A conceptual model to evaluate these effects has been borrowed from Edmonds et al. [2010]. They used the model to analyze the effects of trade liberalization on schooling outcomes of old children in India while this paper focuses on the mining shocks emanating from the rising coal prices world-wide.

The likely mechanisms through which coal price movements would affect the schooling decisions of children living in mining regions include the changing living standards of the family, changing returns to education & costs of education and demand for child labor. The returns to education to a great extent is influenced by the household preferences and characteristics, while costs of education are affected by changing environmental landscape of these regions.

In the model, it is assumed that there is a household with one adult, one child and a single decision maker in the family.[4] The household incomes when the child attends school is assumed lower than when the child doesn't attend school. This is because, even though primary schooling may be technically free in India, there are still costs related to education through schooling costs – 'c' (cost of books, uniforms, transportation charges etc.) and opportunity costs of attending school – 'w' (loss in economic contribution to the household that was made by the child).

Therefore,

$$y_a = y_n - c - w \tag{2.1}$$

where y_n is the household income when the child does not attend school, and y_a is the household income when the child attends school.

It can be difficult to determine the exact measure for 'w', even though the value of 'c' can be potentially high in rural economies of India given the limited infrastructural setup.

[4]Having a single family decision maker or the head of the family is common in Indian households and a lot of times it is not the same person who is the main earning person of the family.

According to the household decision making model, a household decides to send the child to school when the utility from schooling is greater than utility from not attending school. In the model, attendance is denoted via $'a$' and non-attendance via 'n'.

Therefore,

$$U(y_a, a) + \varepsilon_a \geq U(y_n, n) + \varepsilon_n \tag{2.2}$$

$\varepsilon_s, s \in (a, n) \sim iid(0, N)$and mean separable

The return from schooling is considered to affect the future welfare of the child which is assumed to be additively separable from present consumption given the constraints on borrowing in rural economies of India [Rosenzweig and Wolpin, 1993]. The stochastic terms (ε_s, s) in Equation 2 are thus additively separable from the utility and reflect the random factors affecting the schooling returns. The utility from schooling can further be described in terms of returns to schooling (r) and the costs related to schooling $(w\&c)$:

$$U(y_a, a) = V(y_n - w - c, p) + \alpha \centerdot r \tag{2.3}$$

The family preferences for education are reflected via α, which is essentially the weight on child's return to education. These can be captured by household characteristics and education level of the household head in data. It has been established through various studies that child schooling outcomes particularly school enrollment and educational attainment are positively correlated with parental education and preferences [Strauss and Thomas, 1995].

In Eq.2.3, the utility function is expressed as an indirect utility function in monetary terms at given level of prices in the economy (***p***-price vector). This equation can be used to define the probability for the child to attend school.

$$Pr.(s = a) = Pr.[(V(y_n - w - c, p) + \alpha \centerdot r - V(y_n, p)) \geq (\varepsilon_n - \varepsilon_a)] \tag{2.4}$$

Let $\varepsilon_n - \varepsilon_a = u$; where u has c.d.f. $F(u) = 0$ and a p.d.f $f(u) > 0$

Using the above,

$$Pr.(s = a) = F[V(y_n - w - c, p) + \alpha \centerdot r - V(y_n, p)] \tag{2.5}$$

The Equation 2.5 highlights the two effects at play in determining the probability for a child to attend school, namely the income effect (through ***y,p,r***) and the substitution effect (through ***w and c***). According to the claim made, the income effects arise via rising family incomes (standard of living), greater prices in the local economy (positive spillovers on related industries generating more employment to meet rising production needs) and greater expected future returns on educating the children. The substitution effects play via the greater employment opportunities available for children and the rising costs of education.

Decomposing the probability into these effects,

$$d(Pr.(s=a)) = f(u) \cdot [(\frac{\partial V_a}{\partial y} - \frac{\partial V_n}{\partial y})dy_n + \alpha \cdot dr - \frac{\partial V_a}{\partial y}dw - \frac{\partial V_n}{\partial y}dc + (\frac{\partial V_a}{\partial p} - \frac{\partial V_n}{\partial p})dp] \quad (2.6)$$

If the effect of rising coal prices world wide is captured by M, then this shock is assumed to affect the individuals living in regions with active mines. Therefore, dM will be 0 for non-mining regions.

Now,

$$d(Pr.(s=a)) = f(u).[(\frac{\partial V_a}{\partial y} - \frac{\partial V_n}{\partial y})\frac{\partial y}{\partial M}dM + (\frac{\partial V_a}{\partial p} - \frac{\partial V_n}{\partial p})\frac{\partial p}{\partial M}dM + \alpha \cdot \frac{\partial r}{\partial M}dM - \frac{\partial V_n}{\partial y}\frac{\partial c}{\partial M}dM - \frac{\partial V_a}{\partial y}\frac{\partial w}{\partial M}dM] \quad (2.7)$$

Analysis of the effects of the coal price rise on schooling probability can be broken into five segments from Eq. 2.7. Theoretically, the first component, which is the effect of mining shock on the household income is generally positive ($\frac{\partial y}{\partial M} > 0$) and by using the principle of diminishing marginal utility of income, the model describes - $\frac{\partial V_a}{\partial y} > \frac{\partial V_n}{\partial y} > 0$ as y_a is lower than y_n by definition.

The local prices in the region (such as wages or prices of goods related to coal industry) are expected to rise through this shock, thus $\frac{\partial P}{\partial M} > 0$ [Aragón, 2015]. With greater earnings and employment opportunities due to production effects, these income effects will also favor the probability of child schooling. This can be shown through the impact of monthly per capita expenditures by the families on the schooling attendance of their children as well as through the presence of wealth (land assets) in the family, the presence or absence of which could alter the household decision regarding the child's attendance in school eitther way.

$\frac{\partial r}{\partial M}$ will also be positive as educational returns for local population must rise with skilled jobs opening in the mining economy. So, *with a positive value of* α placed by households (as education is assumed to be a 'good' in the household welfare function) [5] and a positive effect on expected returns from education, the probability of schooling should rise via this mechanism. The positive returns on education can be shown through the logarithmic wage gap between different economic sectors in the economy for mining and non-mining regions.

For the substitution effects, the opportunity costs of child education would rise with rising coal prices world-wide as children may find more mining jobs that they will have to give up in order to pursue education, therefore $\frac{\partial w}{\partial M}$ will be positive, which would indicate the the incidence of child labor would be higher in these regions. Lastly, concerning the cost of education, they too are expected to rise given the environmental and health concerns associated with coal mining, thus, $\frac{\partial c}{\partial M}$ will also be positive, which would mean that schooling infrastructure would be of inferior quality and accounting for these in the main analysis could impact the schooling outcomes. These effects will cause the probability of schooling to reduce for children living in coal mining regions of India.

From the above discussion, the positive effects on schooling probability through rising family incomes and positive returns on education can be categorized as the income effects while the negative effects on schooling probability through rising costs of education and loss of economic contribution by the child to the family can be categorized as the substitution effect. The dominance of a particular effect over the other will determine how households living in mining regions react to rising coal prices for making educational decisions for their children.

[5] The value of α even though positive can vary with respect to the household characteristics; such as wealth held by the family. For poorer households, education even though a 'good' in their welfare function will have lower preference compared to other goods when the income shocks are witnessed and for very rich families, the neutral perferences between other goods and education for their children may prevail. It is for the middle-category families that the preferences for education for their children will be higher. This should reflect in heterogeneous results with respect to wealth of families.

2.3.2 Data

The empirical analysis for examining the impact of rising world coal prices on schooling decisions for individuals in mining regions of India relies primarily on the rural sample of the Employment and Unemployment Schedule of the National Sample Survey (NSS) of India. Three rounds of NSS are used for the main analysis, which include the 55th round (1999-2000), 61st round (2004-05) and 68th round (2011-12).[6] These are cross-sectional household surveys carried out at all-India level to generate estimates of various characteristics pertaining to employment and unemployment and labor force characteristics at the national and state levels. This data set contains information on the demographic characteristics, educational indicators, economic activity and labor force participation for all individuals in the surveyed households.

2.3.2.1 Data description for education related variables

To capture the educational outcomes in coal rich regions, the variable reflecting the school attendance of children was used.[7] This variable apart from providing broad details on attendance in schools also gives detailed information on the reasons for non-attendance in that case. The schooling probability of more than 245,000 children (age 5-14 years) is examined over the three NSS rounds in this study. The analysis also considers a segregated sample of around 96,000 young children (5-9 years) and around 120,000 old children (10-14 years) for examining the schooling effects.

The NSS data also provides details on the completed educational level for each individual surveyed. This variable contains many categories: not literate, literate but below primary, primary education, middle education, secondary, higher secondary, diploma/certificate course, graduate and above, postgraduate and above. These were further collapsed into five broad categories for analysis. The categories were (1) Illiterate (no formal schooling), (2) Informal Schooling (AEC, TLS etc.), (3) Primary – Middle School, (4) Upper Secondary – High School and (5) Diploma, Graduate & Post-graduate or above. This variable though not used as the

[6] NSS 66 (2009-10) is also used for estimating certain relationships, however it is dropped from main regressions as it is too close to the 68th round which is relatively a thicker round.

[7] As such, this variable gives data for individuals in the reported age group below 30, but for this analysis I will consider this variable for children (5-14 years).

dependent variable due to endogeneity concerns, is used for examining the educational level of the household head and for the population above the age of 25 years to conduct falsification exercise for the main analysis.

The average school attendance for children is shown in Table 2.1, along with their other activity status. The work category is based on the usual principal activity status described in the surveys. A child is considered working if s(he) is working in own farm/enterprise, as a salaried/wage earner, performing domestic duties for household, or begging. In cases where the child is not attending school and only working, s(he) is categorized as 'working only'. These are the cases of child labor. The work category can be divided into market work (which is wage or salary oriented) and domestic work (which involves domestic duties, free collection of goods, sewing, tailoring etc. for household use) [Table 2.1].

Table 2.1 – Child Activity Status over the three NSS rounds

Variables	**NSS 55 (1999-2000)**	**NSS 61 (2004-05)**	**NSS 68 (2011-12)**
Attending school	0.698	0.807	0.897
Working only (child labor)	0.286	0.181	0.093
Idle - looking for work	0.0007	0.001	0.001
Not working - receiving benefits; disabled	0.001	0.002	0.002

Variables	**NSS 55 (1999-2000)**	**NSS 61 (2004-05)**	**NSS 68 (2011-12)**
Working	0.3	0.18	0.099
Market Work (wage work)	0.25	0.14	0.08
Domestic Work (household work)	0.05	0.04	0.019

Note: The table presents weighted proportion of children [age 5-14 years] engaged in different activities. Children reported attending school as the primary activity (code 91) are represented under first sub-heading. Market work category corresponds to the following activities: worked in a household enterprise as paid/unpaid worker, worked as regular wage/salaried employee, worked as casual wage worker in public works or in other types of works, and worked as a beggar etc. (codes 11-51 and 96). Domestic work category includes: attended to domestic duties, engaged in free collection of goods, sewing, tailoring, or weaving for household use (codes 92-93).

The average school attendance for children in rural areas has increased by approx. 29% over the years while this data shows a decline in average incidence in child labor by approx. 67%. The average estimates for school attendance are very similar when evaluated for young children and old children separately.

2.3.2.2 Identification strategy and its potential threats

The identification strategy used in the paper exploits the spatio-temporal variation by the interaction of the treatment variable that is the presence of a coal mine in a region (in the year 2011) with the international coal prices over time (1999-2011). [8]The estimation strategy in the paper relies on the assumption that the placement of mines is not driven entirely by the local changes, such as trends in local labor market participation, women's empowerment or population characteristics. The main factor that drives the presence of a mine in a region is the presence of the mineral deposits itself which are geographical anomalies and not determined by the human capital or labor availability. These mineral deposits are available in clusters in specific regions [Eggert, 2001].

With respect to Coal, their deposits are formed deep under Earth's crust due to extreme pressure and in India are found in regions with a higher gradient in the Central and Eastern parts [Refer: Figure 2.1].

The presence of mineral deposits is determined naturally and therefore can serve as a random experiment. Even though, the determination of a mineral deposit does depend on the exploratory intensity which is not entirely exogenous and apart from being affected by the volume of mineral deposits also depends other factors such as: a) institutions, b) royalties and tax policies in the region, c) accessibility [Eggert, 2001] and d) expected profitability. The possibility of endogenous mine placement is therefore a big threat to the identification strategy which captures the spatial variation via the presence of a coal mine in a region.

The institutional factors that affect the mine placement cover a wide range of determinants such as the mineral property rights, openness to foreign direct investment, rules for revenue sharing and taxes, and environmental regulation. These factors along with the topography of the region also affect the cost of mining in the region. Coal mines in India are set up in regions with easier access in terms of clearances and revenue policies. But this doesn't threaten the identification much as these institutional factors vary at the state (sub-national) level in India but are homogeneous within the state and thus a district level analysis is immune to such variation as I use the district and year fixed effects in my analysis.

[8]US Central Appalachian spot price index (USD/tonne) used for the international coal price movements

The identification strategy is strengthened using international coal price changes over time which not only add the time variation to the model but also bring the desired exogeneity. These international prices are independent of the institutional factors and tax policies within India and affect the outcome variable only through their impact on the domestic coal prices and production as established via the 'price-pass-through' regressions [Refer Tables 2.2;2.3;2.4].

International coal prices

Coal production in a mine is likely higher when the coal prices are higher. The world coal price has shown an average rise of approx. 192% since 1999 till 2011 (period of analysis in this paper), with a great jump in 2008 [Refer: Figure 2.4]. This price rise has shown to have pass-through effects on domestic coal prices and production as well. Therefore, it is usual that these rising prices of coal around the world have local effects as they trickle down the economy in terms of local employment and wage gains. Therefore, world coal prices are used instead of local coal production volumes to measure the intensity of coal mining as coal production volumes can also be endogenous to other factors that affect the outcome variables. The world coal price rise on the other hand will always be completely exogenous to local population characteristics.

The world coal prices are interacted with the presence of a coal mine instead of presence of coal deposits as the presence of a mine allows to capture the industrial shock directly whereas the presence of a deposit doesn't guarantee any industry in the region necessarily.

District level variation in infrastructure facilities such as water, electricity, roads, schools, medical facilities etc. can bias the decision of mine placement as well. Mining industry especially coal mining industry in India is known to bring investment in road network, schools and hospitals in the mining communities [Hota and Behera, 2016][9] which can affect the outcome variable. This is not a major threat to the analysis as the analysis is geared towards the effect of the total industrial shock in general due to coal mines.

However, if coal mines are set up in regions where schools or medical facilities and other

[9] They describe in their paper as to how coal mining in Ib Valley of Odisha in India, brings positive and negative outcomes for the local population. The positive outcomes are visible through the expansion of physical (infrastructure) and financial (employment) capital; whereas the negative outcomes are seen in the degradation of the ecosystem (natural capital) adversely affecting the agricultural productivity, forest and animal husbandry.

such infrastructural facilities are developing, then it could give biased estimates. For this reason, the school supply factors are controlled for in the education regressions.

Migration of individuals to mining regions is another possible threat to the identification strategy. If families with school going children migrate to regions with mining opportunities, then this self-selection mechanism among individuals could completely bias the estimates. To address this issue, a check on migration is performed at a regional level in India. It is already established that rural migration is negligible in India [Munshi and Rosenzweig, 2009]. Moreover, a test on change in rural population over time across districts shows insignificant effects when viewed under the lens of the treatment effect described in this paper [Refer:Table 2.18].

2.3.2.3 Data description of treatment variables and other factors

The treatment intensity in this paper is measured through the international coal prices over time for the districts with active coal mines during the survey. The unit of analysis will be at the individual level while exploiting the district level variation as the identification of coal mines is performed at a district level in India.[10]The number of districts in India increased from 519 in NSS 55 (1999-2000) to 627 in NSS 68 (2011-12) as several new states were created in the year 2000 along with the breakup of various old districts into multiple new districts.[11]The locations and district codes were matched across the several rounds and made consistent according to the NSS 68 criteria for uniformity.

Since, district-wise data for presence of coal mines is available readily beginning 2010, I consider the 2011 active mine status as the treatment effect. Moreover, the state level data on number of coal mines reveals negligible change in active mine status over the states. Therefore, without loss of generality it is convenient to assume that active mine status at a district level also remained similar over the years. This can also be witnessed in data available post 2010 at a district level. The opening and closing of mines therefore don't provide adequate base for a treatment effect as the variation is extremely low. There are 52 major districts that have reported any coal or lignite mining in NSS 68 survey data (these are the treatment districts for

[10]The district is the lowest administrative unit within a state at which data is readily available in India. It typically covers a radius of 40 km

[11]Otherwise, the boundaries of districts have remained fairly stable since colonial times.

this paper). The number of districts with coal deposits is larger. There is a positive correlation between the quantity of coal deposits and number of mines across districts in India (as seen in 2011-12) [Refer: Figure 2.2].

The data on international coal prices is available from the World Bank Commodity Price Data and on the domestic prices at a national level is available from the Coal Controller of India[12]. The domestic coal prices of coal vary according to the grade of coal.[13]

The principal activity status and occupation status of each household and individual across NSS rounds was matched to the National Industrial Classification 2008 and National Occupation Classification 2004 for consistency. Following this, the five-digit industrial classification criteria was narrowed down to two-digit level for a broader identification of the occupation. The data from NSS shows that majority of individuals working in mines are found in the rural sector of the country. This adds on to the argument, that impact of mining is mainly felt at rural level as the impacts of mining if any in terms of health, labor displacement, education levels or declining agricultural productivity [Aragón et al., 2015] affect those in closer proximity to the mines.[14]The urban centers usually see the professional jobs related to mining with the headquarters of the mining companies. For this reason, the sample of this paper is restricted to the child population of the rural regions of India.

Separate analysis in the paper require data on domestic coal prices and district level data on demographic features, literacy levels, income levels and educational supply.

The domestic coal prices are not directly available at a district or state level and therefore the purchase price of domestic coal by firms is used to calculate the average district level price of coal for each year. This analysis is performed using the Annual Survey of Industries (ASI) data set (1999-2011) which is a firm level survey data set collected annually in India. This data provides location wise firm level details of all the inputs used with their prices and output produced with its value along with firm specific details on the labor, capital and resources used and generated.

Educational indicators for every district have been used from District Information System

[12]Both these data variables are made available in the Coal Directory of India 2011-12.

[13]There were 93 districts in the 68th round and 79 districts in 55th round having coal or lignite deposits.

[14]Mines are generally placed in backward regions where urbanization is tough due to the natural geography as such.

for Education (DISE) in India. The variables – number of schools, number of teachers and enrollment in rural parts of Indian districts are used for the years 2002-2016. Data on district level sex-ratio, female and adult literacy rates, and population density were used from Census India database for the years 2001 and 2011 respectively. All district codes from DISE and Census data were matched in uniformity with the NSS data (for 68th round).

State level data on per capita domestic product and labor force participation rates (overall rural population) for survey years were used from RBI database and NSS data respectively.

2.3.3 Empirical Strategy and Discussion of Results

The empirical model exploits the geographic heterogeneity within India in the presence of coal mines to assess the impact of coal mining on the school attendance of children (young and old). The three main survey years of NSS data are used as the main period of analysis for this study. A repeated cross-section of individual level data set is combined with district and state level parameters on education, income and demographics to shape this analysis.

The empirical analysis is categorized under three main headings; the i) Price-Pass through regressions, ii) Baseline regressions and iii) Robustness checks followed by some falsification tests.

2.3.3.1 Price-Pass Through Regressions

The identification of this model relies on the exogenous movement of international coal prices. It has been established earlier that Indian coal sector is driven mainly by the Central Government and the production is governed by two major government owned companies. In such a scenario, it is prime to establish an active economic link between the world coal prices and the corresponding adjustment in domestic coal prices and production. This Price-Pass through mechanism is the first link that is established in this paper.

Since data on coal prices are generated at the national level by Coal Controller of India, a state level analysis using the ASI data facilitates the construction of average coal prices.[15]

[15]Coal Controller of India does provide state level data on domestic coal production even though domestic price data is not available at the state level

The average domestic coal prices are generated at a state level through purchase price of coal and its quantity consumed by each firm in every state. The domestic prices are then brought in conformation with the international prices using conversion rates based on the PPP index.

Thus, Price-Pass through models estimating the percentage change in domestic coal price (and domestic coal production) due to a percentage change in international coal price (both measured in USD/tonne) are set up:

$$P_{st} = \alpha_0 + \alpha_1 \cdot P_t^* + \gamma_s + \theta_t + \varepsilon_{st} \tag{2.8}$$

The Eq. 2.8, shows the effect of international coal prices P^* at time t on the domestic coal prices P in a given state s at time t also controlling for state (γ_s) and time (θ_t) fixed effects. Several versions of these price-pass through regressions are carried out using two different sets of same ASI data (1999-2011)– one which is yearly (with location codes and no unique firm identifiers over time) and one which has panel settings (Firm-Year panel data but without location codes).

The results on price-pass through regressions suggest a positive and significant pass-through from international coal prices on both domestic coal prices and production of coal, which are robust to the inclusion of varied fixed effects. A 10% increase in world coal prices brings a 7-9% point increase in the domestic coal price while the domestic production increases by 0.5-1.2% points.[16]

Table 2.2 – Price-Pass Through Regression Results

Indian Coal Price	(1) Model 1	(2) Model 2
World Coal Price	0.903***	0.739***
	(0.0301)	(0.0286)
Constant	1.181***	1.900***
	(0.115)	(0.128)
Observations	49,715	49,715
R-squared	0.319	0.338
Year FE	Yes	No
State FE	Yes	No
State-Year FE	No	Yes

Note:Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; ASI Yearly Data 2001-02 -2010-11; All variables in logs.

[16]These results correspond to the use of yearly data; with panel data the coefficients are much smaller: 0.9-3%.

Table 2.3 – Price-Pass Through Regression Results

Indian Coal Price	(1) Model 1	(2) Dynamic Panel
Lag_India Coal Price		0.638***
		(0.0376)
World Coal Price	0.378***	0.0986***
	(0.00723)	(0.0155)
FD_World Coal Price		
Constant	2.665***	1.172***
	(0.0297)	(0.118)
Observations	45,100	10,368
R-squared	0.103	
Number of factory id	22,480	4,336
Panel FE	Yes	Yes

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; ASI Panel Data: Factory and Year Panel 2001-02 – 2010-11; All Variables in logs; FD_World Coal Price – First difference in log world coal price

Table 2.4 – Production-Pass Through Regression Results

Indian Coal Production	(1) model 1	(2) model 2	(3) model 3	(4) Dynamic Panel
Indian Coal price		0.0947**		
		(0.0416)		
World Coal price	0.124**	0.0673*		0.0521***
	(0.0460)	(0.0372)		(0.0198)
FD_world coal price			0.0199	
			(0.0155)	
Lag_coal production				0.736***
				(0.163)
Constant	0.537***	0.411	0.0197***	0.0777
	(0.190)	(0.249)	(0.00690)	(0.120)
Observations	312	298	281	248
R-squared	0.085	0.117	0.005	
Number of States	32	30		31
Panel FE	Yes	Yes		
FD-FE			Yes	

Note: standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; ASI Yearly Data: 2001-02 – 2010-11 used, Collapsed at State level using means; Panel setup: State – Year

Since, the economic link between domestic coal prices and world coal prices is now established, it is now suitable to discuss the potential linkages between the coal price movements around the world and educational outcomes of children living in districts with coal mines in India.

2.3.3.2 School Attendance and Coal Mining - Baseline Regressions

In an attempt to address the schooling outcomes for children living in coal mining regions of India, I use the international coal price movements as an instrument given it's correlation with the domestic coal prices and production and independence with the domestic policies and institutions. The outcome variable for this study is a dichotomous variable that captures attendance of school going children.

The treatment variable captures the changing value of international coal prices in mining districts of India. Child schooling outcomes particularly the schooling attainment and enrollment are known to be positively correlated with the education of parents [Strauss and Thomas, 1995]. The household characteristics are also controlled for in the analysis. The various attributes of households such as their monthly per capita expenditures, religion, ethnicity and land ownership are used from the NSS data. This data is also used to derive details on the household head, such as their gender, education levels and literacy levels. For individual controls, the age and gender are used interactively through a third order polynomial for age to account for the higher work opportunities available to older children differentiated by their gender. Also, considering that exploration intensity (presence of mines) is driven by institutional quality, investment climate in the region or environmental regulation, these effects will be taken care of by the region-specific and time fixed effects [de Haas and Poelhekke, 2014]. Let Y_{ihdt} denote the dichotomous variable reflecting school attendance for the child i in household h and district d at time t (survey period). Thus, the baseline specification would be:

$$Y_{ihdt} = \alpha + \beta \cdot (M_d * P_t) + X_{hdt} + C_{ihdt} + \Pi(A_{it}, G_{it}) + \gamma_d + T_t + \varepsilon_{ihdt} \tag{2.9}$$

where $(M_d * P_t)$ captures the treatment effect and the changing world coal prices across mining districts over time, while X_{hdt} captures household controls and C_{ihdt}captures individual child controls. The age and gender of the child are incorporated through a third order polynomial of interacted age and gender effects captured by $\Pi(A_{it}, G_{it})$. District and Time fixed effects are captured by γ_d and T_t respectively. Since, the treatment variable registers a district-level variation, ε_{ihdt}captures the individual stochastic shocks clustered at the district level to account for any correlation in shocks at the district level .

The above specification is also strengthened by adding state and district specific time varying controls such as the per capita state domestic product, overall rural labor force participation at the state level and rural enrollment in schools at a district level. This allows to capture any time-varying state and district specific policy changes that may be affecting the school attendance of children in the mining regions thus making the identification strategy less reliant on similar trends across regions.

The alternate specification thus becomes;

$$Y_{ihdt} = \alpha + \beta \centerdot (M_d * P_t) + X_{hdt} + C_{ihdt} + \Pi(A_{it}, G_{it}) + \gamma_d + T_t + S_{st} + D_{dt} + \varepsilon_{ihdt} \qquad (2.10)$$

Since the dependent variable is a binary variable, the Linear Probability Model is used for testing the above specifications;[17]

$$Pr.(Y_{ihd} = 1) = 1 - \Phi[\Omega_{ihd} - u] \qquad (2.11)$$

where $Y_{ihd} = 1$ indicates that child i belonging to household h attends school in district d, and Ω_{ihd} incorporates the combination of all explanatory variables as discussed in Eq. 2.9 & 2.10.

Heterogeneous effects with respect to age are also presented, with separate results for young (5-9 years) and old (10-14 years) children. Following the different mechanisms discussed in the conceptual background, young children are less likely to find better paid jobs compared to the older children due to their work capacity and skill (thus lower 'w' compared to older children). Young children will also have lower costs of education as most of the primary education is free in India and availability of primary schools in the vicinity is higher than elementary and high schools (thus a lower 'c') and households attach a higher weight to primary schooling than higher education as the substitution effects start kicking in (thus the 'α' will be higher

[17]The results with a Probit analysis were also similar, but LPM was chosen as it allows a more convenient interpretation of the results.

for younger children). With regards to the other income effects coming via rising family incomes and rising expected returns from education, it is assumed that these affect the schooling decisions of young and older children alike.

This allows us to narrow down the impact of coal wealth on the specific section of the child population as each group might get affected differently which might not be completely reflected in the regressions based on overall child sample.

Results

Schooling outcomes for children (age 5-14 years) has increased on an average by 20% between 1999-2010 The baseline specifications present a positive picture for school attendance of children living in mining districts of India. The outcome is consistent across all sample sizes of children considered. Therefore, for an average increase in world coal prices (1.92) between 1999-2010, the probaility for a child (age 5-9; 10-14; 5-14 years) living in coal districts of India to attend school increases by 7.6-9.2% points relative to the national trends. The income and wealth of the households which is captured by the per capita expenditures and the land ownership titles, also positively affect the school attendance of children which indicates that income effects are stronger in this model as better-off families prefer sending their children to school rather than to work.

These results indicate that the substitution effects which could have differentiated the outcomes for young and old children (via 'w' and 'c') are not dominant and the income effects (via 'y', 'p' and 'r') which were expected to have similar results for young and older children alike are the dominant factor.

Table 2.5 – Regression results for the child sample in rural regions of India

Pr.(attend school)	(1a) All children	(1b) All Children	(2a) Old Children	(2b) Old Children	(3a) Young Children	(3b) Young Children
Coal prices*Active mine	0.0452***	0.0434**	0.0445***	0.0478***	0.0485**	0.0397*
	(0.0171)	(0.0179)	(0.0165)	(0.0177)	(0.0205)	(0.0214)
MPCE	0.0770***	0.0782***	0.0799***	0.0825***	0.0758***	0.0756***
	(0.00417)	(0.00433)	(0.00481)	(0.00506)	(0.00473)	(0.00481)
Land indicator	0.0339***	0.0306***	0.0358***	0.0301***	0.0343***	0.0333***
	(0.00591)	(0.00628)	(0.00696)	(0.00735)	(0.00664)	(0.00706)
Age of child	0.699***	0.702***	0.879***	0.789**	2.091***	2.103***
	(0.0189)	(0.0197)	(0.312)	(0.333)	(0.126)	(0.133)
Female	0.138**	0.162**	-0.340	-1.323	0.248	0.248
	(0.0677)	(0.0707)	(1.899)	(1.995)	(0.401)	(0.425)
Female*age	-0.0502**	-0.0588**	0.0725	0.319	-0.0858	-0.0839
	(0.0228)	(0.0238)	(0.483)	(0.507)	(0.175)	(0.186)
Constant	-2.194***	-0.945***	-3.484***	-1.551	-5.278***	-4.450***
	(0.109)	(0.319)	(1.248)	(1.352)	(0.311)	(0.534)
R-squared	0.224	0.230	0.193	0.200	0.264	0.270
Child controls	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District controls	No	Yes	No	Yes	No	Yes
State controls	No	Yes	No	Yes	No	Yes
Observations	243,926	221,982	122,432	111,246	121,494	110,736

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; Young – 5-9 yrs, Old – 10-14 yrs; MPCE – Monthly per capita expenditures by the household Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11).District controls include rural enrollment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Regressions based on linear probability method for rural child sample

The results are robust to the addition of time varying area specific controls as well, with an approximate 8% point increase in probability for school attendance for rural children living in mining districts relative to national trends when there is an average increaese in the world coal prices (1.92).

The dominating income effect in the household decision making process can be understood via the various channels outlined in the Section 2.3.1 of this paper. The mining activity is known to create spillovers on related industries and economy of the region. These spillovers can induce either positive effects on educational ouctomes of children through greater returns on education ('r') and rising family incomes ('y' and 'p') or negative effects on education through rising demand for child labor ('w'). It could well be the case that better economic opportunities through advancement in mining techniques is raising the demand for skilled labor which is providing enough incentive for households to educate their children. [18]The magnitude of these mechanisms needs further evaluation.

The supply of educational inputs (teachers and schools) in coal mining regions is also benefited through a rise in world coal prices through additonal revenues in these regions. Better educational quality and infrastructure can lower the direct costs of education (negative substituition effect) and also serve as an income effect. This could also be a contributing factor in raising the probability of schooling for children in coal mining districts of India as well. Therefore, as an added check, the educational supply factors are also controlled for in the baseline regressions. The results for the treatment effect are not affected by the inclusion of educational supply controls, thus indicating that an increase in schooling probability of children in coal mining regions of India is independent of any educational supply shocks and can be attributed to a great extent on the rising world prices of coal. The results in Table 2.6 suggest that, with everything else equal, as there is a percent increase in number of teachers, the probability of children to attend school in mining regions also increases by 8% points, with the impact on older children to be lesser (4% points) compared to younger children (12% points). This result is in line with Marchand and Weber [2020], where they show that revenue growth through Texas boom in shale oil and gas drilling was not sufficient in retaining quality teachers in light of rising private sector wages which had a detrimental effect on student attendance and performance. Therefore teacher quality and quantity is an essential input in improving school attendance which can be seen through results in this paper as well. While, the increase in number of schools is seen to have adverse effects on the schooling attendance of children in these regions. This result is in contrast to similar scenarios in literature where greater school construction generally enhances the schooling years and attendance [Duflo, 2001]. This could be further evaluated in light of quality of schools in future research.

[18]Given that labor mobility is low across regions in India, the benefits of skilled job creation should be reaped by local population initially.

