Pollution and Labor Productivity: Evidence from Chilean Cities

Charl Jooste[1], Ted Loch-Temzelides[1,2], James Sampi[1], and Hasan Dudu[1]

[1]World Bank
[2]Rice University

October 2022

Abstract

This paper investigates the effects of pollution on labor productivity in Chile. Data on fine particulate matter pollution in Chile were collected and matched to sectoral labor productivity at the city level. The endogeneity between labor productivity and pollution is controlled for by instrumenting on the presence of coal and diesel power plants. The paper finds that pollution reduces labor productivity. A series of robustness checks demonstrate that pollution has a statistically significant effect on productivity when the analysis controls for labor costs and entry rates. The paper provides extensive evidence to support a causal interpretation of this finding. The identification strategy is based on a stylized macroeconomic model. The pollution elasticity of labor productivity is used to demonstrate how the co-benefits of reducing pollution can be incorporated into mitigation policies in a general equilibrium framework.

JEL classification: E24; Q52; Q53
Keywords: Labor productivity; Pollution; Developing economies

*We thank the multi-donor Climate Support Facility for funding this project. We thank Paulina Schulz Antipa, Juan Jose Miranda, Ivailo Izvorski, Benigna Leiss and Erik von Uexkull for helpful comments and suggestions. All views expressed and remaining errors are those of the authors and not the World Bank or the Climate Support Facility.

1 Introduction and literature review

Air pollution has a significant and well-documented negative impact on human health. This results in income loss as well as in various adverse socioeconomic consequences and these effects are present in both developed and developing countries. For a proper accounting of the effects associated with fossil fuel use, such costs need to be incorporated into the analysis. Put differently, economic policy modeling designed to internalize costs associated with fossil fuel use will be -at best- incomplete without taking these additional effects into account. A proper inclusion of air pollution in macro models poses several challenges. As a result, different approaches in the existing literature often lead to inconclusive, or even inconsistent findings. We propose a theoretical model to analyze the impact of air pollution on both the intensive and extensive margins of labor supply. We then employ a novel identification approach to quantify these effects on labor productivity. Our framework allows us to estimate the impact of pollution on labor productivity at the city level.Our purpose is two-fold: (1) to find a generic causal identification scheme that can be applied across countries and (2) to use these estimates to analyze the effects of pollution in a macroeconomic model.

The two-way relationship between macroeconomic performance and environmental effects has been the focus of several studies. Initially, the emphasis was mainly on documenting the effect of economic growth on pollution levels. In an influential paper, Grossman and Krueger (1995) investigated the relationship between per capita income and various environmental indicators, including urban air pollution. They found a non-monotonic relationship, where initially economic growth is associated with a deterioration in environmental quality, followed by a subsequent phase of improvement. More recently, several studies investigate how pollution might have a feedback on economic growth, mainly through premature deaths and adverse effects on human health. Bakhsh et al. (2017) performed an empirical study of the relationship between economic growth and pollution in Pakistan. They concentrated on the role of foreign direct investment. They found that, once a particular threshold level of pollution is reached, further increases in overall pollution cause a significant reduction in economic growth in the country.

The narrower question of the impact of air pollution on labor productivity has also been the subject of several studies in recent years. Findings reported in the literature draw a complicated picture, depending on the identification strategy employed and the study's spatial and temporal focus. The channels through which local pollution can affect labor productivity can be far-reaching. As an example of the wide-ranging related effects, Victor et al. (2014) studied the relationship between cognitive performance and ambient PM2.5 pollution exposure in Israel. They used a sample of high-school examinations during 2000-2002 and found evidence of a strong negative relationship between performance outcomes and pollution concentrations. Their results suggest that reduced cognitive performance due to pollution could provide a channel to reduced labor productivity. Chang et al. (2016) studied the relationship between PM2.5 and worker productivity using daily panel data from an indoor pear-packing factory in Northern California. They found that a 10 $\mu g/m3$ increase in PM2.5 reduces productivity by $0.41/hour (approximately 6 percent of average hourly earnings), with PM2.5 adversely affecting productivity even at levels lower than current US air quality standards. They did not find evidence of a labor supply response to PM2.5 flows. Likewise, they found that outdoor pollutants such as ozone have negligible effects on labor productivity.

Hanna and Oliva (2015) and Hansen-Lewis (2018) argue that pollution-related effects on productivity might be economically significant even if the pollution effects are small in absolute terms. Chen and Zhang (2021) argue that the causal effect strengthens at higher pollution levels, and the effect might be different for different age groups. Chang et al. (2019) point out that the effects can be significant even for desk jobs that require minimal physical effort. He et al. (2019) point to significant adverse output effects from prolonged pollution exposure, with more productive workers having a greater response to pollution. More recently, Adhvaryu et al. (2022a) document the adverse effects of PM pollution on worker productivity in a garment firm in India. They find an approximately linear relationship between air pollution and productivity, with a one standard deviation increase in pollution decreasing efficiency mean productivity by about 1.6 percent. Their analysis focuses on the role of managers in mitigating these impacts through reassignments. It should be noted, however, that estimating the impact of pollution on non-health indicators (such as GDP or labor productivity) is notoriously hard and requires a host of hypothesis testing to rule out false findings (Aguilar-Gomez et al. (2022)).

More recently, China, whose major cities are subject to highly elevated levels of pollution, has been the subject of an extensive list of studies; see, for example, Fu et al. (2021); Li et al. (2015); Chen and Zhang (2021); Chang et al. (2019), 2019; He et al. (2019)). A few studies focus on the United States; see Goodenberger et al. (2020); Graff Zivin and Neidell (2012). Additional studies concentrate on other countries with significant pollution problems like India, see Hansen-Lewis (2018), Mexico, see Hanna and Oliva (2015) and Peru, see Aragon et al. (2016). The identification strategies differ depending on the country context and data availability. These instruments have included atmospheric inversion, see Chen and Zhang (2021) and Fu et al. (2021), and wind-velocity, see Hansen-Lewis (2018). Finally, some studies abstract from the identification problem altogether; see Goodenberger et al. (2020), Graff Zivin and Neidell (2012), Chang et al. (2019), He et al. (2019), or they employ a natural experiment, seeHanna and Oliva (2015).

Overall, the literature seems to agree on the negative impact of pollution. However, the studies differ substantially in their findings on the quantification of this impact. The estimates of the elasticity of labor productivity to air pollution levels vary between -0.44 (Fu et al. (2021)) and -0.175 (Hanna and Oliva (2015)). A 10 ppb increase in air quality is linked to a decline in labor productivity between 0.35% (Chang et al. (2019)) and 5.5% (Graff Zivin and Neidell (2012)). Hansen-Lewis (2018) report a very small impact of pollution on productivity for India. Although the impact on labor is sizable, the impact on productivity is small in their study due to low labor shares and low returns to labor in the firms sampled. Fu et al. (2021) feed their estimations into a dynamic general equilibrium model and report a 0.4% decline in GDP resulting from an 1% increase in air pollution.

