Beyond the Dam Failure: Iron Ore Mining and Water Quality Degradation in Mariana, Brazil

Área de Economia Regional

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In 2015, the Brazilian city of Mariana experienced a major environmental disaster following the collapse of a tailings dam. This paper advances a more nuanced hypothesis: the disaster may be a manifestation of a deeper structural problem, whereby iron ore production has been degrading the surrounding environment both before and after the dam failure. We test this hypothesis using quarterly data from 2003 to 2020 and employ SVAR, proxy SVAR, and BVAR models. Our results show that iron ore production deteriorates the water quality of rivers surrounding Mariana. The estimates indicate that the negative impact on water quality ranges from 4% to 76% over a ten-year horizon. These findings suggest that while disasters are extreme events that merit attention, they may obscure a persistent and cumulative environmental impact associated with ongoing mining activity. From a policy perspective, we argue in favor of imposing a tax on iron ore production. Such a policy could slowdown extractive activity, mitigate environmental degradation, and generate public revenues that may be used to offset environmental damages and support remediation efforts.
Key words: Water quality, Iron Ore, Mariana, Environment.
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Em 2015, o município brasileiro de Mariana foi palco de um dos maiores desastres ambientais da história do país, após o rompimento de uma barragem de rejeitos de mineração. Este artigo propõe uma hipótese mais abrangente: o desastre pode representar a manifestação de um problema estrutural mais profundo, no qual a produção de minério de ferro vem degradando o meio ambiente da região tanto antes quanto após o rompimento da barragem. Para testar essa hipótese, utilizamos dados trimestrais de 2003 a 2020 e estimamos modelos SVAR, Proxy SVAR e BVAR. Os resultados mostram que a produção de minério de ferro deteriora a qualidade da água dos rios no entorno de Mariana. As estimativas indicam que o impacto negativo sobre a qualidade da água varia entre 4% e 76% ao longo de um horizonte de dez anos. Esses resultados sugerem que, embora desastres ambientais sejam eventos extremos que demandam atenção, eles podem ocultar um processo persistente e cumulativo de degradação ambiental associado à atividade mineradora. Do ponto de vista das políticas públicas, argumenta-se pela adoção de um imposto sobre a produção de minério de ferro. Essa medida poderia desacelerar a atividade extrativa, mitigar a degradação ambiental e gerar receitas públicas destinadas à compensação dos danos ambientais e ao financiamento de ações de recuperação.
Palavras-chave: Qualidade da água; Minério de ferro; Mariana; Meio ambiente.

1. Introduction

Mineral extraction is one of the main drivers of economic growth in municipalities where it is carried out, due to its substantial capacity to generate income, employment, and revenue from taxes and royalties (Fernandes et al., 2025). At the national level, Brazil stands out for hosting some of the world's largest mineral reserves, establishing itself as one of the leading producers and exporters of high-quality ores and mineral products (Lovon-Canchumani et al., 2025). This relevance is reinforced by the country's broad geological diversity, which gives Brazil a strategic position in the global mineral landscape. In particular, iron ore production plays a central role, representing a significant share of Brazil's mineral exports.

However, mining activity also has the potential to generate substantial negative externalities for the environment and for the health of local populations (Kolala et al., 2020). Among the most recurrent adverse impacts are contamination of water, soil, and air, as well as a consequent reduction in the quality of life of communities located near mining operations (Bai et al., 2022).

Beyond these issues, iron ore extraction involves the generation of large volumes of tailings, whose disposal in containment dams poses continuous environmental and safety risks to nearby populations. As noted by Islam and Murakami (2021), tailings dam failures have occurred repeatedly around the world for several decades and, although the number of incidents is not high, their socio-environmental consequences tend to be extensive and devastating. In cases of rupture, the tailings wave can reach areas located several kilometers downstream, significantly amplifying the extent of the damage.

Brazil has nearly 600 registered tailings dams and has experienced recent accidents involving their failure (Pacheco et al., 2025). One of the most emblematic episodes—widely recognized for the magnitude of its environmental impacts—is the 2015 disaster in the district of Bento Rodrigues, in Mariana, Minas Gerais. As highlighted by Gomes et al. (2021), the collapse of the dam released approximately 50 million m^3 of tailings into the Rio Doce (Doce River), drastically affecting the environmental and ecological quality of more than 600 km of the basin downstream.

The literature has shown that regions with intensive mineral exploitation tend to exhibit significant deterioration in water quality, which becomes even more pronounced in contexts involving tailings dam failures. Events of this nature not only intensify existing impacts but also greatly amplify the ecological and socio-environmental risks associated with mining.

Following the collapse of the iron ore tailings dam in Mariana, research on the environmental impacts of iron ore extraction gained greater prominence. Despite this progress, there remains a gap in the literature regarding studies that examine the effects of mining on water quality over longer time horizons, given the high potential of mining activity to deteriorate river basins.

Junior et al. (2018) and Batista and Firme (2025) showed that the disaster in Mariana harmed both the environment and local economies. However, these investigations—and the literature in general—do not analyze the dynamics in Mariana over time. In other words, they do not answer the question: has iron ore activity in Mariana been affecting the environment *since* the disaster?

Figure 1 shows the water quality of the Rio Doce over the years. The water quality index captures several indicators—such as pH levels, turbidity, and temperature—to assess overall water conditions. When the index decreases, it suggests a deterioration in water quality. The dashed line represents the linear trend, indicating a persistent decline in water quality over the years, not only during the 2015 disaster.

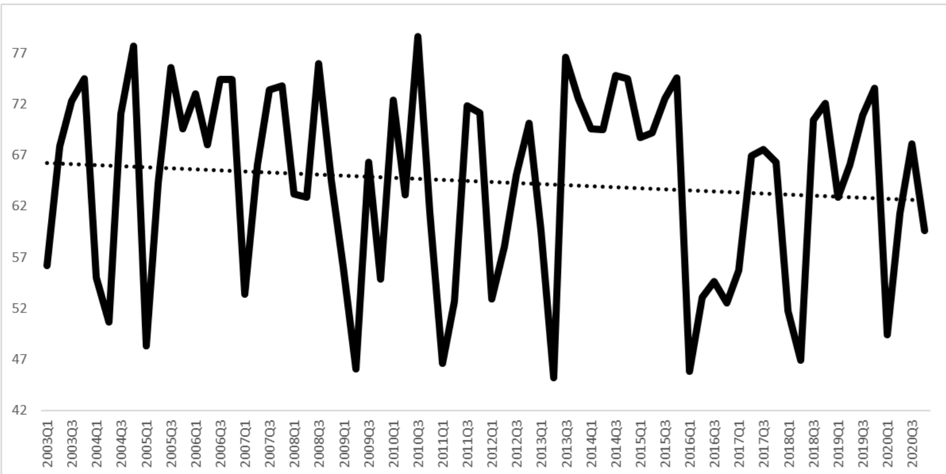

Figure 1: Water Quality of Rio Doce

Note: Water quality is an index that evaluates key characteristics of the river, such as pH levels, turbidity, and temperature. Lower values indicate a deterioration in water quality. The solid line represents the water quality index, while the dashed line shows its linear trend. See Table 1 for additional details. Source: IGAM (see Table 1).