Table 2.6 – Regression results for schooling probability of rural children after controlling for educational supply factors

Pr.(attend school)	(1) All children	(2) Old Children	(3) Young Children
Coal prices*Active mine	0.0443**	0.0510**	0.0400*
	(0.0195)	(0.0199)	(0.0237)
MPCE	0.0839***	0.0914***	0.0791***
	(0.00529)	(0.00600)	(0.00701)
Land indicator	0.0276***	0.0205*	0.0348***
	(0.00915)	(0.0110)	(0.0105)
Age of child	0.739***	1.045**	2.295***
	(0.0293)	(0.531)	(0.192)
Female	0.145	-1.869	0.523
	(0.114)	(3.360)	(0.652)
Female*Age	-0.0505	0.482	-0.215
	(0.0391)	(0.858)	(0.286)
Schools	-0.0563**	-0.0182	-0.0940***
	(0.0232)	(0.0227)	(0.0313)
Teachers	0.0867***	0.0476***	0.122***
	(0.0188)	(0.0182)	(0.0255)
Constant	-0.647	-2.046	-4.794***
	(0.434)	(2.119)	(0.728)
Observations	221,982	111,246	110,736
R-squared	0.226	0.200	0.268
Child controls	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses - *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; Young – 5-9 yrs, Old – 10-14 yrs; MPCE – Monthly per capita expenditures by the household Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). Teachers and schools are considered for rural areas only. Data for teachers and schools taken from District Information on Schools (DISE) India ; World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). Regressions based on linear probability method for rural child sample .

2.3.3.3 Robustness checks

The study evaluates the effect of coal mines on educational status of school-going children in India. It is to be noted that out of 627 districts in 2011, only 52 districts had active coal mines (around 8%). As per the NSS data set used in the paper, the children (age group 5-14 years) living in these regions also constitute 8% of the total child sample living in rural areas.

The treatment group which is only 8% of the total sample is arguably smaller than the control group. In cases such as these, a synthetic control can be created as a counterfactual which is relatively smaller than the control group and allows for an unbiased difference in difference analysis.

Matching Propensity Score Method

The synthetic control method for creating matched samples is limited by the fact that it allows only a single treated unit to be evaluated and a specific intervention period also needs to be specified.

Matching probability method on the other hand doesn't require a specific policy period but needs the estimation of treatment probability. Here, the probability for a control region to be considered as a treated region based on different baseline characteristics of districts is evaluated.

The baseline characteristics of districts included in the analysis are the initial survey year (NSS 55) features of these districts - population density, land cultivated, and wages earned.

Regions with similar treatment probability are included in the matched sample. This implies that for every treatment region, control regions with very similar treatment probability conditional on baseline characteristics serve as matched counterfactual set. In doing so, 1:1 nearest neighbor matching is avoided as every district or region in a district-level data set can have multiple regions matched to them when based on underlying features of these regions. As a relatively safe option, 1:5 nearest neighbor matching is chosen as the preferred method.[19]

With the matching exercise, for the 49 districts that had active mines (as identified in NSS 55), the 1:5 nearest neighbor matching method resulted in 164 districts out of the control pool to be matched.[20] The combined sample of 213 districts was then used to carry out the regressions as specified in Eq. 2.10. This matching method is given preference over the synthetic control method for robustness exercise owing to its better sample size and scheme of implementation.

[19] Although results with nearest neighbor matching of the order 1:1, 1:2 ,1:3 & 1:4 are also significant, the best estimates overall are achieved via 1:5 nearest neighbor matching.

[20] 41 districts were matched in 1:1 matching; 73 districts in 1:2 method, 105 districts in 1:3 method and 133 districts in 1:4 method

Table 2.7 – Results based on Propensity Score Method (Baseline model with area specific controls)

Pr.(attend school)	(1) All children	(2) Old Children	(3) Young Children
Coal prices*Active mine	0.0390**	0.0372*	0.0418*
	(0.0189)	(0.0194)	(0.0226)
MPCE	0.0692***	0.0747***	0.0657***
	(0.00677)	(0.00816)	(0.00744)
Land indicator	0.0192*	0.0210	0.0193*
	(0.0105)	(0.0127)	(0.0110)
Age of child	0.747***	0.791	2.282***
	(0.0336)	(0.549)	(0.221)
Female	0.257**	-3.996	1.006
	(0.108)	(3.297)	(0.710)
Female*Age	-0.0868**	0.974	-0.406
	(0.0365)	(0.839)	(0.310)
Constant	-1.597***	-1.737	-5.531***
	(0.547)	(2.272)	(0.891)
R-squared	0.222	0.204	0.260
Child controls	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	86,458	43,059	43,399

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; Young – 5-9 yrs, Old – 10-14 yrs; MPCE – Monthly per capita expenditures by the household; Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). District controls include rural enrollment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Regressions based on linear probability method for rural child sample; Nearest neighbor matching method: 1:5 matching performed on NSS 55 dataset; sample of 213 districts used for overall LPM regressions.

The restricted sample based on propensity score matching controls for the baseline characteristics among the districts and the time varying district and state controls. The treatment effect though positive and robust, slows a bit as the analysis is conducted for districts which are similar.The results on the treatment effect are still approximately 4 percentage points (through a 100% shock in world coal prices). This validates the outcomes from the baseline model that an average increase in world coal prices causes the incidence of school attendance among children in coal mining districts of India to rise by 8% points relative to the national trends.

In an additional robustness exercise, the mining districts are compared with the non-mining districts in the states which have active coal mines. The baseline results are still robust in these regressions. The estimates again show an increase of approximately 3-4 percentage points (through a 100% increase in world coal prices) as also seen in the matching propensity method estimates. These estimates allow us to eliminate any confounding effects of state specific policies that could be biasing the outcomes.

Table 2.8 – Regression results for comparing the schooling probability between mining and non-mining regions within coal rich states

Pr.(school attend)	(1) All children	(2) Young children	(3) Old children
Coal prices*Active mine	0.0349**	0.0383*	0.0344**
	(0.0173)	(0.0207)	(0.0168)
MPCE	0.0759***	0.0736***	0.0802***
	(0.00457)	(0.00508)	(0.00538)
Land indicator	0.0410***	0.0410***	0.0433***
	(0.00655)	(0.00726)	(0.00782)
Age of child	0.716***	2.096***	1.073***
	(0.0202)	(0.139)	(0.349)
Female	0.133*	0.117	-0.414
	(0.0746)	(0.440)	(2.129)
Female*Age	-0.0487*	-0.0249	0.0909
	(0.0253)	(0.193)	(0.542)
Constant	-2.254***	-5.253***	-4.374***
	(0.129)	(0.340)	(1.409)
R-squared	0.227	0.266	0.197
Child controls	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	207,726	104,292	103,434

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1 Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; Young – 5-9 yrs, Old – 10-14 yrs; MPCE – Monthly per capita expenditures by the household; Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). District controls include rural enrollment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). States with active coal mines are chosen. Regressions based on linear probability method for rural child sample

The positive effects of coal mining on the school attendance of children living in those regions has been established. Falsification tests and Placebo exercise can shed more light on to the extent of generality of these results.

2.3.3.4 Falsification exercise

The several regression outcomes presented in the previous sections highlight the effects of coal mining on the education of children living in coal mining regions of India. A few falsification tests presented in this section indicate whether these results are strictly limited to the 'children living in mining regions' or not.

The first test examines the educational attainment of adults above the age of 25 years when exposed to the coal price shock. The educational parameters chosen are the completed educational level of the individuals. Since people above the age of 25 years should have already completed their elementary and higher education and attained at least a college degree, the rising coal prices should have no significant positive effect on these outcomes.

In Table 2.9, results with completed education levels for adults show that an increase in world coal prices have no significant effect on the educational attainment of the population aged above 25 years, except for the case when a graduate and above degree is considered (Column 3). Even in that case, the result is negative and significant as the category in question considers individuals who have completed any degree or diploma (such as bachelors, masters (other post-graduate levels etc.)) which is still considered as an option by population above the age of 25 years . [21]

[21] Also, according to that result, the rising coal prices, and thus rising demand for labor in the economy is strong to demotivate this population from pursuing any graduate or post-graduate level study.

Table 2.9 – Falsification tests: Completed Education by adult individuals

Pr.(Completed education)	(1) Elementary	(2) High school	(3) Graduate
Coal prices*Active mine	0.00473	0.0102	-0.0155*
	(0.0224)	(0.00786)	(0.00808)
MPCE	0.0176***	0.0279***	0.0694***
	(0.00508)	(0.00440)	(0.00413)
Land indicator	0.0277***	0.00734**	-0.00899**
	(0.00933)	(0.00372)	(0.00414)
Age	-0.944	0.477	-2.580*
	(3.010)	(1.762)	(1.511)
Constant	9.110	-4.786	22.96
	(27.95)	(16.36)	(14.04)
R-squared	0.144	0.097	0.218
Ind controls	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Dist controls	Yes	Yes	Yes
State controls	Yes	Yes	Yes
Observations	57,109	57,109	57,109

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age); MPCE – Monthly per capita expenditures by the household; Probability of completed education by individuals above the age of 25 years tested: Elementary – middle; secondary, senior secondary; High School – Higher secondary; Graduate – Diploma, Graduate degree, Post-graduate. Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61, NSS 66 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). District controls include rural enrollment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Regressions based on linear probability method;

Thus, it can be safely concluded that this falsification exercise stands true and the rising international coal prices change the economic conditions in the coal mining districts of India, altering the incentives only for child education in favor of higher school attendance.

In another falsification exercise, the control districts which do not have any coal mine are randomly assigned the treatment effect. Half of the control districts are exposed to the treatment effect and a similar analysis for children is performed to analyze their schooling outcomes. The results indicate that schooling probability for children living in control regions is unaffected at any significant rate due to the coal price rise around the world.

Table 2.10 – Falsification test: Regression results for schooling outcome of children living in control regions

Pr.(attend school)	(1) All children	(2) Old Children	(3) Young Children
Coal price*Random treated	-0.0153	-0.0129	-0.0165
	(0.0112)	(0.0120)	(0.0133)
MPCE	0.0747***	0.0769***	0.0743***
	(0.00450)	(0.00530)	(0.00503)
Land indicator	0.0365***	0.0356***	0.0391***
	(0.00681)	(0.00778)	(0.00769)
Female	0.152**	-1.579	0.0833
	(0.0749)	(2.089)	(0.440)
Age of child	0.694***	0.804**	2.003***
	(0.0203)	(0.349)	(0.137)
Female*Age	-0.0560**	0.384	-0.0168
	(0.0253)	(0.531)	(0.192)
Enrolment	0.00699***	0.00357*	0.0104***
	(0.00233)	(0.00216)	(0.00319)
Constant	-2.320***	-3.367**	-5.180***
	(0.135)	(1.398)	(0.354)
R-squared	0.228	0.197	0.269
Child controls	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	201,595	101,088	100,507

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1 Placebo Treatment variable - ln(world coal prices)*random assignment to control regions. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; Young – 5-9 yrs, Old – 10-14 yrs; MPCE – Monthly per capita expenditures by the household; Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). Sample includes the Indian districts with no coal mines; 50% of these districts are exposed to the treatment effect randomly. District controls include rural enrollment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Regressions based on linear probability method for rural child sample

This falsification exercise further verifies that the schooling probabilities are affected for children living in coal mining regions only, when exposed to the international coal price rise. Therefore, these positive schooling outcomes for rural children in mining regions can not be generalized to the adult population in the similar way (as shown in Table 2.9) and are also not applicable to the child population in non-coal mining regions of India (Table 2.10).

2.3.4 Channels of Impact

Coal price shocks around the world yield positive schooling outcomes for rural children in coal mining regions of India, is a promising outcome. This impact can be understood through the different channels discussed in the conceptual framework presented in Section 3.1 of this paper.

The positive effects of coal price rise on school attendance of children in mining districts of India is very promising and extends support to the channels of income effect domination in the household decision making. The positive educational returns owing to better and more jobs in mining sector along with higher incomes for families in these regions due to spillovers (with increased industrial activity and infrastructural growth) and rising wages in coal mining sector are responsible for the better educational prospects in these regions for the young population. [22][23]

2.3.4.1 Evaluating the substitution effects

As discussed previously, the substitution effects in household decision making when exposed to the international coal price shock emerge when the economic incentives in the affected regional economy are altered in a manner such that families find it lucrative to send their children to work to gain greater family incomes.

This is however, not true in the case of coal mining regional economies in India, where the probability to perform any child labor (whether in family owned work or market work) is significantly reduced when exposed to the international coal price shock over the time period of analysis [Refer: Table 2.11].

[22] This can be seen through the industrial decomposition in coal rich regions over the years seen through NSS data; or also through the ASI data (which reflects the distribution of firms across Indian regions). See appendix

[23] See Appendix; average weekly earnings of coal mine workers in India

Table 2.11 – Regression results for showing the child activity status in mining versus non-mining regions

Model Probabilities	(1) Schooling	(2) Labor	(3) Work only	(4) Market work	(5) Domestic work	(6) Idle
Coal prices*Active mine	0.0434**	-0.0601***	-0.0474***	-0.0572***	-0.00284	0.000895
	(0.0179)	(0.0195)	(0.0182)	(0.0186)	(0.00437)	(0.000821)
MPCE	0.0782***	-0.0781***	-0.0753***	-0.0649***	-0.0132***	-0.000502***
	(0.00433)	(0.00432)	(0.00420)	(0.00386)	(0.00127)	(0.000189)
Land indicator	0.0306***	-0.0355***	-0.0325***	-0.0369***	0.00134	-0.000696
	(0.00628)	(0.00589)	(0.00591)	(0.00521)	(0.00232)	(0.000423)
Female	0.162**	-0.150**	-0.179***	-0.159**	0.00837	0.0163***
	(0.0707)	(0.0693)	(0.0688)	(0.0673)	(0.0276)	(0.00450)
Age of child	0.702***	-0.715***	-0.684***	-0.731***	0.0158***	0.00671***
	(0.0197)	(0.0195)	(0.0191)	(0.0189)	(0.00544)	(0.00150)
Female*Age	-0.0588**	0.0584**	0.0666***	0.0567**	0.00170	-0.00651***
	(0.0238)	(0.0234)	(0.0232)	(0.0226)	(0.0104)	(0.00173)
Constant	-0.945***	1.995***	1.759***	2.311***	-0.316***	-0.0117
	(0.319)	(0.326)	(0.325)	(0.313)	(0.112)	(0.0126)
R-squared	0.230	0.236	0.231	0.232	0.110	0.008
Child controls	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	221,982	222,961	222,961	222,961	222,961	222,961

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; Young – 5-9 yrs, Old – 10-14 yrs; MPCE – Monthly per capita expenditures by the household. Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). District controls include rural enrollment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage) . Dependent variables are the probabilities for different activities children can engage in. Regressions based on linear probability method for rural child sample

The probability to perform domestic work or being idle at home is not significantly affected through the international coal price shock for children living in coal mining regions of the country. Therefore, dominance of substitution effects in the household decision making is not a valid channel in the coal mining regional economies of the country.

Also, the costs of education haven't significantly increased in the period of analysis, to hamper the schooling outcomes in these regions. Coal price shocks have on the contrary, caused a significant increase in schools and teachers in these regions.

2.3.4.2 Evaluating the income effects

The positive schooling outcomes in coal mining regions of the country can be certainly explained via the 'income effects' in the household decision making process of families living in these regions. The coal price shocks, create positive economic incentives enabling the literate families and wealthy families to educate their children. This supports the channel of 'higher returns to education' due to the spillover effects generated via the coal mining industry. Future or expected wages reflect the returns on education via the earning capacity each sector brings through the degree of education required in them.

Results in Tables 2.12,2.13 and 2.14, indicate the differing returns to education in different industrial sectors for individuals differentiated through their geographical location (living in coal region vs. non-coal region). Mincer type wage regressions are carried out to reflect the logarithmic gap in wages between the two regions for the three industrial sectors. Three important participation controls used are the number of dependent children and elderly in the family and the wealth (measured by land holdings) owned by the household [Schultz, 1990, Tansel, 1994].

Table 2.12 – Regression results for the 'returns to education' for primary sector

Ln(daily wage)	(1) Coal Mine Regions	(2) Coal Mine Regions	(3) Non-Coal Mine Regions	(4) Non-Coal Mine Regions
Years of education	0.0524***		0.0375***	
	(0.00622)		(0.00206)	
Female	-0.567***		-0.267***	
	(0.0608)		(0.0142)	
Experience	0.0265***		0.0157***	
	(0.00786)		(0.00204)	
Experience_squared	-0.000240		-0.000202***	
	(0.000155)		(4.07e-05)	
Ln(Land owned)		-0.236***		-0.234***
		(0.00784)		(0.00275)
No. dependent children		-0.0378***		-0.0537***
		(0.0126)		(0.00427)
No. dependent elderly		-0.0732**		-0.113***
		(0.0330)		(0.0111)
Constant	-3.655***	-0.477***	-3.896***	-0.644***
	(1.316)	(0.0427)	(0.827)	(0.0142)
Observations	17,143	17,143	167,762	167,762
Individual controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sample	Age 15-65	Age 15-65	Age 15-65	Age 15-65

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1Working age group: 15-65 yrs; Districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). . Dependent variable is the probability of working in coal region versus non-coal region. Independent variables include: Variables: years of education, hectares of land owned (in logs), number of dependent children and elderly, gender indicator and age (all accessed via the Unemployment and Employment Schedules of NSS Surveys India).District controls include rural enrolment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Mincer wage regressions using participation restrictions (results column 2 & 4) (participation restrictions – wealth measured by land holdings and dependency level through children and elderly in family that need to be supported). These regressions are carried out for working population in primary sector (agriculture, mining, fishing, and allied activities). Experience is calculated as: Experience = Age – Years of education – 5; or Age – 14 if years of education is less than 7 (assuming children start schooling at the age of 4-5 years in India).

Table 2.13 – Regression results for the 'returns to education' for manufacturing sector

Ln(daily wage)	(1) Coal Mine Regions	(2)	(3) Non-Coal Mine Regions	(4)
Years of education	0.0283***		0.0513***	
	(0.0103)		(0.00301)	
Female	-0.942***		-0.568***	
	(0.149)		(0.0331)	
Experience	0.0226*		0.0393***	
	(0.0127)		(0.00396)	
Experience_squared	-0.000320		-0.000517***	
	(0.000321)		(8.46e-05)	
Ln(Land owned)		-0.0294*		-0.0293***
		(0.0154)		(0.00495)
No. dependent children		-0.0505*		-0.0946***
		(0.0267)		(0.00789)
No. dependent elderly		-0.102		-0.0153
		(0.0756)		(0.0193)
Constant	-0.217	-1.228***	-2.807**	-0.988***
	(3.069)	(0.0792)	(1.094)	(0.0228)
Observations	2,376	2,376	20,416	20,416
Individual controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sample	Age 15-65	Age 15-65	Age 15-65	Age 15-65

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1Working age group: 15-65 yrs; Districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). . Dependent variable is the probability of working in coal region versus non-coal region. Independent variables include: Variables: years of education, hectares of land owned (in logs), number of dependent children and elderly, gender indicator and age (all accessed via the Unemployment and Employment Schedules of NSS Surveys India).District controls include rural enrolment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Mincer wage regressions using participation restrictions (results column 2 & 4) (participation restrictions – wealth measured by land holdings and dependency level through children and elderly in family that need to be supported). These regressions are carried out for working population in manufacturing sector. Experience is calculated as: Experience = Age – Years of education – 5; or Age – 14 if years of education is less than 7 (assuming children start schooling at the age of 4-5 years in India).

Table 2.14 – Regression results for the 'returns to education' for services sector

Ln(daily wage)	(1)	(2)	(3)	(4)
	Coal Mine Regions		Non-Coal Mine Regions	
Years of education	0.0815***		0.0796***	
	(0.00356)		(0.00103)	
Female	-0.334***		-0.366***	
	(0.0440)		(0.0119)	
Experience	0.0480***		0.0430***	
	(0.00596)		(0.00167)	
Experience_squared	-0.000482***		-0.000430***	
	(0.000128)		(3.52e-05)	
Ln(Land owned)		0.0469***		0.0656***
		(0.00658)		(0.00209)
No. dependent children		-0.0942***		-0.0991***
		(0.0121)		(0.00348)
No. dependent elderly		-0.0934***		-0.0819***
		(0.0288)		(0.00833)
Constant	-2.135**	-0.596***	0.0422	-0.639***
	(1.083)	(0.0362)	(0.729)	(0.0112)
Observations	5,880	5,880	66,459	66,459
Individual controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sample	Age 15-65	Age 15-65	Age 15-65	Age 15-65

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1Working age group: 15-65 yrs; Districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). . Dependent variable is the probability of working in coal region versus non-coal region. Independent variables include: Variables: years of education, hectares of land owned (in logs), number of dependent children and elderly, gender indicator and age (all accessed via the Unemployment and Employment Schedules of NSS Surveys India).District controls include rural enrolment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Mincer wage regressions using participation restrictions (results column 2 & 4) (participation restrictions – wealth measured by land holdings and dependency level through children and elderly in family that need to be supported). These regressions are carried out for working population in services sector. Experience is calculated as: Experience = Age – Years of education – 5; or Age – 14 if years of education is less than 7 (assuming children start schooling at the age of 4-5 years in India).

Results indicate that every additional year in education brings higher returns in terms of daily wages for each sector of the economy. The positive effect on wages reflects that education always has positive returns. In coal mining regions, this effect does prevail and is significant too. On comparing the logarithmic wage gap between the coal regions and non-coal regions for each industrial sector, it is found that individuals working in agriculture, mining and allied sector and services sector gain from education much more than individuals working in the manufacturing sector when they live in regions with coal mines. This is true as manufacturing sector does work with unskilled labor force much more than services sector and therefore the wage jump in coal regions isn't at par with the wage jump seen in non-coal regions. However, employment has significantly increased in manufacturing sector much more than agricultural or services sector (as also shown in Chapter 4 of this dissertation using ASI data), which is a source for positive income spillovers for families living in coal regions. This result indicates that coal mining is a relatively labor-intensive sector in India [Pelzl and Poelhekke, 2018]. Thus, individuals in coal regions benefit through higher wages in agricultural and services sector and greater employment in manufacturing sector, strengthening the income effect. Therefore, the higher 'returns to education' is a valid channel to explain the positive schooling probabilities for children in coal regions of India.

The 'income effects' in the household decision making with respect to the schooling decisions are also visible via the heterogeneity in the wealth of the families. In Table 2.15, it can be seen that wealthy families with land have positive schooling probabilities with respect to the treatment effect contrary to the families with no land holdings. Therefore, it is the wealthy families in coal regions that benefit with child schooling more when exposed to the international coal price shock. Families with no land do not have significant treatment effects. Therefore, there is no evidence that substitution effects dominate otherwise.

International coal price shock add incomes to the families living in the coal regions of India through various spillover effects (agglomeration economies). These wealthy families give preference to their child's education over market wage opportunities for them.

Table 2.15 – Heterogeneous effects based on land ownership

Pr.(Attend school)	(1a) All children	(1b) All children	(2a) Old Children	(2b) Old Children	(3a) Young Children	(3b) Young Children
Coal prices*Active mine	0.0449**	-0.0167	0.0485***	0.0319	0.0427**	-0.0387
	(0.0178)	(0.0574)	(0.0177)	(0.0871)	(0.0214)	(0.0576)
MPCE	0.0780***	0.0617***	0.0832***	0.0652***	0.0745***	0.0625***
	(0.00421)	(0.0130)	(0.00500)	(0.0159)	(0.00479)	(0.0167)
Female	0.155**	0.446	-1.316	0.164	0.252	-0.303
	(0.0740)	(0.276)	(2.038)	(11.35)	(0.436)	(1.951)
Age of child	0.712***	0.576***	0.820**	0.716	2.141***	1.230**
	(0.0197)	(0.0753)	(0.337)	(1.704)	(0.133)	(0.608)
Female*Age	-0.0575**	-0.138	0.316	-0.0663	-0.0859	0.165
	(0.0249)	(0.0959)	(0.519)	(2.890)	(0.190)	(0.864)
Constant	-1.134***	-0.779	-1.797	-1.833	-4.609***	-2.369
	(0.326)	(0.832)	(1.367)	(6.691)	(0.535)	(1.845)
R-squared	0.226	0.357	0.198	0.354	0.266	0.412
Child controls	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Land owned	Yes	No	Yes	No	Yes	No
Observations	210,690	11,292	105,924	5,322	104,766	5,970

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; Young – 5-9 yrs, Old – 10-14 yrs; MPCE – Monthly per capita expenditures by the household. Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). District controls include rural enrollment in schools (collected from DISE India) and State Controls include, per capita Net State Dometsic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Regressions based on linear probability method for rural child sample

Apart from examining the heterogeneous effects of coal mining with respect to ownership of land per se, in Table 2.16, results are presented for the heterogeneous effects of coal mining on education of children belonging to different wealth quintiles. The wealth here is measured by the units of land owned by the families which is considered a valuable asset in India being a potential source of revenue generation through several self-employment opportunities. . Through the five wealth quintiles, it is the families with middle-level wealth who witness a positive and significant change in the schooling probabilities for their children. These outcomes reiterate the discussion on the household preferences for education (α) presented in Section 3.1. The richer the family, more neutral the preferences for 'education' in comparison to 'other goods' become. Children of these families are already at an advantageous position in terms of schooling and do not participate in market work much, therefore as the wealth of the family progresses, the coefficient on schooling probability becomes less significant and eventually insignificant for the wealthiest quintile. For the poorest families, an income shock does make them favor education of their children but not over the consumption of other goods that are important for the sustenance of the family in general. The income effects for these families are the weakest and almost absent. For families that are able to meet their basic needs, an income shock creates enormous income effects in favor of schooling probabilities for their children.

Table 2.16 – Heterogeneous effects based on wealth quintiles

Pr.(attend school)	(1) W1	(2) W2	(3) W3	(4) W4	(5) W5
Coal prices*Active mine	-0.00254	0.118***	0.0806**	0.0722**	0.0526
	(0.0326)	(0.0331)	(0.0341)	(0.0313)	(0.0358)
LMPCE	0.136***	0.119***	0.121***	0.113***	0.0668***
	(0.0101)	(0.0104)	(0.00909)	(0.00820)	(0.00992)
Female*Age	0.168	0.980	0.467	-1.133	2.312**
	(1.218)	(1.178)	(1.113)	(1.222)	(1.175)
Female	-0.747	-3.858	-1.995	4.252	-9.052**
	(4.771)	(4.638)	(4.361)	(4.789)	(4.605)
Age of child	1.300	0.0942	0.504	1.194	0.397
	(0.797)	(0.757)	(0.727)	(0.758)	(0.700)
Constant	-3.310	1.102	-0.225	-2.730	-0.198
	(3.169)	(2.996)	(2.923)	(2.994)	(2.885)
R-squared	0.220	0.200	0.204	0.198	0.172
Child controls	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Sample	All children	All children	All children	All children	All children
Observations	23,692	22,388	23,029	21,398	20,739

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; MPCE – Monthly per capita expenditures by the household. Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). District controls include rural enrollment in schools (collected from DISE India) and State Controls include, per capita Net State Domestic Product and Rural Labor Force Participation rates (available at Reserve Bank of India database webpage). Regressions based on linear probability method for rural child sample. W1-W5: are the five wealth quintiles in ascending order (poorest to richest); wealth is measured as the land owned by household in hectares.

Income effects therefore operate through two channels in coal mining regions of India, firstly due to the greater wealth effects and the second due to the greater returns to education.

2.4 Conclusion

The inequality in educational outcomes across the rural regions of India is a major impediment to development of these regions. The cause of such variations could be attributed to various household decision making parameters which include work opportunities in the region, quality of education provided in their region and their family characteristics.

In this study, presence of natural resources such as coal in these regions is also considered a parameter while making such choices due to the nature of work opportunities it creates and the nature of educational infrastructure it enables.

The rising prices of coal internationally are responsible for increasing wealth in regions with active coal mines. Using the NSS data in India spanning 1999-2011, the impact of rising world coal prices is estimated on schooling probability of children in the age group of 5-14 years, also segregating the effect for young children (age 5-9 years) and older children (age 10-14 years).

Average school attendance has in general improved over the sample period considered, however this paper contributes towards the impact of coal mining in affecting this probability. Various factors shape the relation between the value of this sub-surface wealth in a region and the educational outcomes of children residing there. The analysis conducted at a district level over time in India reveals a 4-5 percentage point increase in the probability to attend school by children living in mining districts when exposed to a 100% increase in the international coal prices. These results are consistent for all age groups and robust to the addition of time varying area specific controls as well to the use of restricted samples created by propensity score matching methods.

These results are informative and indicate the dominance of income effects in the decision-making process for the households in mining communities. Rising wages in coal sector and ancillary industries do create multiple job opportunities, despite which families are not choosing short term income gains by sending their children to work, instead the long-term benefits through higher returns to education are being appreciated by families.

Also, an important channel that deserves merit is the education infrastructure that is created by the mining companies along with governments in these regions. These regions have a positive impact on the number of schools and teachers in general. The better educational supply is also a supporting factor in household decision making in favor of child schooling.

The results of this research are promising and can be revised with further data improvements. With availability of data on employment shares in coal mines and other mine statistics in previous years, more robust estimates on the educational impact would be expected. [24]

The study possesses much scope for improvement and future research in the context of extractive industry impact on the development in regions hosting the industry at a micro level. This paper is one of the first papers to discuss the economic effects of coal mining on education of children at a local level in India. This would therefore, contribute in general to the much talked about literature on economic effects of resource abundance at a local level which has evolved significantly over the last decade though focusing primarily on macro level studies until recently. At the same time, with focus on a developing country like India, it allows policy makers to imitate the findings in this paper on similar developing nations around the world.

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[24] Earlier volumes on Statistics of Mines, [Coal] need to be accessed. Currently, I possess volumes after the year 2010.

Appendix Tables

Robustness check

Similar analysis is repeated for major 18 states in India which do not witness any conflicts either internally or externally. The estimates from this restricted sample also proves the robustness of the baseline results. All these estimations with restricted sample size have a slightly lower treatment effect, even though it is always positive and significant.

Table 2.17 – Regression results with 18 major states in India

Pr.(school attend)	(1) All children	(2) Young children	(3) Old children
Coal prices*Active mine	0.0345**	0.0404*	0.0307*
	(0.0173)	(0.0209)	(0.0166)
MPCE	0.0806***	0.0790***	0.0838***
	(0.00427)	(0.00479)	(0.00513)
Land indicator	0.0384***	0.0424***	0.0361***
	(0.00658)	(0.00736)	(0.00785)
Age of child	0.719***	2.103***	1.251***
	(0.0204)	(0.138)	(0.359)
Female	0.163**	0.222	-0.00224
	(0.0752)	(0.438)	(2.179)
Female*Age	-0.0606**	-0.0751	-0.0237
	(0.0254)	(0.191)	(0.554)
Constant	-2.286***	-5.257***	-5.139***
	(0.137)	(0.340)	(1.449)
R-squared	0.224	0.264	0.197
Child controls	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	208,560	105,007	103,553

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs (except the indicator variables and age of child); Child age group: Overall -5-14 yrs; Young – 5-9 yrs, Old – 10-14 yrs; MPCE – Monthly per capita expenditures by the household; Data used from Employment and Unemployment schedule of NSS surveys (NSS 55, NSS 61 & NSS 68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11). 18 major Indian States are a part of this sample (Andhra Pradesh, Assam, Bihar, Gujarat, Haryana, Jammu & Kashmir, Karnataka, Kerala, MP, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, West Bengal. Chattisgarh and Jharkhand are also added to list as they have abundant coal mines). Regressions based on linear probability method for rural child sample

Table 2.18 – Testing for rural migration

Population Composition	(1) Log(Population)	(2) Sex ratio
Coal prices *Active mine	0.00744	-0.0145
	(0.0493)	(0.0243)
Labor Force Participation	0.133	-0.00139
	(0.0921)	(0.0334)
Schools	0.0687	-0.0463
	(0.0622)	(0.0403)
Teachers	0.112**	0.0320
	(0.0493)	(0.0311)
Constant	12.42***	1.114***
	(0.296)	(0.165)
R-squared	0.051	0.005
Number of districts	605	605
Panel effects	District-Year	District-Year
Year Effects	Yes	Yes
Observations	1,553	1,553

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs; District level data on rural labor force participation compiled from the Employment and Unemployment Surveys of NSS (NSS55, NSS61, & NSS68); District level data on number of schools and teachers is used from the District Information on Schools (DISE) India Data (Years: 2000, 2005, 2011) ; World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11).