Macroeconomic models are increasingly expanded in order to incorporate damages associated with climate change and are used by practitioners to assist in evaluating various climate scenarios and policies. Incorporating the adverse effects from local pollution on labor productivity into macroeconomic modeling is an important complementary goal. Reducing GHG emissions, for example, via carbon taxes, typically comes at an economic cost; see, for example, Känzig (2021). Evaluating and incorporating the health and other co-benefits resulting from a reduction in local pollution would lead to more accurate evaluations of such costs. In addition, as the costs associated with local pollution, including those related to labor supply and labor productivity, are suffered locally, there are additional incentives to design effective mitigation policies at the local or national level. This is in contrast to costs related to climate change, which are subject to a global commons problem. OECD (2016) reports on findings from its ENV-Linkages model, a computable general equilibrium model used to create projections up to 2060. Their projected increase in PM2.5 and in ozone concentrations are estimated to lead to substantial negative effects on the world economy. More precisely, they project that global air pollution-related health care costs will increase to USD 176 billion by 2060, with the annual number of lost working days globally projected to reach 3.7 billion by that date. The total market impacts of outdoor air pollution are projected to reach 1 percent of global GDP.

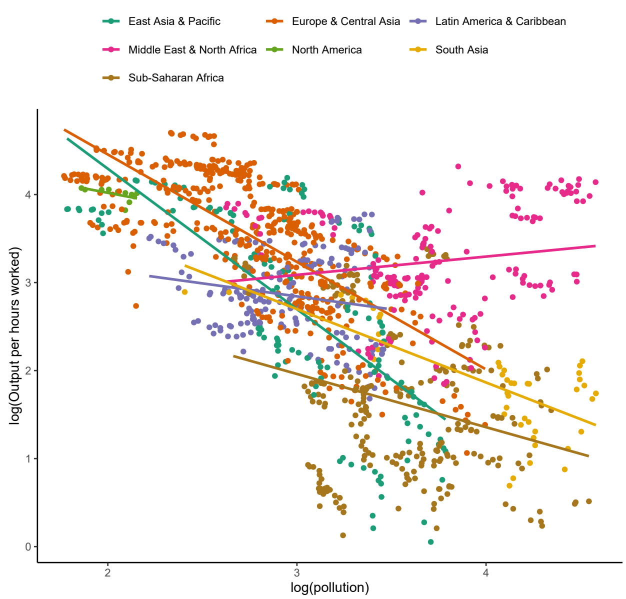
Our contribution in this paper is two-fold. First, we provide microeconomic evidence of the causal effects of pollution on labor productivity using a valid instrument that could in principle be applied to any country. Our second methodological contribution involves extending a standard macro model to account in a tractable way for the links between local pollution and labor productivity.

The remainder of the paper is organized as follows: Section 2 presents anecdotal macroeconomic evidence documenting the negative relation between labor productivity and pollution. Section 3 performs the empirical analysis for Chile, and discusses why electricity production serves as an instrument. We then outline our methodology and empirical structure. Section 6 presents our results. A brief conclusion follows.

2 The cross-country impact of pollution on labor productivity

There is strong anecdotal evidence that pollution (as measured by PM2.5) is strongly correlated with a reduction in labor productivity. Figure 1 shows that the correlation is negative using two standard labor productivity measures (output per worker and output per hour worked). This negative relationship is fairly consistent regardless of income level.

Figure 1: Pollution and labor productivity



Source: ILO, WDI and authors' calculations

Note: The Figure uses World Bank region definitions. Fitted values generated using non-parametric smoothing. Shaded are are confidence regions.

These correlations can be extracted when accounting for country idiosyncrasies and time fixed effects using a linear regression of the log of pollution $(PM2.5)$ on the log of labor productivity as defined by the ratio of total value added with respect to the total number of workers in the economy $\left(\frac{Y_{it}}{N_{it}}\right)$.

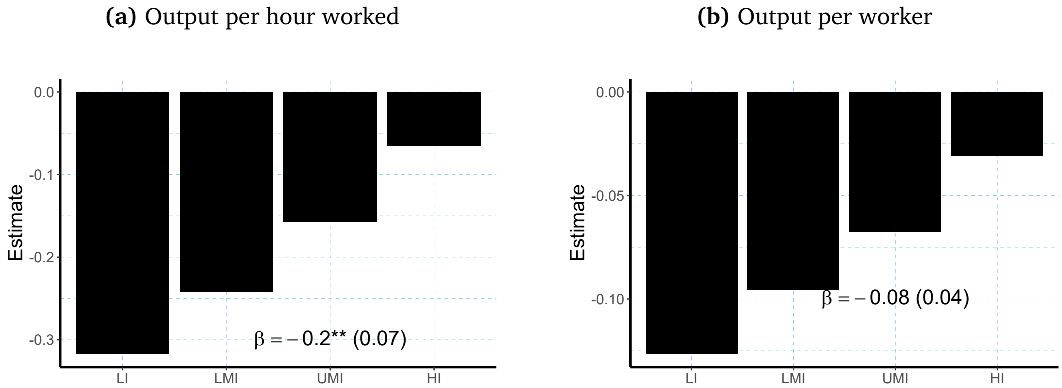
$$\ln\left(\frac{Y_{it}}{N_{it}}\right) = \alpha_i + \gamma_t + \beta \ln(PM2.5) + \varepsilon_{it}$$

or in terms of output per hour worked:

$$\ln\left(\frac{Y_{it}}{H_{it}}\right) = \alpha_i + \gamma_t + \beta \ln(PM2.5) + \varepsilon_{it}$$

The results indicate that pollution negatively correlates with labor productivity. Specifically, a 1 percent increase in PM2.5 correlates with a decline of 0.20 and 0.08 percent in labor productivity, depending on whether labor productivity is measured as value added per number of workers or hours worked, respectively (see Figure 2). Furthermore, we note that the effects are more pronounced for low-income-countries (LI)

Figure 2: Macro estimates of pollution on labor productivity



relative to lower-middle-income (LMI) and upper-middle-income (UMI) and high-income-countries (HI). These estimates are relatively large and the structural identification can always be questioned. Such macro estimates are thus best viewed as correlation estimates.

The macro observations require an accompanying structural identification. Of course, the possible endogeneity between pollution and productivity needs to be taken into account. As an example, an increase in energy demand related to a boost in productivity may also lead to an increase in pollution, if that demand is met through polluting sources, such as internal combustion engines in transportation or coal-fired power plants in electricity production. This would lead to a positive association between productivity and pollution (e.g., The Middle-East and North Africa slope in Figure 2). Conversely, labor productivity may deteriorate with an increase in pollution if there are continuous or sharp exposures to pollutants. In that case, the relationship between pollution and productivity would be negative. Other unobserved factors may also bias productivity-air pollution estimates. As an example, if there is endogenous adaptation, then the impact of pollution may decline over time. In this case, adaptation and related technology innovations may reduce the impact of pollution on labor productivity. Adhvaryu et al. (2022b) show that managers in the garment industry can reduce the impact of pollution on productivity by reallocating sensitive workers to worker-to-task matches, and this simultaneously results in a reduction in pollution.

3 Pollution and electricity production in Chile: The empirical strategy

3.1 Electricity generation in Chile

Chile has recently established a national transmission system that unified energy supplied in the south and the north of the country. Power supply in the country is largely determined by private incentives, with a private contracting system being the dominant determinant in allocating the electricity produced. Like many other countries, Chile is in the midst of an energy transition. It is largely moving away from coal and diversifying its supply, making large investments in solar energy, as well as in LNG imports. The government has committed to closing coal-fired power plants by 2025.

Coal-fired power plants require large, cheap, and reliable supplies of coal. Thus, they tend to be located close to coal mines. In the case where coal needs to be imported, coal plants are often in proximity of ports, in order to minimize transportation costs. Before combustion, the coal needs to be pulverized into a fine powder. Combustion creates heat, used to boil water to steam which, in turn, rotates a turbine, resulting in electricity production. The steam is then cooled, condensed, and returned to the boiler to repeat the cycle.