Consequently, this paper explores a nuance of the disaster: whether the negative environmental impact has continued to occur even in the absence of new disasters. In this sense, our study innovates by going a step further. While previous studies, to the best of our knowledge, analyzed only the punctual impact of the 2015 event, we investigate whether environmental degradation has been happening despite the lack of major disasters.

Our research goal is to analyze the impact of iron ore production on the environment of Minas Gerais, especially in the areas affected during the 2015 disaster. Given this context, this article seeks to investigate whether mineral production exerts significant effects on the deterioration of water quality. Our analysis also focuses on testing the hypothesis that this deterioration is a direct consequence of iron ore extraction and that, therefore, the loss of water quality occurs *independently* of the disaster, which would have merely amplified the adverse effects already in place.

We adopt three econometric models—SVAR, Proxy SVAR, and BVAR—to analyze the period from the second quarter of 2003 to the fourth quarter of 2020. In the SVAR, we use a Cholesky decomposition to provide an economic rationale for the propagation of iron ore shocks. The Proxy SVAR complements this approach by using an external instrument for shock identification. The BVAR, through max-share identification, extracts the most relevant components to identify iron ore shocks and examine their impact on the environment.

The results show that iron ore production harms the environment by reducing water quality. Depending on the econometric model, water quality declines between 3% and 32%. We find both short- and long-term effects of iron ore production on environmental conditions.

We conduct several robustness checks—changing variables, proxies, lags, and identification methods—and the main results remain.

In addition to the contributions of (i) extending the literature by analyzing longer-term effects of iron ore production, and (ii) incorporating time series models into the analysis, we highlight a discussion absent in previous research: environmental harm caused by iron ore production is not limited to the 2015 disaster; it has been occurring since then, despite the absence of new catastrophic events. Our paper calls the attention of environmental authorities and policymakers to design measures that mitigate the negative impacts of iron ore activity.

This paper is structured as follows. Section 2 discusses the literature. Section 3 presents the data and methodology. Section 4 reports the results. Section 5 concludes and offers policy recommendations to reduce environmental damage in Minas Gerais.

2. Mining and the Environment: Impacts of Mineral Extraction on Water Quality Degradation

Mineral exploration plays a fundamental role in the economic development of countries, contributing decisively to industrialization processes and socioeconomic advancement. As highlighted by Mancini and Nuss (2020), mining activities underpin modern civilization by providing essential resources for infrastructure, industry, and technological progress.

However, Antoci et al. (2019) and Sturla-Zerene et al. (2020) emphasize that mining generates both positive and negative effects on national and local development, particularly with respect to environmental outcomes. These impacts tend to be more pronounced in regions with highly concentrated mining activities, directly affecting the living conditions of local populations.

Globally, mining operations produce millions of tons of ore each year. This process, however, also generates large volumes of waste, including tailings, flotation sludge, and minerals with no economic value (Kursunoglu, 2025). In this context, concerns about the environmental consequences of mining have intensified, as these effects have become more severe in recent years.

According to Yilmaz et al. (2015), iron ore extraction requires substantial amounts of natural resources and energy, leading to significant environmental impacts. Among the most relevant are atmospheric emissions, effluent discharges, and the generation of large volumes of waste, all of which compromise environmental quality. Liu et al. (2022) further note that the main impacts associated with mineral extraction and processing include particulate emissions into air and water, environmental toxicity, and contamination of water resources.

From this perspective, Bowker and Chambers (2015) observe that in Brazil, beyond chronic environmental degradation related to soil disturbance, vegetation loss, and watercourse contamination, the intensification of mining activities has increased the risk of tailings dam failures.

Brazil holds the world's second-largest reserves of raw iron ore, estimated at 34 billion tons (USGS, 2024). Production is concentrated primarily in the states of Pará and Minas Gerais (ANM, 2024). Iron ore plays a strategic role in the Brazilian economy, not only as one of the country's main sources of export revenue but also as a key input for national industrial development.

Nevertheless, iron ore mining poses substantial environmental and economic challenges, particularly in regions of intense extraction such as the Iron Quadrangle (*Quadrilátero Ferrífero* in portuguese). In this area, ecosystem degradation, water resource contamination, and adverse socioeconomic impacts on local communities are especially evident.

In recent years, two major tailings dam failures occurred in the municipalities of Mariana and Brumadinho, both located in the state of Minas Gerais. As noted by Pacheco et al. (2025), these disasters produced social and environmental consequences. The authors show that the accidents intensified contamination in the Doce and Paraopeba rivers, where water quality—already compromised—began to exhibit metal concentrations and turbidity levels exceeding legal limits. Kütter et al. (2023) also analyzed the impacts of the Mariana dam collapse on the Doce River and documented a significant deterioration in water quality.

Regarding environmental degradation resulting from mineral exploration, Melo et al. (2020) emphasize that although mining occupies a relatively small fraction of Brazil's national territory, its effects on water quality are substantial.

The debate surrounding the impacts of mineral exploration has intensified in recent years, generating growing interest among researchers, policymakers, and civil society organizations. The academic literature converges on the existence of significant negative environmental externalities associated with mining activities. In the Brazilian context, studies consistently highlight ecosystem degradation, water resource contamination, and the social impacts experienced by communities located near extraction zones.

Given these concerns, and in light of the severe environmental consequences of recent tailings dam failures, it has become increasingly important to empirically investigate the effects of mineral exploration on water quality.

2.2 Empirical Studies

Given the potential impact of iron ore production on the environment, it is surprising how scarce empirical studies are on the relationship between iron ore production and environmental degradation.

The Mariana disaster in 2015 triggered a surge of papers examining the effects of iron ore industry operations. Soares et al. (2025) reviewed the literature and argued that studies on the environmental impacts of iron ore production increased significantly after the disaster.

One key conclusion is that environmental harm—particularly the deterioration of water quality—had already been observed prior to the disaster. However, earlier studies focused on chemical concentrations in water rather than using advanced mathematical or statistical tools to establish a causal link between iron ore production and water quality. In other words, it is not clear that iron ore production is the main driver of the decline in water quality.

Similarly, Fernandes et al. (2016) and Orlando et al. (2020) documented reductions in water quality in rivers near Mariana, using descriptive data and photographic evidence. Yet the underlying challenge remains: in real-world economic environments, multiple events occur simultaneously. How can we be sure that one variable is affecting another? Regional economies involve several overlapping activities that may influence water quality.

Campos et al. (2023), Jiang et al. (2024), and Milanez (2024) applied multiple linear regressions, a computable general equilibrium model, and life cycle assessments (LCA) to analyze how iron ore production relates to economic and environmental variables. However, these techniques overlook important aspects of production impacts on the environment: i) they do not capture spillover effects, and ii) they often treat endogenous variables as exogenous. For instance, the multiple linear regression used by Campos et al. (2023) suffers from this limitation and may produce biased estimates.

Another gap in the literature is the absence of studies simulating the operationalization of a region and its economy and evaluating how these dynamics affect water quality. Additionally, empirical studies must offer reliable inference, which is achieved through econometric tools such as confidence intervals and tests of statistical significance.

By using time series methods with alternative shock identifications, we address these limitations. Importantly, we also test our argument that the worsening of water quality occurred both before and during the disaster. Our empirical strategy allows us to take a step further: Is water quality also getting worse in the future? Consequently, our framework offers a new perspective to the literature by investigating whether the 2015 disaster was a one-off event or part of a trend that has continued since then.