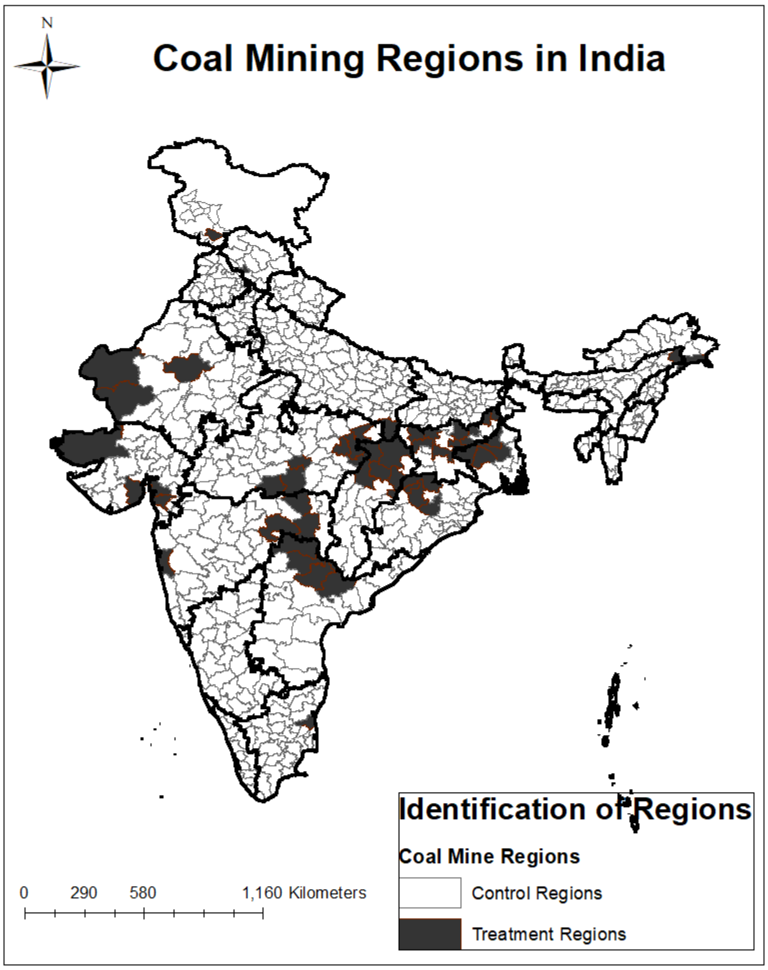
Table 2.19 – Chapter 2 - Summary Statistics

	NSS 55		NSS 61		NSS 68	
	Non-Coal	Coal	Non-Coal	Coal	Non-Coal	Coal
Household characteristics						
HH size	6.734865	6.399822	6.484862	6.181964	6.007656	5.655926
ln(MPCE)	5.889206	5.816438	6.098301	6.023112	6.839143	6.777476
Land owned (indicator)	0.919191	0.95563	0.955215	0.941869	0.955997	0.957641
Religion and Caste Background						
Hindu	0.836111	0.875874	0.818951	0.861015	0.817038	0.822346
Muslim	0.137248	0.086546	0.135482	0.104186	0.144838	0.136198
Christian	0.01457	0.019279	0.016497	0.016236	0.017307	0.018738
Sikh	0.002377	0	0.020356	2.99E-05	0.015202	0.000709
Jain	0.000674	4.86E-05	0.000433	0.000111	0.000497	0.000447
Other religion	0.008961	0.018253	0.008129	0.018423	0.005119	0.021563
General Caste Category	0.291825	0.211071	0.236629	0.179733	0.210277	0.188154
SC/ST	0.312263	0.424681	0.316832	0.438075	0.317725	0.438561
OBC	0.395912	0.364249	0.445756	0.381125	0.471998	0.373285
Child characteristics						
Age child	9.215003	9.269378	9.358557	9.391624	9.534501	9.572
Female indicator	0.471373	0.464824	0.469801	0.46715	0.462985	0.47518
Household Head characteristics						
Female indicator	0.083763	0.045777	0.086674	0.064331	0.091579	0.07138
Age	43.48058	42.45599	43.33546	42.26755	43.2487	42.83979
Literate (or not)	0.479928	0.464993	0.530875	0.513545	0.596676	0.613689
Attended informal school	0.018726	0.02823	0.031909	0.057325	0.008509	0.018488
Attended primary-middle school	0.349767	0.361563	0.372467	0.360015	0.411329	0.441438
Attended high school	0.089337	0.059489	0.095169	0.074994	0.139395	0.124503
Attended graduate courses	0.021264	0.015527	0.030861	0.021211	0.037269	0.028285
State controls						
ln(PCNSDP)	5.769849	5.77181	6.030854	6.178266	6.201122	6.333509
ln(LFP)	6.015449	6.05816	6.063108	6.140677	5.95638	6.049865
District controls						
ln(enrolment)	12.47314	12.4841	12.51613	12.56981	12.23734	12.44178
ln(schools)	7.445362	7.612698	7.47546	7.668337	7.699607	7.906322
ln(teachers)	8.868178	8.927366	8.910316	9.069842	9.351507	9.443943

Note: Weighted averages for the child population (age 5-14 years) in the table for the tree survey rounds. All variables in logs represent Ln(1+x). Coal and Non-Coal regions are identified as defined in the paper.

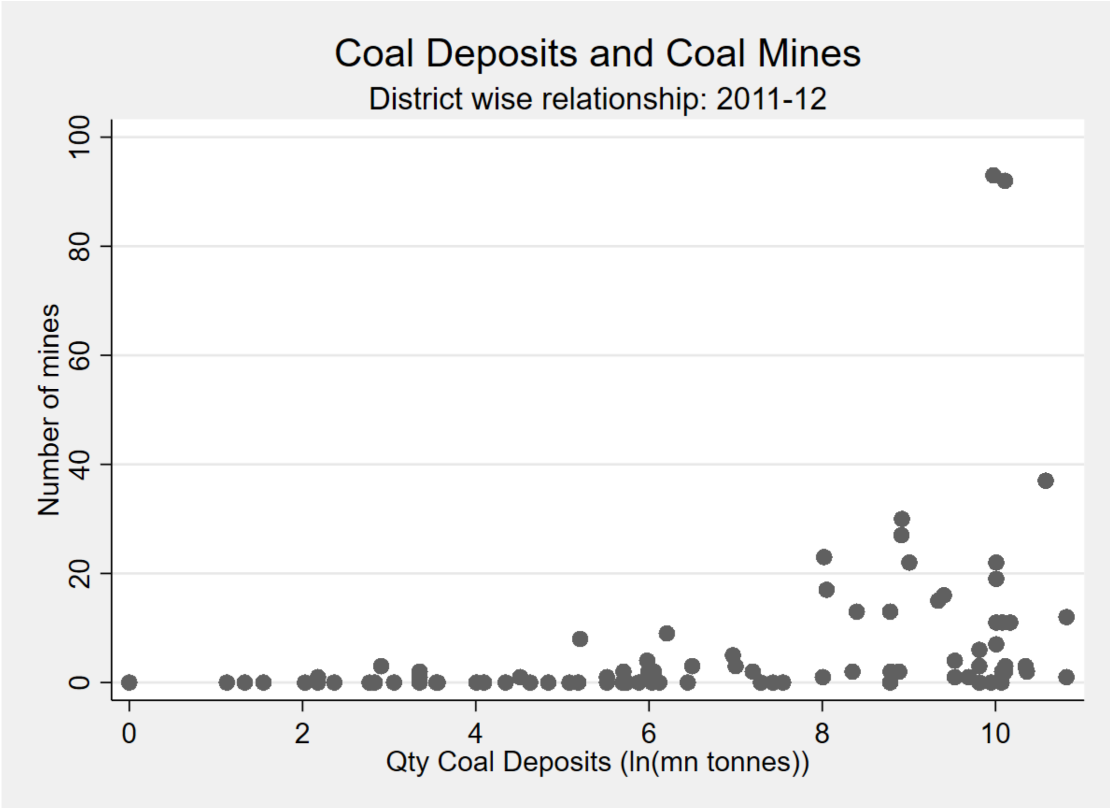
Appendix Figures

Figure 2.1 – India Coal Map: Treatment vs Control Regions



Note: Map generated in Arc GIS, based on the presence of an active coal mine in a district in 2011. Data source:Statistics of Mines 2011, Vol. I (Coal): http://164.100.87.110/writereaddata/UploadFile/MERGED_COAL11.pdf

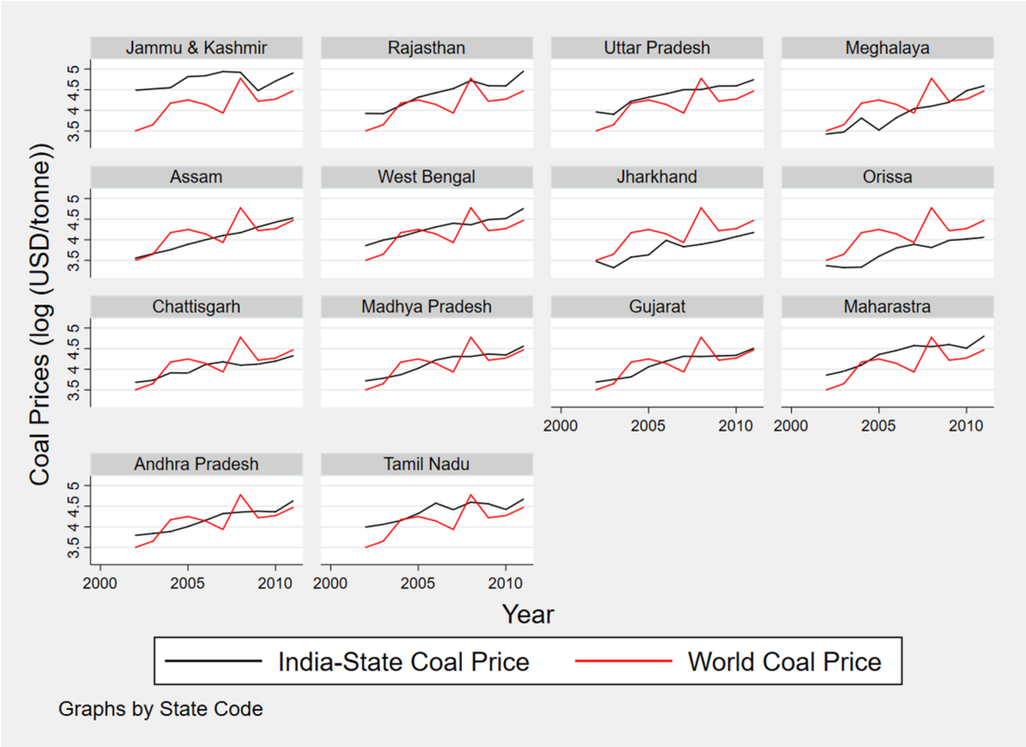
Figure 2.2 – Coal Mines and Deposits



Note: Graph generated in Stata using data on number of coal mines and quantity of coal produced across districts in 2011-12. Data Source: Statistics of Mines, Vol. I (Coal).

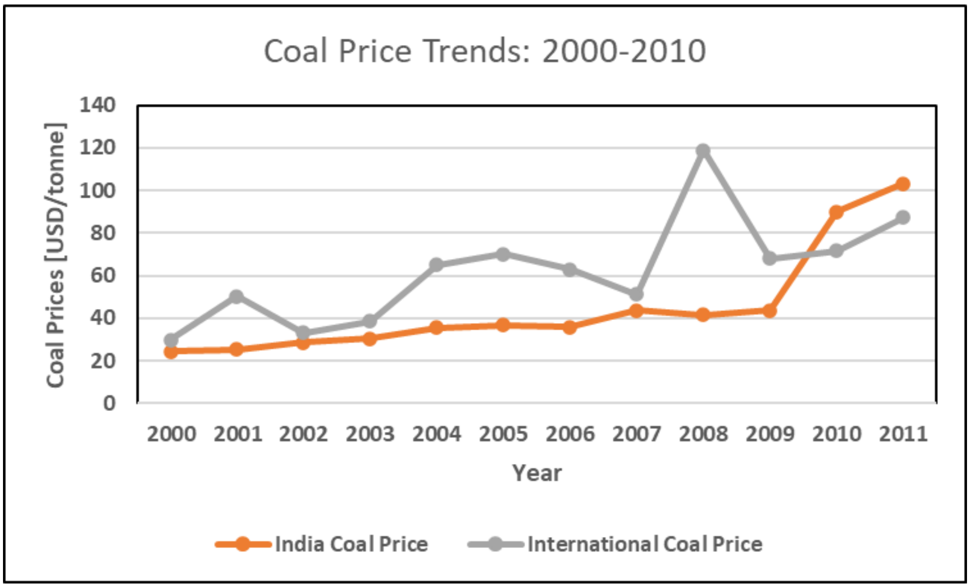
Coal Prices: Trends

Figure 2.3 – Coal Price Trends: Domestic and International



Note: Graph generated in Stata; based on the purchase price of coal by domestic firms in India at state level and international coal prices over the time 2001-2011. Domestic purchase price of coal calculated by aggregating the firm level prices at the state level for the states with active coal mines [Annual Survey of Industries Database 2000-2010]. International coal prices - US Central Appalachian Coal Spot price index [Coal Directory of India 2011-12 (and World Bank Commodity Database)]. The plot shows the trends in domestic coal prices for the 14 states in India which have active coal mines and the impact of international coal prices on these domestic coal prices.

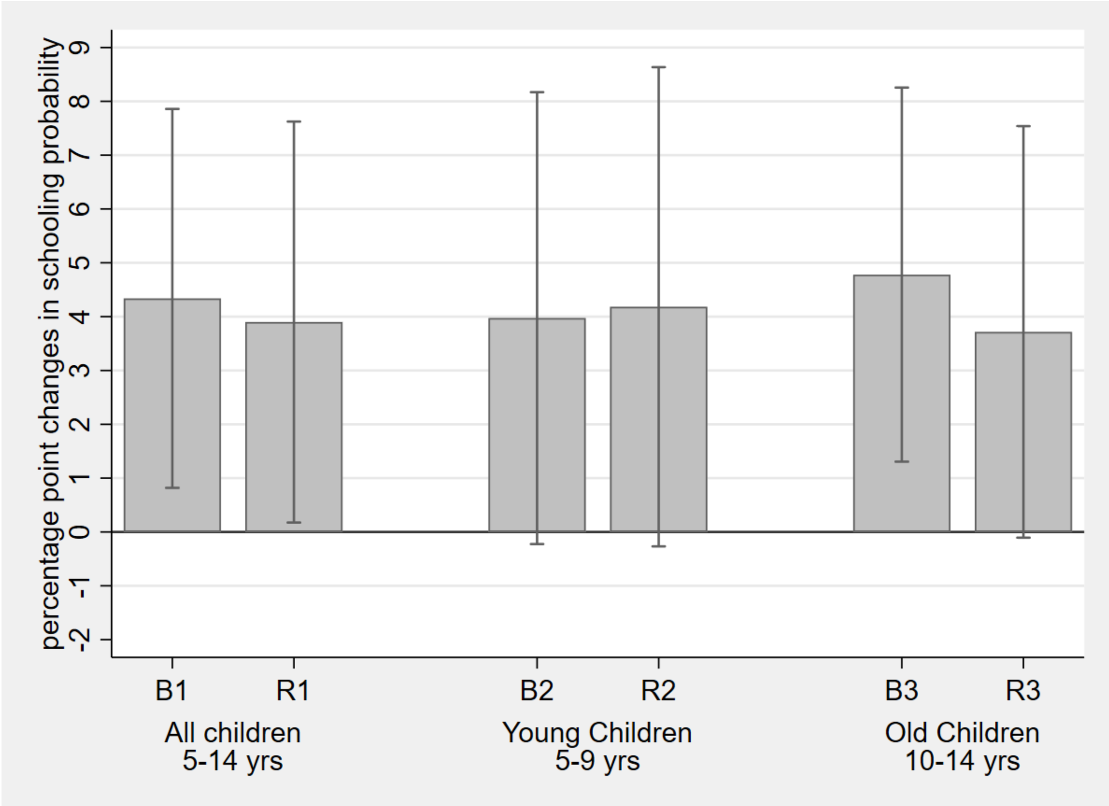
Figure 2.4 – Coal Price Trends



Note: India Coal Prices: Steam Coal for Industry prices (USD/tonne) [Source: Coal Directory of India 2011]; International Coal Prices: US Central Appalachian Coal Spot price index [Coal Directory of India 2011-12 and (World Bank Commodity Database)]

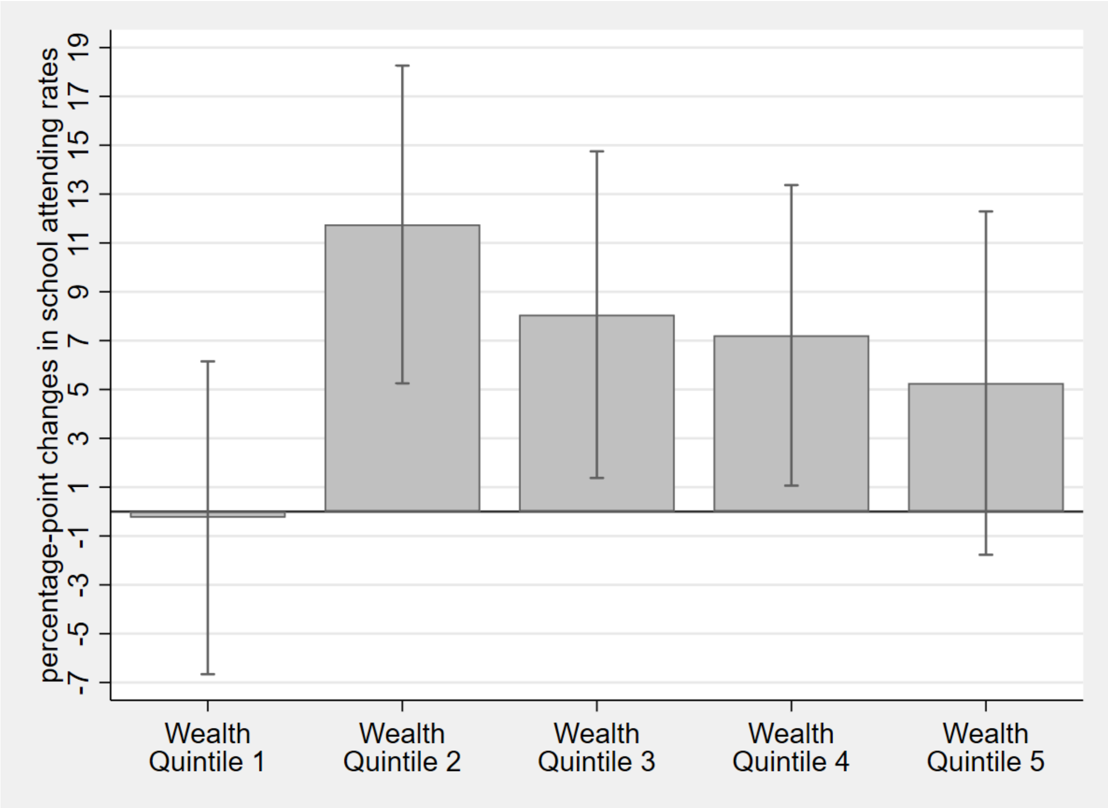
Regression results

Figure 2.5 – Treatment coefficients for baseline and robustness regressions



Note: B: Baseline regressions ; R: Robustness regressions. Regression coefficients for treatment variable based on Table 2.5.

Figure 2.6 – Treatment coefficients w.r.t wealth quintile



Note: Regression coefficients for treatment variable based on Table 2.16

Chapter 3

Local Effects of Coal Mining on Health of Children in India

3.1 Introduction

The effects of mining on human welfare encapsulates several factors other than poverty or income outcomes. Human capital plays an important role in the labor market activity and economic growth [Romer, 1986, Lucas, 1998]. Human capital formation depends on many inputs, and there is a growing literature that supports the role of early childhood health in human capital development [Cunha and Heckman, 2008, Almond and Currie, 2011]. It thus becomes necessary to understand the effects of coal mining or any other extractive industry on the health of individuals living in the vicinity of this industry.

In India similar to any other developing country, the decision to live close to a mine involves a trade-off between the economic opportunities it shall provide versus the health costs it would unleash. The health effects of air pollution that is generated via the industrial process of mining has become an important issue in public economics [Currie et al., 2009, 2014]. Mining activity generates several industry specific pollutants in air and water such as cyanide, lead, arsenic, mercury and other heavy metals [Dudka and Adriano, 1997]. This environmental pollution creates several negative externalities. Mining related pollution has been documented to adversely affect outcomes such as labor productivity [Graff Zivin and Neidell, 2012], agricultural productivity [Aragón and Rud, 2016], educational achievement [Rau et al., 2013] and school and cognitive outcomes [Almond et al., 2009c]. Coal too has been associated with health outcomes for people living in the vicinity of coal mines and plants since several decades [Cropper et al., 2012, Guttikunda et al., 2015].

Children are a vulnerable group whose socio-economic outcomes vary considerably with respect to exogenous shocks and external factors [Cogneau and Jedwab, 2012]. In India, child health outcomes especially in rural and backward regions are not very promising. The prevalence of stunting in children below the age of five years in India in 2004-05 as per IHDS (India Human Development Survey) Data was approx. 55%, while prevalence of underweight children was approx. 43%. [1] Even though, there has been reduction in these prevalence rates over the years (NFHS 4), the statistics are fairly high. It would be advantageous to understand the differentiation in these prevalence rates across regions divided by geography and the presence of natural resources and extractive industry to gain further insights into the subtle mechanisms that impact the nutritional outcomes for children at this age. This can benefit the policy initiatives aimed at improvement of child health especially in backward regions of the country. Improvements in child health outcomes and their nutrition levels goes a long way in paving the way for health and productivity of young adults [Alderman et al., 2006] which as mentioned above is essential for the economic development of any country in general. For developing countries these childhood investments in health are even more important as there are adverse consequences these children face as adults. For instance, in Jamaica, children who suffered stunting in early childhood had to face poor cognitive outcomes and school achievement in their adolescence years [Walker et al., 2005], and in Guatemala, children provided with better nutrition in early years have better cognitive development in adulthood and earn higher wages [Hoddinott et al., 2008, Maluccio et al., 2009].

This paper exploits the exogenous shock in international coal prices between 2004-05 and 2011-12 (in 2008-09) to capture the changes in nutritional outcomes for young children living in the coal mining regions of India. In doing so, the paper uses the India Human Development Survey database (IHDS -I and IHDS -II) for capturing the health and other socio-economic

[1] The prevalence rates according to NFHS 3 data were 48% and 43% respectively for the child age group below 5 years.

aspects of individuals and families living in coal and non-coal regions of India.

This paper therefore addresses the research question as to *"how the health outcomes of children and their mothers are affected due to the coal mining process in India"*. The paper thus, contributes to the scarce literature available in this field particularly for India, with an aim to address the health-wealth trade offs faced by the families in the vicinity of coal mines in India and assessing the channels through which the coal mining affects the health of young children living in it's vicinity.

3.2 Related Literature

Health effects of mining are in general restricted to the environmental and biological literature on the health effects of pollution [Currie et al., 2014, Graff Zivin and Neidell, 2013]. The health economics literature citing the effects of pollution on child health include Chay and Greenstone [2003]; Jayachandran [2009] for infant mortality and Currie and Walker [2011] for low birth weight.

The health effects explained through the channels of economic activity related to mining are recently emerging in literature. Aragón and Rud [2013] find a positive effect on self-reported general health of adults living near Yanacocha mine in Peru while they do not find any significant effect on the health of children. Aragón and Rud [2016] in another study, find adverse effects of mining activity on weight-for-height ratios and the prevalence of cough among children living in the vicinity (<20 km) of gold mines in Ghana, but no effects on stunting and diarrhea.

The literature so far in examining the health effects of pollution has based its analysis on the developed countries [Currie et al., 2009, Lavaine et al., 2013]. Developing countries are also exposed to such effects considerably [Arceo et al., 2016, Tanaka, 2015] given that they have weak regulatory capacity [Oliva, 2015] and their environmental regulations might be riddled with implementation and enforcement issues [Greenstone and Hanna, 2014c]. Moreover, if the dose-response relationship between pollution and health outcomes such as infant mortality is non-linear, that is the marginal damage to health due to pollution is higher at higher levels of pollution, then estimates from developed countries such as U.S.A would underestimate the health effects in developing countries [Arceo et al., 2016].

Some recent studies that focus on the health effects of industrial pollution in developing countries include Chen et al. [2013] for China, Rau et al. [2013] for Chile and Gupta and Spears [2017] for India. [2]

Gupta and Spears [2017] exploit a panel data set on Indian households to find an increased incidence in reported cough among individuals living in closer proximity to coal power plants between 2005 and 2012. There is, however, no significant effect seen on diarrhea or other non-respiratory diseases. The paper by Gupta and Spears [2017] thus adds to the increasing literature on the health effects of air pollution caused via the modern extractive industry especially for India. In addition to these country specific studies, von der Goltz and Barnwal [2019] estimate the health-wealth trade offs due to industrial pollution faced by mining communities in 44 developing countries. They use micro-level data with identification at mine-level and mother-level for panel data, and group effects for cross-sectional data. They find suggestive evidence that mining causes stunting among young children and anemia among women living in the vicinity of mines (<5 km). These effects are strictly validated for households that live near mines that are prone to pollution effects through lead contamination and are not visible for households not living in vicinity of such mines. They also show that the health effects are purely pollution related and occur despite the wealth gains.

Literature cites several evidences where exogenous price shocks for resources and commodities impacts the child health measured via child mortality, anthropometric (nutritional) outcomes and other health aspects such as obesity, sickness, disease etc. These outcomes play out via the interplay of income and substitution effects generated through the price shock [Dehejia and Lleras-Muney, 2004, Ferreira and Schady, 2009].These outcomes also vary with respect to the nature of shocks and the geographic region under consideration, with the health outcomes being counter-cyclical for developed nations and pro cyclical for developing or poorer nations [Ferreira and Schady, 2009].

[2] Chen et al. [2013] assess the reduced life expectancy due to air pollution from power generation in China and Rau et al. [2013] evaluate the academic performance of children living in the vicinity of toxic mineral waste which included lead in Chile.

Infant mortality decreases in events of economic downturns in developed nations [Dehejia and Lleras-Muney, 2004] as the opportunity cost of time is low and mothers are easily able to allocate their time away from labor market to health preserving activities for their children. For middle-income countries the effect of economic downturn on infant mortality is mixed. For instance, the reduction in coffee prices in the early 1990s in Columbia led to a reduction in infant mortality rates [Miller and Urdinola, 2010], while Bhalotra [2010] shows that infant mortality is counter-cyclical to aggregate income shocks in India, with the elasticity being -0.33 in rural India. She finds that health-care seeking declines during recessions in India using an individual data set on 150,000 children born between 1970-1997, merged by cohort and the state of birth. Tolonen [2015] too has contributed extensively in this area. In one paper, her research describes how rapid expansion of gold mining in Sub-Saharan Africa has empowered the women through increased income opportunities within the service sector and has reduced the barriers of self-health care by women by 23% and acceptance of domestic violence by 24% [Tolonen, 2018]. In another paper, she shows how this industrial development (expansion of gold mining) has contributed to a huge decline in infant mortality with a reduction of more than 50% in regions with mine openings (counter-cyclical impact) despite the potential risks of environmental pollution[Benshaul-Tolonen, 2019].

The child health outcomes as measured by the anthropometric measures too witness negative impact in event of economic downturns [Foster, 1995, Maluccio, 2005]. Maluccio [2005] shows how a decline in coffee prices between 2000 and 2002 led to a significant decline in height-for-age z-scores for children aged 6-48 months living in the coffee-growing regions, owing to reduced expenditures and increased labor supply. Cogneau and Jedwab [2012] also show that human capital outcomes for children are mainly pro cyclical using the drastic reduction in administered cocoa price in 1990 in Cote d' Ivoire. Using pre-crisis (1985-88) and post-crisis (1993) data, they show that children of cocoa producing households versus children (age 6-59 months) of other farmers are worse off in terms of height-for-age z-scores post the crisis, with more significant outcomes seen for children of the age group 2-4 years and strong evidence of gender bias against girls in these human capital outcomes. Carter and Maluccio [2003] using a household level panel data from South Africa show that a 1% increase in economic loss reduces the height-for-age z-score for young children by 10%. Therefore they find that, economic losses which adversely affect the household consumption in light of credit constraints in the inter-survey period, and thus bringing malnutrition for children in prenatal times to age three, lead to permanent loss in nutritional outcomes for young children in the second survey round.

With an overview of the literature in this area, there is an ardent need for more studies examining the health effects of extractive industries in developing nations as well. Literature so far discusses the impact of economic shocks on child health outcomes via macroeconomic shocks, weather and climate changes and commodity price fluctuations.The emerging literature in the area is suggestive that ingrained norms regarding gender, particularly the level of female labor force participation would be relevant in examining the effects of mining on child health along with several other parameters.

This paper therefore, contributes to the existing literature by becoming one of the very few studies to capture the impact of natural resource extraction via coal mining on the child health outcomes. It thus works on two strands of literature; 1) economic impact of natural resource abundance on child health outcomes at a local level in a developing nation, and 2) impact of economic price shock on the child health outcomes.

3.3 Impact of Coal Mining on Child Health Outcomes

The impact of coal mining on child health outcomes can be understood in a similar fashion as the impact of aggregate economic shocks on child outcomes. A rise in the international coal price having repercussions in the domestic market works as an economic shock at the local level, particularly for the regions that are directly and indirectly affected by the coal mining industry.

According to Ferreira and Schady [2009], child health is best visualized as an investment, with inputs in period 1 giving way to returns in period 2. They describe as to how investments in the health production function of child through inputs such as health-promoting goods and health-promoting activities, lead to better child health outcomes. Changes in these inputs due to an economic shock affects the health outcomes for children accordingly. These changes can be described as income-effects or substitution-effects based on the inputs that undergo a change. Health-promoting goods (nutritious food, better hygiene, clothes, medicines etc.) are market products and change with respect to changes in family income. Health-promoting activities (breastfeeding, cooking food, doctor visits, antenatal checkups etc.) on the other hand require time allocation by mother or father of the child, and changes to this time-allocation is best understood as the substitution-effects.

Therefore, the impact of economic shocks on child health outcomes can be seen via the changes in family income and employment opportunities for mothers and fathers. Page et al. [2019] using restricted data from National Health Interview Survey and state monthly unemployment rates in United States, show that while fathers employment benefits the child health via increased family income, the employment opportunities for mothers adversely affects the child health due to the time constraints. Thus, time and income, both are essential inputs in child health development. In developing nations, these links are further aggravated due to the absence of well-developed credit markets [Ferreira and Schady, 2009, Carter and Maluccio, 2003].

Foster [1995] shows that credit market imperfections can impede child's growth. Income effects are stronger in those regions where credit markets are weak and fail to smoothen the consumption of a family in event of economic shocks [Ferreira and Schady, 2009].

Apart from these effects, an added substitution effect also emerges due to changes in fertility choices or composition of women giving birth when the economic shock occurs, resulting in changes in wages of women[Ferreira and Schady, 2009]. These effects are also capable to alter the time-allocation patterns of women, and thus need to be accounted for while evaluating any changes in child health outcomes in event of coal mining shocks.

3.3.1 Conceptual Background

The conceptual background to the research problem is borrowed from the work of Tolonen [2015], who has established these relationships for infant mortality in Africa. The model is also loosely based on Rosenzweig and Schultz [1982]. It describes how the utility function for a primary care giver in the family (which can be assumed to be the woman of the house in my case owing to the gendered structure in India) is defined;

$$U = U(X, Y, H) \tag{3.1}$$

where X denotes the basic goods which are neutral to health, Y describes the health related goods or behavior and H is the health status of the child (such as height-for-age and weight-for-age).

