

AIR POLLUTION AND FINANCIAL DECISIONS

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THESIS

Submitted in partial fulfillment of the requirements for the
degree of Master of Science in Finance in the Graduate
School of Business Nazarbayev University, 2025

Astana, Kazakhstan

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Abstract

This thesis explores how air pollution correlates with financial choices in Kazakhstan, which is an emerging economy, dependent on the resources. The paper uses the records of the Kazakhstan Stock Exchange (KASE) on daily and quarterly variations in air quality in terms of PM_{2.5}, PM₁₀, SO₂, and NO₂ and stock returns, the level of trading, and corporate profitability in relation to air quality fluctuations in January 2020 to March 2025. Using fixed-effects regressions and instrumental variable (IV) estimation where wind direction is used as an exogenous variable, the analysis demonstrates that PM_{2.5} has a positive forecast of the daily returns of stocks, and thus investors might use pollution as a positive indicator of industrial and economic activity instead of negative externality. On the firm level, however, the increased PM 2.5 is associated with reduced asset efficiency (ROA), and SO₂, which is mainly due to industrial combustion, is associated with increased profitability indicators (ROA and ROE). These results highlight the duality in air pollution in the market of resources, both as the measure of industrial power and as the possible cause of inefficiency in operations. The findings imply the realities of contextual distinctions between developed and emerging economies, and the significance of making a distinction between the behavioral channel and industrial channel in evaluating the financial aspect of environmental quality.

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1. Introduction

Air pollution is also a phenomenon that has been deemed as a serious environmental and human health issue, but it also has uncountably far-reaching consequences. The article of Sandra Aguilar-Gomez et al. (2022) illuminates the impact of air pollution on economic behavior, corporate choice, and financial markets. Aguilar-Gomez claims that air pollution may serve as an indicator of industrial action, however, influencing investor perceptions, market returns, and firm performance, especially in economies in which industrial production is a significant growth determinant. A good place to investigate these non-health effects is in Kazakhstan which is a resource-based economy with much emphasis on other industrial sectors like energy, oil, gas and mining. Contrary to the findings of studies in developed markets, which usually discover a negative correlation between air pollution and stock returns (e.g., Zhang et al., 2017; Chen et al., 2018), the study reveals a positive association between the PM_{2.5} level and stock returns per day in Kazakhstan. This implied that the investors in the Kazakhstan would interpret the increase in pollution to be a sign of greater industrialization and economic output as opposed to a negative externality. The paper examines the association between air pollution, namely, PM_{2.5}, PM₁₀, SO₂, and NO₂, and the financial market behavior in Kazakhstan during the period January 2020 to March 2025. It looks at the impact of the level of pollution on stock returns, trading volume and profitability levels of firms in terms of Return on Assets (ROA), Return on Equity (ROE) and Gross Profit Margin. The heterogeneity across

industries, markets, and firms is also examined through instrumental variable analysis so that the causality and robustness tests can be checked with the help of alternative pollutants so that the validity of the research may be considered. Exploring these dynamics, this study will be relevant to the rising literature on the non-health implications of air pollution, which will help understand how environmental conditions determine financial results in resource-dependent economies. The results point to the duality of air pollution as a marker of economic activity and a possible risk factor and offer useful insights to policymakers, investors, and researchers that have to manage the complexities of industrialized markets.

2. Literature review

The linkage between air pollution and financial choices has increasingly become the focus of economists and finance scholars who are keen on determining how environmental influence can contribute to investor behavior and firm performance. Although previous research has considered pollution as a health or environmental externality, recent studies have shown that air quality may have economic and financial impacts to the system, both behavioral and productivity. Pollution is not then only a social cost, it may also serve as an indicator of the underlying economic activity particularly in industrial or resource based economies.

An accumulating body of literature indicates that air pollution has a cognitive and emotional influence on investors. The bad air quality has been linked to low attention and mood coupled with poor judgment which are capable of changing trading patterns and investment actions. Chen, Gao, and Li (2018) discover that investors have more behavioral biases on highly polluted days in China, including the disposition effect: the tendency to keep losing stocks and sell winning stocks prematurely, which make the markets less efficient. On the same note, Hong and Li (2017) record that the greater the pollution level, the greater the volatility in the market and the lesser the effectiveness in trading, indicating that financial rationality may be distorted by environmental stress. These results point to the psychological aspect of the effects of pollution: air pollution contributes to making non-optimal financial choices indirectly by deteriorating mood and cognitive clarity.

Unlike this behavioral channel, some other literature school has placed an emphasis on pollution as being a proxy measure of industrial activity. In the economy where major growth factor is manufacturing and extraction of resources, pollution may be construed to mean the intensity of production and economic growth. Studies of China suggest this two-sidedness: in the largest financial centers, investors are more likely to think about pollution as a negative externality, in highly industrialized areas, pollution is regularly positively related to stock returns (Zheng, Kahn, Liu, and Sun, 2019; Liao, Wang, and Zhu, 2020). According to Aguilar-Gomez et al. (2022), investors, in these settings, might take increased

pollution as a sign of increased industrial performance and success. This fact is an inversion of the usual correlation that can be seen in developed markets- where pollution is more likely to repress valuations because of regulatory risks, reputational risks, and environmental risks- into a positive correlation because of growth expectations.