3. Data and Methodology

3.1 Data

Table 1 presents the variables, their definitions, and their sources. The variable iron ore production (*iron*) was collected from the Agência Nacional de Mineração (ANM), from the section *Compensação Financeira pela Exploração de Recursos Minerais* (CFEM). CFEM provides the royalties that Brazilian municipalities receive from mining companies operating within their jurisdiction. By law, companies paid a 2% royalty rate until 2017 and 3.5% since 2018. Of all CFEM revenues collected, 60% are allocated to municipalities.

In the case of Mariana, 99% of its total CFEM revenue comes from iron ore, showing the high concentration of this mineral in its territory. In other words, CFEM revenue is defined as:

$$\text{CFEM} = t \times \text{iron ore revenue} \qquad (1)$$

where t is the royalty rate firms pay on the sales value of iron ore. We divided CFEM by t to obtain the underlying iron ore revenue. Since iron ore revenue equals production multiplied by price, we deflated it using the Brazilian consumer price index, IPCA (*Índice de Preços ao Consumidor Amplo*). IPCA data were collected from the Instituto de Pesquisa Econômica Aplicada (IPEA). By deflating iron ore revenue, we obtain a proxy for the real value of iron ore production, which reflects the underlying production dynamics.

Table 1: Variables, Definitions, and Sources

Variables	Definitions	Sources
iron	Iron ore production (deflated, in R$)	ANM/CFEM, IPEA
water	Water quality	IGAM
gdp	GDP of Minas Gerais (index, 2002 = 100)	FJP
extractive	Extractive production of Minas Gerais (index, 2022 = 100)	IPEA
commo	Commodity Prices (index, 2016 = 100)	IMF/Primary Commodity Prices
e	Exchange rate, R$ per U.S. dollar	IPEA

Water quality data were obtained from the Instituto Mineiro de Gestão das Águas (IGAM). IGAM monitors water conditions across numerous rivers in Minas Gerais, measuring indicators such as pH, temperature, and turbidity. The water quality index is a summary measure based on these evaluations.

Several monitoring stations collect water quality data. We selected those most directly affected by the 2015 disaster. These stations are located along the Rio do Carmo (station RD009), Rio Doce (stations RD019, RD023, and RD035), and Rio Piranga (stations RD001, RD013, and RD007). Some stations were excluded due to missing or insufficient data. We averaged the water quality measures from the selected stations to construct the variable *water*.

The gross domestic product (GDP) of Minas Gerais was collected from the Fundação João Pinheiro (FJP). The GDP series is provided as an index with a base value of 100 in 2002. The extractive production of Minas Gerais was collected from IPEA and is also an index, with a base of 100 in 2022. While GDP reflects all economic activities in the state, extractive production focuses on the extraction of natural resources, including solid minerals (such as coal and metallic ores), liquid fuels (crude oil), and natural gas. It also includes complementary activities associated with mineral extraction.

Because Brazil—and Minas Gerais in particular—is a major global producer and exporter of commodities, especially iron ore, we included international commodity prices from the International Monetary Fund (IMF), obtained from the Primary Commodity Prices database. The variable *commo* is an index with a base of 100 in 2016.

In addition to commodity prices, we included the exchange rate (e) to capture another key characteristic of commodity-exporting economies. The exchange rate was collected from IPEA and is defined as the ratio of the Brazilian currency (reais) to the U.S. dollar. Higher values indicate a depreciation of the Brazilian currency, which increases the profitability of exports, including iron ore.

The period of analysis was determined by the availability of the water quality series. Water quality data begin in the second quarter of 2003, so the initial observation is 2003Q2. The series ends in 2020Q4, resulting in a sample from 2003Q2 to 2020Q4. Because water quality is a quarterly indicator, all other variables were converted to quarterly frequency by averaging their monthly values.

In sum, these variables capture the iron ore production dynamics in Mariana and the water quality conditions in the nearby rivers. The next sections present the econometric models that link iron ore production to water quality. We also include nominal variables (*commo* and *e*) to incorporate economic incentives for producers, as well as state-level characteristics of Minas Gerais, where Mariana is located.

3.2 SVAR Model

The first econometric model is the SVAR. As in the subsequent models (Proxy-SVAR and BVAR), all variables are treated as endogenous, allowing us to capture spillover effects and to interpret the shocks according to the identification strategy employed.

We adopt a recursive (Cholesky) identification scheme, ordering the variables from the most exogenous to the most endogenous:

$$SVAR = (iron_t, extractive_t, commo_t, e_t, water_t) \quad (2)$$

This ordering assumes that iron ore production contemporaneously affects extractive production. Changes in extractive production influence global markets—commodity prices—which then affect the exchange rate, likely due to variations in export revenues and capital flows. Finally, these economic adjustments propagate to water quality.

3.3 Proxy SVAR Model

The Proxy SVAR provides an alternative identification strategy for structural shocks. Instead of relying on recursive (Cholesky) restrictions, it uses an external instrument to isolate the structural shock of interest.

We begin with the reduced-form VAR:

$$Y_t = C(L)Y_{t-1} + u_t \quad (3)$$

Where Y_t are the vector of variables, C(L) is a lag polynomial matrix, and $u_t$is the vector of reduced-form innovations.

The goal is to recover the structural shocks ε_t, which satisfy:

$$u_t = A\varepsilon_t \quad (4)$$

In Equation 4, where A is the contemporaneous impact matrix and ε_t is the vector of structural shocks.

In the standard SVAR, A is identified using the Cholesky decomposition. In the Proxy SVAR, however, we rely on an external instrument z_t that satisfies the following conditions:

$$E[z_t\ \varepsilon_{iron,t}] \neq 0$$
$$E\big[z_t\ \varepsilon_{j,t}\big] = 0, for\ j \neq iron \quad (5)$$

The instrument must be correlated with the iron ore structural shock and uncorrelated with all the remaining structural shocks.

In our empirical application, we use commodity prices as the instrument. Thus, Equation 5 becomes:

$$E[commo_t\ \varepsilon_{iron,t}] \neq 0$$
$$E\big[commo_t\ \varepsilon_{j,t}\big] = 0 \quad (6)$$

3.4 BVAR Model

We present the max-share shock identification by rewriting Equation (4) as:

$$u_t = A(L)\varepsilon_t \ (7)$$

The lag polynomial is defined as:

$$A(L) \equiv \sum_{-\infty}^{\infty} A_k L^k \quad (8)$$

In the standard SVAR and Proxy-SVAR, the matrix $A(L)$ is treated as a contemporaneous impact matrix obtained through identification restrictions. In contrast, the max-share identification begins by assuming $A(L) = A_0$, and uses the moving-average representation of the VAR:

$$Y_t = \sum_{k=0}^{\infty} B_k A_0 \varepsilon_{t-k} \ (9)$$

In Equation 9, B_k is the coefficients of the infinite moving average process and $B(L) \equiv (I - C(L))^{-1}$.

The h-step forecast error of the iron ore production shock is:

$$iron_{t+h} - E_{t-1}(iron_{t+h}) = \sum_{\tau=0}^{h-1} B_\tau A_0 \varepsilon_{t+h-\tau} \quad (10)$$

The corresponding forecast-error variance is:

$$var[iron_{t+h} - E_{t-1}(iron_{t+h})] = \sum_{\tau=0}^{h-1} B_\tau A_0 ee' A_0' B_\tau' \ (11)$$

where e is the selection vector that extracts the component of ε_t associated with the structural shock of interest (iron ore production).