The health (or nutrition) production of the child is then captured by;

$$H = H(Y, M, N, \theta) \tag{3.2}$$

where M and N are the health-related market inputs and natural environment respectively, θ reflects the initial health endowment by the child (such as the birth weight).

According to the health production function, child's nutritional intake depends on a set of health 'inputs': quantity and quality of health care given by mother such as breastfeeding, preparation of nutritious food etc. (measured by Y), medical services and market purchased food and health inputs (measured by M) and the environmental quality and presence of infectious diseases (measured by N).

The women of the household in this model would ideally maximize their utility function given the health production of their children and the income levels I at their disposal, and the time available with them (which depends on their labor force participation rates).

This leads to the budget constraint she faces in general,

$$I = P_x.X + P_y.Y + P_m.M \tag{3.3}$$

In Eq. 3.3, the price for Y reflects the opportunity cost of devoting time to her children and home (which is the earnings lost by not working). This is reflective of the limited time available with her that she must divide between work and health care of her children (assuming health care provision and other household duties go together).

The disposable income with the women would depend on their earnings and the share of earnings that their husbands transfer them for spending on household decisions under their responsibility. The share of household income that the female has the right to decide over (her disposable income) also determines her bargaining power in the house. Let that share be defined as, b. Mother's bargaining power in the household is relevant as her preferences for child health may vary from other adult family members.

$$b = F(I_f, I_m, \frac{I_f}{I_m}) \tag{3.4}$$

Here the subscripts f and m denote the female and male of the household. And, the income in Eq. 3.3 reflects the disposable income with women, which will be a fraction-(b) of the total income held by her.

With new mines and rising coal prices world-wide, a rise in wages of coal mine workers along with the wages in ancillary industries is expected. Rising employment and incomes for women will drive the value of b and eventually also affect the child health, H. It is believed that women who have greater autonomy in the household through better education and other decision making abilites have better health outcome for themselves [Keats, 2018], and women with better nutritional outcomes have children with better nutritional outcomes as well [Rahman et al., 1993]. This is examined in the analysis on mechanisms explaining nutritional outcomes of children in coal regions of India in this paper as the presence of 'income effects' in the household decision making model.

Better health facilities via mining companies' social responsibility programs will cause the prices of health goods (P_m) to decline, which could make the doctor visits or prenatal visits by women during pregnancy more accesible which are known to have a direct and positive effect on the nutritional status of children [Mosley and Chen, 1984]. At the same time, a rise in prices of other goods (P_x) is also a natural outcome, and a rise in women wages would raise the opportunity cost of child rearing (P_y) even though it generates higher income for the household. This is examined in the paper through the impact of coal price shock on the working hours of women and the time they devote to child rearing activities. Quality of the natural environment also suffers with more mining.

Therefore, with female labor force participation, there can be higher consumption of market purchased health inputs (nutritious items, doctor visits etc.) and other goods - (income effects), but reductions in level or quality of time in health-related activities (substitution effects) is also a potential outcome. Accounting for the above positive and negative effects, the outcome of child health in coal mining districts of India can be evaluated corresponding to the rising coal prices world-wide.

3.4 Data Description

This paper makes use of the India Human Development Survey (IHDS) database. It is a nationally representative panel survey of approximately 40,000 households in 33 states and union territories, 384 districts, 1420 villages and 1042 urban neighborhoods across India. Two surveys were carried out in 2004-05 and 2011-12 covering multiple topics including health, education, employment, economic status, marriage, fertility, gender relations, and social capital. IHDS-II re-interviewed 83% of the households from IHDS-I as well as the split households (if located within the same village or town) to trace changes in their lives[Desai and Vanneman, 2015].

The paper makes use of pooled cross-sectional data at the individual level with 215,754 individuals in Wave-I and 204,568 individuals in Wave-II of the survey[Desai and Vanneman, 2005b, 2015]. The survey years were merged at the individual level resulting in 150,988 unique observations for each survey year, thus creating a panel data at the individual level. The panel data has also been used for several robustness checks.

The IHDS has been widely used, such as in studies of human capital [Shah and Steinberg, 2017], education and social identity [Borooah, 2012], and the nutritional effects of sanitation [Duh and Spears, 2017].

3.4.1 Health Status of Children

The paper aims to explore the health of children living in the vicinity of coal mines in India and the various mechanisms that impact it in the background . The IHDS data set thus allows to capture the health related variables for young children as well as other socio-economic, behavioral, household environment related and fertility related variables for other adult individuals. The working age population is more exposed to the harsh working conditions in coal mining districts and their quality of life gets affected due to the nature of work opportunities available to them. The children on the other hand are affected via their nutritional status. The nourishment of children under the age of 5 years is very crucial for their overall development and is directly affected by the economic status of the household as well as the household conditions and bargaining power of each parent in the household decision making. These factors are in turn affected by the nature of economic opportunities available to men and women in the region as well as their relative contribution to household decision making. Presence of a coal mine in the vicinity can have an impact on all these factors.

In this paper, I focus on the anthropometric measures provided for household members to estimate the nutritional status of young children (age < 5 years). For young children, their nutritional status is estimated by comparing their height and weight with the World Health Organization (WHO) 2006 universal standards for growth of children aged zero to five years.[3] The height-for-age (HFA) and weight-for-age (WFA) z-scores are thus created for analyzing the child nourishment levels among children living in close vicinity of coal mines in India.[4] HFA Z-scores measure investments in child health over the longer time horizons. A HFA Z-score below minus 2 suggests that the child's height is 2 S.D. below the median height of the reference population with similar age and gender. These children are referred to as 'stunted' for the purpose of analysis in this paper. Similarly, a WFA Z-score below minus 2 suggests that the child's weight is 2 S.D. below the median weight of the reference population with similar age and gender. These children are referred to as 'underweight' and such a nutritional deficiency reflects shortcomings in investments in child health over the short-run. For precise outcomes, any outliers where the HFA and WFA Z-scores are below -5.99 are removed from

[3]The WHO standard describes how children should grow if they receive proper nutrition and health care. It is premised on the fact that the height distribution among children under age five who receive adequate nutrition and health care has been shown to be similar in most ethnic groups [Group and de Onis, 2006b](WHO Multicentre Growth Reference Study Group 2006a). The WHO constructs the height distribution using a sample of children from six affluent populations across five continents (Brazil, Ghana, India, Norway, Oman, and the United States) with no known health or environmental constraints to growth and who received recommended nutrition and health inputs [Group and de Onis, 2006a](WHO Multicentre Growth Reference Study Group 2006b).

[4]According to Mei and Grummer-Strawn [2007], the S.D. of the HFA and WFA Z-scores are relatively constant across populations and therefore, can be used effectively for measuring nutritional status among children.

analysis as they generally do not conform to any reference population and may be a result of data inaccuracy.[5]

Similarly, for children who are in their school-going age (5-19 years), the nutritional estimates are calculated with reference to the WHO 2007 growth standards.[6] For these older children and adolescents, the HFA Z-scores are available till the age of 19 years, however, the WFA Z-scores are not available beyond the age of 10 years as once the children start hitting their puberty, the reference weights are not consistent among populations as different children experience puberty differently. Children may show excess weight through WFA even though they may just be getting tall. Therefore, the Z-scores for older children and adolescents are used for falsification tests to judge the generality of the nutritional outcomes among the child population.

As per the IHDS data, the proportion of children who are stunted and underweight has slightly increased in non-coal districts whereas the percentage has witnessed a decline in coal districts of the country [Refer Table 3.1]. The average height as seen from the HFA Z-scores was lower in coal districts compared to non-coal districts in 2004-05, but post the coal price shock in 2008, there has been an improvement in heights (HFA Z-scores) and weights (WFA Z-scores) of children in coal districts vis-vis non-coal districts[Figure 3.5].

[5] For estimating these Z-Scores, Stata program by Leroy [2011] is used.

[6] The WHO Reference 2007 is a reconstruction of the 1977 National Center for Health Statistics (NCHS)/WHO reference. It uses the original NCHS data set supplemented with data from the WHO child growth standards sample for under-fives. To develop this reference the same statistical methodology was used as in the construction of the WHO standards.

Table 3.1 – Proportion of children 'stunted' and 'underweight' between 2005-2011

Health Outcomes	**2004-05**		**2011-12**	
Age 0-60 months	**Mean**	**S.D**	**Mean**	**S.D**
	Coal Districts			
HFA Z-Score	-2.27	2.17	-2.08	1.98
WFA Z-Score	-1.95	1.73	-2.01	1.55
Proportion of Stunted children	0.60	0.48	0.55	0.49
Proportion of Underweight children	0.48	0.50	0.49	0.50
	Non-Coal Districts			
HFA Z-Score	-1.96	2.32	-2.20	1.99
WFA Z-Score	-1.61	1.8	-1.72	1.55
Proportion of Stunted children	0.54	0.49	0.58	0.49
Proportion of Underweight children	0.42	0.49	0.43	0.49

Note: Estimates are based on the IHDS Data Wave I (2004-05) and Wave II (2011-12). All statistics make use of the sample household weights.

3.4.2 Identification Strategy

The identification strategy used in the paper exploits the spatio-temporal variation by the interaction of the treatment variable that is the presence of a coal mine in a region with the international coal prices over time. [7]The estimation strategy in the paper relies on the assumption that the placement of mines is not driven entirely by the local changes, such as trends in local labor market participation, health of individuals or population characteristics. The main factor that drives the presence of a mine in a region is the presence of the mineral deposits itself which are geographical anomalies and not determined by the human capital or labor availability. These mineral deposits are available in clusters in specific regions [Eggert, 2001].

With respect to Coal, the coal deposits are formed deep under Earth's crust due to extreme pressure and in India are found in regions with a higher gradient in the Central and Eastern parts [Refer: Figure 3.1].

The presence of mineral deposits is determined naturally and therefore can serve as a random experiment. Even though, the determination of a mineral deposit does depend on the exploratory intensity which is not entirely exogenous and apart from being affected by the vol-

[7]US Central Appalachian spot price index (USD/tonne) used for the international coal price movements

ume of mineral deposits also depends other factors such as: a) institutions, b) royalties and tax policies in the region, c) accessibility [Eggert, 2001] and d) expected profitability. The possibility of endogenous mine placement is therefore a big threat to the identification strategy which captures the spatial variation via the presence of a coal mine in a region.

The institutional factors that affect the mine placement cover a wide range of determinants such as the mineral property rights, openness to foreign direct investment, rules for revenue sharing and taxes, and environmental regulation. These factors along with the topography of the region also affect the cost of mining in the region. Coal mines in India are set up in regions with easier access in terms of clearances and revenue policies. But this doesn't threaten the identification much as these institutional factors vary at the state (sub-national) level in India but are homogeneous within the state and thus a district level analysis is immune to such variation as I use the district and year fixed effects in the analysis.

The identification strategy is strengthened using international coal price change over time which not only add the time variation to the model but also bring the desired exogeneity. These international prices are independent of the institutional factors and tax policies within India and affect the outcome variable only through their impact on the domestic coal prices and production as established via the 'price-pass-through' regressions.

The IHDS data set allows to control for 33 districts as the coal mining regions of the country, even though there are 52 districts in India with active coal mines (Statistics of Mines 2011, Vol. 1 Coal). The remaining 19 districts don't have any data collected in the IHDS sampling. IHDS samples 384 districts out of the 627 districts in India. Thus, 8.5% of the reported districts in the IHDS sample have active coal mines.[8]

Out of the 19,488 young children (Age <5 years) in Wave-I, 1885 children live in the coal mining districts and out of the 17,025 young children (Age <5 years) in Wave-II, 1581 children live in coal mining districts. Therefore, approximately 9% of the young children live in coal mining regions of India and similarly for older children (5-19 years), approximately 8.8% children live in coal mining regions. Approximately 9000 working-age individuals (age 20-60 years) live in coal mining regions of the country in each year. That is, 9% of the working age

[8]The percentage of coal districts reported in IHDS sample is similar to the actual percentage as otherwise too approximately 8% of the total Indian districts have active coal mines in them.

population lives in regions with active coal mines in each survey year.

Coal production in a mine is likely higher when the coal prices are higher. The world coal price has shown a rise of approx. 25% since 2005 till 2011 (period of analysis in this paper), with a massive jump in 2008 before stabilizing back in 2011[Refer: Figure 3.4]. This price rise has shown to have pass-through effects on domestic coal prices and production as well. Therefore, it is usual that these rising prices of coal around the world have local effects as they trickle down the economy in terms of local employment and wage gains. Therefore, world coal prices are used instead of local coal production volumes to measure the intensity of coal mining as coal production volumes can also be endogenous to other factors that affect the outcome variables. The world coal price rise on the other hand will always be completely exogenous to local population characteristics.

The world coal prices are interacted with the presence of a coal mine instead of presence of coal deposits as the presence of a mine allows to capture the industrial shock directly whereas the presence of a deposit doesn't guarantee any industry in the region necessarily.

District level variation in infrastructure facilities such as water, electricity, roads, schools, medical facilities etc. can bias the decision of mine placement as well. Mining industry especially coal mining industry in India is known to bring investment in road network, schools and hospitals in the mining communities [Hota and Behera, 2016][9] which can affect the outcome variable. This is not a major threat to the analysis as the analysis is geared towards the effect of the total industrial shock in general due to coal mines.

Migration of individuals to mining regions is another possible threat to the identification strategy. If families with healthy children migrate to regions with mining opportunities, then this self-selection mechanism among individuals could completely bias the estimates. To address this issue, a check on migration is performed at a regional level in India. It is already established that rural migration is negligible in India [Munshi and Rosenzweig, 2009]. Moreover, a test on change in rural population over time across districts shows insignificant effects when viewed under the lens of the treatment effect [Refer:Table 3.15]. There are also no signif-

[9]They describe in their paper as to how coal mining in Ib Valley of Odisha in India, brings positive and negative outcomes for the local population. The positive outcomes are visible through the expansion of physical (infrastructure) and financial (employment) capital; whereas the negative outcomes are seen in the degradation of the ecosystem (natural capital) adversely affecting the agricultural productivity, forest and animal husbandry.

icant effects on labor force participation for both males and females in the coal mining regions of India [Refer: Table 3.16]. This indicates that there has been no self-selection bias when witnessing a significant and positive effect on the child health in these regions. Therefore, households with healthy young children do not self-select in these regions.

3.5 Empirical Methodology and Results

3.5.1 Empirical Methods and Variables

The empirical methodology in this paper is comprised of three parts: 1) establishing significant price-pass through effect between international coal prices and domestic coal prices; 2) baseline health regressions for children using presence of active coal mines in district as the treatment effect, and 3) robustness check to verify the accuracy of results.

3.5.1.1 Price-Pass Through Regressions

Price-Pass through models estimating the percentage change in domestic coal price (and domestic coal production) due to a percentage change in international coal price (both measured in USD/tonne) are set up:

$$P_{st} = \alpha_0 + \alpha_1 \cdot P_t^* + \gamma_s + \theta_t + \varepsilon_{st} \tag{3.5}$$

The Eq. 3.5, shows the effect of international coal prices P^* at time t on the domestic coal prices P in a given state s at time t also controlling for state (γ_s) and time (θ_t) fixed effects. Several versions of these price-pass through regressions are carried out using two different sets of same Annual Survey of Industries data for India (1999-2011)– one which is yearly (with location codes and no unique firm identifiers over time) and one which has panel settings (Firm-Year panel data but without location codes).

The results on price-pass through regressions suggest a positive and significant pass-through from international coal prices on both domestic coal prices and production of coal, which are robust to the inclusion of varied fixed effects. A 10% increase in world coal prices brings a

7-9% increase in the domestic coal price [Table 3.17] while the domestic production increases by 0.5-1.2%[Table 3.18].[10]

3.5.1.2 Baseline Regressions

In order to estimate the health outcomes for children living in coal mining regions of India, I use the international coal price movements as an instrument given that they have significant pass-through effects towards the domestic coal prices and production and are independent with respect to the domestic policies and institutions. The outcome variable for this study is a dichotomous variable that captures nutritional status of young children below the age of 5 years. It is believed that household decision-making has a greater impact on the health of younger children compared to older children. School-going children above the age of five years are exposed to several external factors which also control their health status other than the usual household decisions.Therefore, I focus on the estimating the probability of young children living in coal districts of India to be 'stunted'[11] or 'underweight'[12] post the coal price shock between 2004 and 2011. In addition to these estimations, the impact of coal price shock on the height-for-age and weight-for-age z-scores for young children is also assessed.

The treatment variable captures the changing value of international coal prices in mining districts of India.

Let Y_{ihdt} denote the dichotomous variable reflecting nutritional status for the child i in household h and district d at time t (survey period- 2004/2011). The Eq. 3.6 would be carried for two outcomes - probability of the child being a) 'stunted' and b) 'underweight'. Thus, the baseline specification would be:

$$Y_{ihdt} = \alpha + \beta \cdot (R_d * P_t) + C_{ihdt} + X_{hdt} + M_{hdt} + E_{hdt} + H_{hdt} + \gamma_v + T_t + \varepsilon_{ihdt} \tag{3.6}$$

where $(R_d * P_t)$ captures the treatment effect which is the changing world coal prices across coal-mining districts in India between 2004 and 2011, while X_{hdt} captures household controls, C_{ihdt}captures individual child controls, M_{hdt}captures the mother specific controls, H_{hdt} cap-

[10]These results correspond to the use of yearly data; with panel data the coefficients are much smaller: 0.9-3%.
[11]In this study, children are referred to as stunted when their HFA Z-score < (-2).
[12]In this study, children are referred to as stunted when their WFA Z-score < (-2).

tures the controls for the household head and E_{hdt} captures the controls for the environment of the home (respiratory and water conditions in the home). Since, the treatment variable registers a district-level variation, ε_{ihdt} captures the individual stochastic shocks clustered at the district level to account for any correlation in unobserved shocks at the district level as most of the policies that can affect health of children are usually framed at district level. Also, considering that exploration intensity (presence of mines) is driven by institutional quality, investment climate in the region or environmental regulation, these effects will be taken care of by the region-specific and time fixed effects [de Haas and Poelhekke, 2014]. Region and Time fixed effects are captured by γ_v and T_t respectively.[13]

The IHDS data provides information on all the variables which act as controls in these health regressions. The economic situation of the households is controlled via the monthly per capita expenditures of the household and the ownership or cultivation of any land which acts as the wealth indicator. The demographics are captured via the household size, the number of children (0-14 years) in the household and the number of married women in the house. These variables allow controlling for the demographic burden and responsibility sharing in the household. The individual characteristics such as place of residence (rural/urban indicator), religion, caste, gender and age (in months of the child) are also controlled for in every regression. Characteristics of the household head such as their literacy level, age and gender are also controlled as the household head plays an important role in the household decision-making process.

The health regressions also control for the bargaining power of women in the house as women play an essential role in the care-taking process in the household. The decision-making ability of women in the house is assessed via two variables; their decision on the number of children to raise and their decision-making capability when the child is sick in the family. The mother attributes are also controlled separately as the mother's participation is an essential component in the child's nourishment. Therefore, mother's age and education levels (primary,

[13] γ_v captures the fixed effects at the level of primary sampling unit (PSU) in this analysis. A PSU is the level at which sampling was performed in collecting the IHDS data. It is a unit smaller than the district level, which can be considered as the village in rural areas or a town in urban areas. The analysis is not performed at this level however, as the identification is only possible at the district level. Since, health of children can be affected by unknown shocks specific to a community (village or town), the PSU fixed effects are added to the model to control for any unobserved heterogeneity at the regional level.

secondary, high school, graduate and above) are controlled for in all regressions with the child sample. Mother's health as reported through her BMI index and self-reported health status (poor, fine, good) is also examined in the light of coal price shock as mother's health can be endogenous to the child health regressions but serves as an important channel in affecting the child health when evaluated exogenously.

Other factors at the household level that are controlled in these regression include the home conditions such as the hours for which electricity and stove is used, whether kitchen is outside or inside the home, traditional or stone type stove used, whether family members wash hands after washroom usage and whether purified water is used in house or not. Controlling for these factors is essential as these factors affect the health of family members especially the children through it's respiratory and hygiene related impacts. Health network of the household also plays an important role in affecting the nourishment of children as families with good medical networks and health insurance have an advantage regarding the health of their children. Therefore, these variables are also controlled in the health regressions as specified above.

Other district controls that vary with time are also added using the Census 2001 and Census 2011 data sets. The variables include the district level literacy rates and sex ratio which are indicative of the district specific policies in those years. This allows me to control for any unobserved heterogeneity at the district level which may bias the health outcomes for the children in coal districts of India. The above specification is therefore strengthened by making the identification strategy less reliant on similar trends across regions.

The extended specification thus becomes;

$$Y_{ihdt} = \alpha + \beta \cdot (R_d * P_t) + C_{ihdt} + X_{hdt} + M_{hdt} + E_{hdt} + H_{hdt} + D_{dt} + \gamma_v + T_t + \varepsilon_{ihdt} \tag{3.7}$$

Since the dependent variable is a binary variable, the Linear Probability Model is used for testing the above specifications;[14]

[14] The results with a Probit analysis were also similar, but LPM was chosen as it allows a more convenient interpretation of the results.

$$Pr.(Y_{ihd} = 1) = 1 - \Phi[\Omega_{ihd} - u] \tag{3.8}$$

where $Y_{ihd} = 1$ indicates that child i belonging to household h is 'stunted'/'underweight' in district d, and Ω_{ihd} incorporates the combination of all explanatory variables as discussed in Eq. 3.6 & 3.7.

In an alternate specification, the outcome variable as specified in Eq. 3.6 & 3.7 is replaced with the height-for-age (HFA) and weight-for-age (WFA) Z-scores for young children. These regressions then become linear regressions with robust standard errors clustered at district level. The objective of these regressions is to extend support to the regressions with outcome variable as the probability of being 'stunted' or 'underweight' among children.

3.5.1.3 Baseline Results

The results based on the baseline specifications [Eq. 3.6 & 3.7], indicate a decline in the probability for a young child living in coal districts of India to be stunted or underweight when exposed to the coal price shock. The results are presented in Table 3.2, where col (1) & (3) show how the probability of a young child being stunted gets affected due to the coal price shock with col (3) including the time-varying district controls as well. Similarly, probability of child being underweight is evaluated in col (2) & (4), with col (4) including the time-varying district controls. An average increase in world coal prices (0.25) between 2004 and 2011 causes the probability for a young child living in a coal district of India to be 'stunted' to reduce by approximately 1.3% points and to be 'underweight' by 1-1.5% points relative to the national trends respectively, holding everything else equal.

These results paint a positive picture for the health status of children living in coal districts of India post the coal price rise. The reduction in probability of being stunted and underweight implies that there have been positive changes to health status of children in these regions both in the long-term as well as in the short-term.

Table 3.2 – Effect of Coal Price Shock on proportion of children 'stunted' and 'underweight' in India

Young children Health status	(1) Stunting	(2) Underweight	(3) Stunting	(4) Underweight
Coal prices*Active mine	-0.0544***	-0.0423**	-0.0561**	-0.0612***
	(0.0197)	(0.0212)	(0.0246)	(0.0236)
Child Age in months	-0.000423	0.000549**	-0.000630**	0.000583**
	(0.000273)	(0.000228)	(0.000293)	(0.000247)
Female	-0.00879	-0.0106	-0.0129	-0.00626
	(0.00822)	(0.00742)	(0.00867)	(0.00763)
Head is literate	-0.0413***	-0.0278***	-0.0358***	-0.0307***
	(0.0110)	(0.00987)	(0.0118)	(0.0107)
Land	-0.0106	-0.0283**	-0.00155	-0.0274**
	(0.0123)	(0.0116)	(0.0123)	(0.0120)
Ln(MPCE)	-0.0393***	-0.0383***	-0.0436***	-0.0393***
	(0.00925)	(0.00927)	(0.00986)	(0.0100)
Mother's age	-0.00186***	-0.00157***	-0.00168***	-0.00161***
	(0.000565)	(0.000527)	(0.000602)	(0.000566)
Constant	1.041***	0.903***	2.597	3.904
	(0.207)	(0.149)	(5.197)	(3.637)
Observations	18,290	21,219	16,317	18,743
R-squared	0.191	0.188	0.199	0.195
Child controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes
Mother controls	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-Time controls	No	No	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Probability Regressions carried out for young children (age < 5 years). Dependent variables include: probability of a child being 'stunted' (HFA Z-score < -2) and probability of child being 'underweight' (WFA Z-score <-2). All variables excecpt the indicator variables are in logs. Treatment variable - ln(world coal prices)*active mine status. MPCE - monthly per capita expenditure for the household. District controls: sex-ratio in the district and literacy levels in the district are used from Census 2001 and Census 2011 datasets.

Greater investments in child health which give long-term benefits through increased height-for-age and short-term benefits through improved weight-for-age are visible through the results presented in Table 3.3. A 10 percentage increase in the world coal price results in the height-for-age z-score to increase by 0.03 z-scores from the mean and the weight-for-age z-scores to improve by 0.02-0.03 z-scores from the mean. These results extend support to the results presented in Table 3.2 and suggest improvements in the nutritional status of young children living in coal districts of India.

Table 3.3 – Effect of coal price shock on the Height-for-Age and Weight-for-Age Z-scores for Young children

Nutrition Z-Scores	(1) HFA	(2) WFA	(3) HFA	(4) WFA
Coal Prices * Active mine	0.336***	0.218***	0.333***	0.282***
	(0.0860)	(0.0830)	(0.107)	(0.0927)
Child Age in months	-0.00423***	-0.00677***	-0.00338**	-0.00672***
	(0.00125)	(0.000810)	(0.00134)	(0.000847)
Female	0.000154	0.0257	0.00954	0.0136
	(0.0356)	(0.0250)	(0.0364)	(0.0250)
Head is literate	0.182***	0.0921***	0.167***	0.0986***
	(0.0490)	(0.0336)	(0.0527)	(0.0356)
Land	0.0569	0.0442	0.0526	0.0500
	(0.0521)	(0.0399)	(0.0545)	(0.0410)
Ln(MPCE)	0.138***	0.145***	0.160***	0.147***
	(0.0420)	(0.0313)	(0.0448)	(0.0324)
Mother's age	0.0101***	0.00454***	0.00897***	0.00367**
	(0.00248)	(0.00166)	(0.00258)	(0.00178)
Constant	-4.005***	-3.199***	-17.87	-15.32
	(0.697)	(0.611)	(27.24)	(13.64)
Observations	18,290	21,219	16,317	18,743
R-squared	0.208	0.214	0.218	0.222
Child controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes
Mother controls	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-Time controls	No	No	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Regressions carried out for young children (age < 5 years). Dependent variables include: HFA Z-score WFA Z-score. All variables except the indicator variables are in logs. Treatment variable - ln(world coal prices)*active mine status. MPCE - monthly per capita expenditure for the household. District controls: sex-ratio in the district and literacy levels in the district are used from Census 2001 and Census 2011 datasets.

The results from Table 3.2 & 3.3 suggest that there is a counter-cyclical relation between the coal price rise and child malnutrition in India.

3.5.1.4 Robustness checks

To validate the robustness of the results presented through the baseline regressions, I ensure that the children in the treatment and control regions are comparable. In order to do this, I make use of two specifications by dropping children belonging to; a) metropolitan cities and b) non-coal states. This not only enables me to maintain an appropriate comparison group for the treatment regions by dropping districts and regions with larger populations (e.g. metropolitan cities) but also allows me to maintain uniformity in demographic and economic characteristics of children across treatment and control regions (by considering children living in states (provinces) with active coal mines). With uniformity in various characteristics of children across the treatment and control regions, the impact of coal price shock on the nutritional outcomes of young children in coal districts would not be confounded by other economic, cultural or demographic similarities at the regional level.

Results presented in Table 3.4 prove the robustness of the baseline results. A 10% increase in world coal price reduces the probability of child living in coal mining districts of India to be stunted by 1.27% points (when metro cities are excluded) and the similar probability to be underweight reduces by 1.34% points (when metro cities are excluded). The magnitudes of these effects are higher than baseline results, and should be read with caution however they do indicate that positive nutritional effects for children do not fade away when major cities are removed from the analysis. The robustness exercise when carried with the sample of coal rich states, by comparing coal and non-coal districts shows that an average increase in world coal prices reduces the incidence of stunting in children living in coal districts by 1.25% points and reduces the incidence of underweight in those children by 1% points relative to national trends respectively. These results are similar in sign and magnitude compared to baseline regressions thereby validating them.

Table 3.4 – Effect of Coal Price Shock on proportion of children 'stunted' and 'underweight' in India

Young children Health Status	(1) Stunting	(2) Underweight	(3) Stunting	(4) Underweight
Coal prices*Active mine	-0.127***	-0.134***	-0.0502*	-0.0457*
	(0.0132)	(0.0289)	(0.0272)	(0.0252)
Child Age in months	-0.00182***	-0.000918**	-0.000334	0.000702***
	(0.000462)	(0.000366)	(0.000302)	(0.000264)
Female	-0.0293*	0.00223	-0.0135	-0.00809
	(0.0151)	(0.0115)	(0.00935)	(0.00827)
Head is literate	-0.0209	-0.0334	0.00687	-0.0187
	(0.0208)	(0.0204)	(0.0132)	(0.0134)
Land	-0.0615***	-0.0448***	-0.0392***	-0.0387***
	(0.0166)	(0.0171)	(0.0106)	(0.0108)
Ln(MPCE)	-0.0239	-0.0379**	-0.0335***	-0.0311***
	(0.0202)	(0.0184)	(0.0123)	(0.0115)
Mother's age	-0.00109	-0.00163**	-0.00190***	-0.00164***
	(0.000839)	(0.000757)	(0.000670)	(0.000631)
Constant	1.100***	1.233***	2.757	5.483
	(0.252)	(0.257)	(5.567)	(3.739)
Observations	7,551	8,534	13,726	15,750
R-squared	0.311	0.303	0.195	0.192
Child controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes
Mother controls	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sample	No Metro Cities	No Metro Cities	Coal States	Coal States

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Probability Regressions carried out for young children (age < 5 years). Dependent variables include: probability of a child being 'stunted' (HFA Z-score < -2) and probability of child being 'underweight' (WFA Z-score <-2). All variables excecpt the indicator variables are in logs. Treatment variable - ln(world coal prices)*active mine status. MPCE - monthly per capita expenditure for the household. District controls: sex-ratio in the district and literacy levels in the district are used from Census 2001 and Census 2011 datasets. Metro cities [6 major cities]: Delhi, Mumbai, Kolkata, Chennai, Hyderabad and Bangalore. Coal States in India [21 out of 33 states in India have coal mines]: Andhra Pradesh, Arunachal Pradesh, Chhattisgarh, Gujarat, Jammu & Kashmir, Jharkhand, Kerala, Madhya Pradesh, Maharashtra, Meghalaya, Nagaland, Orissa, Pondicherry, Rajasthan, Sikkim, Tamil Nadu, Uttar Pradesh, West Bengal.

In Table 3.5, the analysis is performed on the anthropometric z-scores for young children, excluding the metro cities and non-coal states from the analysis. The results show a positive and significant effect on the height-for-age and weight-for-age z-scores with the restricted samples as well, thus validating the robustness of the results presented in Table 3.3.

Table 3.5 – Effect of coal price shock on the Height-for-Age and Weight-for-Age Z-scores for Young children

Young children Z-Scores	(1) HFA	(2) WFA	(3) HFA	(4) WFA
Coal prices*Active mine	0.543***	0.473***	0.309***	0.248**
	(0.0528)	(0.0624)	(0.114)	(0.0993)
Child Age in months	0.00551***	0.00128	-0.00427***	-0.00682***
	(0.00174)	(0.00120)	(0.00141)	(0.000918)
Female	0.0370	-0.0240	0.0168	0.0331
	(0.0566)	(0.0343)	(0.0389)	(0.0276)
Head is literate	0.102	0.152***	0.183***	0.0920**
	(0.0817)	(0.0539)	(0.0553)	(0.0386)
Land	0.175**	0.0680	0.0126	0.0124
	(0.0774)	(0.0618)	(0.0581)	(0.0460)
Ln(MPCE)	0.149**	0.182***	0.143***	0.149***
	(0.0735)	(0.0494)	(0.0498)	(0.0354)
Mother's age	0.00468	0.00197	0.0108***	0.00435**
	(0.00358)	(0.00240)	(0.00286)	(0.00201)
Constant	-3.478***	-4.194***	-23.11	-18.21
	(1.115)	(1.147)	(28.38)	(13.78)
Observations	7,551	8,534	13,726	15,750
R-squared	0.343	0.339	0.215	0.220
Child controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes
Mother controls	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sample	No Metro Cities	No Metro Cities	Coal States	Coal States

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Regressions carried out for young children (age < 5 years). Dependent variables include: HFA Z-score WFA Z-score. All variables except the indicator variables are in logs. Treatment variable - ln(world coal prices)*active mine status. MPCE - monthly per capita expenditure for the household. District controls: sex-ratio in the district and literacy levels in the district are used from Census 2001 and Census 2011 datasets. Metro cities [6 major cities]: Delhi, Mumbai, Kolkata, Chennai, Hyderabad and Bangalore. Coal States in India [21 out of 33 states in India have coal mines]: Andhra Pradesh, Arunachal Pradesh, Chhattisgarh, Gujarat, Jammu & Kashmir, Jharkhand, Kerala, Madhya Pradesh, Maharashtra, Meghalaya, Nagaland, Orissa, Pondicherry, Rajasthan, Sikkim, Tamil Nadu, Uttar Pradesh, West Bengal.