In fact, the research conducted in the developed economies mostly confirms the negative correlation between pollution and financial performance. Zhang, Zhang and Zhao (2017) indicate that in Chinese manufacturing, pollution declines productivity and increases costs of operation whereas Chava (2014) indicates that companies with greater environmental risk have more expensive costs of capital. In a similar vein, Albuquerque, Koskinen, and Zhang (2019) show that the higher the corporate social responsibility (CSR) profile of a firm, the lower the firm risk and improved the long-term performance, which implies that firms rewarded by markets are those that are environmentally responsible. These are researches that indicate that pollution is a sign of inefficiency, risk, and reputation hurt particularly in the environment where the regulations are good and the investors are conscious.

The situation however changes in resource dependent markets. In such environments, pollution of the air is usually an indicator of industrial growth and not inefficiency. Aguilar-Gomez et al. (2022) observe that this trend is particularly pronounced in such economies as Kazakhstan, where the oil, gas, and mining industry are the major sources of pollution, and whose industries are at the heart of the national development. This pollution can hence be considered by the investors

as a short term indication of increased production and revenues. This meaning is congruent with the results of Bolton and Kacperczyk (2021), who reveal that carbon-intensive companies could exhibit a greater payoff during the periods of industrial growth, despite having a long-term, environmental liability. Therefore, pollution in industrial economies can be viewed as a kind of an industrial signal, that stimulates optimistic investor expectations and an increase in market returns, regardless of the adverse environmental connotations of such pollution.

At the firm-level, it has also been found that air pollution has affected the financial performance via the impact on the labor productivity and the cost. Graff Zivin and Neidell (2012) present at the outset that, low air quality affects the productivity of workers, even in those industries which do not work on physical capacity but on mental effort. This mechanism is confirmed by Chang et al. (2019) based on the data of Chinese call centers whose results show that even the slight increase in the level of particulate matter can significantly reduce the productivity of employees. These productivity losses may drain profitability, yet again; the relationship is relative. In the intensely polluting industries, the additional emissions can be accompanied by the growth of the capacity utilization, and the short-term profits are likely to be stronger. As demonstrated by Liao et al. (2020), the overall impact of pollution is that it reduces the productivity of firms, although it does it to a lesser extent than in firms that are in an industry with a strong connection between pollution and output.

On the whole, the data in the literature demonstrate two interconnected processes according to which air pollution affects financial decision-making. The behavioral process works according to the human perception and thinking pollutants deteriorate mood and judgments, lessening market efficiency and returns decadence. The economic mechanism, however, does not work in an abstract way but by the activity that takes place in the real sense- pollution as a result of industrial production and pollution as an indicator of economic growth in resource-intensive situations. This is influenced by what form of mechanism prevails according to the economic structure of a nation: in a developed economy, pollution can be viewed as a risk factor; in a resource-based economy, it can be regarded as an indicator of prosperity. The two-sided quality of pollution as a shared evil and a personal indicator outlines the ambiguity of the impact of pollution on finances. In the case of countries like Kazakhstan, in which industrial industries are the main growth engine and the main sources of emission, the interpretation of these opposing mechanisms is the key to understanding how environmental factors determine investor mood and the performance of firms.

3. Data and methodology

The dataset combines financial, accounting, and environmental information for companies that are listed on the Kazakhstan Stock Exchange (KASE). All data is from January 1, 2020, till March 31, 2020, because of availability of pollution data for this period.

Financial Data. Daily stock prices and trading volumes were obtained from Bloomberg for companies with headquarters in Almaty and Astana,

Accounting Data. Quarterly financial statements were taken from KASE disclosures and used to compute profitability ratios such as ROA, ROE, and gross margin, as well as controls like leverage, cash holdings and etc.

Environmental Data. Daily PM2.5, PM10, NO2, and SO2 concentrations were collected from U.S. Embassy monitoring stations in Almaty and Astana.

Meteorological Data. Daily temperature, wind speed, cloudiness, and humidity data were obtained from the national hydrometeorological service, Kazhydromet.

Market Return. Market return is return of KASE, data were taken from Bloomberg.

The initial dataset included all firms that listed on KASE with available daily prices. However, trading frequency and data completeness varied widely. Some companies have constant prices of stocks and zero trading volume for months, while others reported prices only at quarterly intervals.

To ensure consistent variation and proper alignment with daily pollution data, I excluded firms that:

1. Had extended periods of constant prices, which indicates no active trading.
2. Reported prices only on quarterly or irregular dates.

3. Lacked sufficient overlap between financial and environmental data for their city.

Firms, that I excluded, had very limited trading activity or large data gaps, which make daily returns unreliable. The final sample includes only 11 companies that have consistent daily trading and complete pollution and weather coverage. This sample represents the liquid portion of KASE and has approximately 5,000 firm-day observations for the investor-level analysis and the same 11 firms at a quarterly frequency for the firm-level analysis.