Thus, the max-share identification selects the linear combination of reduced-form shocks that maximizes the contribution of the resulting structural shock to the forecast-error variance of the target variable.

In our case, because iron ore production is the variable of interest, the max-share procedure identifies the linear combination of shocks that generates the highest forecast-error variance share of iron ore production over the chosen horizon.

In the BVAR, we use the Minnesota prior. This prior treats each time series as a separate random walk, giving more weight to recent observations and shrinking the influence of other variables. A key distinction between the BVAR and the SVAR/Proxy-SVAR is that, while the latter two rely purely on the data to construct the system of equations, the BVAR incorporates prior beliefs to model the dynamics.

The three econometric models complement each other. The SVAR, identified via Cholesky decomposition, orders the variables in a theoretically grounded way, providing a rationale for the shocks and their propagation. The Proxy-SVAR allows us to test the robustness of the results using an alternative identification scheme in which the shock is instrumentalized.

By using the Minnesota prior, the BVAR mitigates issues such as nonstationarity. Another advantage is that the Minnesota prior places more weight on information close to the contemporaneous values of the variables, reducing the influence of distant past observations.

The max-share shock identification aggregates all information about the target shock, showing how well the set of variables explains the structural shock and how strongly this shock affects water quality.

Throughout the estimation, we use 68% confidence intervals, and all variables are expressed in logarithms. We adopt 2 lags in all models.

We analyze impulse response functions (IRFs) and forecast error variance decompositions (FEVDs). IRFs show how variables respond to a one-standard-deviation shock, while the FEVD measures how much of the forecast error variance of each variable is explained by the structural shock. In our context, we are interested in how water quality responds to iron ore production shocks, and in quantifying how much these shocks contribute to changes in water quality.

Sims et al. (1990) argue that the class of VAR models may be estimated in levels even when some time series exhibit unit roots. Transforming variables—for instance, from levels to first differences—may alter the statistical properties of the series, lead to information loss, and change the interpretation of the results. These considerations are particularly relevant when the objective of the analysis is to study dynamic responses, such as those obtained through impulse response functions, for which estimating variables in levels may be appropriate.

Following this approach, we begin our analysis by estimating all models using variables in levels. However, as reported in Table A, in the appendix, which presents the unit root test results, all series exhibit unit roots, with the exception of iron production and water quality.

Therefore, as robustness checks, we also re-estimate the models accounting for nonstationarity. In the SVAR framework, we test the robustness of the results by estimating a SVAR with all variables expressed in first differences. In the BVAR framework, such transformations are not strictly required, as the Minnesota prior accommodates nonstationary behavior. Nevertheless, we further assess robustness by estimating a BVECM with cointegrating relationships and identifying structural shocks that target long-run effects.

4. Results

4.1 Impact of Iron Ore Production

Figure 2 presents the effects of an iron ore production shock. The responses are statistically significant when the confidence interval bands lie entirely within the same quadrant. The shock corresponds to an increase of approximately 0.5% in iron ore production. Following the shock, extractive production and commodity prices rise, while the exchange rate appreciates. The most important result is the decline in water quality in the first quarter after the shock.

The appreciation of the exchange rate can be interpreted as a consequence of higher exports. Increased iron ore production leads to larger foreign currency inflows—primarily U.S. dollars—which strengthen the Brazilian currency. The increase in commodity prices may reflect Brazil's position as a major global producer and exporter of iron ore and related commodities. In this context, domestic supply conditions can influence international prices.

The reduction in water quality indicates that iron ore production negatively affects local well-being, likely through environmental contamination and potential health risks. Since water quality is a key environmental indicator, the results suggest that higher iron ore production has harmful effects on environmental conditions in Brazil.

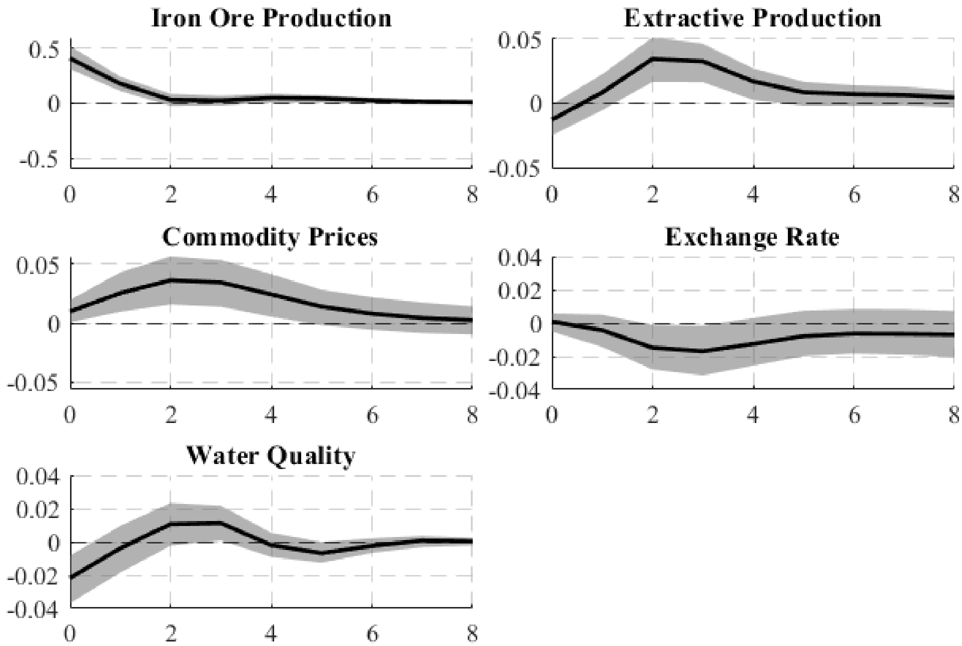

Figure 2: Shock of iron ore production and responses of variables (SVAR model)

Note: The vertical axis reports the magnitude of the variables in response to the shock, while the horizontal axis shows the time horizon (in periods). The solid line represents the average estimated response. The shaded area denotes the 68% confidence interval. A response is statistically significant when the entire confidence band lies within the same quadrant.

Haque et al. (2015) and Hoang and Nguyen (2018) showed that iron ore production affects the exchange rate and other macroeconomic variables in Australia. Our results extend these findings to Brazil, indicating that iron ore production also influences the Brazilian currency and commodity prices.

Regarding environmental impacts, Ferreira and Leite (2015) found that the use of grinding media is the main source of environmental harm in the iron ore production chain. Lovón-Canchumani et al. (2025) reinforced this conclusion by showing that Brazilian iron ore production affects the environment through the consumption of inputs and resources during the production process, such as fossil fuels. According to Haque (2022), iron ore production is highly energy intensive and releases substantial amounts of carbon, thereby negatively affecting the environment. Our findings are consistent with this literature, as we detect a deterioration in water quality following an iron ore production shock.

Table 2 presents the variance decomposition of the variables in response to the iron production shock. Unlike Figure 2, we extend the horizon to period 40 (10 years) in order to capture the long-term effects of the shock.