This process, together with coal washing used to remove impurities from coal pre-combustion, requires large quantities of water. Thus, a second factor in the choice of location for coal-fired power plants is the proximity to a body of water.

Naturally, these general considerations were also relevant for the choice of location of the power plants in our sample. Chile has few coal deposits, which have mostly been depleted over the years. The majority of the coal used in electricity production has been imported, hence the usefulness of the proximity of coal plants to a port. The ports of Antofagasta and Huasco are close to local copper mines, that are heavy users of electricity. Valparaiso, also a port, is close to Santiago, a big demand center. Coronel is in the proximity of the main coal mines in Chile. These have been mostly depleted by now and the power-plants in this area are being phased out. In summary, while both access to inputs, such as coal and water, and transmission costs related to supplying electricity to demand centers are important, the location of coal-fired power plants in Chile appears to be mainly in order to minimize production costs, see, for example, Smith (1973). Coal-fired power plants are among the most polluting. While the amounts of pollutants released in the atmosphere depend on the grade and quality of the coal used, emitted pollutants always include significant amounts of nitrogen oxides (NOx), sulfur oxides (SOx), as well as particulate matter (PM2.5), in addition to greenhouse gases like carbon dioxide (CO2) and methane (CH4). We will concentrate on particulate matter (PM2.5) in what follows.

3.2 Coal-fired power plants as a valid instrument

Our analysis focuses on city-level pollution and productivity data from Chile. As noted by Graff Zivin and Neidell (2012), several issues emerge when identifying the causal relationship between pollution and labor productivity. First, selection issues arise from how workers allocate their labor in the presence of high pollution levels. Given that most databases use annual frequency, workers who experience negative effects from local pollution may in the meantime decide to leave the area and work in a different region, or transition to a different sector that is less exposed to pollution. This labor mobility may occur within a year. Another potential source of concern is the presence of a confounder and the possibility of simultaneity bias. Increases in economic output lead to corresponding increases in energy demand. If the response of the energy supply is mainly through an increase in fossil fuel use, this could also lead to an increase in pollution. Arguably, this raises concerns about the orthogonality between pollution, PM2.5, and labor productivity. This, in turn, could affect the unbiased and consistency properties of any coefficient estimate. Several controls and instruments have been used in the literature to overcome the non-orthogonality issue. Given that we require one instrument for our explanatory variable, we can estimate the effect of pollution on labor productivity consistently using an IV-regression. In our case, the instrument needs to be strongly correlated with pollution (PM2.5) and uncorrelated with labor productivity.

We argue that the installation of fossil fuel power stations, specifically coal and diesel-fired power stations, can serve as such an instrument. Two arguments support this assertion. First, power stations plug into four regional grids, and are hence isolated from productivity developments that are specific to certain sectors and cities. Regional time fixed effects can control for regional specific effects related to productivity. Finally, as mentioned earlier, while both transportation costs for inputs and transmission costs related to proximity to demand centers are important determining factors, consistent with other countries, the location of coal-fired power plants in Chile appears to have been mainly driven by supply-side considerations. While there is no formal exogeneity test, our analysis shows that coal-fired power-plants are not correlated with labor productivity. In summary, we employ coal-fired power-plants, as their operation is highly correlated with PM2.5 and largely uncorrelated with labor productivity. We note that while this study focuses on PM2.5 that causes respiratory problems, other pollutants that affect labor productivity also exist.

3.2.1 A statistical validation of the instrument

We test the validity of our instrument by assessing the probability that labor productivity performance has led to the installation of coal-fired power stations. This is done by assessing the effect of labor productivity on coal-fired stations. We include lagged and lead effects to rule out endogeneity. Lead effects are included to rule out the anticipated productivity effects on an expansion in electricity provision by building new plants, while lagged effects are used to rule out the impact of previous growth effects on the supply of electricity from coal-fired power plants. We also control for other effects, such as city sales and wages. We use a standard logit regression:

$$P[D_{j,k,t} = 1] = \frac{e^{\mathbf{X}\beta}}{1 + e^{\mathbf{X}\beta}} \tag{1}$$

The vector X contains fixed effects, as well as the various lags and leads of labor productivity, while our dependent variable is a dummy ($D_{j,k,t}$), taking the value of 1 in the year the power plant was built in city j of region k at time t, and 0 otherwise.

Table 1 summarizes the results for our orthogonality test. Both lead and lagged labor productivity do not significantly impact the choice of building power plants. We conclude that our narrative regarding the exogeneity or the validity of the instrument is supported by the standard F-stat statistic (see IV first-stage estimates below), as well estimates from labor productivity on building power plants.

Table 1: Impact of labor productivity on building power plants

	Dummy	Dummy
$\log \frac{Y_{i,t-1}}{N_{i,t-1}}$	-0.06	
	(0.03)	
$\log \frac{Y_{i,t+1}}{N_{i,t+1}}$		-0.06
		(0.03)
FE (Year)	Yes	Yes
FE (Sub-Sector)	Yes	Yes
FE (Province)	Yes	Yes
Observations	35,197	35,197
Pseudo R^2	0.32	0.33

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

4 Structural estimates of pollution on labor productivity

In order to analyze the impact of pollution on labor productivity, we estimate the following panel regression,

$$Y_{i,j,k,t} = \alpha_i + \alpha_j + \alpha_t + \alpha_{k,t} + \phi P\hat{O}L_{j,k,t} + \mathbb{X}_{j,k,t}\beta + \varepsilon_{i,j,k,t} \tag{2}$$

where $Y_{i,j,k,t}$ is the log of labor productivity in sector i in city j and in region k, with $n \times 1$ observations. The set $\mathbb{X}_{i,j,k,t}$ gives the control variables, with size $n \times p$, $P\hat{O}L_{j,k,t}$ stands for log pollution (mean PM2.5 concentrations), and $\varepsilon_{i,j,k,t}$ is the residual, which is assumed to be normally distributed $\varepsilon_{i,j,k,t} \sim N(0, \sigma^2)$. Finally, t stands for the time indicator for region k. The parameter ϕ should be interpreted as an elasticity. In Appendix A we illustrate how the elasticity is mapped to an otherwise standard macroeconomic model.

In (2) we control for unobserved sector specific labor productivity fixed effects (α_i), unobserved city effects (α_j), and time fixed effects (α_t), capturing yearly trends, as well as region-time fixed effects ($\alpha_{k,t}$). As an additional control, we control for the distance of each city (and hence economic sector) from the power stations. We calculate the distance of each city from each power station using the Haversine formula (Robusto (1957)),[1]

$$d_j = 2rsin^{-1}\left(\sqrt{sin^2\left(\frac{\phi_{2,j}-\phi_{1,r}}{2}\right)+cos(\phi_{1,r})*cos(\phi_{2,j})*sin^2\left(\frac{\lambda_{2,j}-\lambda_{1,r}}{2}\right)}\right) \tag{3}$$

where d_j is the distance of each city to a reference location containing a coal-fired power station (r), using the longitude (ϕ) and latitude (λ) as inputs. We then use the nearest power station of each city as the control variable. There is evidence that neighborhoods in close proximity to power stations are especially sensitive to pollution (Zhang et al. (2022)).