3.5.1.5 Falsification tests

The regression results for the nutritional outcomes for children in coal districts of India show that young children benefit in their short-term and long-term health outcomes when exposed to the coal price shock. In this section, I conduct a few falsification tests to validate those results and show that such effects are purely restricted to young children living in coal districts of India and positive nutritional outcomes for children living in coal districts are not spurious.

In Table 3.6, I perform the analysis similar to the baseline model for the school-going children (age 5-19 years). The results for their nutritional outcomes when exposed to the coal price shock aren't statistically significant. This could be because there are numerable other factors outside the domain of household decision making that influence the health of older children such as the provision of mid-day meals in schools, work opportunities etc. Therefore, the health effects of coal price shock are limited to young children who are under the direct influence of household decisions that are altered when families are exposed to the coal price rise.

Table 3.6 – Effect of Coal Price Shock on proportion of school-going children 'stunted' and 'underweight' in India

Nutritional status	(1) Stunting	(2) Underweight	(3) HFA	(4) WFA
Coal prices*Active mine	0.00769	-0.0377	-0.0484	-0.00388
	(0.0303)	(0.0276)	(0.0998)	(0.0720)
Age	-0.0188	0.141***	0.0414	-0.564***
	(0.0131)	(0.0380)	(0.0462)	(0.111)
Female	0.0375	-0.0932	0.0587	0.337*
	(0.0300)	(0.0628)	(0.103)	(0.181)
School attending	-0.0932***	-0.126***	0.406***	0.378***
	(0.0218)	(0.0306)	(0.0804)	(0.104)
Land	-0.0287***	-0.0104	0.0877**	0.00480
	(0.0109)	(0.0152)	(0.0368)	(0.0415)
Ln(MPCE)	-0.0589***	-0.0708***	0.204***	0.231***
	(0.00950)	(0.0129)	(0.0320)	(0.0373)
Head is literate	-0.0151	-0.0165	0.0799**	0.0747*
	(0.0106)	(0.0153)	(0.0340)	(0.0418)
Mother's age	-0.000953	-0.00317***	0.00616**	
	(0.000726)	(0.00109)	(0.00249)	
Constant	-0.627	0.260	-7.724	0.0287
	(5.267)	(5.548)	(19.28)	(18.72)
Observations	25,066	12,570	25,066	12,630
R-squared	0.186	0.270	0.224	0.332
Child controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes
Mother controls	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Probability Regressions carried out for school-going children (age: 5-19 years). Dependent variables include: probability of a child being 'stunted' (HFA Z-score < -2) and probability of child being 'underweight' (WFA Z-score <-2). All variables excecpt the indicator variables are in logs. Treatment variable - ln(world coal prices)*active mine status. MPCE - monthly per capita expenditure for the household. District controls: sex-ratio in the district and literacy levels in the district are used from Census 2001 and Census 2011 datasets.

In Table 3.7, results for the impact on the nutritional outcomes for young children living in control regions are presented. The sample for control regions is divided such that 50% of these districts are assigned the treatment effect. This allows me to test if the presence of an active coal mine is an identifying factor in analyzing the nutritional effects of children. The results are not statistically significant in these regressions. Therefore, it can be safely concluded that the health effects for children when exposed to the coal price shock are significantly visible only when they live in coal districts of India, that is near an active coal mine.

Table 3.7 – Placebo Effects: Random assignment of treatment districts

Nutritional Status	(1) Stunting	(2) Underweight	(3) HFA	(4) WFA
Coal prices*Random treatment	-0.0503	-0.0811	0.475	0.269
	(0.0783)	(0.0565)	(0.367)	(0.210)
Age	-0.0535***	-0.0370***	0.205***	0.116***
	(0.00453)	(0.00422)	(0.0192)	(0.0142)
Female	-0.0573***	-0.0298**	0.164**	0.0766
	(0.0175)	(0.0148)	(0.0729)	(0.0495)
Head is literate	-0.0387***	-0.0309***	0.157***	0.104***
	(0.0126)	(0.0108)	(0.0560)	(0.0378)
Land	-0.00645	-0.0326***	0.0784	0.0593
	(0.0132)	(0.0124)	(0.0581)	(0.0429)
Mother's age	-0.00136**	-0.00105*	0.00784***	0.00134
	(0.000628)	(0.000611)	(0.00264)	(0.00187)
Constant	1.239	0.283	-11.75	-4.911
	(5.214)	(3.495)	(27.42)	(13.05)
Observations	14,615	16,790	14,615	16,790
R-squared	0.210	0.197	0.221	0.213
Child controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes
Mother controls	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-Time controls	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Regressions carried out for young children (age < 5 years). Dependent variables include: HFA Z-score WFA Z-score. All variables except the indicator variables are in logs. Placebo Treatment variable - ln(world coal prices)* random assignment to control regions. MPCE - monthly per capita expenditure for the household. District controls: sex-ratio in the district and literacy levels in the district are used from Census 2001 and Census 2011 datasets. Random treated effect: out of the control regions 50% are randomly assigned as the treated regions; the indicator of these regions interacted with world coal price gives random treated effect.

3.5.2 Mechanisms

The impact of coal price shock on the nutritional outcomes of children living in coal districts of India can be understood via the income and substitution effects generated which inturn affect the household decision-making process. The relative magnitude of each effect determines the direction of the overall impact.

3.5.2.1 Substitution effects

As discussed in Section 3.1, the substitution effects generated through the coal price shock impact the child's health via the time-allocation mechanism preferably by the mother of the child. In general, mothers play a vital role in the child-rearing process around the world, and this factor is even more predominant in India.

In Table 3.8, two regressions are carried to understand how the time-allocation by a mother in coal districts of India is affected when exposed to the rise in world coal prices. In Col. (1), the effect of coal price shock on the working hours of an eligible woman in a year is evaluated, and in Col. (2), effect of coal price shock on the probability that the mother takes care of the child when s(he) is sick is considered. The results show that, an average increase in world coal prices (0.25) reduces the working hours devoted by mothers in coal districts post the price rise by 13.25% points relative to national trends and increases their probability to take care of their child when sick by 9.5% points relative to national trends.

Table 3.8 – Impact on the working hours for women and the probability of women to take care of children when sick

Mother's time allocation	(1) Working hours	(2) Care when sick
Coal prices*Active mine	-0.530**	0.380**
	(0.253)	(0.176)
No. Persons	-0.0186***	-0.0125***
	(0.00552)	(0.00196)
No. Children	0.00715	0.0165***
	(0.00821)	(0.00295)
Urban	-0.0918	-0.0266
	(0.162)	(0.0300)
Land	-0.309***	-0.0183
	(0.0276)	(0.0141)
Ln(working hours)		-0.00796
		(0.00592)
Constant	7.460***	0.757***
	(0.151)	(0.118)
Observations	27,390	49,058
R-squared	0.394	0.327
Household effects	Yes	Yes
Year FE	Yes	Yes
PSU FE	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Regressions carried out for eligible women (age 15-49 years). Treatment variable - ln(world coal prices)*active mine status. Dependent variables include: log of working hours devoted by the woman (in an year), and the probability that woman take care of child when sick.

These results indicate that coal price shock in India does not generate significant substitution effects, and women in particular turn away from work responsibilities, gearing more towards the household duties. This results in greater time available for the child. According to Ruhm [2000], parental leave is a cost-effective way to improve the child's health. Maternal labor supply tends to reduce the time available for various health-care activities undertaken during and post pregnancy, such as antenatal visits [Miles-Doan and Brewster, 1998] and breastfeeding [Baker and Milligan, 2008]. With better care and other healthy activities in place, the nutritional status of the child improves overall.

Health promoting activities undertaken by the women (mothers) are an important factor that determine the health of their children. An inherent part of the child's health status is determined via the health-care provided to the unborn fetus [Kuhnt and Vollmer, 2017]. This directly affects the health endowment of the child, which has been shown to impact the health status of the child in the forming years [Section 3.1] [15].

In Table 3.9, results are shown for the effects on health-status of women during their last pregnancy, the incidence of undergoing various check-ups to ensure a healthy pregnancy and the post-pregnancy steps taken such as breastfeeding to ensure the healthy development of their child. In Col. (1), the impact of coal price shock on the incidence of anemia in women living in coal districts of India shows a negative trend, which is suggestive that a woman living in coal district was generally healthier during her last pregnancy post the coal price shock. This outcome can impact the child's health endowment in positive manner. In Col.(2) and Col.(3), it can be seen that coal price shocks increase the incidence of pre-natal check-ups such as blood test or urine test during pregnancy for the women living in coal districts of the country. This as already discussed has an important contribution in shaping the nutritional status of the child. In Col. (4), the incidence of taking iron & folic dosages during and post pregnancy increases by 5% points relative to national trends for the eligible women in coal districts of India when exposed to an average coal price shock. Similarly an average increase in coal prices results in the probability to breastfeed for at least three months by a mother in coal districts of India by 1% points relative to national trends for eligible women.

Together, these outcomes suggest that there has been an upward trend in health-promoting activities undertaken by women living in coal districts of India when exposed to the world coal price rise. These women have also registered a decline the working hours as shown in Table 3.8, making more time available for child-rearing activities. This has proven to be beneficial for the child's health production in these regions. Moreover, women undertaking health-promoting activities is also suggestive of greater women autonomy in these regions [Rizkianti et al., 2020, Imai et al., 2014].

[15] Pre-natal care has known to have benefits for child health that become apparent as the child grows and reaches the age of five years [Noonan et al., 2013].

Table 3.9 – Pregnancy related health of women, incidence of pre-natal checkups and breast-feeding during last birth

Health practices & care	(1) Anemia	(2) Blood test	(3) Urine test	(4) Iron & Folic	(5) Breastfeed
Coal prices*Active mine	-0.219**	0.155*	0.230**	0.211**	0.0447**
	(0.105)	(0.0820)	(0.0900)	(0.105)	(0.0197)
Urban	-0.0504	-0.0181	0.0631	0.0794	-0.0278*
	(0.0628)	(0.0473)	(0.0476)	(0.0654)	(0.0148)
Land	-0.00516	0.00464	-0.000225	0.00946	
	(0.00831)	(0.00764)	(0.00782)	(0.00948)	
Mother_edu1	0.0173*	0.0387***	0.0408***	0.0575***	0.00549
	(0.00974)	(0.0101)	(0.0105)	(0.0126)	(0.00344)
Mother_edu2	0.00135	0.0984***	0.0988***	0.108***	0.00470
	(0.00965)	(0.00983)	(0.00999)	(0.0121)	(0.00341)
Mother_edu3	-0.0382***	0.128***	0.123***	0.141***	0.00315
	(0.0147)	(0.0127)	(0.0130)	(0.0167)	(0.00554)
Mother_edu4	-0.0491***	0.142***	0.144***	0.158***	0.00592
	(0.0165)	(0.0129)	(0.0131)	(0.0194)	(0.00583)
Mother_edu5	-0.0491	0.103***	0.107***	0.184***	0.0180*
	(0.0306)	(0.0191)	(0.0175)	(0.0282)	(0.0101)
Constant	0.326***	0.487***	0.408***	0.392***	0.971***
	(0.0629)	(0.0522)	(0.0557)	(0.0668)	(0.0115)
Observations	22,599	21,948	21,939	16,836	16,564
R-squared	0.225	0.498	0.487	0.489	0.189
Household effects	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Regressions carried out for eligible women (age 15-49 years). Treatment variable - ln(world coal prices)*active mine status. Dependent variables include various health care practices by women during last pregnancy: a) incidence of anemia during last pregnancy b) probability that the woman took a blood test during last pregnancy c) probability that the woman took urine test during last pregnancy d) whether the woman took iron & folic tablets or syrup during and post last pregnancy e) whether the woman breastfed the child for at least 3 months in the last pregnancy. Mother's education is included as a categorical variable in the regressions where:edu0 :illiterate, edu1: primary education, edu2: secondary education, edu3: higher secondary, edu4: graduate, edu5: post-graduate.

3.5.2.2 Income effects

The positive child health outcomes in coal districts of India as shown in Section 5.1.3, could be explained by the presence of income effects that positively affect the household-decision making in favor of child's health production. These income effects are modeled via the rise in disposable income with the household women, such that health of family members improves overall. This has been modeled in this paper through the health-status of women in the house. With greater incomes at their disposal in general, mother's own health should also improve which would have a positive effect on the child's health [Duflo, 2000, Rahman et al., 1993].[16]

In Tables 3.10 & 3.11, mother's health status is modeled through her BMI status and her self-reported health status respectively. The various controls used include her age polynomial (assuming, with greater age the health effects can deteriorate), land ownership status, place of residence, her education levels and other household characteristics. Results in Table 3.10 indicate that the probability of a woman living in coal districts of India to be 'underweight' reduces by 2.3% points relative to national trends, to be 'obese' reduces by 0.98% points relative to national trends and to be of 'normal weight' increases by 2.87% points relative to national trends when exposed to an average increase (0.25) in coal price world-wide between 2004-2010. These nutritional outcomes for women are calculated based on their Body Mass Index (BMI) levels, where a BMI (Kg/mt2) less than 18.5 is considered 'underweight', in the range of 18.5 to 25 is considered a 'normal weight' and above 30 is considered 'obese'. A woman who is either 'underweight' or 'obese' is considered unhealthy. It is ideal to have a 'normal weight' on the BMI scale.

[16]Mother's health status is an important determinant in explaining the child health outcomes, even though it is in general endogenous to the health production of a child. Therefore, mother's health status is examined exogenously in light of the income effects due to the coal price shock.

Table 3.10 – Impact on the women's health status in terms of her BMI status

Mother's BMI Categories	(1) Underweight	(2) Normal weight	(3) Overweight	(4) Obese
Coal prices*Active mine	-0.0926*	0.115**	0.0119	-0.0395**
	(0.0511)	(0.0523)	(0.0356)	(0.0161)
Age	-0.0207***	0.00158	0.0153***	0.00447***
	(0.00143)	(0.00177)	(0.00120)	(0.000740)
Age_sq	0.000205***	-4.46e-05*	-0.000139***	-3.17e-05***
	(1.89e-05)	(2.38e-05)	(1.67e-05)	(1.04e-05)
Land	-0.000547	-0.00138	0.00187	0.000525
	(0.00504)	(0.00599)	(0.00410)	(0.00224)
Urban	-0.0147	-0.0587*	0.0386	0.0320***
	(0.0201)	(0.0311)	(0.0259)	(0.0117)
Mother_edu1	-0.0367***	-0.00515	0.0314***	0.0109***
	(0.00552)	(0.00672)	(0.00435)	(0.00271)
Mother_edu2	-0.0499***	-0.0142**	0.0435***	0.0206***
	(0.00535)	(0.00642)	(0.00433)	(0.00278)
Mother_edu3	-0.0527***	-0.0201*	0.0600***	0.0137***
	(0.00797)	(0.0107)	(0.00840)	(0.00525)
Mother_edu4	-0.0738***	0.00242	0.0632***	0.00863
	(0.00796)	(0.0118)	(0.00970)	(0.00672)
Mother_edu5	-0.0640***	-0.0208	0.0663***	0.00408
	(0.0122)	(0.0226)	(0.0197)	(0.0139)
Constant	0.701***	0.617***	-0.274***	-0.112***
	(0.0573)	(0.0952)	(0.0625)	(0.0382)
Observations	61,978	61,978	61,978	61,978
R-squared	0.146	0.079	0.135	0.109
Women FE	Yes	Yes	Yes	Yes
Household effects	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Regressions carried out for eligible women (age 15-49 years). Treatment variable - ln(world coal prices)*active mine status. Dependent variables include the mother's health status measured by her probability of being: a) Underweight: BMI (Kg/m2) status 0-18.5, b) Normal weight: BMI(Kg/m2) 18.5-25, c) Overweight: BMI (Kg/m2) 25-30, d) Obese: BMI(Kg/m2) 30 and above. Mother's education is included as a categorical variable in the regressions where: edu0 :illiterate, edu1: primary education, edu2: secondary education, edu3: higher secondary, edu4: graduate, edu5: post-graduate.

In Table 3.11, women's self-reported health status registers an improvement when exposed to the treatment effect. For a woman living in coal regions of India, an average increase in the world coal prices (0.25) during 2004-2010, results in an increase in the probability to report 'good health' by 8% points and a decrease in probability to report 'fine health' by 8% points relative to national trends. There is no significant effect on the incidence of women reporting 'poor health' however. These results also support the arguments specified in this section, claiming that women are now better-off in terms of the disposable incomes which has favorably affected their health status, as also shown in literature otherwise [Alaimo et al., 2001].

Table 3.11 – Impact on self-reported health status of eligible women

Mother's health status	(1) Poor health	(2) Fine health	(3) Good health
Coal prices*Active mine	0.0124	-0.326***	0.323***
	(0.0354)	(0.0802)	(0.0798)
Age	-0.00179*	0.00198	-0.000320
	(0.000934)	(0.00143)	(0.00154)
Age_sq	5.14e-05***	-4.53e-06	-4.47e-05**
	(1.32e-05)	(1.93e-05)	(2.10e-05)
Land	0.00320	-0.0106**	0.00708
	(0.00300)	(0.00489)	(0.00516)
Urban	0.0254	0.0217	-0.0461
	(0.0172)	(0.0443)	(0.0526)
Mother_edu1	-0.00146	-0.0137***	0.0151***
	(0.00339)	(0.00524)	(0.00567)
Mother_edu2	-0.0112***	-0.0220***	0.0336***
	(0.00301)	(0.00481)	(0.00522)
Mother_edu3	-0.0202***	-0.0401***	0.0602***
	(0.00415)	(0.00764)	(0.00821)
Mother_edu4	-0.0243***	-0.0569***	0.0818***
	(0.00460)	(0.00893)	(0.00955)
Mother_edu5	-0.0280***	-0.0397**	0.0705***
	(0.00821)	(0.0155)	(0.0168)
Constant	-0.0359	0.412***	0.624***
	(0.0468)	(0.0794)	(0.0928)
Observations	61,978	61,978	61,978
R-squared	0.122	0.194	0.214
Women FE	Yes	Yes	Yes
Household effects	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Regressions carried out for eligible women (age 15-49 years). Treatment variable - ln(world coal prices)*active mine status. Dependent variables include the mother's self-reported health status measured by probability of reporting a) poor health, b) fine health and c) good health . Mother's education is included as a categorical variable in the regressions where: edu0 :illiterate, edu1: primary education, edu2: secondary education, edu3: higher secondary, edu4: graduate, edu5: post-graduate.

Positive income effects described in this section are believed to promote better nutritional outcomes for children in coal districts of India. Therefore, mother's health status is an important determinant in explaining the health outcomes for young children.

3.5.3 Heterogeneous effects

The baseline results in Section 5.1.3 suggested that nutritional outcomes improve for all young children living in coal districts of India when exposed to an international coal price shock. In this section, I break down these effects for young children with respect to the wealth status of their family and their gender. These heterogeneous effects are likely to throw further light on the intensity and channel of these nutritional impacts, as household wealth is an important determinant for child health in India [Chalasani and Rutstein, 2014].

In Table 3.12, heterogeneous effects with respect to the income level of the family are presented. Three broad categories are considered for reflecting the income level of the household; the poorest income quintile (1st quintile), the middle income category (3rd income quintile) and the richest (5th income quintile). The other income categories are not presented as the results for the 'poor' (2nd income quintile) and 'rich' (4th income quintile) are not very different from the 'poorest' and 'richest' income quintile respectively.

The probability of a child being 'underweight' reduces significantly for all income quintiles, with the greatest impact for the middle income category. This suggests that positive nutritional outcomes for young children is driven by the substitution effects where the time-allocation by the mother towards the children plays a crucial role. The income effects drive the nutritional outcomes but only in the short-run, that is they can enhance the weight-for-age of young children which manifests in the short run but do not play a vital role in enhancing the height-for-age which takes longer run to manifest.

The probability of child to be 'stunted' on other hand reduces significantly for the middle income and rich families with the greatest impact felt on middle income families. Therefore, an income shock to the poorer families is not significant enough to drive enough investments in health of their children leading to improvement in their heights. For the richer families, they are already at an advantage in terms to better access to health facilities and products [Semyonov et al., 2013] and so an income shock to their family doesn't contribute excessively towards the health of their children and they are likely to invest in other products. The middle income families fare better-off in terms of this income shock as the increased family incomes gives them enough scope to invest in the health production function of their children, thereby reaping the maximum benefits in child health both in short-term and in long-term.

Table 3.12 – Effects of coal price shock on nutritional status of young children w.r.t income quintile of the household

Health status Wealth effects	(1) Stunting	(2) Underweight	(3) Stunting	(4) Underweight	(5) Stunting	(6) Underweight
Coal prices*Active mine	-0.127	-0.351***	-0.246***	-0.255***	-0.0872*	-0.0783**
	(0.0895)	(0.114)	(0.0578)	(0.0582)	(0.0449)	(0.0377)
Child age months	-0.000269	-5.44e-05	-5.31e-05	-0.000233	-0.00309***	-0.000970
	(0.00104)	(0.000813)	(0.000852)	(0.000655)	(0.000783)	(0.000619)
Female	-0.0440*	0.00581	0.0119	0.0107	-0.0303	-0.0283
	(0.0264)	(0.0244)	(0.0261)	(0.0235)	(0.0255)	(0.0198)
Head is literate	-0.0207	-0.0523	-0.0370	0.0173	-0.0640	-0.0658
	(0.0414)	(0.0380)	(0.0448)	(0.0359)	(0.0453)	(0.0403)
Mother's age	-0.000386	-0.00467**	-0.00243	-0.000163	-0.00173	-0.000758
	(0.00307)	(0.00228)	(0.00187)	(0.00168)	(0.00191)	(0.00156)
Constant	19.88	20.85	-10.25	-6.064	24.30**	27.29***
	(19.66)	(16.80)	(13.84)	(10.89)	(10.66)	(9.596)
Observations	2,511	2,903	3,436	3,943	3,530	4,065
R-squared	0.414	0.422	0.460	0.433	0.455	0.431
Child controls	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes	Yes	Yes
Mother controls	Yes	Yes	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Time Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample	**Poorest Quintile**	**Poorest Quintile**	**Middle Income**	**Middle Income**	**Richest Quintile**	**Richest Quintile**

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Probability Regressions carried out for young children (age < 5 years). Treatment variable - ln(world coal prices)*active mine status. Dependent variables include: probability of a child being 'stunted' (HFA Z-score < -2) and probability of child being 'underweight' (WFA Z-score <-2). All variables excecpt the indicator variables are in logs. MPCE - monthly per capita expenditure for the household. District controls: sex-ratio in the district and literacy levels in the district are used from Census 2001 and Census 2011 datasets. Income quintiles are described as: 1st quintile (poorest quintile), 3rd quintile (middle income), 5th quintile (richest quintile).

In Table 3.13, heterogeneous effects in child nutritional outcomes with respect to their gender are presented. The results show that the positive nutritional outcomes are significant only for the male children and the female children do not find any significant effects on their nutritional status. The probability for a male child living in coal regions of India, to be 'stunted' reduces by 2.3% points relative to national trends and to be 'underweight' reduces by 2.2% points relative to national trends when faced with an average increase in world coal prices. Therefore, there appears to be a strong bias in household decision making in coal regions of India in favor of the male child. This outcome corroborates the idea of 'son-preference' in India especially in the backward regions of the country [Jayachandran and Pande, 2017]. Coal mines are also located in not so affluent regions of the country and the prevalence of positive nutritional outcomes for only the male children in the event of a coal price shock indicate the orthodox mindset of the families in these regions when it comes to spending resources (time and income) for the health of their children.

Table 3.13 – Effects of coal price shock on nutritional status of young children w.r.t gender of the child

Health Status w.r.t gender	(1) Stunting	(2) Stunting	(3) Underweight	(4) Underweight
Coal prices*Active mine	-0.0951***	-0.0256	-0.0882**	-0.0521
	(0.0348)	(0.0359)	(0.0371)	(0.0337)
Child age months	-0.00120***	0.000142	0.000148	0.00120***
	(0.000444)	(0.000477)	(0.000379)	(0.000400)
Head is literate	-0.0424**	-0.0286	-0.0367**	-0.0255
	(0.0181)	(0.0203)	(0.0150)	(0.0189)
Land	0.000302	-0.00621	-0.0335*	-0.0250
	(0.0184)	(0.0205)	(0.0189)	(0.0197)
Ln(MPCE)	-0.0363***	-0.0536***	-0.0344**	-0.0435***
	(0.0139)	(0.0175)	(0.0142)	(0.0161)
Mother's age	-0.00198**	-0.00117	-0.00205**	-0.00143
	(0.000992)	(0.000954)	(0.000886)	(0.000958)
Constant	-6.516	8.694	-0.261	6.763
	(7.271)	(7.486)	(5.592)	(5.897)
Observations	8,497	7,820	9,803	8,940
R-squared	0.295	0.312	0.273	0.299
Child controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
HH head controls	Yes	Yes	Yes	Yes
Mother controls	Yes	Yes	Yes	Yes
PSU FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-Time Controls	Yes	Yes	Yes	Yes
Sample	**Male (<5yrs)**	**Female (<5yrs)**	**Male (<5 yrs)**	**Female (<5yrs)**

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Probability Regressions carried out for young children (age < 5 years). Treatment variable - ln(world coal prices)*active mine status. Dependent variables include: probability of a child being 'stunted' (HFA Z-score < -2) and probability of child being 'underweight' (WFA Z-score <-2). All variables excecpt the indicator variables are in logs. MPCE - monthly per capita expenditure for the household. District controls: sex-ratio in the district and literacy levels in the district are used from Census 2001 and Census 2011 datasets.

3.5.4 Other Factors

In this section, I discuss the impact of the treatment effect on the fertility choices among women living in coal districts of India when exposed to the coal price shock in order to rule out any confounding parallel trends which may cause self-selection of healthy children in coal regions of the country, thereby the biasing the baseline results.

In Table 3.14, I discuss the effect of coal price shock on the fertility trends in coal regions. The results show that there are no significant effects on the use of contraceptives or on the incidence of miscarriages among women in the coal regions of India when exposed to rising world coal prices. This shows that there is no presence of parallel trends in terms of fertility choices among women living in these regions which can potentially bias the nutritional outcomes of children living in these regions.

Table 3.14 – Fertility trends - Parallel trends

Fertility Trends	(1) Contraceptive use	(2) No. Miscarriages
Coal prices*Active mine	0.0314	-0.0768
	(0.0662)	(0.0573)
Urban	0.0555	0.0402
	(0.0396)	(0.0358)
Land	0.00800	0.00276
	(0.00539)	(0.00637)
Mother_edu1	-0.00944*	0.0325***
	(0.00557)	(0.00733)
Mother_edu2	-0.0424***	0.0215***
	(0.00552)	(0.00624)
Mother_edu3	-0.0837***	0.00695
	(0.00945)	(0.0105)
Mother_edu4	-0.0811***	0.00751
	(0.0107)	(0.0117)
Mother_edu5	-0.127***	-0.0486**
	(0.0191)	(0.0219)
Constant	0.562***	0.148***
	(0.0368)	(0.0361)
Observations	65,397	70,204
R-squared	0.214	0.083
Household effects	Yes	Yes
Year FE	Yes	Yes
PSU FE	Yes	Yes

Note: Robust standard errors clustered at district level in parentheses. Statistical significance of coefficients denoted by: *** p<0.001, ** p<0.05, * p<0.1. Data source: India Human Development Survey (2004-05 & 2011-12). Linear Regressions carried out for eligible women (age 15-49 years). Treatment variable - ln(world coal prices)*active mine status. Dependent variables include the fertility trends through a) probability of using a contraceptive and b)number of miscarriages faced by mother. Mother's education is included as a categorical variable in the regressions where: edu0 :illiterate, edu1: primary education, edu2: secondary education, edu3: higher secondary, edu4: graduate, edu5: post-graduate.

Moreover, a closer look at the descriptive statistics also reveals that demographic profile of women (age, religious background) has not changed significantly in coal regions vs the non-coal regions and nor have the fertility trends (number of children born, number of children considered ideal in a family). The average changes in these variables are merely a product of the time effects and evolve uniformly in all regions.

3.6 Conclusion

Coal is an important and abundant fossil fuel in India, fulfilling 55% of the country's energy requirements (Ministry of Coal, GOI). The country's industrial heritage owes special mention to indigenous coal. Given the strategic importance of this extractive mineral industry, it becomes relevant to understand the various mechanisms through which the mining of this natural resource affects the socio-economic outcomes for the individuals living in regions with coal mines.

There is abundant literature to show that early childhood health plays an important role in overall development of a child which has tremendous consequences for the economic development of a region. In this paper, I therefore explore the health outcomes for children living in coal districts of India via the effects on the household decision making process in these regions.

Coal prices world-wide have registered an increasing trend for over a decade. I make use of the rising international coal prices as an instrument in analyzing the local health effects for children in coal districts of India. International coal prices have significant pass-through effects towards the domestic coal prices and production which are relatively governed by the administrative structure of the coal industry in India. Making use of these pass-through effects, I construct my treatment effect by interacting the international coal price with the dummy variable for a region having an active coal mine. India Human Development Survey (IHDS) provides data for several health and other socio-economic characteristics for the population over 384 districts in the country. 33 out of the total 52 districts in India that have active coal mines are sampled in this database. With two survey years in 2004 and 2011, I make use of the coal price shock that occurred in 2008 as the identifying treatment effect, allowing me to capture the local health effects for children living in coal regions of India post the price shock, using a difference-in-difference analysis.

The nutritional outcomes for young children below the age of five years living in coal districts of India witness an improvement with decreasing incidences of stunting and underweight among them. The analysis shows that negative substitution effects and increasing income effects in household decision making contribute to such positive nutritional outcomes for children in these regions. The coal price shock, reduces the working hours of women which has a direct and positive effect on the time available for child health promoting activities. There is a greater incidence of pregnancy related care among women living in coal regions and the incidence of breastfeeding also increases post the coal price shock. The rising family incomes due to the price shock, leave additional disposable income with the females of the house which not only enhances their autonomy (and thus, their bargaining power in the house) but also leads to improvements in their health status. Mother's health status is an important factor that affects the child's health and development. Therefore, positive income shocks contribute in better nutritional outcomes for children through increased women autonomy and health status.

These mechanisms on a closer analysis also indicate that while positive income effects help improve the nutritional outcomes for children in the short term, they are only mildly helpful for the long term nutritional benefits (that is for improving the height-for-age of children). The long term health benefits for children in terms of reduced stunting requires a strong negative substitution effect and a strong positive income effect, which works best for the children belonging to the middle-income families who are on the edge waiting for an income push enabling them to attain better health standards.

The heterogeneous effects in child nutrition analysis in coal regions also provides significant evidence for a strong 'son-preference' in allocation of time and wealth resources in the health production function by the households.

These results actively meet the falsification tests and verify that the outcomes are not spurious, proving the counter-cyclical nature of nutritional outcomes of children when exposed to the coal price shock in India. However, the results can be extended at various levels to better understand the nuances for household decision making in coal regions of India, leaving room for further research in this area.

The evidence from this study certainly have policy implications and highlight the orthodoxy in household decisions regarding health of children in coal regions of India. There is need for measures for effective investments in health of all children in all regions of India especially those who are plagued by the environmental effects of resource extraction. Stronger income effects in household decision making needs to be present to overcome the shortages in nutritional status of children across different family backgrounds and across genders.