Table 2: Variance decomposition of variables due to the iron production shock

Horizon	Iron Ore Production	Extractive Production	Commodity Prices	Exchange Rate	Water Quality
1	88.6	4.1	5.4	1.1	5.6
	[83.0, 97.4]	[0.0, 6.8]	[0.0, 9.7]	[0.0, 2.0]	[0.0, 9.4]
4	72.9	18.1	13.1	4.2	7.7
	[62.6, 85.6]	[5.0, 27.4]	[0.0, 22.9]	[0.0, 7.5]	[0.0, 12.1]
8	68.3	17.5	12.0	4.0	8.3
	[56.6, 82.2]	[3.7, 26.5]	[0.0, 20.3]	[0.0, 7.0]	[0.2, 13.0]
40	49.5	9.9	10.2	3.3	8.4
	[29.3, 67.9]	[0.0, 15.9]	[0.0, 16.9]	[0.0, 6.0]	[0.7, 13.1]

Note: The first column reports the time horizons (periods). Each subsequent column shows the percentage influence of the iron production shock on the corresponding variables. The values in brackets denote the confidence intervals.

The interpretation of Table 2—and the subsequent tables—is as follows. In period 1, the iron production shock explains 88% of its own variance. Extractive production is explained by 4%, commodity prices by 5%, the exchange rate by 1%, and water quality by 5%. These proportions evolve over time. By the final period (40), iron ore production is explained by 49%, extractive production by 9%, commodity prices by 10%, the exchange rate by 3%, and water quality by 8%.

An interesting pattern emerges between periods 8 and 40: the contributions of the shock to commodity prices, the exchange rate, and water quality remain relatively stable. This suggests that the effects of the iron production shock are largely realized within the first eight quarters.

Overall, Table 2 confirms that the iron production shock has persistent effects on both economic and environmental variables.

Figure 3 presents the responses of water quality to the different shocks. Water quality declines following shocks to iron ore production (as previously documented), extractive production, commodity prices, and exchange rate depreciation.

The initial increase in response to extractive production is unexpected and may reflect the fact that extractive production includes other activities that could temporarily improve measured water quality before the negative effects dominate. The decline after commodity price shocks is consistent with the idea that higher prices incentivize additional iron ore production. The response to exchange rate depreciation suggests a similar mechanism, as a weaker Brazilian currency stimulates exports; however, this effect is statistically nonsignificant.

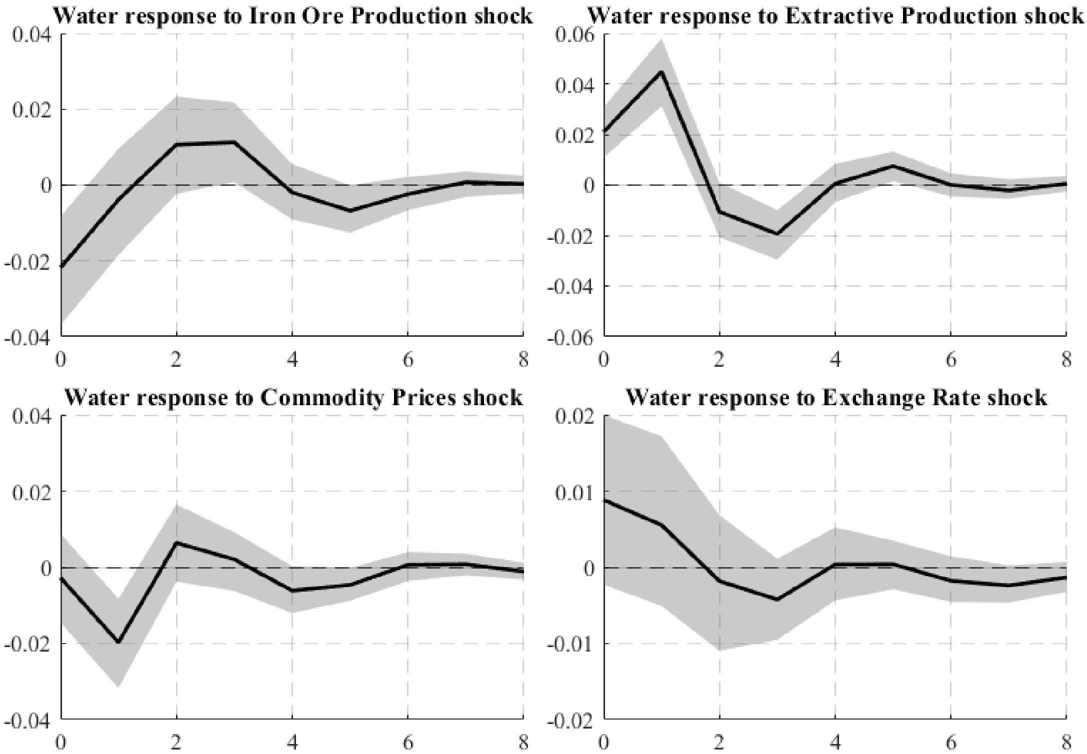

Figure 3: Responses of water quality to shocks (SVAR model)

Note: The vertical axis reports the magnitude of the variables in response to the shock, while the horizontal axis shows the time horizon (in periods). The solid line represents the average estimated response. The shaded area denotes the 68% confidence interval. A response is statistically significant when the entire confidence band lies within the same quadrant.

Overall, this section demonstrates that increases in iron ore production harm the environment through the deterioration of water quality. The estimates indicate that these adverse effects are persistent, lasting for at least ten years.

4.2 Alternative SVAR

The alternative specification excludes nominal variables (commodity prices and exchange rates) and incorporates the GDP of Minas Gerais—the state where the city of Mariana is located. In economic terms, this implies that the model now relies exclusively on real variables, that is, variables that do not directly depend on prices or inflation.

The GDP of Minas Gerais was obtained from the Fundação João Pinheiro (FJP). The series is published as an index with a base value of 100 in 2002.

The ordering of the structural shocks is iron ore production → GDP → extractive production → water quality. The rationale is that iron ore production may affect state GDP, which in turn influences extractive production and subsequently water quality.

Figure 4 presents the results. A positive shock to iron ore production increases GDP for two years (eight quarters) and extractive production for about one year (four quarters). The response of extractive production loses statistical significance after the first year, whereas the effect on GDP remains statistically significant over the entire horizon. This underscores the central economic importance of iron ore activity for the state of Minas Gerais (Silva et al., 2021).

Consistent with previous specifications, water quality deteriorates in the first quarter following the shock, although the effect becomes statistically insignificant thereafter.