Because of the potential endogeneity issues raised previously, we utilize the predicted value of pollution by using the building of coal-fired stations as an instrument; that is

$$P\hat{O}L_{j,k,t} = \hat{\gamma}D_{j,k,t} \tag{4}$$

the variable $D_{j,k,t}$ takes the value of either 0 or 1, therefore, the estimated pollution variable is a dichotomous variable of 0 or a real number below 1, $\hat{\gamma}_{j,k,t} \in (0,1]$. Therefore, equation 2 can be considered as a difference in difference regression. The coefficient ϕ measures the relative marginal effects of pollution in cities containing a coal-fired station relative to cities with no coal-fired stations within the same province or region. In addition, $P\hat{O}L_{j,k,t}$ captures the intensity of pollution on affected cities by coal-fired plants. Specifically, $\hat{\gamma}_{j,k,t}$ is larger for cities with higher pollution levels, introducing an extra distinction within cities with coal-fired plants.

5 Data

Here we describe the data availability for pollution and labor productivity at the city level. Chile is administratively divided into 15 regions, with 50 provinces and 346 cities, called ”comunas”. Meanwhile, the sectoral information is provided following ISIC rev.4 standards.

5.1 Pollution data

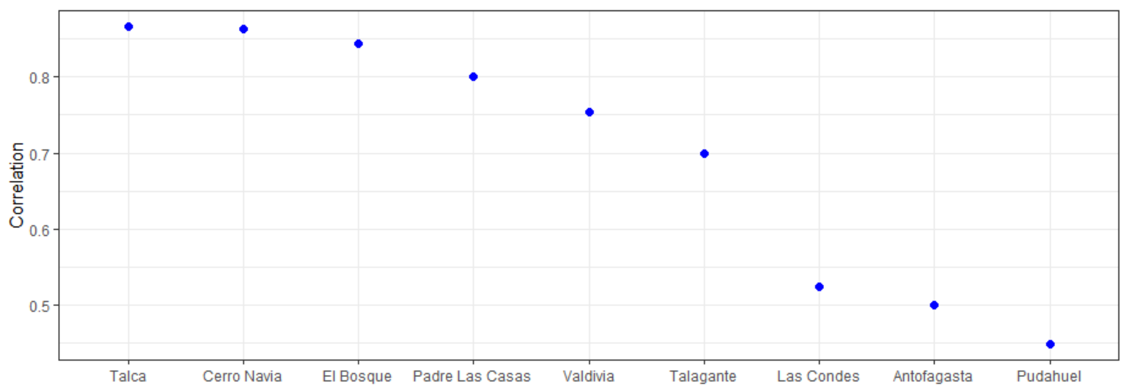
Data for particulate matter (PM2.5) concentrations was sourced from van Donkelaar et al. (2016). This data contains annual global surface concentrations (micrograms per cubic meter) of mineral dust and sea-salt filtered fine particulate matter of 2.5 micrometers or smaller in diameter. This annual data set is gridded at 0.01 degrees, which allows us to connect pollution concentration levels for each city.

Chilean pollution data from the Ministry of Environment[2] is compared to the gridded data. For the majority of the cities the correlation between official and satellite data over time is high. Figure 3 presents the correlation for selected cities.

[1] We could easily use Euclidean distance, but this is a straight line distance measure, where as the Haversine distance measure accounts for great-circle distances, typically applicable for the earth's geometry.

[2] httpss://sinca.mma.gob.cl/

Figure 3: Pollution correlation between gridded data and official data

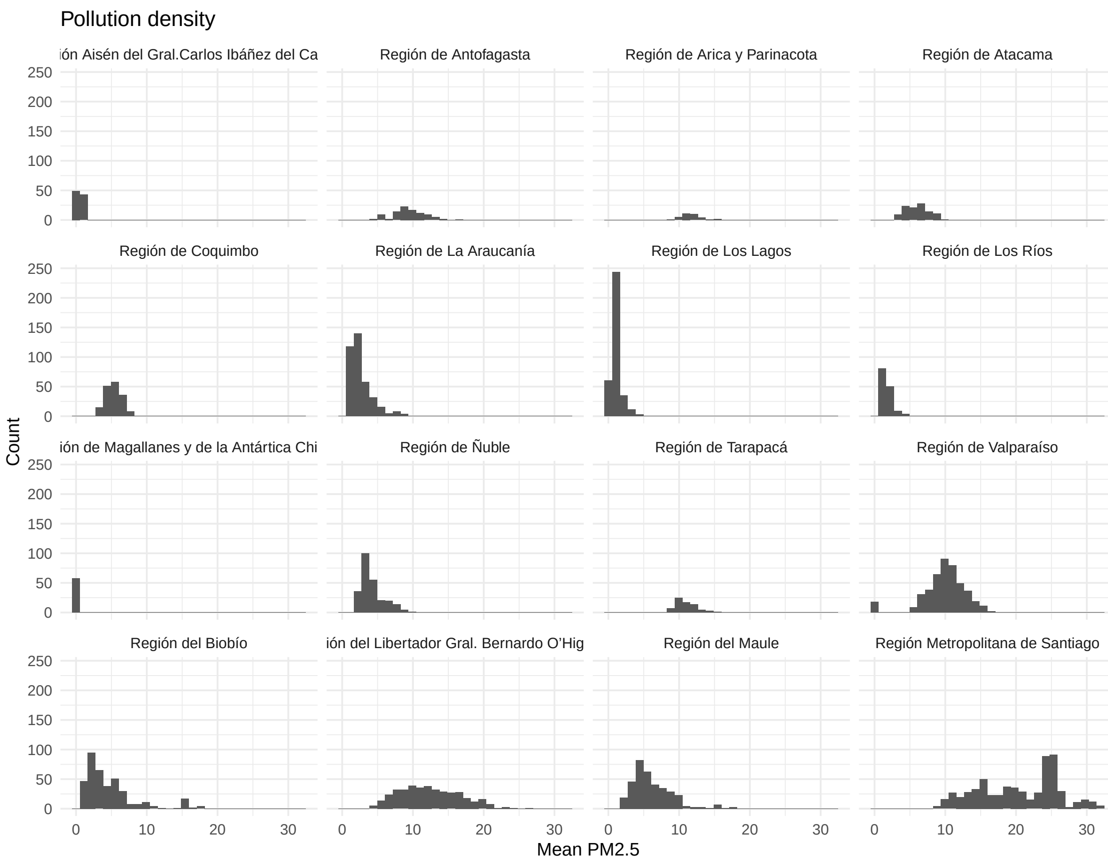


Source: Ministry of Environment, van Donkelaar et al. (2016) and author calculations

Note: The online official data has PM2.5 measures for some cities. We also only include data that have at least five years' worth of information.

The gridded data for PM2.5 shows that there are distinct differences in pollution concentration estimates by regions. As an example, estimates are very concentrated in the region de Coquimbo or the region Aisén del General Carlos Ibáñez del Campo. Some of these high estimates are due to the location to power plants, while others are in more dense industrial areas.

Figure 4: Pollution estimates by region



Source: Authors' calculations using van Donkelaar et al. (2016)

5.2 City-level productivity data

Our economic dataset consists of region/city-level data, which contains several productivity indicators that are relevant for our the analysis. For each of the 346 cities (i) there are 21 sectors and 183 sub-sectors (j). For each of the indicators within each city, the annual data (t) span from 2005 to 2016. From the city level data we construct real output per worker, our proxy for labor productivity.[3] The data tracks nominal sales of firms within each city. We have estimates of city-level sales values, but not for individual firms. As we do not have access to city-level CPI data, or to sub-sector CPI data, we deflate nominal sales using sector-level national account deflators for Chile as a whole. The pollution data is provided in a coordinate-system. We merge this data using city-level coordinates for both the productivity and the pollution data-set. Table 2 shows that annual pollution concentration for Chile during the period of study exceeds the recommended annual $5ug/m^3$.