This study contributes to the literature in various segments, which include the local effects of natural resource abundance in a region and the effects of aggregate economic shocks on the local health effects of children in a region. In addition to this, the study also claims to be one of the first studies to address this issue in India, which is a prominent developing nation having implications for similar emerging economies.

Appendix Tables

Table 3.15 – Testing for rural migration

Population Composition	(1) Log(Population)	(2) Sex ratio
Coal prices *Active mine	0.00744	-0.0145
	(0.0493)	(0.0243)
Labor Force Participation	0.133	-0.00139
	(0.0921)	(0.0334)
Schools	0.0687	-0.0463
	(0.0622)	(0.0403)
Teachers	0.112**	0.0320
	(0.0493)	(0.0311)
Constant	12.42***	1.114***
	(0.296)	(0.165)
R-squared	0.051	0.005
Number of districts	605	605
Panel effects	District-Year	District-Year
Year Effects	Yes	Yes
Observations	1,553	1,553

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. Treatment variable - ln(world coal prices)*active mine status. All variables in logs; District level data on rural labor force participation compiled from the Employment and Unemployment Surveys of NSS (NSS55, NSS61, & NSS68); District level data on number of schools and teachers is used from the District Information on Schools (DISE) India Data (Years: 2000, 2005, 2011) ; World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11).

Table 3.16 – Testing for Migration

Labor Composition	(1) LFP	(2) Female LFP	(3) Male LFP
Coal prices*Active mine	0.00384	-0.00462	0.00256
	(0.0235)	(0.0524)	(0.0484)
Constant	-0.633***	3.497***	11.32***
	(0.167)	(0.537)	(0.367)
Observations	1,553	1,553	1,546
R-squared	0.136	0.022	0.062
No. districts	605	605	604
Year FE	Yes	Yes	Yes
Panel	District-Year	District-Year	District-Year
Population	Total Working Age	Female Working Age	Male Working Age

Note: Robust standard errors clustered at district level in parentheses *** p<0.01, ** p<0.05, * p<0.1. LFP: Labor Force Participation. Treatment variable - ln(world coal prices)*active mine status. All variables in logs; District level data on rural labor force participation compiled from the Employment and Unemployment Surveys of NSS (NSS55, NSS61, & NSS68); World Coal prices are taken from World Bank Commodity Price Database and the districts with coal mines are identified using the Statistics of Mines in India, Volume I (Coal) (Year 2010-11).

Table 3.17 – Price-Pass Through Regression Results

Indian Coal Price	(1) Model 1	(2) Model 2
World Coal Price	0.903***	0.739***
	(0.0301)	(0.0286)
Constant	1.181***	1.900***
	(0.115)	(0.128)
Observations	49,715	49,715
R-squared	0.319	0.338
Year FE	Yes	No
State FE	Yes	No
State-Year FE	No	Yes

Note:Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; ASI Yearly Data 2001-02 -2010-11; All variables in logs.

Table 3.18 – Production-Pass Through Regression Results

Indian Coal Production	(1) model 1	(2) model 2	(3) model 3	(4) Dynamic Panel
Indian Coal price		0.0947**		
		(0.0416)		
World Coal price	0.124**	0.0673*		0.0521***
	(0.0460)	(0.0372)		(0.0198)
FD_world coal price			0.0199	
			(0.0155)	
Lag_coal production				0.736***
				(0.163)
Constant	0.537***	0.411	0.0197***	0.0777
	(0.190)	(0.249)	(0.00690)	(0.120)
Observations	312	298	281	248
R-squared	0.085	0.117	0.005	
Number of States	32	30		31
Panel FE	Yes	Yes		
FD-FE			Yes	

Note: standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; ASI Yearly Data: 2001-02 – 2010-11 used, Collapsed at State level using means; Panel setup: State – Year

Chapter 3 - Summary Statistics

Table 3.19 – Summary Statistics: Household, Child and Maternal Characteristics

	IHDS -I 2004-05		IHDS -II 2011-12	
	Non-Coal	Coal	Non-Coal	Coal
Household Characteristics				
Household size	6.42	6.2	5.86	5.74
No. married women	1.46	1.44	1.413	1.416
No. children 0-14 yrs	2.26	2.12	1.84	1.76
ln(1+MPCE)	6.43	6.29	7.31	7.19
Child Characteristics				
Age in months	37.05	37.25	41.99	45.52
Female	0.47	0.48	0.47	0.5
Hindu	0.81	0.767	0.804	0.769
Muslim	0.141	0.167	0.156	0.187
Christian	0.017	0.021	0.014	0.018
Sikh	0.013	0.001	0.01	0.0008
Other religion	0.016	0.041	0.013	0.023
Brahmin	0.04	0.036	0.038	0.04
OBC	0.437	0.396	0.186	0.183
SC/ST	0.302	0.407	0.682	0.603
Other caste	0.21	0.159	0.09	0.172
Urban	0.258	0.198	0.262	0.222
Maternal Characteristics				
Age	32.94	32.22	34.17	33.34
Primary education	0.166	0.167	0.159	0.176
Secondary education	0.313	0.275	0.392	0.37
Graduate	0.047	0.0296	0.066	0.049
Poor health	0.058	0.063	0.073	0.089
Fine health	0.282	0.398	0.15	0.11
Good health	0.659	0.538	0.772	0.8
BMI level (Kg/mt2)	21.57	20.62	22.65	21.79

Note: Weighted averages using data from IHDS-I and IHDS -II database.

Table 3.20 – Summary Statistics: Household head and Maternal decision making

	IHDS -I 2004-05		IHDS -II 2011-12	
	Non-Coal	Coal	Non-Coal	Coal
Household Head				
Age	48.18	46.36	50.11	48.74
Female	0.078	0.061	0.121	0.098
Literate (or not)	0.644	0.627	0.67	0.667
Mother decision making				
Mother Cooking Respondent	0.944	0.935	0.912	0.872
Mother N children Respondent	0.813	0.699	0.913	0.887
Mother Child ill Respondent	0.862	0.776	0.89	0.864
Mother Homework Respondent	0.315	0.278	0.5	0.547

Note: Weighted averages using data from IHDS-I and IHDS -II database.

Table 3.21 – Summary Statistics: Pregnancy check-ups, vaccinations for children, fertility trends

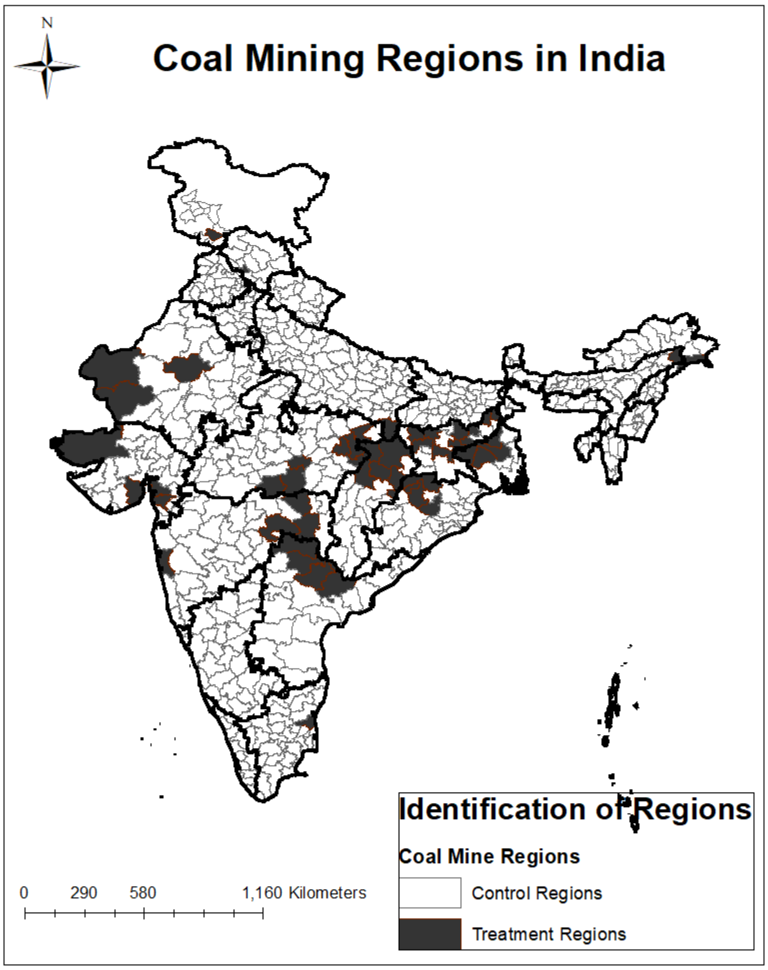
	IHDS -I 2004-05		IHDS -II 2011-12	
	Non-Coal	Coal	Non-Coal	Coal
Last Birth Pregnancy check-ups				
Antenatal checkup	0.739	0.846	0.849	0.904
Blood Test	0.549	0.573	0.7165	0.801
Urine Test	0.539	0.549	0.724	0.816
Abdomen check	0.606	0.654	0.774	0.808
Amino checkup	0.077	0.066	0.15	0.1208
Anaemia	0.174	0.223	0.284	0.246
Iron tablets	-0.328	-0.234	1.179	1.38
Vaccinations given [last birth]				
BCG given	0.745	0.795	0.9448	0.934
# DPT given	1.83	2.188	2.282	2.418
Polio frequency	4.206	3.342	4.09	3.655
months Vitamin A given	7.314	8.795	13.59	9.65
Breastfeeding	0.972	0.983	0.972	0.946
AWC beneficiary	0.359	0.465	1.09	1.351
Fertility trends				
Contraceptive usage	0.54	0.56	0.709	0.754
Total N children born	2.84	2.79	2.701	2.55
No. still births	0.062	0.09	0.074	0.062
No. miscarriages	0.166	0.176	0.204	0.179
No. children ideally	2.33	2.37	2.412	2.316
No. sons ideally	1.327	1.327	1.35	1.29
No. daughters ideally	1.032	1.07	1.129	1.09

Note: Weighted averages using data from IHDS-I and IHDS -II database.

Appendix Figures

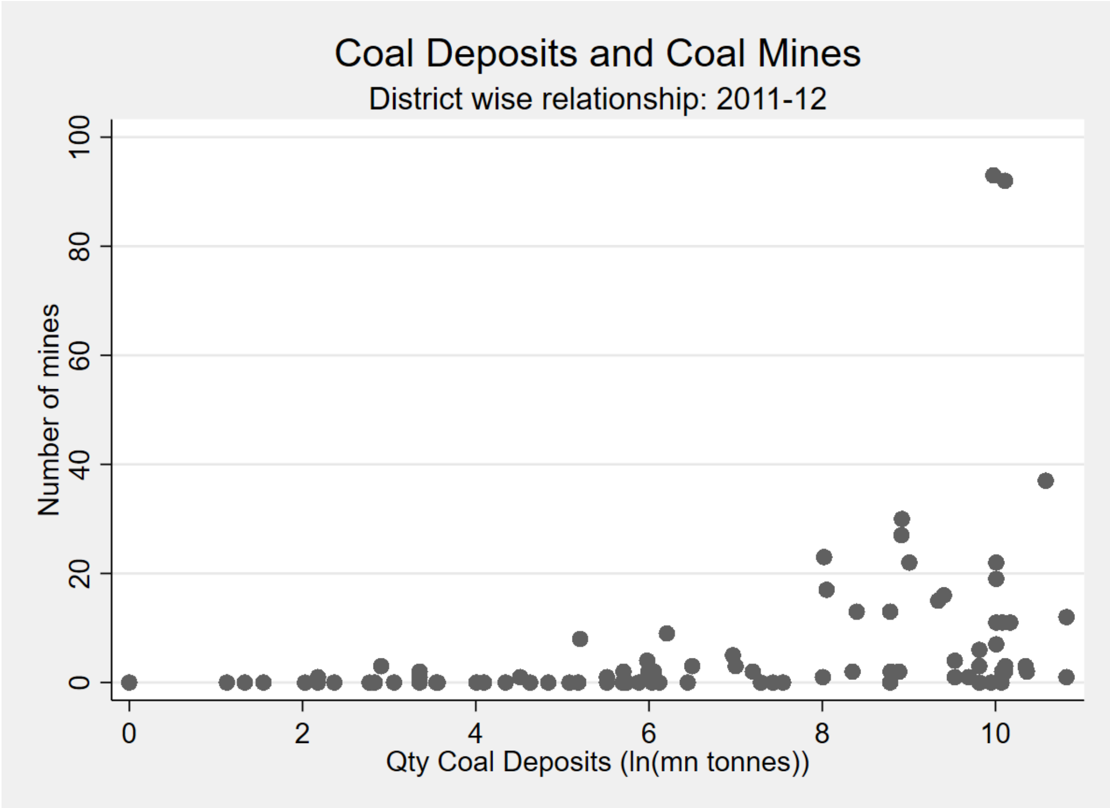
India Coal Map: Treatment vs Control Regions

Figure 3.1 – India Coal Map: Treatment vs Control Regions



Note: Map generated in Arc GIS, based on the presence of an active coal mine in a district in 2011. Data source:Statistics of Mines 2011, Vol. I (Coal): http://164.100.87.110/writereaddata/UploadFile/MERGED_COAL11.pdf

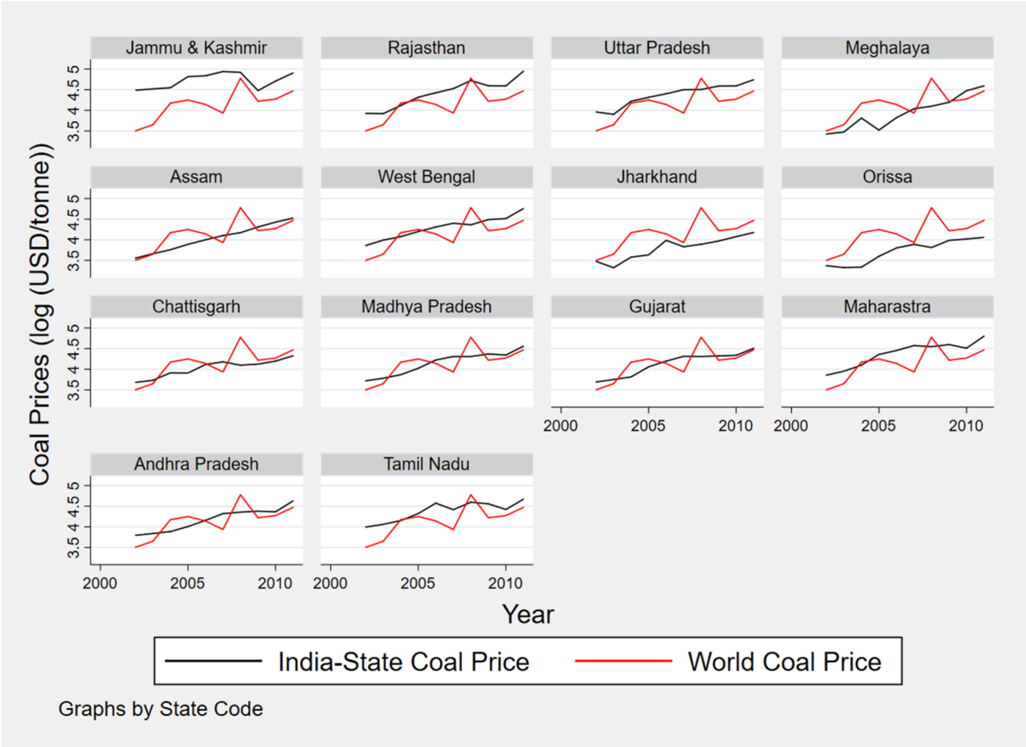
Figure 3.2 – Coal Mines and Deposits



Note: Graph generated in Stata using data on number of coal mines and quantity of coal produced across districts in 2011-12. Data Source: Statistics of Mines, Vol. I (Coal).

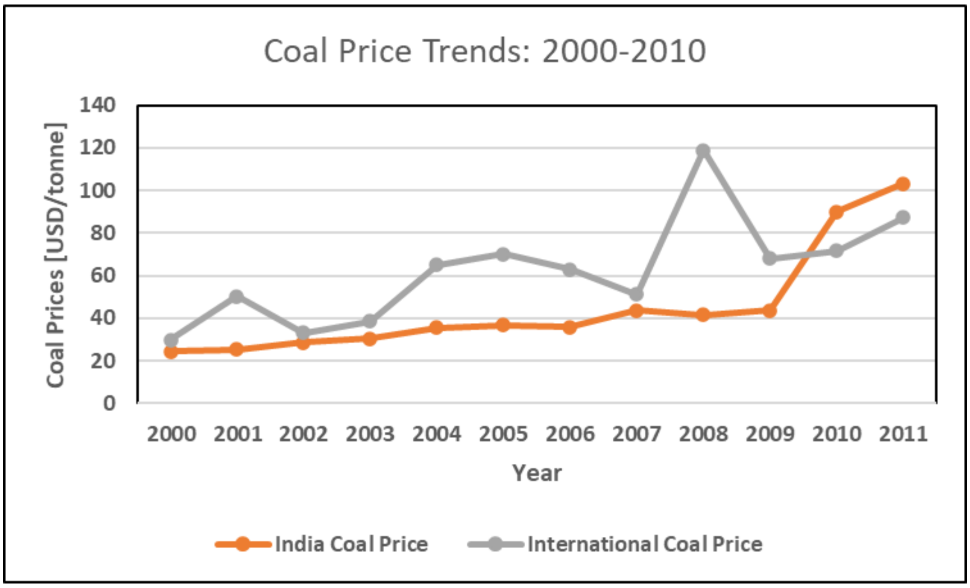
Coal Prices: Trends

Figure 3.3 – Coal Price Trends: Domestic and International



Note: Graph generated in Stata; based on the purchase price of coal by domestic firms in India at state level and international coal prices over the time 2001-2011. Domestic purchase price of coal calculated by aggregating the firm level prices at the state level for the states with active coal mines [Annual Survey of Industries Database 2000-2010]. International coal prices - US Central Appalachian Coal Spot price index [Coal Directory of India 2011-12 (and World Bank Commodity Database)]. The plot shows the trends in domestic coal prices for the 14 states in India which have active coal mines and the impact of international coal prices on these domestic coal prices.

Figure 3.4 – Coal Price Trends



Note: India Coal Prices: Steam Coal for Industry prices (USD/tonne) [Source: Coal Directory of India 2011]; International Coal Prices: US Central Appalachian Coal Spot price index [Coal Directory of India 2011-12 and (World Bank Commodity Database)]

Nutritional Trends

Figure 3.5 – Kernel Density Curves for Height-for-Age and Weight-for-Age Z-scores

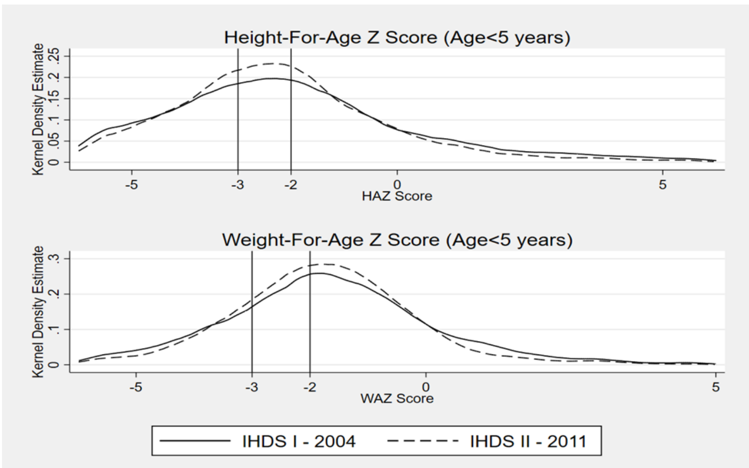
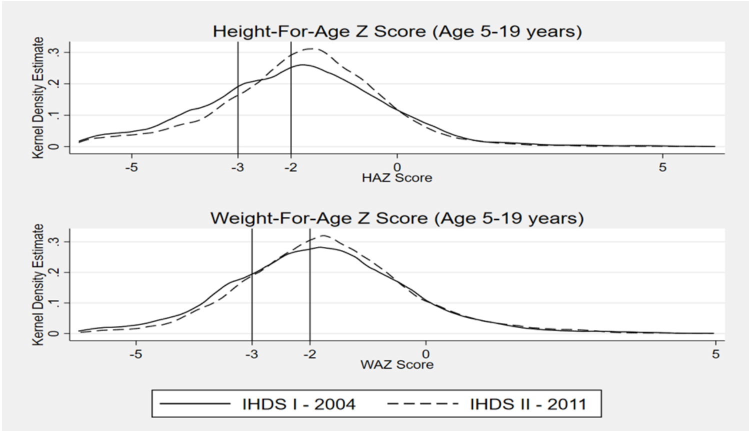


Figure 3.6 – Kernel Density Curves for Height-for-Age and Weight-for-Age Z-scores



Chapter 4

Local Effects of Coal Mining on Firm Productivity in India

4.1 Introduction

The economic impact of natural resource abundance on economic growth at a macro level and on human welfare outcomes at a micro level has received significant attention in the economic literature over the past two decades [Rosser, 2006, Aragón et al., 2015, Marchand and Weber, 2018b]. The non-renewable resources which are geographically concentrated are at the core of this analysis. The finite nature of such resources makes it imperative to consider the potential costs and benefits of resource extraction, thus identifying the ways for their sustainable use.

Mining of non-renewable resources is seen by many as having enclave effects [Hirschman, 1958], that is without any backward or forward linkages in the local economy. There is other literature that indicates positive demand shocks at a local level resulting in increase in demand for local goods and inputs due to resource booms [Aragón et al., 2015]. The local labor market effects of resource abundance and extraction have begun to be discussed in literature [Kotsadam and Tolonen, 2015, Aragón et al., 2018].[1] In relation to this literature, in this paper I attempt to examine the impact of resource abundance on firm productivity in India. This is a departure from the conventional literature available in this field which mainly focuses on socio-economic

[1]Detailed literature review on the labor market effects of natural resource abundance are discussed by [Marchand and Weber, 2018b].

outcomes for individuals and households. The analysis of firm productivity and employment behavior in mining regions allows a different take on the impact of resource abundance on real incomes in the regional economy.

In order to capture the impact of resource abundance on firm behavior at a local level, I use the presence of active coal mines in a district in India as an identifying factor along with the exogenous shock in the international coal prices. Since local coal mining activity is exogenous to firm performance in a region, and is mainly governed by local geology and domestic coal prices (in case of India), I am able to identify the impact of coal mining activity on firm performance at a local level in India. The Annual Survey of Industries database between 1999-2010, which is a detailed firm-level data in India is used for this analysis.

The paper contributes to the growing literature on the local effects of resource abundance in a developing country. It helps to visualize the impact of resource abundance from the vantage point of a modern industry which creates spillovers in the local economy resulting in spending effects, agglomeration effects and/ or congestion of limited resources resulting in factor re-allocation among local industries. This paper is one of the very first papers to address the impact of resource abundance on firm behavior at a local level and perhaps the first to address this in case of India having policy implications for similar developing nations around the world.

4.2 Literature Review

This paper aims to address the impact of natural resource abundance on the firm productivity at a local level in a developing country. In doing so, it firstly contributes to the existing and growing literature on economic impact of resource abundance which has established the various channels of its transmission at the macro level [Sachs and Warner, 1995, Gylfason, 2006, Mehlum et al., 2006]. At the sub-national level too, empirical studies have enriched this literature such as Boyce and Emery [2011] and Papyrakis and Gerlagh [2007] for US states, Asher and Novosad [2014a] for India and Zuo and Jack [2014] for Chinese provinces. These studies indicate a negative impact of resource abundance on economic growth. Moreover, it has also been established that the 'point' resources such as minerals and oil are more prone to generating the curse in economic growth at a macro level due to the appropriability of the resource [Boschini et al., 2004, Isham et al., 2005].[2]

The second strand of literature that this paper associates with is the local effects of resource abundance examined at a micro level. The localized effects of a resource boom or expansion of a resource sector are much more relevant in understanding the policy implications for a specific country and for the targeted stakeholders. These studies allow for greater dis-aggregation of economic responses and exogenous identification of impacts [Cust and Poelhekke, 2015].

This framework has potential for empirical analysis relating mining and resource booms to indicators of health, labor productivity, education, firm and agricultural productivity which can provide a better picture of human well-being than just analyzing their incomes and poverty indicators. Studies which directly relate mining activities to these outcomes are few. Mining pollution related impacts on health are shown by Von der Goltz and Barnwal [2014], on educational achievement are shown by Rau et al. [2013] and on agricultural productivity is shown by Aragón and Rud [2016]. The local effects of mining on real incomes, poverty and health outcomes for adults are discussed by Aragón and Rud [2013] and Loayza et al. [2013].[3][4] With regards to health outcomes, Aragón and Rud [2016] in another study, find adverse effects of mining activity on weight-for-height ratios and the prevalence of cough among children living in the vicinity (<20 km) of gold mines in Ghana, but no effects on stunting and diarrhea.

This paper strongly relates to the literature on local labor effects of resource abundance. Marchand and Weber [2018b] have detailed a review on local economic impacts of resource extraction by focusing on labor market outcomes. They have established that even though the broader consensus on economic linkages related to resource extraction seems bleak, it is seen that poverty fell in all regions with higher resource intensity. The local effects on employment spillovers due to coal 'boom' and 'bust' are examined by Black et al. [2005] in north-eastern United States, by Aragón et al. [2018] for coal mine closures in United Kingdom and by Kot-

[2] For a detailed literature survey of resource curse at macro level, refer Van der Ploeg [2011] and Rosser [2006].

[3] Aragón and Rud [2013] use difference-in-difference approach on micro-data at household level in Peru, to exploit the increase in the demand for local inputs in Yanacocha gold mine to find that strong backward linkages foster a positive economic impact on real income and poverty reduction among local population not directly linked to mining, such as farmers and service workers. Loayza et al. [2013] show positive impact on local living standards in Peru using district level data-set.

[4] Detailed review of literature at micro level is available in Aragón et al. [2015]

sadam and Tolonen [2015] in Sub-Saharan Africa for gender differentiated effects of gold mine openings and closings.[5] These studies in general indicate a permanent and persistent labor market shift towards manufacturing and services sector in times of mine closures or mining bust.

Following Aragón and Rud [2016], the paper aims to add to this literature by shifting the focus from households to firms to gain further insights into the mechanisms through which mining affects local economic activity (and ultimately household incomes).[6] In doing so, it could potentially relate to a parallel literature examining impact of resource booms and busts on industry outcomes through the theory of agglomeration economies and local Dutch disease arguments.

In a recent paper by Fafchamps et al. [2017], agglomeration effects are held accountable for increase in non-farm activities near gold mines in Ghana. Their study depicts that locations near gold mines show signs of proto-urbanization, having higher population densities and are the sites where sophisticated economic activity agglomerates.

In specific regards to firm productivity across countries, De Haas and Poelhekke [2019] estimate impact of local mining activity on business constraints faced by local firms in eight emerging economies to find that presence of active mines in immediate vicinity (<20km) enhances business constraints whereas this link weakens as firms move away in distance.[7] These constraints tend to stunt firm growth in terms of employment and sales. This reflects the local version of the Corden and Neary [1982] resource movement and spending effects model. It mimics the idea of Chinitz [1961] to some extent that mining towns may specialize in heavy industries with large scale economies. This can crowd out entrepreneurship by reducing access to inputs, capital and investment in skills thus reducing employment growth in such cities [Glaeser et al., 2015].

In contrast to this, [Michaels, 2010] examines the long-term economic impact of oil discov-

[5]The study indicates a modest increase in non-coal jobs during a boom and a reversal during the bust which seems more persistent in the long run. This labor market asymmetry is also seen during coal mine closures in United Kingdom [Aragón et al., 2018]. Kotsadam and Tolonen [2015] indicate labor market shift in favor of men on closures of mines with employment in manufacturing and services rising for men and decreasing for women. The structural shifts seem persistent and permanent even after the boom-bust situation ends especially for women.

[6]In Aragón and Rud [2016], the Ghanaian gold mining is held accountable for declining agricultural productivity in regions closer to mines and rising respiratory diseases and malnutrition in children.

[7]The sample includes Brazil, Chile, China, Kazakhstan, Mexico, Mongolia, Russia, and Ukraine.

eries in Southern U.S. counties exploiting geological variation in oil abundance during 1940 to 1990, to find that oil discoveries rather than leading to de-industrialization (as per local Dutch Disease argument), instead leads to an overall increase in employment levels suggesting presence of agglomeration economies. Similarly, [Allcott and Keniston, 2018] who by using manufacturing census data for US show that oil and gas booms have rather lead to agglomeration at a county level. They also however, point that wages did rise in resource booms but the effects of Dutch disease were very narrowly defined. Moreover, the gains from booms were also offset during busts.

Even though, the results in Allcott and Keniston [2018], Michaels [2010] and Black et al. [2005] reflect clean identification, it remains that these are very specific to the case of US. Further research at a similarly dis-aggregated level from less developed countries may shed more light on the phenomenon of Dutch disease or agglomeration at a local level in mining regions.

Therefore, this paper aims to address such questions at a local level in India with local revenue sharing schemes and industrial structure much different from that of US. Within India, micro level studies evaluating the impact of mining on development are limited mainly to sustainable livelihoods approach (case studies), such as Mishra [2009] shows, coal mining in Ib valley, Odisha has a positive impact on financial capital in the region, however, it reduces the social, natural and human capital in the region. At a sub-national level in India, Asher and Novosad [2014a], show that exogenous increases in mineral resource wealth result in broad-based economic growth in nearby towns, increasing employment across all manufacturing and service sectors. Thus, they find no strong evidence that growth in natural resource wealth results in a decline in sectors that compete for local factors of production is found in the long run. These results differ only in the short run, indicating that geography of the mineral rich regions might be the culprit rather than economic crowding out phenomenon.

4.3 Impact of Coal Mining on the Firm Productivity

The existing economic literature highlights two main mechanisms through which natural resources can impact the performance and output of manufacturing firms in general:

1. Resource abundance can be analyzed as change in endowments, and thus resource rich regions can be assumed as small open economies. In local regional economies, one can witness the crowding out of manufacturing sector at the expense of the resource rich primary sector due to rise in input prices for labor (assuming labor is immobile), land and capital. This is a variant of the local Dutch Disease model.

   So, if the traded sector is associated with knowledge spillovers and learning by doing benefits, then crowding out of this sector will hamper the economic growth of the region. However, in India, labor is immobile at a regional level, and land is fixed too, therefore changing local prices could only affect re-allocation of resources across the economic sectors within the regional economy.

2. Extractive industry can generate local demand shocks due to presence of backward linkages in the local economy. These impacts can be studied through spatial equilibrium models also used by urban economists to study housing demand and labor supply.[8] These models predict an increase in local population owing to local demand shocks if the labor is mobile in the region. Local population growth can then lead to negative externalities (congestion) or positive externalities (agglomeration) at the local level. Congestion occurs when there is additional pressure on local services such as education and health and competition for limited supply of infrastructure. Agglomeration effects emerge when spatially proximate firms benefit due to clustering of economic activity resulting in better availability of services and intermediate goods, and knowledge spillovers [Marshall et al., 1920].[9]

   Evidence on the magnitude of agglomeration economies generated by extractive industries is however not profound. Though, it is seen through De Haas and Poelhekke [2019]

[8] Discussion on this modeling approach linking with resource extraction has been done in detail by Aragón et al. [2015].

[9] See Combes and Gobillon [2015] for a survey of the agglomeration literature.

and also modeled by Moretti [2010], that the effects of an extractive industry can be heterogeneous, such that it would benefit the non-tradable sector such as services whereas have an ambiguous effect on tradable manufacturing sector.

In light of the mechanisms discussed above, I can test two hypothesis regarding the impact of coal mining on firm performance at a local level in India:

1. Coal price shocks result in higher wages and input prices in the regional economy. Factor re-allocation crowds out the availability of adequate resources for the manufacturing and services sector and result in a decline in their productivity.

2. Coal price shocks result in greater aggregate demand in the regional economies. This channels into greater demand of inputs and products from all industries (mining and other ancillary industries). Spending effects are also witnessed with greater aggregate demand, through greater investments by governments, mining companies and other industries. These result in benefits of agglomeration and a pervasive increase in firm productivity is witnessed in the mining economies.