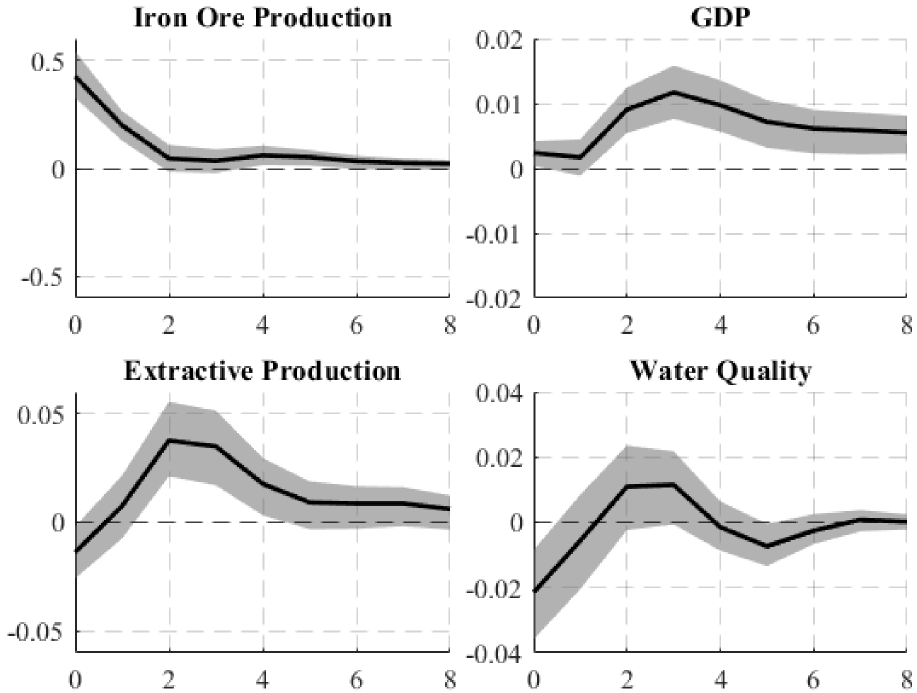

Figure 4: Shock of iron ore production and responses of variables (alternative SVAR)

Note: The vertical axis reports the magnitude of the variables in response to the shock, while the horizontal axis shows the time horizon (in periods). The solid line represents the average estimated response. The shaded area denotes the 68% confidence interval. A response is statistically significant when the entire confidence band lies within the same quadrant.

Table 3 reports the variance decomposition of the variables due to the iron ore production shock, following the same structure as Table 2. The effect of the shock on water quality is essentially unchanged relative to the baseline specification: after eight quarters, iron ore production explains about 8% of the variation in water quality. This share remains the same at the 40-quarter horizon, indicating that the impact of the shock is fully realized within two years.

Table 3: Variance decomposition of variables due to the iron production shock (alternative SVAR)

Horizon	Iron Ore Production	GDP	Extractive Production	Water Quality
1	89.0	2.3	3.5	5.2
	[83.0, 98.2]	[0.0, 4.0]	[0.0, 5.7]	[0.0, 8.9]
4	74.8	25.0	18.2	7.8
	[63.4, 90.5]	[9.6, 37.5]	[4.7, 28.4]	[0.1, 12.1]
8	72.3	26.8	18.1	8.6
	[59.9, 88.3]	[9.2, 41.3]	[4.0, 28.2]	[0.5, 13.2]
40	70.2	25.7	17.9	8.6
	[57.3, 86.9]	[6.5, 40.6]	[4.2, 28.0]	[0.5, 13.3]

Note: The first column reports the time horizons (periods). Each subsequent column shows the percentage influence of the iron production shock on the corresponding variables. The values in brackets denote the confidence intervals.

At the 40-quarter horizon, iron ore production accounts for 25% of the variation in GDP, 17% of the variation in extractive production, and 8% of the variation in water quality.

Milanez et al. (2024) and Júnior et al. (2024) highlight the relevance of iron ore production for Minas Gerais and for Brazil as a whole, particularly through its contributions to GDP and trade surpluses. The estimates of this study reinforce these findings: the impulse response functions indicate that iron ore production increases the GDP of Minas Gerais, and the variance decomposition confirms that roughly one-quarter of the state's GDP is driven by iron ore dynamics.

This section shows that even after modifying the model, the central result remains: iron ore production has a harmful effect on water quality.

4.3 Proxy SVAR Model

This section employs a proxy SVAR, which identifies the structural shock through an external instrument. In this case, commodity prices are used to instrument the structural innovation in iron ore production.

Figure 5 presents the shock. Iron ore production increases for two quarters before losing statistical significance. Extractive production and the exchange rate exhibit statistically insignificant responses—although the signs of their movements align with expectations. Water quality declines in the first quarter, consistent with the results obtained in previous econometric specifications.

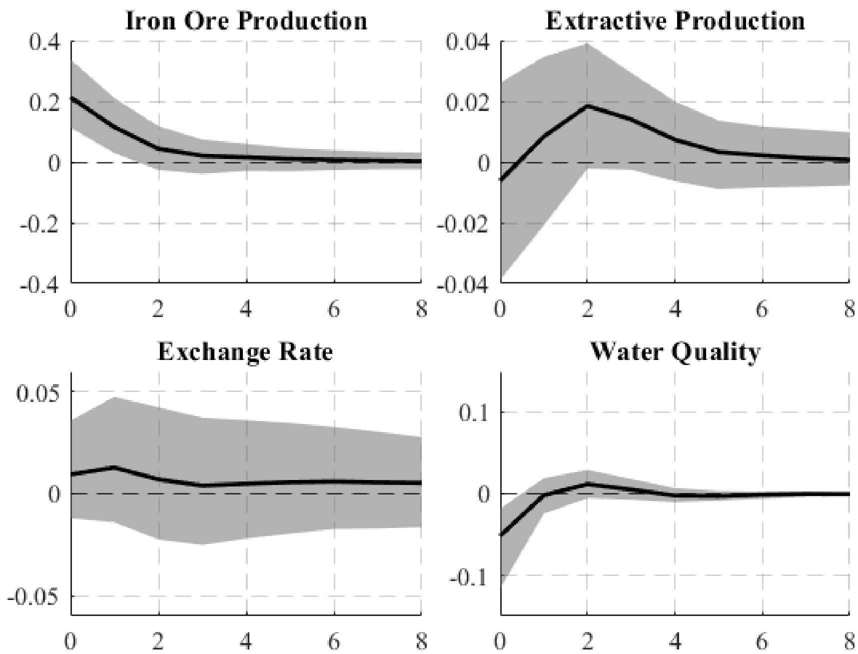

Figure 5: Shock of iron ore production and responses of variables (Proxy SVAR)

Note: The vertical axis reports the magnitude of the variables in response to the shock, while the horizontal axis shows the time horizon (in periods). The solid line represents the average estimated response. The shaded area denotes the 68% confidence interval. A response is statistically significant when the entire confidence band lies within the same quadrant.

Table 4 reports the variance decomposition associated with the proxy SVAR. Under this framework, the influence of the shock on water quality increases substantially: the shock explains 30% of the variation in water quality by the eighth quarter, compared to 8% in the baseline results.

Table 4: Variance decomposition of variables due to the iron production shock (Proxy SVAR)

Horizon	Iron Ore Production	Extractive Production	Exchange Rate	Water Quality
1	27.4	10.1	10.9	32.0
	[0.0, 49.3]	[0.0, 17.5]	[0.0, 20.2]	[3.0, 55.6]
4	27.2	14.7	11.2	30.8
	[1.0, 46.0]	[0.0, 23.9]	[0.0, 20.2]	[4.8, 52.2]
8	26.2	14.5	11.3	30.5
	[3.0, 43.6]	[0.0, 23.0]	[0.0, 20.6]	[5.5, 51.3]
40	24.8	15.0	11.3	30.4
	[3.8, 40.4]	[0.3, 23.5]	[0.0, 20.7]	[5.6, 51.0]

Note: The first column reports the time horizons (periods). Each subsequent column shows the percentage influence of the iron production shock on the corresponding variables. The values in brackets denote the confidence intervals.

Another difference is the impact of the shock on iron ore production itself. Because the shock is instrumentalized, it is common for the variance share attributed to iron ore production to fall, reflecting the partial identification inherent in proxy SVARs.

Despite these differences, the main finding remains robust: even with the proxy SVAR and an alternative identification strategy, iron ore production continues to generate harmful effects on water quality.