[3] The industry classification follows ISIC Rev.4. Furthermore, we did not obtain data on hours worked, which precludes analysis on this measure of productivity.

Table 2: Summary data

	Min	Max	Mean	Observations
Pollution, annual concentration (ug/m^3)	0.10	40.40	7.30	39,885
Annual Sales	6.64	217,146,739	491,574	39,885
Employees	0	19,480.00	250.00	39,885
Wages	0	4,724,614	51,613	
Number of unique firms				1,204
Periods				11
Number of cities in 2016 above the average of $5ug/m^3$				82

5.3 Power-sector data

The power sector in Chile is mostly privately owned, with generation, transmission, and distribution being privately run.[4] A comprehensive effort to make generating companies more competitive in the early 1980s resulted in significant reforms that led to the privatization of the two largest government generators (Serra, 2022). Part of the reform, as stipulated by the 1982 Electricity Law and subsequent amendments, was to ensure that electricity companies in the same area are connected in order to maintain service security and to minimize system operating costs.

The unbundling mechanism resulted in two large interconnected systems; the Central Interconnected System, which accounts for approximately 75% of the country's power generation and serves mostly households, and the Big North Interconnected System, which serves mostly mining operations. Generators that are connected to the grid are subject to the instructions of the Independent Co-ordinator of the National Electricity System (ICNES). Generators can sell surplus electricity in the spot market at marginal cost, or the cost of production of energy by the least efficient generation facility per hour. They may also sell to private companies whose capacity exceeds 5 MW at an agreed upon price. Finally, generators can sell to distribution companies at a price determined by a public bid.[5]

Most of Chile's generation is provided by five producers (Jiménez et al., 2020). According to Article 7 of the Electricity Law, national transmission companies cannot participate in generation. Interestingly, in spite of pro-competitive laws, no large generators have entered the market (in the central system that supplies most of the electricity). This is partly due to high fixed costs, but also due to opposition from civil society organizations (Serra, 2022).[6]

There are emissions standards in place for the maximum PM2.5 emissions from thermal plants. A clean national intervention in 2010 states that all companies need to generate electricity from a given percentage of renewables (5% in 2010 – but scaling up in subsequent years) (Jiménez et al., 2020).[7] Although regulated, thermal power units create large levels of pollution. The correlation between coal-fired power stations and pollution will be used as an instrument in what follows. Although coal-fired power plants create large amounts of pollution, the largest sources of pollution according to the Global Carbon Project in Hannah Ritchie and Rosado (2020) are oil and gas. For our instrument to be effective, the location of the power-plants should not be dependent on the economic development of the closest city. As argued earlier, there are several justifications for using the power sector as an instrument for pollution. Power stations in Chile plug into regional grids and are hence isolated from demand that is specific to cities. The location of a

[4] see `http://generadoras.cl/english` for more details.

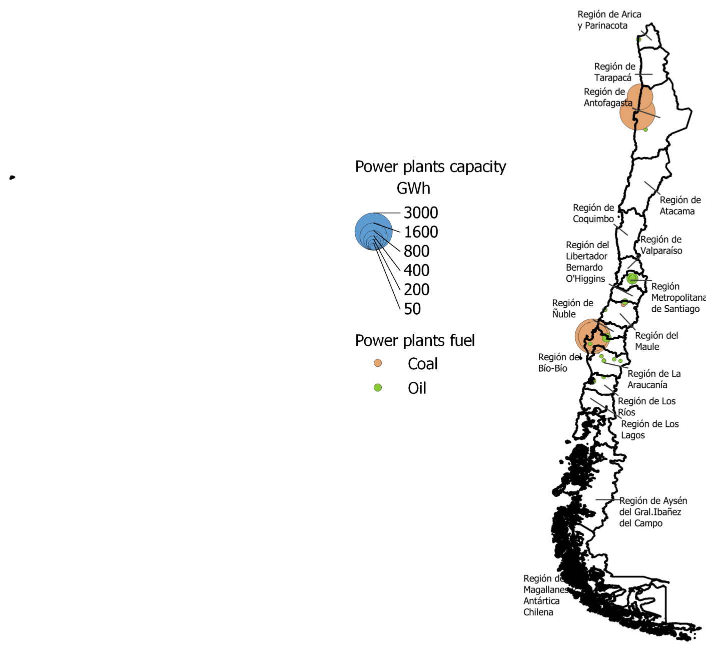
[5] `https://uk.practicallaw.thomsonreuters.com/w-019-3060?transitionType=Default&contextData=(sc.Default)&firstPage=true`

[6] New plants are restricted from being around residential and commercial areas. In this sense, the location of the plant is independent of a city's economic activity. This is a function of Law 19300, which requires an environmental impact assessment.

[7] Law No. 20,257 could in principle serve as an instrument in the analysis, but would likely be negatively correlated with pollution.

coal-fired power station seems to be at a distance from renewable energy sources. Finally, while both transportation costs for inputs and transmission costs related to proximity to demand centers are important, the location of coal-fired power plants in Chile appear to have been mainly driven by supply-side considerations. There are roughly 36 coal and diesel power units in Chile, of which 26 were built during the 2006-2016, which overlaps with the time domain of the productivity data set.

Figure 5: Coal and diesel fired power stations



Source: Authors' using data World Resource Institute and van Donkelaar et al. (2016)

6 Results

Running a standard regression of output per worker on pollution would lead to biased estimates. In most cases, one is likely to observe only correlations between pollution and labor productivity. These unobserved correlates may be due to city, region, time, and interacting effects. While fixed effects may sweep up some of these correlates, careful attention must be paid to the potential cross-flow between productivity and pollution. Increases in output may lead to an increase in activities that require energy. If the source of energy is concentrated around fossil fuel use, this will likely lead to increased pollution. As described above, our instrument is the building of new diesel and coal-fired power plants.

Our results are summarized in Table 3. The fixed effects assumptions play an important role in determining the size and sign of the pollution effects on labor productivity. Columns 1-6 include different specifications and assumptions regarding our controls. Column 2 is the standard set of fixed effects, controlling for city and time. However, these fixed effects assumptions are too restrictive, since they preclude any changes over time that occur within each province and sub-sector. In column 3 we add sub-sector fixed effects to control for within sector variations. This control changes the sign of the coefficient - a 1% increase in pollution now reduces labor productivity by 0.17%.

In column 4 we add the interaction of time and sub-sector as well as time and province-level fixed effects to account for shifts over time at both the province and the sectoral level. Important shifts may entail province-level growth effects that may be different across the different provinces in Chile, as well as sub-sector shifts within each province. These assumptions do not materially change the results on the estimated impact of pollution on labor productivity. The final column of Table 3 controls for possible endogeneity. The instrument is significant at a 1% level and positive. The coal and diesel power units imply a positive association with pollution (the F-statistic is larger than 20). The instrument does not alter the impact of pollution on productivity materially. The final column controls for city-level fixed effects, and excludes province-level fixed effects to test for possible spillovers across cities in the same province. The spillover effect across cities in the same region is not statistically significant, indicating that pollution effects on labor productivity are local.