4.4 Data description

The study data-set comprises the unit level Annual Survey of Industries (ASI) series from 1999-2000 through 2010-11.[10]The unit of observation is a factory in case of manufacturing industries and a firm for agriculture and service related industry. It covers registered factories/plants, i.e., units with 10 or more workers in plants using electric power or 20 or more workers in plants using no electric power (and as registered under sections 2m(1) and 2m(11) of the Factory Act, 1948).[11]It consists of (i) a census of firms with over 50 employees with power (99 without power) and (ii) a sample of the remaining registered plants or factories with 10-50 employees with power (20-99 employees without power.) The reference period for annual coverage of premises is the preceding 12 months. The information generated from the ASI data includes

[10]Data accessed from Central Statistical Organization (CSO), MoSPI, Government of India during a previous economic study for Ministry of Science and Technology, GOI.

[11]Refer for details on ASI data: http://www.mospi.gov.in/asi

number of workers and number of employees besides the detailed economic profile of the plants. The data used in the paper is at 5-digit industry level of dis-aggregation.

The industrial classification used in ASI is based on NIC (National Industrial Classification) which has changed from NIC 1998 to NIC 2004 to NIC 2008 in this study sample. The data was made consistent to allow for these changes by following the concordance tables published by the Central Statistical Organization in India. The NIC 1998, based on UNISIC, 1990 (Rev. 3) was used from ASI 1998-99 to ASI 2003-04. NIC 2004, based on UNISIC 2002 (Rev. 3.1) had been used from ASI 2004-05 to 2007-08. NIC 2008 based on UNISIC Rev 4 has been adopted from ASI 2008-09 on wards.[12]

To avoid capturing inflation effects in the analysis while using nominal variables, each industry group data is deflated using the wholesale price index (WPI) corresponding to that industry product. The WPI is the most broad-based deflator available. Different WPI series were spliced to keep 2004-05 as the base year with the latest WPI series being used for 2004-05.

The yearly data set used from 1999-2000 till 2010-11, does not provide unique identifiers for each firm over the years but is still used in this study over the panel data set for the same time period as it also provides the location details (state code/district code) for each firm which is suppressed in panel data for protecting the identity of firms. All other details in these data sets are same and therefore with further identification exercises through the firm characteristics such as age of firm or size or firm, the panel data could be used for future analysis.

4.4.1 Identification strategy

In this paper, the treatment intensity is measured through the interaction of international coal prices over the time period 1999-2010, with the presence of active coal mines in a district. The unit of analysis will be at the individual firm level while exploiting the district level variation as the identification of coal mines is performed at a district level in India.[13]The number of districts in India increased from 519 in 1999-2000 to 627 in 2011-12 as several new states were created

[12]UNISIC: United Nations International Standard Industrial Classification of All Economic Activities. The ISIC Rev. 4 can be accessed from: https://unstats.un.org/unsd/cr/registry/isic-4.asp

[13]The district is the lowest administrative unit within a state at which data is readily available in India. It typically covers a radius of 40 km

in the year 2000 along with the breakup of various old districts into multiple new districts.[14]The locations and district codes were matched across the years and made consistent for uniformity.

Since, district-wise data for presence of coal mines is available readily beginning 2010, I consider the 2011 active mine status as the treatment effect. Moreover, the state level data on number of coal mines reveals negligible change in active mine status across the states. Therefore, without loss of generality it is convenient to assume that active mine status at a district level also remained similar over the years. This can also be witnessed in data available post 2010 at a district level. The opening and closing of mines therefore, do not serve as an adequate base for treatment effect as the variation is extremely low. There are 52 major districts that have reported any coal or lignite mining in 2010-11 (these are the treatment districts for this paper).

The identification strategy exploits the fact that local presence of mining deposits is exogenously determined and it can be considered as a quasi-experimental setting allowing me to estimate the general equilibrium effects of mining activity on local firm output. Assuming, that exploration intensity is driven by institutional quality, investment climate in the region or environmental regulation, these effects will be taken care of by the region specific fixed effects and trends [De Haas and Poelhekke, 2019].

Based on this identification principle, 52 major districts in 13 states in India out of 34 states are identified as rich in coal & lignite. These states constitute around 64% of the firms surveyed through ASI data over the sample years (Table 4.11).

The data on international coal prices is available from the World Bank Commodity Price Data and on the domestic prices at a national level is available from the Coal Controller of India[15]. The domestic coal prices of coal vary according to the grade of coal.[16] The domestic coal prices are not directly available at a district or state level and therefore the purchase price of domestic coal by firms is used to calculate the average district level price of coal for each year. This analysis is also performed using the Annual Survey of Industries (ASI) data-set (1999-2011). With data on international coal prices and domestic coal prices at the state level

[14]Otherwise, the boundaries of districts have remained fairly stable since colonial times.

[15]Both these data variables are made available in the Coal Directory of India 2011-12.

[16]There were 93 districts in the 68th round and 79 districts in 55th round having coal or lignite deposits.

in India, price-pass through regressions are performed to validate the use of international coal prices as an independent instrument in the model.

Thus, Price-Pass through models estimating the percentage change in domestic coal price (and domestic coal production) due to a percentage change in international coal price (both measured in USD/tonne) are set up:

$$P_{st} = \alpha_0 + \alpha_1 \cdot P_t^* + \gamma_s + \theta_t + \varepsilon_{st} \tag{4.1}$$

The Eq. 4.1, shows the effect of international coal prices P^* at time t on the domestic coal prices P in a given state s at time t also controlling for state (γ_s) and time (θ_t) fixed effects.

The results on price-pass through regressions suggest a positive and significant pass-through from international coal prices on both domestic coal prices and production of coal, which are robust to the inclusion of varied fixed effects. A 10% increase in world coal prices brings a 7-9% increase in the domestic coal price while the domestic production increases by 0.5-1.2%.[17]

Table 4.1 – Price-Pass Through Regression Results

Indian Coal Price	(1) Model 1	(2) Model 2
World Coal Price	0.903***	0.739***
	(0.0301)	(0.0286)
Constant	1.181***	1.900***
	(0.115)	(0.128)
Observations	49,715	49,715
R-squared	0.319	0.338
Year FE	Yes	No
State FE	Yes	No
State-Year FE	No	Yes

Note:Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; ASI Yearly Data 2001-02 -2010-11; All variables in logs.

[17]These results correspond to the use of yearly data; with panel data the coefficients are much smaller: 0.9-3%.

Table 4.2 – Production-Pass Through Regression Results

Indian Coal Production	(1) model 1	(2) model 2	(3) model 3	(4) Dynamic Panel
Indian Coal price		0.0947**		
		(0.0416)		
World Coal price	0.124**	0.0673*		0.0521***
	(0.0460)	(0.0372)		(0.0198)
FD_world coal price			0.0199	
			(0.0155)	
Lag_coal production				0.736***
				(0.163)
Constant	0.537***	0.411	0.0197***	0.0777
	(0.190)	(0.249)	(0.00690)	(0.120)
Observations	312	298	281	248
R-squared	0.085	0.117	0.005	
Number of States	32	30		31
Panel FE	Yes	Yes		
FD-FE			Yes	

Note: standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; ASI Yearly Data: 2001-02 – 2010-11 used, Collapsed at State level using means; Panel setup: State – Year

4.4.2 Variables used in analysis

The variables used in the analysis include Ex-factory value of output for measuring firm output, Net value of fixed assets used by firm as on closing date for fixed capital, working capital used by firm as on closing date for working capital, total number of employees or man days worked in a year for labor.[18] All value variables are measured in Rupees (Rs.) which is the currency denomination in India.

The Ex-factory value of output is the value of gross output for the firm which is defined to include the ex-factory value, (i.e., exclusive of taxes, duties, etc. on sale and inclusive of subsidies etc., if any) of products and by-products manufactured during the accounting year, and the net value of the semi-finished goods, work-in-process. This variable is the main dependent variable in the analysis and can be analyzed separately for different kind of firms such as manufacturing, agriculture and service sector.

Fixed Capital represents the depreciated value of fixed assets owned by the factory as on the opening day of the accounting year. Fixed assets are those, which have normal productive life of more than one year. It would include land, building, plant and machinery, transport equipment

[18] 31st March is the closing date for the financial year based on which each firm keeps its accounting books.

etc. Working Capital is the sum-total of the physical working capital (physical inventories of intermediate inputs used such as fuel, lubricants etc.) and the cash deposits in hand and at bank, minus liabilities if any.

In addition to these variables, purchase value of all intermediate inputs and purchase value of imported inputs is also included in the model. The firm specific factors such as location of the firm and the type of ownership (public/ private/ joint ownership) are controlled to account for firm heterogeneity.

4.5 Empirical Methodology and Discussion of Results

4.5.1 Empirical Method

The aim of the empirical analysis is to explore the importance of coal and lignite mining on manufacturing activity. In doing so, the analytical framework discussed above allows me to estimate a production function conditional on inputs and evaluate the effect of mining on the firm productivity. This method and discussion of the empirical strategy is similar to Aragón and Rud [2016] where they estimate the 'agricultural' production function for Ghana controlling for distance to nearest gold mines to estimate impact of gold mining on agricultural productivity. While, in this paper I estimate the 'firm' production function for India controlling for the presence of an active coal mine in the district.

The formulation of the firm production function is as below:

$$Q_{idt} = A_{idt}.L_{it}^{\alpha}.T_{it}^{\beta}.\varepsilon_{idt} \tag{4.2}$$

Where Q is the expected output, A is the total factor productivity, L and T are labor and fixed capital respectively. All these variables vary for firm i in region d over time t. The region can be defined as a district in India,

The above production function can be further estimated using the observed output (Y) through the function defined below (Eq.4.3).

$$Y_{idt} = Q_{idt}.e^{\varepsilon_{idt}} \tag{4.3}$$

The total factor productivity (A_{idt}) for a firm is assumed to be comprising of three components; firm heterogeneity (η_i), time invariant local economic factors (ρ_d) and some time varying factors which I assume are related to the presence of mining activity (M_{dt}).

$$A_{idt} = exp(\eta_i + \rho_d + \mu.M_{dt}) \tag{4.4}$$

The above production function which is assumed to be of the Cobb-Douglas variety can then be expressed as Eq. 4.5, with y, l & t as logs of observed output, labor and fixed capital respectively.

$$y_{idt} = \alpha.l_{idt} + \beta.t_{idt} + \mu.M_{dt} + \eta_i + \rho_d + \varepsilon_{idt} \tag{4.5}$$

If presence of mining activity in the region constrains the availability of inputs thereby causing crowding out of manufacturing output, then it would be channeled through change in input prices and not through the productivity parameter (A). As a consequence, if mining affects the firm productivity through non-market spillovers such as congestion or agglomeration then it would be captured through A. Since, much of these productivity effects are affected by the presence of mining activity, the coefficient on M (which is μ) would reflect it assuming time invariant firm characteristics and time varying factors are controlled for. Productivity decline due to 'congestion' would imply a negative μ and productivity increase due 'agglomeration' would imply a positive μ.

The specification in Eq. 4.5 is subject to certain empirical challenges. The first challenge is based on the identification assumption that coal rich and non-coal rich regions are exogenously determined by the presence of deposits and business constraints do not endogenously affect the presence of mines as such, therefore, there can be systematic differences in productivity between the regions implying that $E(M_{dt}.\rho_d) \neq 0$ and ρ_d is unobservable. This omitted variable problem may lead to endogeneity issues, thus generating biased estimates. To account for this, time variation in the repeated cross-section can be exploited to compare evolution of productivity in mining regions versus non-mining regions. This way the productivity can now be reflected by the variable ($coalmine_{active} * coal_{price}$), where $coalmine_{active}$ is a dummy variable reflecting the presence of coal mine in the region and $coal_{price}$ is the international coal price over the time period 1999-2010. With a strong economic link between international coal prices and domestic coal prices and production, the identification challenge is further alleviated as international coal prices are completely independent of any domestic factors that can affect the location of firms and mines in specific regions. The use of these price trends therefore, serves as an instrument variable in the analysis which addresses various endogeneity concerns. This allows me to capture the fact that the value of coal production has been growing over the sample years as well (Table 4.10).

The second challenge with regards to the above specification is the simultaneity bias that is predominant with estimation of production functions as output and inputs are simultaneously determined. Due to this, the unobserved firm characteristics (which are mapped by η_i) would enter the error term and lead to endogeneity issues in estimating input coefficients. This problem can be solved by using a panel data and using instruments based on lagged input decisions.[19] However, the data used for analysis in this paper is a repeated cross-section and even though a panel data set for firms in India is available, it can't be used without various identification restrictions due to the absence of location details of firms in that data-set which is crucial for the identification exercise. Therefore, a proxy for η_i & ρ_d is used by controlling for observable firm characteristics and region fixed effects respectively.

The new specification that is tested in the paper thus becomes:

$$y_{idt} = \mu.M_{dt} + \alpha.l_{idt} + \beta.t_{idt} + \vartheta.Z_i + \phi_d + \varepsilon_{idt} \tag{4.6}$$

Where μ as the coefficient on treatment intensity will capture the impact of firm productivity, α and β – capture the impact of labor and capital inputs, ϑ the impact of firm controls and ϕ_d will be the region (district) fixed effects. The unobserved heterogeneity in η_i & ρ_d will then fall into the error term ε_{idt}.

[19]It has been dealt in empirical literature through two approaches dynamic panel models and structural estimation methods. See for example Blundell and Bond [2000] and Levinsohn and Petrin [2003].

The set of firm controls that will be used include, ownership status of the firm (public/private) and region in which the firm operates (urban/rural).

Under the assumption that use of inputs is uncorrelated to the unobserved heterogeneity captured by error term in Eq. 4.6, a simple OLS on the repeated cross-section can be performed. Further, any unknown/unmeasurable parameters that are specific to each state and year can impact the firm productivity in a region. These in general fall into the error term as well. In order to avoid any correlation of such errors across state-year combination, I use standard errors that are clustered at the State-year level.

4.5.2 Discussion of Results

The regressions based on the firm production function described in previous section, show that the ex-factory output for firms responds positively and significantly to inflow of working capital, basic inputs purchased domestically and imported. The opening value of fixed capital has a negative and significant effect as the fixed capital faces depreciation over the year and is used up in the process, therefore factory level output is negatively affected by it.

Apart from the main inputs, the treatment effect, which is assumed to capture the productivity effect, is also positive and significant. The level of significance improves in the second model as the state-year interacted fixed effects are introduced. These fixed effects account for the state specific policy changes that occur every year which can impact the firm's productivity indirectly. The standard errors are also clustered at the interacted state-year level to control for any correlations in standard errors at the state level every year. This was done as, in India the state policies have a major role in impacting the climate for firm operation located in those states. The district policies are not relevant in this context as such, as the revenue generation and taxation etc. are all taken care by the state governments. The state policies are subject to changes every year and therefore, a state-year interaction was used for clustering the standard errors along with it's use in the form of fixed effects.

The baseline results suggest a rise of 7.68% points (Col1) - 10.34% points (Col2) in productivity [with coal price elasticity for firm output being 0.04-0.05] for the firms relative to national trends in coal districts of India, when exposed to an average rise in international coal prices (192%) over the time period 1999-2010, holding all other factors and inputs constant.

Table 4.3 – Impact of Coal Mining on Firm Productivity

Ln(ex-factory output)	(1) Model 1	(2) Model 2
Coal prices*Active mine	0.0420*	0.0539**
	(0.0234)	(0.0246)
Ln(Fixed capital)	-0.0165***	-0.0165***
	(0.00227)	(0.00226)
Ln(Working capital)	0.0134***	0.0135***
	(0.00227)	(0.00226)
Ln(Purchase value inputs)	0.873***	0.873***
	(0.00801)	(0.00806)
Ln(Purchase value imports)	0.0436***	0.0436***
	(0.00100)	(0.001000)
Ln(Total wages employees)	0.130***	0.130***
	(0.00538)	(0.00541)
Constant	0.247***	0.238***
	(0.0641)	(0.0643)
Observations	283,459	283,459
R-squared	0.881	0.881
Firm effects	Yes	Yes
Industry FE	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	No
State-Year FE	No	Yes

Note: Robust standard errors clustered at state-year level, in parentheses *** p<0.01, ** p<0.05, * p<0.1. Data source: Annual Survey of Industries (1999-2010). Industry FE: two digit industry classification based on NIC 2008. Treatment variable - ln(world coal prices)*active mine status. Firm controls: Location of firm; Type of ownership. Fixed capital and Working capital are opening values of fixed and working capital.

The positive impact on the firm productivity as suggested in Table 4.3, can be attributed to positive demand shocks that are generated when exposed to the coal price shock. Rising coal prices possibly cause the prices in the local economy to rise, resulting in positive aggregate demand shocks, thus benefiting other industries and firms in the local economy through greater demand for products. As seen from ASI data 2000-2010, coal is an important input in most manufacturing industries ranging from food products, grains, animal feeds, beverages, tobacco products, textiles, leather, wood products, paper to metals, minerals and alloys. This is also seen in input output tables published by Ministry of Statistics and Policy Implementation (MoSPI 2008-09). Hence, with extensive forward linkages in local economy, rising coal prices would impact other prices in local economy too. At the same time, coal mining has extensive backward linkages too (as discussed in Section 1.1 of this thesis), therefore causing the local wages to rise due to increased demand for labor. This points in the direction of agglomeration theory that is hypothesized in Section 3.

In order to clearly demarcate the productivity rise through the various sectors in the regional economy, production function regressions are carried out for three broad economic sectors: agriculture and allied sector, manufacturing sector and services sector. In Table 4.4, the production regressions are shown for the manufacturing sector as the treatment effect is not significant for agriculture and services sector, even though the general response to fixed and intermediary inputs is positive and significant for all sectors. The results for manufacturing sector are very similar to the results presented in Table 4.3 for all firms in general. This indicates that the productivity rise is mainly driven by the manufacturing sector. It is also true that agriculture and service sectors are relatively small in the regional economy compared to the manufacturing sector. This could justify the manufacturing sector driving the firm productivity in mining economies in India.

Table 4.4 – Impact of coal mining on manufacturing output

Ln(ex-factory output)	(1) Model 1	(2) Model 2
Coal prices*Active mine	0.0399*	0.0557**
	(0.0232)	(0.0239)
Ln(Fixed capital)	-0.0135***	-0.0135***
	(0.00222)	(0.00222)
Ln(Working capital)	0.0139***	0.0140***
	(0.00227)	(0.00226)
Ln(Purchase value inputs)	0.878***	0.878***
	(0.00775)	(0.00778)
Ln(Purchase value imports)	0.0457***	0.0457***
	(0.000960)	(0.000959)
Ln(Total wages employees)	0.142***	0.142***
	(0.00584)	(0.00586)
Constant	0.363***	0.354***
	(0.0416)	(0.0423)
Observations	280,061	280,061
R-squared	0.884	0.884
Firm effects	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	No
State-Year FE	No	Yes

Note: Robust standard errors clustered at state-year level, in parentheses *** p<0.01, ** p<0.05, * p<0.1. Data source: Annual Survey of Industries (1999-2010). Industry FE: two digit industry classification based on NIC 2008. Treatment variable - ln(world coal prices)*active mine status. Firm controls: Location of firm; Type of ownership. Fixed capital and Working capital are opening values of fixed and working capital.

4.5.3 Mechanisms

The rising firm output and productivity in regions with coal mines can be examined in detail via the impact of coal price shock on the demand for local inputs such as labor and on the fixed capital such as plant and machinery which are crucial inputs and investments in a production function for enhancing the firm outputs.

In Table 4.5, the impact of treatment effect is seen on the employment levels across the different economic sectors. Two kinds of employment related variables are used to study the impact, the average person worked in every firm and the total number of employees in a firm. In both analysis the coal price rise has a positive and significant effect on the employment level in a firm (in any sector) in the coal mining regions of India. This impact is however, highest for the agriculture and allied sector as this sector also comprises of the mining activities which get an instant push due to the coal price rise. Increased demand of labor is a plausible explanation of the rising aggregate demand in the local economy owing to the rising prices of coal world-wide.

Table 4.5 – Impact on coal mining on employment status

Ln(avg person worked)	(1) Agriculture and allied	(2) Manufacturing	(3) Services
Coal prices*Active mine	0.159***	0.0419**	0.0276***
	(0.0214)	(0.0168)	(0.00996)
Constant	3.674***	5.126***	3.562***
	(0.216)	(0.0603)	(0.0869)
Observations	7,360	400,675	15,367
R-squared	0.128	0.067	0.071
Ln(total employment)	**Agriculture and allied**	**Manufacturing**	**Services**
Coal prices*Active mine	0.165***	0.0457**	0.0289***
	(0.0246)	(0.0190)	(0.0105)
Constant	8.860***	10.85***	9.305***
	(0.251)	(0.0662)	(0.0909)
Observations	7,360	400,675	15,367
R-squared	0.073	0.059	0.063
Firm effects	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Note: Robust standard errors clustered at state-year level, in parentheses *** p<0.01, ** p<0.05, * p<0.1. Data source: Annual Survey of Industries (1999-2010). Treatment variable - ln(world coal prices)*active mine status.

In Table 4.6, the impact of coal price rise on the value of plant and machinery used by firms is examined across the Indian regions. The results suggest an increase of approx. 15.36% in the value of plant and machinery used by firms in coal districts of India over the time period 1999-2010, when exposed to the average coal price shock. This supports the idea that firms in coal districts of India are investing more in the technology when faced with rising coal prices, thus suggesting that aggregate demand is higher in the local economy .

Table 4.6 – Coal Price Shock: Value of Plant and Machinery in firms

Ln(Closing value Plant and Machinery)	**(1) Model 1**	**(2) Model 2**
Coal prices * Active mine	0.0810***	0.0811***
	(0.0283)	(0.0287)
Constant	13.09***	13.43***
	(0.203)	(0.197)
Observations	405,745	405,745
R-squared	0.078	0.082
Firm effects	Yes	Yes
Industry FE	Yes	Yes
Year Fe	Yes	No
State FE	Yes	Yes
State-Year FE	No	Yes

Note: Robust standard errors clustered at state-year level, in parentheses *** p<0.01, ** p<0.05, * p<0.1. Data source: Annual Survey of Industries (1999-2010). Firm controls: Location of firm; Type of ownership. Industry FE: two digit industry classification based on NIC 2008. Treatment variable - ln(world coal prices)*active mine status.

Together, these effects on labor demand and investment in technology are indicative of the agglomeration effects that are visible in these regions. These positive demand shocks that generate due to the coal price rise are held accountable for rising firm productivity.

4.5.4 Heterogeneous Effects

In this section, I discuss the heterogeneous effects of coal price shock on the employment levels and wages across the three economic sectors for male and female workers. In addition to these effects, I also examine how the investments in plant and machinery vary according to the different economic sectors when exposed to the coal price shock.

In Table 4.7, the sectoral distribution of changes in employment of workers directly employed in the three main sectors shows an upward trend for both males and females in the coal districts of India over the time period 1999-2010. The employment of males has been statistically significant and higher than females in all sectors whereas the female employment has increased mainly in agriculture and allied sector and the manufacturing sector with a greater shift towards the agriculture and allied sector.

This shows that when international coal prices rise, male workers in coal districts of India find jobs in all sectors with their employment impact greater than female workers as well. Males and females are both drawn to the agricultural and mining related sector alike owing to the growing wages in that sector. The coal price rise brings greater employment in agricultural and mining sectors followed by manufacturing and services.

Table 4.7 – Coal Price Shock: Gender and Industry wise employment status

	Agriculture and allied		Manufacturing		Services	
Ln(number workers)	Males	Females	Males	Females	Males	Females
Coal prices *Active mine	0.190***	0.0682***	0.0555**	0.0292**	0.0222*	0.0108
	(0.0252)	(0.0242)	(0.0223)	(0.0140)	(0.0129)	(0.103)
Constant	7.839***	8.192***	10.34***	8.457***	8.700***	6.817***
	(0.283)	(0.242)	(0.0634)	(0.0769)	(0.101)	(0.399)
Observations	6,172	3,935	365,257	110,698	14,413	790
R-squared	0.160	0.055	0.070	0.111	0.067	0.108
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at state-year level, in parentheses *** p<0.01, ** p<0.05, * p<0.1. Data source: Annual Survey of Industries (1999-2010). Firm controls: Location of firm; Type of ownership. Treatment variable - ln(world coal prices)*active mine status.

The sectoral distribution of worker wages for both male and female workers reflect that in the coal mining districts, the coal price rise has led to an increase in wages in all sectors with the maximum impact being in the agriculture and mining related sector followed by the manufacturing and services sector (Table 4.8) . The wages for male workers increase significantly in all sectors whereas females only witness a significant increase in the agriculture and mining sector. The increase in wages is in general higher for males than females in any sector. This also mirrors in the employment distribution of male and female workers living in coal districts of India across the three sectors post the rise in world coal prices.

Table 4.8 – Coal Price Shock: Gender and Industry wise effect on employee wages

Ln(worker wages)	Agriculture and allied Males	Agriculture and allied Females	Manufacturing Males	Manufacturing Females	Services Males	Services Females
Coal prices * Active mine	0.186***	0.0614**	0.0526*	0.00720	0.0314*	-0.0455
	(0.0242)	(0.0260)	(0.0278)	(0.0179)	(0.0165)	(0.0987)
Constant	8.495***	8.509***	11.77***	9.579***	10.31***	8.072***
	(0.314)	(0.260)	(0.0725)	(0.0887)	(0.124)	(0.446)
Observations	6,172	3,935	365,257	110,698	14,413	790
R-squared	0.193	0.066	0.100	0.102	0.158	0.196
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at state-year level, in parentheses *** p<0.01, ** p<0.05, * p<0.1. Data source: Annual Survey of Industries (1999-2010). Firm controls: Location of firm; Type of ownership. Treatment variable - ln(world coal prices)*active mine status.

In Table 4.9, the changes in the investments in plant and machinery by the firms across different economic sectors when exposed to the coal price shock are examined. The Net closing value of Plant and Machinery shows a significant increase w.r.t the treatment effect in the manufacturing sector only. Therefore, the stock of plant and machinery has significantly increased for manufacturing sector in the districts with active coal mines over the years experiencing a positive coal price shock from 1999-2010. A 10% increase in world coal prices causes the value of plant and machinery to increase in manufacturing firms by 8% points over 1999-2010.

This is a potential mechanism for explaining the positive productivity increase in firms located in districts with active coal mines over the years 1999-2010 when exposed to increasing world coal prices. These results especially highlight the idea that manufacturing firms in coal region of India secure the greatest advantage in rising levels of firm productivity when international coal prices rise. The increasing value of investments in technology in the manufacturing sector play a vital role in bringing this productivity jump.

Other economic sectors too benefit from the coal price shock due to increased employment levels, but the manufacturing firms in coal regions fare the highest productivity rise as they benefit both in employment levels and in increased technological investments.

Table 4.9 – Coal Price Shock: Industry wise impact on value of plant and machinery

Ln(P&M closing value)	(1) Agriculture and allied	(2) Manufacturing	(3) Services
Coal prices * Active mine	0.0936	0.0866***	0.0458
	(0.0670)	(0.0304)	(0.0299)
Constant	12.34***	15.35***	15.94***
	(0.540)	(0.106)	(0.334)
Observations	4,351	388,066	13,328
R-squared	0.128	0.069	0.273
Firm effects	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Note: Robust standard errors clustered at state-year level, in parentheses *** p<0.01, ** p<0.05, * p<0.1. Data source: Annual Survey of Industries (1999-2010). Firm controls: Location of firm; Type of ownership. Industry FE: two digit industry classification based on NIC 2008. Treatment variable - ln(world coal prices)*active mine status.

These heterogeneous effects indicate that rising international coal prices do result in better firm productivity in coal regions of India, but this result is mainly true for the manufacturing firms as they reap all benefits of increased aggregate demand, other firms in agriculture and service sector do not gain much out of the coal price shock as even though labor doesn't reallocate away from them, they still don't gain enough to be able to invest in technical know-how which is a key factor for rising productivity levels in any firm across the world.

4.6 Conclusion

In this paper, I discuss how the performance of firms is affected by the presence of active coal mines in their regions. The local effects of resource price shock on various socio-economic indicators such as real incomes, health, labor market shifts etc. have been discussed in the literature previously. This paper looks at these local effects from a different angle, which is from the point of view of the industry. Thriving local industry is also as much a prerequisite for local economic development as is the improvements in educational and health status of individuals living in these regions.

Making use of the international coal price rise between 1999-2010 as an instrument and an exogenous shock, this study highlights that presence of coal mining in a region could be beneficial for firm performance in general. The benefits of agglomeration activity are evidently visible in the local economy of regions with coal mines. These effects indicate that mining is not so much of an enclave sector in the Indian economy. The benefits of increased firm output are pervasive for all economic sectors, but it is the manufacturing sector which leads the race by attracting greater investments in technology thereby driving the rise in firm productivity in these regions. The higher firm performance in the coal rich regions could signal higher welfare of individuals living in those regions due to greater availability of work opportunities.

Mining of coal is also seen by many as an environmental externality. Presence of this externality can underestimate the contribution of coal mining to the Indian economy. Currently, the coal mining industry suffers from several snags in acquiring clearances and licenses for operation by private firms. The positive spillovers of this industry in this regard could be considered as a guide to allow for greater private participation given that Indian coal mining is still under its capacity with reserves much higher than current production levels and a domestic demand which is surpassing the supply since the last few years.

The study only presents a preliminary picture of the impact of coal mining on firm productivity and there is a scope for improvement and further research to address the endoegenity concerns. This can be improved with better data availability on various variables. The study is one of the first to implore the local effects of mining on firm productivity and the only study of such kind for India. It thus contributes to the growing literature on local effects of resource abundance particularly in a developing country.