4.4 BVAR Model

This section extends the analysis to a BVAR. Table 5 presents the variance decomposition of the iron ore production shock under the baseline specification.

With the exception of iron ore production itself, the variance shares are relatively stable across horizons. Iron ore production explains between 27% and 73% of its own forecast error variance, while it accounts for 4.7–5% of extractive production, 3.9–4% of commodity prices, 2.8–3.2% of the exchange rate, and 3.2–3.9% of water quality.

Table 5: Variance decomposition of variables due to the iron production shock (BVAR)

Horizon	Iron Ore Production	Extractive Production	Commodity Prices	Exchange Rate	Water Quality
Short- term (0-8)	73.2	5.0	4.0	2.8	3.2
	[56.2, 86.1]	[1.1, 21.7]	[1.0, 12.7]	[0.6, 10.5]	[0.8, 9.7]
Long-term (40+)	27.0	4.7	3.9	3.2	3.9
	[4.7, 61.3]	[0.6, 19.4]	[0.5, 14.2]	[0.3, 14.0]	[0.5, 14.6]

Note: The first column reports the time horizons (periods). Each subsequent column shows the percentage influence of the iron production shock on the corresponding variables. The values in brackets denote the confidence intervals.

Table 6 presents the results for the alternative specification estimated with the BVAR. Under this configuration, iron ore production continues to influence all variables. Of particular interest to our research question, the last column shows that water quality is affected by 4.9% in the short-term (the first eight quarters) and by 8.8% at the 40-quarter horizon (long-term). These values are close to those obtained in the SVAR models (Tables 2 and 3).

Table 6: Variance decomposition of variables due to the iron production shock (alternative BVAR)

Horizon	Iron Ore Production	GDP	Extractive Production	Water Quality
Short- term (0-8)	64.0	11.4	12.9	4.9
	[45.3, 83.5]	[0.9, 47.7]	[2.6, 40.6]	[1.2, 14.5]
Long-term (40+)	68.7	12.1	14.3	8.8
	[24.3, 89.8]	[1.1, 48.7]	[1.8, 59.5]	[1.1, 42.0]

Note: The first column reports the time horizons (periods). Each subsequent column shows the percentage influence of the iron production shock on the corresponding variables. The values in brackets denote the confidence intervals.

In summary, the estimates indicate that the main findings are robust to alternative model specifications and to different approaches to shock identification.

4.4 SVAR in Log Differences

In all previous estimations, the variables were used in levels. This section employs the variables in log differences to test the robustness of the results. Figure 6 replicates the base SVAR model using all variables in log differences.

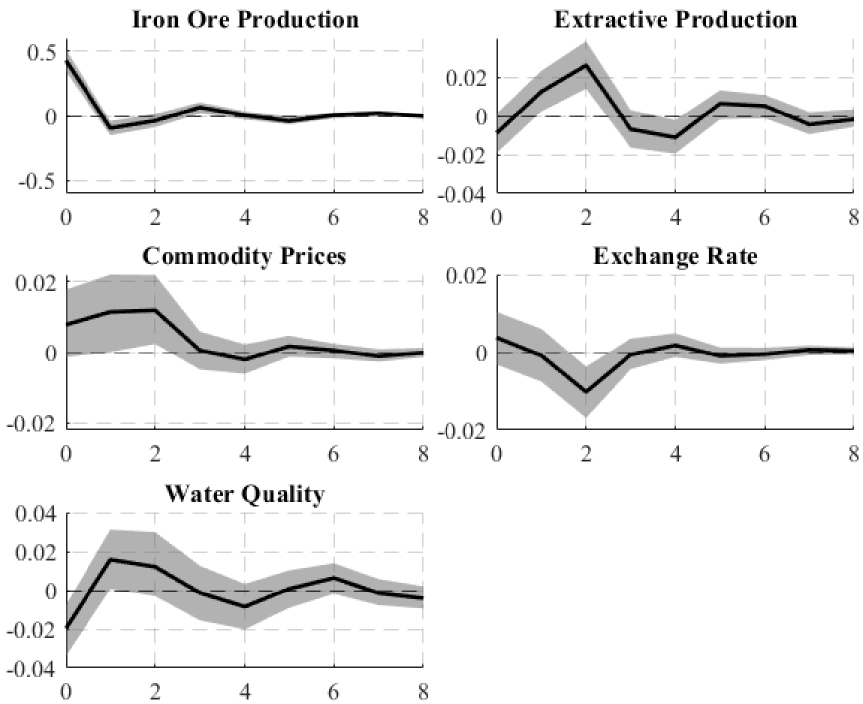

Figure 6: Shock of iron ore production and responses of variables (SVAR in log-diff)

Note: The vertical axis reports the magnitude of the variables in response to the shock, while the horizontal axis shows the time horizon (in periods). The solid line represents the average estimated response. The shaded area denotes the 68% confidence interval. A response is statistically significant when the entire confidence band lies within the same quadrant.

The results are similar to those in Figure 2, which used the SVAR in levels. The exchange rate decreases, while commodity prices and extractive production increase due to the iron ore production shock. The main finding remains: water quality decreases at the beginning of the shock.

One qualitative difference is that the responses are less smooth than those in Figure 2.

Overall, the results suggest that unit roots are not a problem in the estimates.

4.5 Alternative lags

All models used two lags. We adopted two lags partly because the number of observations is limited; additional lags could harm the estimates and compromise model stability. Moreover, two lags are standard in the literature (Attílio and Mollick, 2024; Chahrour et al., 2024).

We test the base model using four lags. Figure 7 presents the results of an iron ore production shock under this specification.

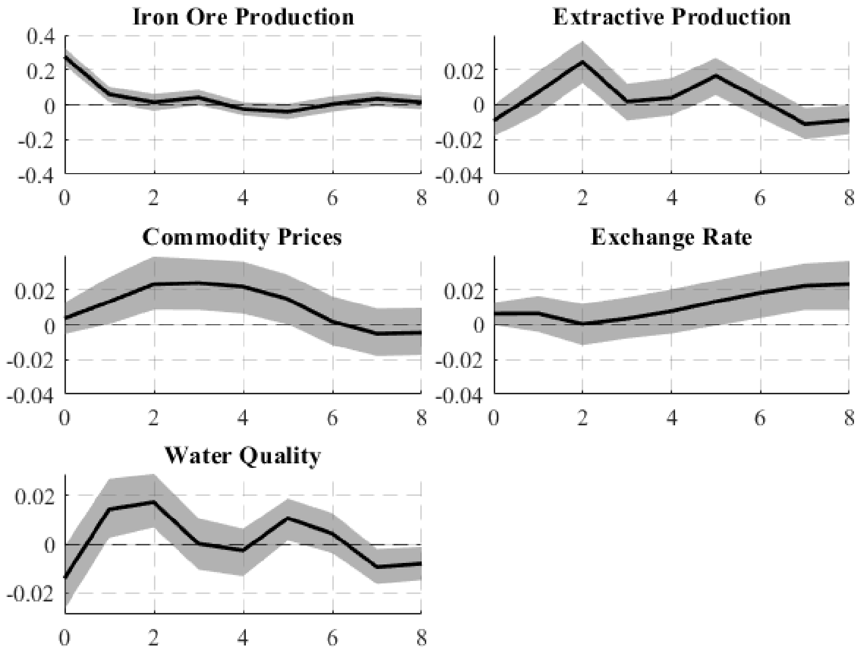

Figure 7: Shock of iron ore production and responses of variables (SVAR with 4 lags)

Note: The vertical axis reports the magnitude of the variables in response to the shock, while the horizontal axis shows the time horizon (in periods). The solid line represents the average estimated response. The shaded area denotes the 68% confidence interval. A response is statistically significant when the entire confidence band lies within the same quadrant.