Table 3: Estimates on the effects of pollution on productivity

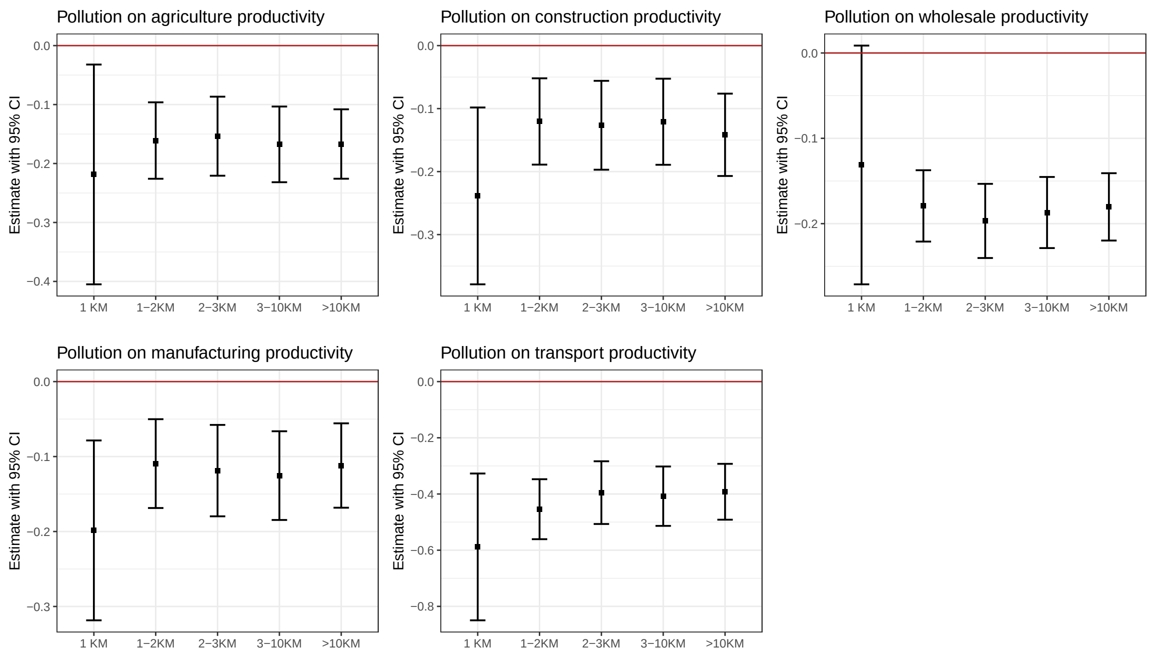
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			$\log(Y/L)$			
$\log(PM2.5)$	-0.082	-0.079***	-0.174***	-0.171***	-0.342*	-0.531
	(0.062)	(0.008)	(0.0167)	(0.0169)	(0.0198)	(0.9103)
Instrument					0.164***	0.170***
					(0.00545)	(0.0141)
FE Sector	No	No	No	No	No	No
FE Sub-sector	No	No	Yes	No	No	No
FE province	No	No	Yes	Yes	Yes	No
FE city	Yes	No	No	No	No	Yes
FE time	Yes	Yes	Yes	Yes	Yes	Yes
FE time X city	No	No	No	No	No	Yes
FE time X sector	No	No	No	No	No	No
FE time X sub-sector	No	No	No	Yes	Yes	Yes
FE time X province	No	No	No	Yes	Yes	No
Observations	39,885	39,885	39,885	39,885	39,885	39,885
R^2	0.001	0.002	0.005	0.467	0.469	0.50
F-Stat instrument					748.60***	81.00***

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

The aggregate results are consistent with sectoral estimates (Figure 6). We generate a categorical variable that measures the impact of pollution on sectoral productivity conditional on the distance of the sector in a city to power plants. The closer the proximity to a power plant, the larger the impact of pollution on productivity. Note that the estimate ranges are also larger when one gets closer to a power plant.

While PM2.5 may not be the most important component in the reduction of yields in the agriculture sector (c.f. Highlights (2013)), we show that the productivity impact is larger. For most sectors, when exposed to pollution, productivity falls between 0.15% and 0.60%.

Figure 6: Sectoral productivity responses to pollution



In the Appendix we analyze sensitivity through the lens of a macroeconomic model that accounts for both intensive and extensive margins of labor supply. The results show that a higher sensitivity of labor productivity to pollution has a substantial impact on output. We demonstrate this by evaluating the shifts in the steady state values of output, pollution, and consumption (Figure 8). The steady state for output is lower under a higher elasticity with regards to pollution. However, pollution is also lower in steady state, reflecting a lower output overall. The elasticity thus acts as a wedge in the model. This suggests that steady state production should be lower in countries that have a higher share of their labor exposed to pollution. There are thus potentially strong economic benefits from reducing emissions. The reduction in emissions, e.g., through a carbon tax, would lower pollution, which has co-benefits in terms of higher output and consumption.

6.1 Robustness

We design our robustness check around a propensity score matching dataset (see Heckman et al. (1997)). This allows us to compare treated areas (the ones that built power stations) with control areas (those that did not build power stations). These areas would share similar characteristics in terms of wages, pollution, and labor productivity. Using this data set we test the strength of our exogeneity assumption, as well as whether the labor productivity responses are purely attributable to productivity effects and not also due to changes in marginal costs.

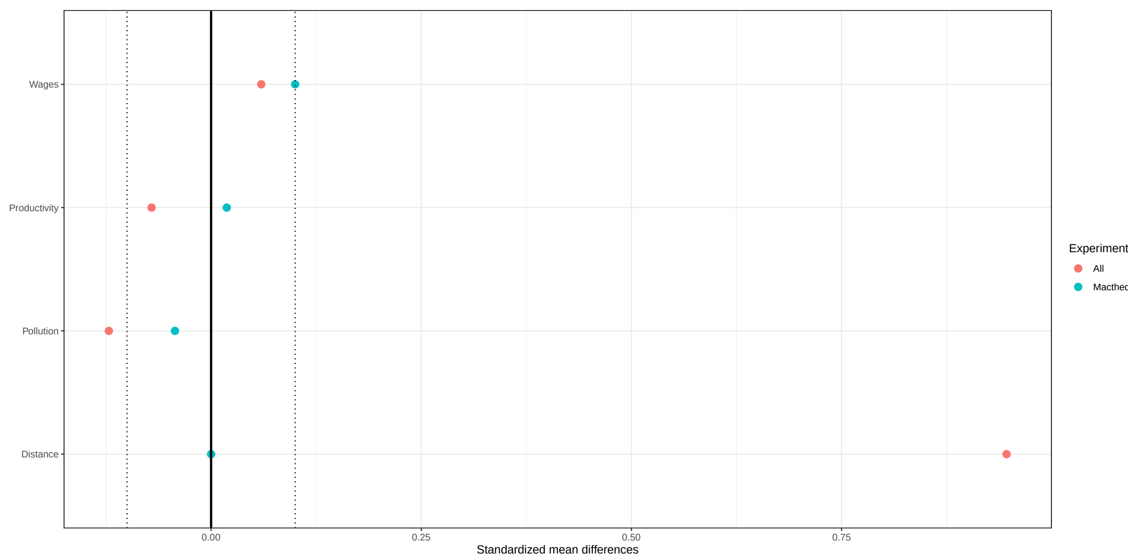
The propensity score matching is done in two steps. First, a logit model is estimated to determine the conditional probability (in this case the score) for a city to build a power station given its pre-treatment characteristics (i.e., real wages, labor productivity, pollution levels, and multi-level effects such as year, province and sector characteristics). In the second stage, the scores for creating the matched control sector group are based on a nearest-neighborhood matching with a replacement procedure:

$$A_{r,j} = \left(kj' \in I_0 : \hat{p}_{kj'} = \underbrace{min}_{kj' \in I_0} |\hat{p}_{rj} - \hat{p}_{kj'}| < 0.1\hat{\sigma}_p; j = j' \right)$$

where r is the treatment sector, k a control sector, I_0 is the sample of sectors, and $\hat{p}$ is the propensity score. The matching is applied when the treatment and control sectors are part of the same cluster $(j = j')$. A caliper of a tenth of the standard deviation of the estimated propensity score is applied to define the maximum tolerated distance between matched firms; for a description see Diamond and Sekhon (2013); Sekhon (2011). These estimates form a new database, allowing us to test whether pollution materially impacts real wages and whether our instrument is valid.