Appendix Tables

Table 4.10 – Coal mining trends in India

Year	No. of mines	Qty. Produced (million tonnes)	Value of Production (Billion USD)	Average Number Employees
2002-03	562	367.3	3.87	422594
2003-04	562	389.2	4.10	416767
2004-05	571	413.1	4.87	405211
2005-06	556	437.1	5.35	398890
2006-07	570	462.1	5.59	385736
2007-08	570	491.1	6.18	371713
2008-09	574	525.2	7.35	369414
2009-10	573	566.1	8.22	373950
2010-11	573	570.4	9.90	368864
2011-12	573	582.3	11.27	368864

Source: Indian Bureau of Mines 2011-12 (1 USD = Rs. 67)

Table 4.11 – Firms reported in ASI Data: identification strategy

Identified on basis of Coal & Lignite		
year	Non-Rich	Rich
2002	15,452	26,790
2003	15,166	26,680
2004	21,205	35,684
2005	35,050	63,630
2006	41,546	73,062
2007	24,770	42,105
2008	21,645	35,243
2009	19,175	35,175
2010	19,643	37,471
2011	15,541	28,078
Total	**229193**	**403918**

Source: Self; Unit level ASI data set

Table 4.12 – Decomposition of firms based on industry classification (NIC 2008) in 2010-11

Decomposition of Industries in Coal & Lignite Rich Vs Non-Rich States (2010-11)		
Industry Category	Non Coal & Lignite	Coal & Lignite
Food products	1,997	4,634
Beverages	218	371
Tobacco	239	449
Textiles	1,262	2,552
Wearing apparel	610	1,278
Leather Products	152	738
Wooden products	568	759
Paper products	408	698
Printing & recorded media Products	227	645
Petroleum refining	98	222
Chemical industry	853	1,511
Pharmaceutical industry	463	673
Rubber & Plastic	828	1,241
Non-metallic minerals	1,920	2,367
Basic metals	806	1,688
Fabricated metal products	956	1,736
Computer products	299	462
Electrical equipment	627	1,057
Other machinery	1,113	1,430
Automobile industry	481	975
Other transport equipment	344	363
Furniture	110	192
Other manufacturing	297	508
Machinery Repair	69	145
Electricity, gas, steam supply	67	166
Water treatment & supply	6	16
Sewerage	8	13
Waste treatment & disposal	32	30
Other waste management	1	2
Building construction	1	
Civil engineering	1	
Wholesale/Retail motor trade	346	683
Other wholesale/retail trade		2
Land Transport - pipelines		2
Warehousing	44	293
Publishing activities	21	41
Motion picture/TV/Music	7	28
Computer programming	2	
Architecture		2
Other prof/scientific/technical	10	9
Building service/landscaping	5	2
Office administration	6	15
Social service	13	10
Repair -personal goods	11	43
Other personal	15	27
Total	**15541**	**28078**
(Based on ASI unit level data for 2010-11; NIC 2008)		

Table 4.13 – Chapter 4 - Summary Statistics

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Non-Coal Regions											
Net Opening Value Fixed Assets	10.92	11.05	11.25	11.36	11.08	10.99	10.98	11.23	11.53	11.56	11.56
Net Closing Value Fixed Assets	11.00	11.13	11.32	11.43	11.17	11.14	11.24	11.50	11.77	11.76	11.77
Opening Working Capital	10.45	10.56	10.78	10.89	10.70	10.60	10.53	10.74	11.01	11.06	11.05
Closing Working Capital	10.66	10.73	10.96	11.07	10.92	10.89	10.92	11.17	11.44	11.37	11.42
Net Closing Value of Plant & Machinery	13.68	13.86	14.09	14.15	13.85	13.78	13.95	14.11	14.48	14.59	14.57
Gross Sale Value of Output	13.00	13.06	13.17	13.29	13.14	13.20	13.22	13.43	13.67	13.69	13.65
Ex-Factory Value Output	12.88	12.94	13.04	13.14	12.99	13.05	13.10	13.32	13.56	13.58	13.56
Purchase Value Total Import	2.15	2.27	2.37	2.41	2.22	2.32	2.21	2.28	2.50	2.60	2.44
Purchase Value Total Domestic Input	12.54	12.63	12.70	12.82	12.69	12.76	12.80	13.01	13.23	13.23	13.21
Total Worker Wages	9.62	9.75	9.88	10.01	9.83	9.89	9.93	10.17	10.40	10.43	10.51
Toal Employee Wages	10.23	10.22	10.36	10.51	10.27	10.24	10.29	10.50	10.76	10.75	10.78
Average Person Worked	3.65	3.77	3.85	3.89	3.68	3.68	3.69	3.77	3.92	3.96	3.88
Male workers directly employed	8.61	8.69	8.74	8.77	8.56	8.53	8.54	8.61	8.76	8.79	8.71
Female Workers directly employed	8.09	8.19	8.28	8.36	8.14	8.16	8.16	8.24	8.37	8.38	8.22
Wages Male Workers	9.32	9.42	9.52	9.64	9.47	9.50	9.55	9.78	10.00	10.01	10.10
Wages Female Workers	8.50	8.62	8.75	8.93	8.75	8.82	8.87	9.12	9.33	9.30	9.33
Coal Regions											
Net Opening Value Fixed Assets	11.18	11.31	11.38	11.57	11.11	11.15	11.30	11.59	12.03	12.04	12.01
Net Closing Value Fixed Assets	11.21	11.32	11.41	11.63	11.22	11.35	11.58	11.77	12.18	12.22	12.19
Net Closing Value of Plant & Machinery	13.97	14.14	14.37	14.55	14.05	14.08	14.42	14.54	15.07	15.20	15.12
Opening Working Capital	10.70	10.82	10.93	11.07	10.70	10.75	10.85	11.08	11.48	11.53	11.44
Closing Working Capital	10.90	11.02	11.11	11.36	10.92	11.10	11.22	11.46	11.75	11.80	11.80
Gross Sale Value of Output	13.21	13.20	13.28	13.44	13.17	13.25	13.31	13.54	13.87	13.97	13.88
Ex-Factory Value Output	13.02	13.07	13.12	13.31	13.00	13.08	13.21	13.44	13.76	13.86	13.80
Purchase Value Total Import	2.15	2.34	2.31	2.47	1.96	2.46	2.46	2.28	2.75	3.04	2.85
Purchase Value Total Domestic Input	12.77	12.75	12.80	12.99	12.70	12.78	12.86	13.08	13.37	13.48	13.34
Total Worker Wages	9.78	9.91	9.96	10.15	9.84	10.02	10.03	10.25	10.57	10.68	10.72
Toal Employee Wages	10.34	10.41	10.45	10.66	10.24	10.33	10.40	10.49	10.84	10.95	10.89
Average Person Worked	3.79	3.92	3.96	4.04	3.74	3.82	3.81	3.85	4.08	4.18	3.96
Male workers directly employed	8.82	8.91	8.93	9.00	8.65	8.73	8.74	8.83	9.08	9.09	9.01
Female Workers directly employed	7.98	7.90	7.78	8.00	7.75	7.70	7.64	7.88	7.92	7.88	7.87
Wages Male Workers	9.49	9.61	9.62	9.81	9.48	9.67	9.71	9.95	10.26	10.32	10.36
Wages Female Workers	8.40	8.31	8.15	8.58	8.27	8.34	8.32	8.75	8.86	8.88	9.10

Note: All variables in logs. Average values presented in the table. Data source: Annual Survey of Industries 1999-2010.

Bibliography

NITI Aayog and IEE Japan. Energizing india: A joint project report of niti aayog and ieej, 2017.

Anjali Adukia, Sam Asher, and Paul Novosad. Educational investment responses to economic opportunity: evidence from indian road construction. *American Economic Journal: Applied Economics*, 12(1):348–76, 2020.

Pelle Ahlerup, Thushyanthan Baskaran, and Arne Bigsten. Gold mining and education: a long-run resource curse in africa? 2016.

Katherine Alaimo, Christine M Olson, Edward A Frongillo Jr, and Ronette R Briefel. Food insufficiency, family income, and health in us preschool and school-aged children. *American journal of public health*, 91(5):781, 2001.

Harold Alderman, John Hoddinott, and Bill Kinsey. Long term consequences of early childhood malnutrition. *Oxford economic papers*, 58(3):450–474, 2006.

Michael Alexeev and Robert Conrad. The elusive curse of oil. *The Review of Economics and Statistics*, 91(3):586–598, 2009.

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

Douglas Almond and Janet Currie. Killing me softly: The fetal origins hypothesis. *Journal of economic perspectives*, 25(3):153–72, 2011.

Douglas Almond, Lena Edlund, and Mårten Palme. Chernobyl's subclinical legacy: prenatal exposure to radioactive fallout and school outcomes in sweden. *The Quarterly journal of economics*, 124(4):1729–1772, 2009a.

Douglas Almond, Lena Edlund, and Mårten Palme. Chernobyl's subclinical legacy: prenatal exposure to radioactive fallout and school outcomes in sweden. *The Quarterly journal of economics*, 124(4):1729–1772, 2009b.

Douglas Almond, Lena Edlund, and Mårten Palme. Chernobyl's subclinical legacy: prenatal exposure to radioactive fallout and school outcomes in sweden. *The Quarterly journal of economics*, 124(4):1729–1772, 2009c.

Tobenna D Anekwe and Santosh Kumar. The effect of a vaccination program on child anthropometry: evidence from india's universal immunization program. *Journal of Public Health*, 34(4):489–497, 2012.

Fernando M Aragón. Do better property rights improve local income?: Evidence from first nations' treaties. *Journal of Development Economics*, 116:43–56, 2015.

Fernando M Aragón and Juan Pablo Rud. Natural resources and local communities: evidence from a peruvian gold mine. *American Economic Journal: Economic Policy*, 5(2):1–25, 2013.

Fernando M Aragón and Juan Pablo Rud. Polluting industries and agricultural productivity: Evidence from mining in ghana. *The Economic Journal*, 126(597):1980–2011, 2016.

Fernando M Aragón, Punam Chuhan-Pole, and Bryan Christopher Land. *The local economic impacts of resource abundance: What have we learned?* The World Bank, 2015.

Fernando M Aragón, Juan Pablo Rud, and Gerhard Toews. Resource shocks, employment, and gender: evidence from the collapse of the uk coal industry. *Labour Economics*, 52:54–67, 2018.

Eva Arceo, Rema Hanna, and Paulina Oliva. Does the effect of pollution on infant mortality differ between developing and developed countries? evidence from mexico city. *The Economic Journal*, 126(591):257–280, 2016.

Sam Asher and Paul Novosad. Digging for development: Mining booms and local economic development in india. In *Technical Report*. Working Paper. Oxford University (April), 2014a.

Sam Asher and Paul Novosad. Dirty politics: Natural resource wealth and politics in india. *Unpublished manuscript*, 2014b.

David Atkin. Endogenous skill acquisition and export manufacturing in mexico. *American Economic Review*, 106(8):2046–85, 2016.

Richard Auty. *Sustaining development in mineral economies: the resource curse thesis*. Routledge, 2002.

Michael Baker and Kevin Milligan. Maternal employment, breastfeeding, and health: Evidence from maternity leave mandates. *Journal of health economics*, 27(4):871–887, 2008.

Jean-Marie Baland and Jim Robinson. Is child labour inefficient?, journal of political economy, 108 (4), 663-79. 2000.

Kaushik Basu and Pham Hoang Van. The economics of child labor. *American economic review*, pages 412–427, 1998.

Gary Becker. S. human capital: A theoretical and empirical analysis, with special reference to education, 1964.

Gary S Becker. A theory of the allocation of time. *The economic journal*, pages 493–517, 1965.

Gary S Becker. *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago press, 2009.

Anja Benshaul-Tolonen. Local industrial shocks and infant mortality. *The Economic Journal*, 129(620):1561–1592, 2019.

Sonia Bhalotra. Fatal fluctuations? cyclicality in infant mortality in india. *Journal of Development Economics*, 93(1):7–19, 2010.

Chandra Bhushan, Chandra Bhushan, and Monali Zeya Hazra Souparno Banerjee. *Rich Lands Poor People: IssustainableMining Possible*, volume 6. Centre for Science and Environment, 2008.

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

David M Blau, David K Guilkey, and Barry M Popkin. Infant health and the labor supply of mothers. *Journal of Human Resources*, pages 90–139, 1996.

Richard Blundell and Stephen Bond. Gmm estimation with persistent panel data: an application to production functions. *Econometric reviews*, 19(3):321–340, 2000.

Vani K Borooah. Social identity and educational attainment: the role of caste and religion in explaining differences between children in india. *Journal of Development Studies*, 48(7): 887–903, 2012.

Anne D Boschini, Jan Petterson, and Jesper Roine. Resource curse or not. *A Question of Appropriability. Stockholm: Stockholm University: Mimeo*, 2004.

John R Boyce and JC Herbert Emery. Is a negative correlation between resource abundance and growth sufficient evidence that there is a âresource curseâ? *Resources Policy*, 36(1): 1–13, 2011.

Christa N Brunnschweiler. Cursing the blessings? natural resource abundance, institutions, and economic growth. *World development*, 36(3):399–419, 2008.

Michael R Carter and John A Maluccio. Social capital and coping with economic shocks: an analysis of stunting of south african children. *World Development*, 31(7):1147–1163, 2003.

Francesco Caselli and Guy Michaels. Do oil windfalls improve living standards? evidence from brazil. *American Economic Journal: Applied Economics*, 5(1):208–38, 2013.

Satvika Chalasani and Shea Rutstein. Household wealth and child health in india. *Population studies*, 68(1):15–41, 2014.

Patralekha Chatterjee. Child malnutrition rises in india despite economic boom. *The Lancet*, 369(9571):1417–1418, 2007.

Kenneth Y Chay and Michael Greenstone. The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. *The quarterly journal of economics*, 118(3):1121–1167, 2003.

Yuyu Chen, Avraham Ebenstein, Michael Greenstone, and Hongbin Li. Evidence on the impact of sustained exposure to air pollution on life expectancy from chinaâs huai river policy. *Proceedings of the National Academy of Sciences*, 110(32):12936–12941, 2013.

Benjamin Chinitz. Contrasts in agglomeration: New york and pittsburgh. *The American Economic Review*, pages 279–289, 1961.

Denis Cogneau and Rémi Jedwab. Commodity price shocks and child outcomes: The 1990 cocoa crisis in côte dâivoire. *Economic Development and Cultural Change*, 60(3):507–534, 2012.

Pierre-Philippe Combes and Laurent Gobillon. The empirics of agglomeration economies. In *Handbook of regional and urban economics*, volume 5, pages 247–348. Elsevier, 2015.

W Max Corden and J Peter Neary. Booming sector and de-industrialisation in a small open economy. *The economic journal*, 92(368):825–848, 1982.

Warner Max Corden. Booming sector and dutch disease economics: survey and consolidation. *oxford economic Papers*, 36(3):359–380, 1984.

Maureen Cropper, Shama Gamkhar, Kabir Malik, Alexander Limonov, and Ian Partridge. The health effects of coal electricity generation in india. *Resources for the Future Discussion Paper*, (12-25), 2012.

Mark Cully. Coal in india. *Australia Government Office of the Chief Economist, June*, 2015.

Flavio Cunha and James J Heckman. Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of human resources*, 43(4):738–782, 2008.

Flavio Cunha, James J Heckman, and Susanne M Schennach. Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3):883–931, 2010.

Janet Currie. Pollution and infant health. *Child development perspectives*, 7(4):237–242, 2013.

Janet Currie and Matthew Neidell. Air pollution and infant health: what can we learn from california's recent experience? *The Quarterly Journal of Economics*, 120(3):1003–1030, 2005.

Janet Currie and Tom Vogl. Early-life health and adult circumstance in developing countries. *Annu. Rev. Econ.*, 5(1):1–36, 2013.

Janet Currie and Reed Walker. Traffic congestion and infant health: Evidence from e-zpass. *American Economic Journal: Applied Economics*, 3(1):65–90, 2011.

Janet Currie, Eric A Hanushek, E Megan Kahn, Matthew Neidell, and Steven G Rivkin. Does pollution increase school absences? *The Review of Economics and Statistics*, 91(4):682–694, 2009.

Janet Currie, Joshua Graff Zivin, Jamie Mullins, and Matthew Neidell. What do we know about short-and long-term effects of early-life exposure to pollution? *Annu. Rev. Resour. Econ.*, 6 (1):217–247, 2014.

James Cust and Steven Poelhekke. The local economic impacts of natural resource extraction. *Annu. Rev. Resour. Econ.*, 7(1):251–268, 2015.

R de Haas and S Poelhekke. Business constraints in mining regions. *Work. Pap., Dep. Spat. Econ., VU Univ. Amsterdam*, 2014.

Ralph De Haas and Steven Poelhekke. Mining matters: Natural resource extraction and firm-level constraints. *Journal of International Economics*, 117:109–124, 2019.

Rajeev Dehejia and Adriana Lleras-Muney. Booms, busts, and babies' health. *The Quarterly Journal of Economics*, 119(3):1091–1130, 2004.

Sonalde Desai and Reeve Vanneman. National council of applied economic research, new delhi. 2005. *India human development survey (IHDS)*, 2005a.

Sonalde Desai and Reeve Vanneman. National council of applied economic research, new delhi. 2005. *India human development survey (IHDS)*, 2005b.

Sonalde Desai and Reeve Vanneman. National council of applied economic research, new delhi (2015)âindia human development survey-ii (ihds-ii), 2011-12â. *Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor]*, 2015.

Cheryl Doss. Intrahousehold bargaining and resource allocation in developing countries. *The World Bank Research Observer*, 28(1):52–78, 2013.

Oeindrila Dube and Juan F Vargas. Commodity price shocks and civil conflict: Evidence from colombia. *The Review of Economic Studies*, 80(4):1384–1421, 2013.

Stanislaw Dudka and Domy C Adriano. Environmental impacts of metal ore mining and processing: a review. *Journal of environmental quality*, 26(3):590–602, 1997.

Esther Duflo. Child health and household resources in south africa: evidence from the old age pension program. *American Economic Review*, 90(2):393–398, 2000.

Esther Duflo. Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American economic review*, 91(4):795–813, 2001.

Esther Duflo. Women empowerment and economic development. *Journal of Economic literature*, 50(4):1051–79, 2012.

Josephine Duh and Dean Spears. Health and hunger: Disease, energy needs, and the indian calorie consumption puzzle. *The Economic Journal*, 127(606):2378–2409, 2017.

Eric V Edmonds and Nina Pavcnik. Child labor in the global economy. *Journal of Economic Perspectives*, 19(1):199–220, 2005a.

Eric V Edmonds and Nina Pavcnik. The effect of trade liberalization on child labor. *Journal of international Economics*, 65(2):401–419, 2005b.

Eric V Edmonds, Nina Pavcnik, and Petia Topalova. Trade adjustment and human capital investments: Evidence from indian tariff reform. *American Economic Journal: Applied Economics*, 2(4):42–75, 2010.

Roderick G Eggert. Mining and economic sustainability: National economies and local communities. *A Study Prepared for the Mining, Minerals, and Sustainable Development Project, Colorado School of Mines*, 2001.

Glenn Ellison and Edward L Glaeser. Geographic concentration in us manufacturing industries: a dartboard approach. *Journal of political economy*, 105(5):889–927, 1997.

Marcel Fafchamps, Michael Koelle, and Forhad Shilpi. Gold mining and proto-urbanization: recent evidence from ghana. *Journal of Economic Geography*, 17(5):975–1008, 2017.

Francisco HG Ferreira and Norbert Schady. Aggregate economic shocks, child schooling, and child health. *The World Bank Research Observer*, 24(2):147–181, 2009.

David A Fleming and Thomas G Measham. Local job multipliers of mining. *Resources Policy*, 41:9–15, 2014.

David A Fleming and Thomas G Measham. Local economic impacts of an unconventional energy boom: the coal seam gas industry in a ustralia. *Australian Journal of Agricultural and Resource Economics*, 59(1):78–94, 2015.

Andrew D Foster. Prices, credit markets and child growth in low-income rural areas. *The Economic Journal*, 105(430):551–570, 1995.

Edward L Glaeser, Sari Pekkala Kerr, and William R Kerr. Entrepreneurship and urban growth: An empirical assessment with historical mines. *Review of Economics and Statistics*, 97(2): 498–520, 2015.

Paul Glewwe and Michael Kremer. Schools, teachers, and education outcomes in developing countries. *Handbook of the Economics of Education*, 2:945–1017, 2006.

Mark Gradstein and Phoebe Ishak. We don' t need no education: The effect of natural resource income shocks on human capital. 2020.

Joshua Graff Zivin and Matthew Neidell. The impact of pollution on worker productivity. *American Economic Review*, 102(7):3652–73, 2012.

Joshua Graff Zivin and Matthew Neidell. Environment, health, and human capital. *Journal of Economic Literature*, 51(3):689–730, 2013.

Michael Greenstone and Rema Hanna. Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review*, 104(10):3038–72, 2014a.

Michael Greenstone and Rema Hanna. Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review*, 104(10):3038–72, 2014b.

Michael Greenstone and Rema Hanna. Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review*, 104(10):3038–72, 2014c.

WHO Multicentre Growth Reference Study Group and Mercedes de Onis. Assessment of differences in linear growth among populations in the who multicentre growth reference study. *Acta Paediatrica*, 95:56–65, 2006a.

WHO Multicentre Growth Reference Study Group and Mercedes de Onis. Reliability of anthropometric measurements in the who multicentre growth reference study. *Acta Paediatrica*, 95:38–46, 2006b.

Aashish Gupta and Dean Spears. Health externalities of india's expansion of coal plants: Evidence from a national panel of 40,000 households. *Journal of environmental economics and management*, 86:262–276, 2017.

Sarath Guttikunda, Puja Jawahar, and Debi Goenka. Regulating air pollution from coal-fired power plants in india. *Economic & Political Weekly*, 50(1):63, 2015.

Thorvaldur Gylfason. Natural resources, education, and economic development. *European economic review*, 45(4-6):847–859, 2001.

Thorvaldur Gylfason. Natural resources and economic growth: From dependence to diversification. In *Economic liberalization and integration policy*, pages 201–231. Springer, 2006.

Rema Hanna and Paulina Oliva. The effect of pollution on labor supply: Evidence from a natural experiment in mexico city. *Journal of Public Economics*, 122:68–79, 2015.

Michael Herb. No representation without taxation? rents, development, and democracy. *Comparative Politics*, pages 297–316, 2005.

Albert O Hirschman. The strategy of economic development. Technical report, 1958.

John Hoddinott, John A Maluccio, Jere R Behrman, Rafael Flores, and Reynaldo Martorell. Effect of a nutrition intervention during early childhood on economic productivity in guatemalan adults. *The lancet*, 371(9610):411–416, 2008.

Padmanabha Hota and Bhagirath Behera. Opencast coal mining and sustainable local livelihoods in odisha, india. *Mineral Economics*, 29(1):1–13, 2016.

Katsushi S Imai, Samuel Kobina Annim, Veena S Kulkarni, and Raghav Gaiha. Womenâs empowerment and prevalence of stunted and underweight children in rural india. *World Development*, 62:88–105, 2014.

PwC India. The indian coal sector: Challenges and future outlook, 2012. URL `https://www.pwc.in/assets/pdfs/industries/power-mining/icc-coal-report.pdf`.

Jonathan Isham, Michael Woolcock, Lant Pritchett, and Gwen Busby. The varieties of resource experience: natural resource export structures and the political economy of economic growth. *The World Bank Economic Review*, 19(2):141–174, 2005.

Alexander James. Natural resources and education outcomes in the united states. *Resource and Energy Economics*, 49:150–164, 2017.

Seema Jayachandran. Air quality and early-life mortality evidence from indonesiaâs wildfires. *Journal of Human resources*, 44(4):916–954, 2009.

Seema Jayachandran and Rohini Pande. Why are indian children so short? the role of birth order and son preference. *American Economic Review*, 107(9):2600–2629, 2017.

Terry Lynn Karl. *The paradox of plenty: Oil booms and petro-states*, volume 26. Univ of California Press, 1997.

Anthony Keats. Women's schooling, fertility, and child health outcomes: Evidence from uganda's free primary education program. *Journal of Development Economics*, 135:142–159, 2018.

Arpita Asha Khanna. Governance in coal mining: Issues and challenges. *TERI-NFA Working Paper*, 9, 2013.

Maureen Kilkenny and Mark D Partridge. Export sectors and rural development. *American Journal of Agricultural Economics*, 91(4):910–929, 2009.

Andreas Kotsadam and Anja Tolonen. *African mining, gender, and local employment*. The World Bank, 2015.

Diana I Kruger. Coffee production effects on child labor and schooling in rural brazil. *Journal of development Economics*, 82(2):448–463, 2007.

Jana Kuhnt and Sebastian Vollmer. Antenatal care services and its implications for vital and health outcomes of children: evidence from 193 surveys in 69 low-income and middle-income countries. *BMJ open*, 7(11):e017122, 2017.

Philip R Lane and Aaron Tornell. Power, growth, and the voracity effect. *Journal of economic growth*, 1(2):213–241, 1996.

Emmanuelle Lavaine, Matthew Neidell, et al. Energy production and health externalities. Technical report, 2013.

Jef Leroy. Zscore06: Stata module to calculate anthropometric z-scores using the 2006 who child growth standards. 2011.

James Levinsohn and Amil Petrin. Estimating production functions using inputs to control for unobservables. *The review of economic studies*, 70(2):317–341, 2003.

Norman Loayza, Alfredo Mier y Teran, and Jamele Rigolini. *Poverty, inequality, and the local natural resource curse*. The World Bank, 2013.

Robert E Lucas. On the mechanics of economic development. *Econometric Society Monographs*, 29:61–70, 1998.

John A Maluccio. Coping with the âcoffee crisisâ in central america: The role of the nicaraguan red de proteccion social. Technical report, 2005.

John A Maluccio, John Hoddinott, Jere R Behrman, Reynaldo Martorell, Agnes R Quisumbing, and Aryeh D Stein. The impact of improving nutrition during early childhood on education among guatemalan adults. *The Economic Journal*, 119(537):734–763, 2009.

Joseph Marchand and Jeremy Weber. Local labor markets and natural resources: A synthesis of the literature. *Journal of Economic Surveys*, 32(2):469–490, 2018a.

Joseph Marchand and Jeremy Weber. Local labor markets and natural resources: A synthesis of the literature. *Journal of Economic Surveys*, 32(2):469–490, 2018b.

Joseph Marchand and Jeremy G Weber. How local economic conditions affect school finances, teacher quality, and student achievement: Evidence from the texas shale boom. *Journal of Policy Analysis and Management*, 39(1):36–63, 2020.

Alfred Marshall. Principles of economics macmillan. *London (8th ed. Published in 1920)*, 1890.

Alfred Marshall et al. Industry and trade. 1920.

Kiminori Matsuyama. Agricultural productivity, comparative advantage, and economic growth. *Journal of economic theory*, 58(2):317–334, 1992.

Halvor Mehlum, Karl Moene, and Ragnar Torvik. Institutions and the resource curse. *The economic journal*, 116(508):1–20, 2006.

Zuguo Mei and Laurence M Grummer-Strawn. Standard deviation of anthropometric z-scores as a data quality assessment tool using the 2006 who growth standards: a cross country analysis. *Bulletin of the World Health Organization*, 85:441–448, 2007.

Guy Michaels. The long term consequences of resource-based specialisation. *The Economic Journal*, 121(551):31–57, 2010.

Rebecca Miles-Doan and Karin L Brewster. The impact of type of employment on women's use of prenatal-care services and family planning in urban cebu, the philippines. *Studies in Family Planning*, pages 69–78, 1998.

Grant Miller and B Piedad Urdinola. Cyclicality, mortality, and the value of time: The case of coffee price fluctuations and child survival in colombia. *Journal of Political Economy*, 118 (1):113–155, 2010.

Prajna Paramita Mishra. Coal mining and rural livelihoods: Case of the ib valley coalfield, orissa. *Economic and political weekly*, pages 117–123, 2009.

Enrico Moretti. Local multipliers. *American Economic Review*, 100(2):373–77, 2010.

W Henry Mosley and Lincoln C Chen. An analytical framework for the study of child survival in developing countries. *Population and development review*, 10:25–45, 1984.

Seema Mundoli. India's childhood in the 'pits' : A report on the impacts of mining on the children of india, 03 2010.

Kaivan Munshi and Mark Rosenzweig. Why is mobility in india so low? social insurance, inequality, and growth. Technical report, National Bureau of Economic Research, 2009.

Kelly Noonan, Hope Corman, Ofira Schwartz-Soicher, and Nancy E Reichman. Effects of prenatal care on child health at age 5. *Maternal and child health journal*, 17(2):189–199, 2013.

Paulina Oliva. Environmental regulations and corruption: Automobile emissions in mexico city. *Journal of Political Economy*, 123(3):686–724, 2015.

Marianne Page, Jessamyn Schaller, and David Simon. The effects of aggregate and gender-specific labor demand shocks on child health. *Journal of Human Resources*, 54(1):37–78, 2019.

Elissaios Papyrakis and Reyer Gerlagh. Resource abundance and economic growth in the united states. *European Economic Review*, 51(4):1011–1039, 2007.

Paul Pelzl and Steven Poelhekke. Good Mine, Bad Mine: Natural Resource Heterogeneity and Dutch Disease in Indonesia. CESifo Working Paper Series 7284, CESifo, 2018. URL `https://ideas.repec.org/p/ces/ceswps/_7284.html`.

Monica Philalay, Nikolai Drahos, and David Thurtell. Coal in india. *Canberra: Australian Government, Department of Industry, Innovation and Science, Office of the Chief Economist*, 2019.

M Rahman, SK Roy, M Ali, AK Mitra, AN Alam, and MS Akbar. Maternal nutritional status as a determinant of child health. *Journal of Tropical Pediatrics*, 39(2):86–88, 1993.

Tomás Rau, Loreto Reyes, and Sergio S Urzúa. The long-term effects of early lead exposure: evidence from a case of environmental negligence. Technical report, National Bureau of Economic Research, 2013.

Anissa Rizkianti, Tin Afifah, Ika Saptarini, and Mukhammad Fajar Rakhmadi. Women's decision-making autonomy in the household and the use of maternal health services: An indonesian case study. *Midwifery*, 90:102816, 2020.

Paul M Romer. Increasing returns and long-run growth. *Journal of political economy*, 94(5): 1002–1037, 1986.

Mark R Rosenzweig and T Paul Schultz. Market opportunities, genetic endowments, and intrafamily resource distribution: Child survival in rural india. *The American Economic Review*, 72(4):803–815, 1982.

Mark R Rosenzweig and Kenneth I Wolpin. Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in india. *Journal of political economy*, 101(2):223–244, 1993.

Michael L Ross. What do we know about natural resources and civil war? *Journal of peace research*, 41(3):337–356, 2004.

Andrew Rosser. The political economy of the resource curse: A literature survey. 2006.

Walt Whitman Rostow and Walt W Rostow. *The stages of economic growth: A non-communist manifesto*. Cambridge university press, 1990.

Christopher J Ruhm. Parental leave and child health. *Journal of health economics*, 19(6): 931–960, 2000.

Jeffrey D Sachs and Andrew M Warner. Natural resource abundance and economic growth. Technical report, National Bureau of Economic Research, 1995.

Jessamyn Schaller and Mariana Zerpa. Short-run effects of parental job loss on child health. *American Journal of Health Economics*, 5(1):8–41, 2019.

T Paul Schultz. Testing the neoclassical model of family labor supply and fertility. *Journal of Human resources*, pages 599–634, 1990.

Moshe Semyonov, Noah Lewin-Epstein, and Dina Maskileyson. Where wealth matters more for health: The wealth–health gradient in 16 countries. *Social Science & Medicine*, 81: 10–17, 2013.

Manisha Shah and Bryce Millett Steinberg. Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, 125 (2):527–561, 2017.

Brock Smith. The resource curse exorcised: Evidence from a panel of countries. *Journal of Development Economics*, 116:57–73, 2015.

Thomas Spencer, Raghav Pachouri, G Renjith, and Sachi Vohra. Coal transition in india. *The Energy and Resources Institute (TERI): New Delhi, India*, 2018.

Richard C Stedman, Jeffrey B Jacquet, Matthew R Filteau, Fern K Willits, Kathryn J Brasier, and Diane K McLaughlin. Environmental reviews and case studies: Marcellus shale gas development and new boomtown research: Views of new york and pennsylvania residents. *Environmental Practice*, 14(4):382–393, 2012.

Jean-Philippe Stijns. Natural resource abundance and human capital accumulation. *World development*, 34(6):1060–1083, 2006.

Jean-Philippe C Stijns. Natural resource abundance and economic growth revisited. *Resources policy*, 30(2):107–130, 2005.

John Strauss and Duncan Thomas. Human resources: Empirical modeling of household and family decisions. *Handbook of development economics*, 3:1883–2023, 1995.

Shinsuke Tanaka. Environmental regulations on air pollution in china and their impact on infant mortality. *Journal of health economics*, 42:90–103, 2015.

Aysit Tansel. Wage employment, earnings and returns to schooling for men and women in turkey. *Economics of Education Review*, 13(4):305–320, 1994.

Anja Tolonen. Local industrial shocks, female empowerment and infant health: Evidence from africa's gold mining industry. *Job market paper*, 2015.

Anja Tolonen. Endogenous gender norms: Evidence from africaâs gold mining industry. *Research Paper Series*, (209), 2018.

Rahul Tongia and Samantha Gross. Coal in india: Adjusting to transition. 2019.

Aaron Tornell and Philip R Lane. The voracity effect. *American economic review*, 89(1):22–46, 1999.

Ragnar Torvik. Learning by doing and the dutch disease. *European economic review*, 45(2): 285–306, 2001.

Frederick Van der Ploeg. Natural resources: curse or blessing? *Journal of Economic Literature*, 49(2):366–420, 2011.

Pedro C Vicente. Does oil corrupt? evidence from a natural experiment in west africa. *Journal of development Economics*, 92(1):28–38, 2010.

Jan Von der Goltz and Prabhat Barnwal. Mines: the local welfare effects of mineral mining in developing countries. 2014.

Jan von der Goltz and Prabhat Barnwal. Mines: The local wealth and health effects of mineral mining in developing countries. *Journal of Development Economics*, 139:1–16, 2019.

Susan P Walker, Susan M Chang, Christine A Powell, and Sally M Grantham-McGregor. Effects of early childhood psychosocial stimulation and nutritional supplementation on cognition and education in growth-stunted jamaican children: prospective cohort study. *The lancet*, 366(9499):1804–1807, 2005.

Fan Zhang. *In the dark: how much do power sector distortions cost south Asia?* The World Bank, 2018.

Na Zuo and Schieffer Jack. Are resources a curse? an investigation of chinese provinces. Technical report, 2014.