There is a qualitative deterioration in the responses. The dynamics are less stable over time and take longer to converge. Unlike previous results, the exchange rate increases following the shock, suggesting that four lags may not be an appropriate specification for this dataset.

Nonetheless, the main finding remains: despite the fluctuations in water quality, by the end of the horizon water quality decreases in response to the shock.

4.6 BVEC Model

As discussed in the methodology section, Sims et al. (1990) show that estimating models in levels may yield meaningful econometric results even in the presence of unit roots. Nevertheless, we implement robustness checks to explicitly accommodate the nonstationarity observed in some of the time series. Since the Johansen cointegration tests indicate the presence of cointegrating relationships, we estimate a Bayesian Vector Error Correction Model (BVECM).

Table 7 replicates the BVAR analysis using the BVECM framework. The first panel reports the estimates for the baseline model, while the second panel presents results for the alternative specification. In both cases, structural shocks to iron ore production exert substantial effects on water quality. In the baseline model, the contribution of iron ore production to water quality ranges from 14% in the short run to 76% in the long run. In the alternative model, the estimated effects vary between 18% and 19%. Importantly, in both specifications, the impact of iron ore production on water quality exceeds that reported in the BVAR estimates (Tables 5 and 6).

Table 7: Variance decomposition of variables due to the iron production shock (BVEC model)

	Horizon	Iron Ore Production	Extractive Production	Commodity Prices	Exchange Rate	Water Quality
BASE MODEL	Short- term (0-8)	24.7	28.1	37.5	60.8	14.4
		[11.7, 41.8]	[13.8, 54.4]	[14.3, 62.8]	[23.9, 83.0]	[6.0, 31.2]
	Long-term (40+)	92.6	88.5	77.2	90.3	76.5
		[75.9, 98.9]	[67.1, 98.2]	[34.3, 96.3]	[68.1, 98.9]	[30.1, 96.2]

	Horizon	Iron Ore Production	GDP	Extractive Production	Water Quality
ALTERNATIVE MODEL	Short- term (0-8)	40.3	23.9	76.2	19.7
		[22.8, 61.1]	[10.2, 41.9]	[59.9, 87.0]	[8.1, 35.8]
	Long-term (40+)	99.1	34.5	92.3	18.2
		[97.4, 99.6]	[8.0, 74.1]	[77.7, 97.5]	[3.6, 58.5]

Note: The first column reports the time horizons (periods). Each subsequent column presents the percentage contribution of the iron production structural shock to the corresponding variables. Values in brackets denote confidence intervals. The first panel reports results from the baseline model, while the second panel reports results from the alternative model. Both models are estimated using a BVECM.

These findings are not unexpected, as the BVECM explicitly captures long-run equilibrium relationships and, consequently, the long-term effects of structural shocks. The inclusion of cointegrating vectors and long-run dynamics likely improves the identification and transmission of the iron ore production shock to water quality fluctuation.

6. Conclusion

Mineral exploration has the potential to generate negative environmental impacts, particularly with respect to the deterioration of water quality. In the case of iron ore extraction, this issue is intensified by the generation of large volumes of tailings, whose storage in containment dams entails significant structural and environmental risks. When such structures fail, the consequences become even more severe, as large quantities of tailings are released into the environment, intensifying water contamination and amplifying the associated environmental and social damages.

Following the collapse of the tailings dam in Mariana, studies on the environmental impacts of iron ore extraction gained greater visibility. Nevertheless, a gap remains in the literature regarding long-term analyses of the effects of mineral exploration on water quality, despite the well-recognized potential of mining activities to degrade river basins in a continuous and cumulative manner over time.

In this context, this article aimed to assess whether iron ore exploration produces significant effects on the deterioration of water quality. Our analysis also tested the hypothesis that this deterioration is a direct consequence of mining activity and that the loss of water quality *precedes* the disaster and occurs independently of it. Therefore, tailings dam failures intensify and render more visible impacts that *already* exist.

The results indicate that iron ore production in Mariana has adversely affected the environment through a deterioration in water quality. Our estimates suggest that this environmental damage may persist for up to ten years. If extrapolated—an issue that future studies may explore in greater depth—the decline in water quality is likely to generate additional negative effects, such as adverse impacts on human health, with potential fiscal costs for governments and welfare losses for the affected population.

Accordingly, future research could extend our analysis by examining the effects of iron ore production on public health, thereby providing a more comprehensive assessment of the social costs associated with mining activity.

One limitation of this study is the absence of a formal causal analysis, such as difference-in-differences or panel data approaches. This reflects an inherent trade-off. By adopting time-series methods, we are able to capture spillover effects, dynamic interactions, and chain reactions, thus offering a macro-level perspective on the regional economy and environmental dynamics of Mariana and surrounding areas. Nevertheless, future studies may challenge or complement our findings by employing alternative econometric methodologies with explicit causal analysis.

From a policy perspective, our results indicate that iron ore production generates a negative externality. In economic terms, an externality represents a market failure in which part of the social cost of an activity is borne by third parties. In this case, mining companies extract iron ore and earn profits from this activity, yet they do not internalize the environmental costs imposed on society, particularly those related to water quality degradation.

Standard economic theory suggests that an appropriate policy response is to force producers to internalize these external costs. One possible instrument is a tax on iron ore production. Such a tax would serve two purposes. First, by increasing production costs, it would tend to reduce production levels, thereby mitigating the negative impact on water quality. Second, it would generate additional government revenue, which could be allocated to water quality restoration, enhanced environmental regulation and monitoring, and the subsidization of healthcare services for populations affected by water contamination.

In this sense, a tax on iron ore production would contribute to correcting the externality associated with mining activities by aligning private incentives with social costs.

Finally, the central message of this study is that natural disasters—such as the 2015 Mariana dam collapse—may obscure deeper and more persistent environmental consequences of extractive activities. While such disasters are extreme events that attract national and international attention, they can mask the fact that environmental degradation may have been occurring long before the disaster itself. Our empirical results show that iron ore production continues to impose environmental costs on the rivers surrounding Mariana, independently of the dam failure. Thus, the core problem lies not solely in catastrophic events, but in the ongoing environmental pressures generated by mining activity—a pattern that this paper documents for the case of Mariana.

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Appendix

Table A: Unit root tests

	ADF		PP	
	Level	First Difference	Level	First Difference
iron	0.04**	0.00***	0.06*	0.00***
water	0.00***	0.00***	0.00***	0.00***
gdp	0.16	0.00***	0.12	0.00***
extractive	0.65	0.00***	0.12	0.00***
commo	0.11	0.00***	0.17	0.00***
e	0.97	0.00***	0.99	0.00***

Note: ADF denotes the Augmented Dickey–Fuller test, and PP denotes the Phillips–Perron test. The Levels column reports results for the series in levels, while the First Differences column reports results for the series in first differences. Reported values are p-values. In both tests, the null hypothesis is the presence of a unit root. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.