Figure 7 summarizes tests on whether the data set is balanced. It includes the estimates of the standardized mean differences between the treatment and control group in the unadjusted sample and the adjusted sample. We use a threshold value of 0.1; see Austin (2011). The adjusted sample mean differences for all the variables fall within this threshold and are close to zero, indicating a balanced data set.

Figure 7: Propensity score balance plot



6.1.1 Effects on marginal costs and net entry rates

While the results show that pollution materially affects labor productivity, we cannot rule out that some of the variation is due to changes in marginal costs. Similarly, pollution might increase the operation cost for firms, prompting the exit of established firms, or reducing the entry of new firms in the market.

To investigate this possibility, we test whether pollution significantly affects real wages (our proxy for real marginal costs). In a neoclassical framework, the growth rate of labor productivity (in this case, output per worker) should equal the growth rate in total factor productivity (ΔlnA), adjusted for the labor share in income:[8]

$$\Delta\log\left(\frac{Y_{i,t}}{N_{i,t}}\right) = \Delta\log\left(A_{i,t}\right)$$

[8] In steady state capital grows at the same rate as output.

The firm's undistorted first-order conditions imply that growth in real wages (rw) equals the growth in labor productivity, or in this case adjusted TFP:

$$\Delta\log\left(rw_{i,t}\right) = \Delta\ln\left(\frac{Y_{i,t}}{N_{i,t}}\right) = \Delta\log\left(A_{i,t}\right)$$

If pollution affects firms' marginal costs, then the demand for labor (the denominator of our dependent variable) might be affected. We also test whether pollution affects the net entry rate of firms in a sector and within a city. Table 4 summarizes the impact of pollution on both real wages and changes in the number of firms. We control for cities with and without hydrocarbon power plants. Results suggest that pollution does not significantly impact real wages or firm entry rates. We are thus able to rule out that labor productivity effects from pollution are due to changes in marginal costs or changes in the number of firms that operate in a sector within a city.

Table 4: Impact of labor productivity on building power plants

	Real Wages (rw)	Net entry rates
log($PM2.5$) $*$ Dummy=1	0.01	-2.21
	(0.02)	(3.10)
log($PM2.5$) $*$ Dummy=0	-0.02	-0.19
	(0.02)	(3.08)
FE (Year)	Yes	Yes
FE (Sector)	Yes	Yes
FE (Province)	Yes	Yes

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

7 Discussion

Local pollution has a significant negative impact on human health and productivity. Different approaches in the existing literature have led to partially inconclusive findings that can be hard to interpret in a systematic way. Specifically, the causal relationship between economic activity and fossil fuel use, and hence pollution, has biased most of the macroeconomic estimates.

We built an econometric model in order to analyze the impact of local pollution on both the intensive and extensive margins of labor supply. We used a novel identification approach to quantify these effects in the context of local pollution resulting from the operation of fossil fuel power plants in Chile. Our framework allowed us to estimate the elasticity of pollution on labor productivity in an unbiased manner. We provided evidence of the causal negative effects of pollution on labor productivity by instrumenting on the building of new diesel and coal-fired power plants in Chile.

Results suggest that pollution reduces labor productivity by between 8 and 34 percent in cities affected by the building of coal-fired power plants, relative to cities with no plants within the same province. The effects cannot be attributed to either a reduction of marginal costs, or the exit of established firms from the market. Thus, they indicate a real productivity decline. Our instrument could be applied to other countries, leading to reliable cross-country comparisons that can assist policymakers in the cost-benefit analysis of related mitigation policies.

The macromodeling framework shows how the estimated elasticity can be used to inform policies on mitigation. The feedback of the carbon mitigation option on production to energy demand and hence pollution can be fully embedded.

Finally, the approach here could be easily applied across a broad set of countries. The identification strategy should help to identify country-specific elasticities of pollution on labor productivity. These elasticities fit naturally within the macroeconomic framework, which could be used to study mitigation policies and the economic consequences of co-benefits that account for labor productivity shifts from pollution.

References

Adhvaryu, A., Kala, N., and Nyshadham, A. (2022a). Management and shocks to worker productivity. *Journal of Political Economy*, 130(1):12–47.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2022b). Management and shocks to worker productivity. *Journal of Political Economy*, 130(1):1–47.

Aguilar-Gomez, S., Dwyer, H., Graff Zivin, J., and Neidell, M. (2022). This is air: The "nonhealth" effects of air pollution. *Annual Review of Resource Economics*, 14(1):403–425.

Aragon, F., Miranda, J. J., Oliva, P., et al. (2016). Particulate matter and labor supply: evidence from peru. *Simon Fraser University Economics Working Paper. Google Scholar*.

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate behavioral research*, 46(3):399–424.

Bakhsh, K., Sobia, R., Muhammad, F. A., Najid, A., and Muhammad, S. (2017). Economic growth, co2 emissions, renewable waste and fdi relation in pakistan: New evidences from 3sls. *Journal of Environmental Management*, 196:627–632.

Chang, T., Joshua Graff, Z., Tal, G., and Neidell, M. (2016). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, 8(3):141–169.

Chang, T. Y., Graff Zivin, J., Gross, T., and Neidell, M. (2019). The effect of pollution on worker productivity: evidence from call center workers in china. *American Economic Journal: Applied Economics*, 11(1):151–72.

Chen, S. and Zhang, D. (2021). Impact of air pollution on labor productivity: Evidence from prison factory data. *China Economic Quarterly International*, 1(2):148–159.

Diamond, A. and Sekhon, J. S. (2013). Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. *Review of Economics and Statistics*, 95(3):932–945.

Fu, S., Viard, V. B., and Zhang, P. (2021). Air pollution and manufacturing firm productivity: Nationwide estimates for china. *The Economic Journal*, 131(640):3241–3273.

Goodenberger, J., Munk, R., and Senney, G. (2020). The interactive effects of temperature and air pollution on labor productivity. *Available at SSRN*.

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

Grossman, G. and Krueger, A. (1995). Economic growth and the environment. *The Quarterly Journal of Economics*, 110(2):353–377.

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

Hannah Ritchie, M. R. and Rosado, P. (2020). CO_2 and greenhouse gas emissions. *Our World in Data*. https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions.

Hansen-Lewis, J. (2018). Does air pollution lower productivity? evidence from manufacturing in india. In *PAA 2018 Annual Meeting*. PAA.

He, J., Liu, H., and Salvo, A. (2019). Severe air pollution and labor productivity: Evidence from industrial towns in china. *American Economic Journal: Applied Economics*, 11(1):173–201.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, 64(4):605–654.

Highlights, O. P. (2013). Economic consequences of outdoor air pollution. *Paris: Organisation for Economic Cooperation and Development*.

Jiménez, G., Díez, C., and Pérez-Cotapos (2020). Electricity regulation in chile: overview. [Online; 2020].

Känzig, D. R. (2021). The unequal economic consequences of carbon pricing. *Available at SSRN 3786030*.

Li, T., Liu, H., and Salvo, A. (2015). Severe air pollution and labor productivity. Technical report, IZA Discussion Papers.

OECD (2016). The economic consequences of outdoor air pollution. *Policy Highlights*.

Robusto, C. C. (1957). The cosine-haversine formula. *The American Mathematical Monthly*, 64(1):38–40.

Sekhon, J. S. (2011). Multivariate and propensity score matching software with automated balance optimization: The Matching package for R. *Journal of Statistical Software*, 42(7):1–52.

Serra, P. (2022). Chile's electricity markets: Four decades on from their original design. *Energy Strategy Reviews*, 39:100798.

Smith, B. W. (1973). Analysis of the location of coal-fired power plants in the eastern united states. *Economic Geography*, 49(3):243–250.

van Donkelaar, A., Martin, R., Brauer, M. Hsu, N., Kahn, R., Levy, R., Lyapustin, A., Sayer, A., and Winker, D. (2016). Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites. *Environmental Science and Technology*, 50(7):3762–3772.

Victor, L., Ebenstein, A., and Roth, S. (2014). The impact of short term exposure to ambient air pollution on cognitive performance and human capital formation. *NBER*, 20648.

Zhang, C. H., Sears, L., Myers, J. V., Brock, G. N., Sears, C. G., and Zierold, K. M. (2022). Proximity to coal-fired power plants and neurobehavioral symptoms in children. *Journal of exposure science & environmental epidemiology*, 32(1):124–134.

Appendices

Appendix A A macro model with pollution affecting labor productivity

Here we present a way of incorporating the effects of local pollution on labor productivity using a simple representative agent macroeconomic model.

The labor participation rate is assumed to be 100% and the total working population hours are normalized to 1. We assume there is no population growth. We let h indicate the total fraction of time lost due to illnesses associated with pollution and we let γ indicate the fraction of time during work that the representative worker is unproductive (for, example, resting to catch their breath) as a result of being exposed to increased levels of pollution. Thus, our modeling distinguishes between the effect of pollution on labor supply (h), and the effect of pollution on labor productivity (γ). Let X_t stand for the total flow of PM2.5 created in period t. In quantitative implementations, this needs to be calibrated using the fraction of energy coming from oil (x), natural gas (x_2), and coal (x_3), and then using the appropriate conversion factors to translate volumes of each respective fossil fuel burned into resulting PM2.5 concentrations.

The production function is expanded to include energy as a third production factor, in addition to capital and labor. Let E_t stand for the total energy used in period t (this includes all three types of fossil fuel mentioned above). Fossil fuel is treated as an intermediate good. Using coal, natural gas, and oil, the energy production function is given by:

$$E_t = F(x_{1,t}, x_{2,t}, x_{3,t}) = \left(\sum_j \omega_j x_{j,t}^{\rho} \right)^{1/\rho} \tag{5}$$

We can consider $x_{1,t}$, $x_{2,t}$, $x_{3,t}$ as parameters that we will infer from historical data on the respective fossil fuel composition and amounts used. Furthermore, it is assumed that the fossil fuel types are substitutes.

The final good production function is now given by:

$$Y_t = A_t K_t^{\alpha_1} ((1-\gamma_t)N_t)^{\alpha_2} E_t^{\alpha_3} \tag{6}$$

We assume $\alpha_1 + \alpha_2 + \alpha_3 = 1$. Here, N_t stands for the labor supply net of hours lost due to pollution-related reasons. We will also assume:

$$\gamma_t = \exp[-\pi X_t] \tag{7}$$

where π parametrizes the lost productivity due to pollution. The total PM2.5 concentration, X_t, is the sum of the PM2.5 created by each respective fuel:

$$X_t = \sum_j \lambda_j x_{j,t} \tag{8}$$

where λ_j is a conversion factor mentioned above.

The social planner's problem becomes:

$$\max \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} + \frac{(1-h_t-N_t^S)^{1-\psi}}{1-\psi} \right) \tag{9}$$

$$\text{s.t. } Y_t = A_t K_t^{\alpha_1} ((\exp[-\pi X_t])N_t)^{\alpha_2} E_t^{\alpha_3} \tag{10}$$

where

$$E_t = \left(\sum_j \omega_j x_{j,t}^{\rho}\right)^{1/\rho} \tag{11}$$

The consumer's problem in competitive equilibrium can be written as follows.

$$\max \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} + \frac{(1-h_t-N_t^S)^{1-\psi}}{1-\psi}\right) \tag{12}$$

$$\begin{aligned} \text{s.t. } & C_t + K_{t+1} - (1-\delta)K_t + B_t + E_t] \\ & \leq (1+r_{t-1})B_{t-1} + R_t K_t + W_t N_t \\ N_t & \leq 1 - L_t - h_t \\ & \text{all } t \end{aligned}$$

The firm's problem gives

$$\max Y_t - R_t K_t - W_t N_t] \tag{13}$$

$$\text{s.t. } Y_t = A_t K_t^{\alpha_1}((\exp[-\pi X_t])N_t)^{\alpha_2} E^{\alpha_3}$$

Equilibrium implies for all t,

$$\begin{aligned} N_t &= 1 - L_t - h_t \\ C_t &= Y_t = A_t K_t^{\alpha_1}((\exp[-\pi X_t])N_t)^{\alpha_2} E^{\alpha_3} \\ B_t &= 0 \end{aligned}$$

At steady state the FOC become:

$$W = AK^{\alpha_1} E^{\alpha_3} \alpha_2 (\exp[-\pi X]) \left[\exp[-\pi X])N\right]^{\alpha_2 - 1}$$

$$R = A\alpha_1 K^{\alpha_1 - 1}((\exp[-\pi X])N)^{\alpha_2} E^{\alpha_3}$$

$$\frac{\lambda_t}{\lambda_{t+1}} = \frac{1}{\beta} = r$$

$$\text{or: } C^{\sigma}(1-h-N^S)^{\psi} = W$$

$$R = \frac{1}{\beta} - 1 + \delta$$

$$B = 0$$

We calibrate the model and use it to illustrate the importance of the pollution elasticity of productivity. Note that this elasticity in the model is given by $\pi = \frac{\phi}{\alpha 2}$. We vary π by increments of 0.1 and compare the model responses to a baseline with a zero sensitivity to pollution. The following calibration and initial conditions are used in the simulation:

Parameter	Calibration
$\frac{C}{Y}$	0.6
$\frac{I}{Y}$	0.4
α_2	0.5
α_1	0.3
α_3	0.2
β	0.95
σ	1.2
ψ	3
δ	0.05
$\frac{1}{1-\rho} = \sigma_E$	1.4
ω_1	0.3
ω_2	0.3
ω_3	0.4

Table 5: Calibration

The numerical findings are given in Figure 8 below, illustrating significant effects from varying the labor elasticity on the steady state levels of output, consumption, and pollution.

Figure 8: Steady state shifts in relation to varying pollution elasticities