1) Investor-Level Model

For investor-level analysis the following regression with fixed effects were used:

$$Y_{it} = \alpha + \beta_1 \ln (PM2.5_t) + \beta_2 Weather_t + \mu_i + \lambda_t + \varepsilon_{it}$$

where Y_{it} is log return or log trading volume for firm i on day t , $PM2.5_t$ is daily pollution level, $Weather_t$ is weather controls, like temperature, wind, cloudiness, and humidity, μ_i is firm fixed effects and λ_t is day fixed effects. Standard errors are clustered at the firm level. I used fixed effects and weather controls to make sure that I estimated relationship between air pollution (in this case PM2.5 pollutant) and returns/trading volume is not driven by other factors like temperature, wind, humidity and cloudiness, which co-vary with pollution or constants across firms or time.

After running this regression, I checked if results are differed by industries and market conditions.

For heterogeneity analysis by industries, I divided companies into two groups: companies that operate in high-polluted industries and those that operate in low-polluted areas. High-polluted industries are electricity, mining and oil and gas, low-polluted - all others. The purpose of it is to check if the relationship between air pollution and returns differs depending on industries that are linked to pollution producing activities.

The next step is heterogeneity analysis by market conditions; the purpose is to test if the relationship between air pollution and returns depends on overall market movement. The dataset is divided into two groups by market returns, which is returns of KASE, if market returns are positive the observations go to group “market up days”, and if market returns are non-positive the observations go to “market down days” group.

Despite the robust correlations observed, a key concern is endogeneity. The relationship between air pollution and stock returns could be driven by an omitted variable. To address this concern and probe for causality, I employ an Instrumental Variable (IV) approach using a two-stage least square (2SLS) estimator. This approach is consistent with the established way of causal inference in the similar context, which Batkeyev and DeRemer (2023) apply when studying Almaty.

Following this approach, my instrument is a dummy variable for wind direction, for Almaty, it takes a value of 1 if the wind direction is coming from the mountain regions, and for Astana, a value of 1 if the wind direction is between the south-west and north-west. Historical air quality data confirms that winds from these directions are associated with lower PM2.5 concentrations, as they bring cleaner and less polluted air into the area of Almaty and Astana.

The validity of this instrument relies on two conditions. First, the relevance condition is satisfied, as wind direction is a strong predictor of PM2.5 levels, which is confirmed by a significant first-stage F-statistic. Second, the exclusion restriction requires that wind direction affects stock returns only through its impact on PM2.5, conditional on weather controls. This is plausibly satisfied because wind direction is a random meteorological phenomenon that is unlikely to influence financial markets through any channel other than its effect on short-term air quality.

2) Firm level analysis

For firm level analysis the following regression was applied:

$$Profitability_{it} = \alpha + \beta_1 \ln(PM2.5_t) + \beta_2 Weather_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where $Profitability_{it}$ are financial profitability metrics such as Return on Assets, Return on Equity and gross margin profit for firm i in quarter t , $\ln(PM2.5_t)$ and $Weather_t$ are quarterly averages of air pollution and weather conditions, X_{it} are firm-level control variables, such as size, sales growth, leverage, cash holdings and etc, μ_i and λ_t firm fixed effects and quarterly fixed effects. This model estimates if

changes in air pollution are associated with firm financial performance, after controlling for firm characteristics and weather conditions.

Like the investor-level analysis, a heterogeneity test by industry was also applied to the firm level, firms were divided the same way as for investor level. The purpose also remains the same, to examine if the relationship between air pollution and firm performance differs across industries with different pollution activity.

The next step is to make heterogeneity analysis by firm size. The purpose is to see if the effect of pollution on firm performance differs between large and small firms. Companies were divided into two groups: small and large by total assets in the first quarter of each company in the dataset. Firms with total assets above median were classified as large, and those that below median were classified as small. I used the first-quarter total assets because it allows firm size to represent a company's initial scale rather than later performance changes.

To achieve strong inference and attempt to control possible cross-sectional as well as serial correlation in the error terms, standard errors are clustered at the degree of the main time change in the data. In investor-level day-to-day regressions, the error is grouped by day to regulate shared daily shocks like market-wide news, macroeconomic announcements or nationwide pollution incidents, which may jointly be impacting all the stocks. The clustering of the regression of firm-level quarterly data is done by quarter to ensure the common time-specific shocks, such as seasonal economic cycles, changes in regulation, or

shifts in aggregate demand that might affect all firms simultaneously. This would be in line with the econometric advice of clustering at the level of the treatment variation when the explanatory variable of interest, which is air pollution, varies more over time as opposed to across different firms.

To analyze at the firm level, a potential endogeneity can be solved by Instrumental Variable (IV) method, which is implemented through `ivreg2` command in Stata. As in the investor-level analysis, wind direction is employed as a tool of pollution concentrations identification.

3) Robustness check

To ensure the credibility and specificity of results, I conduct a robustness check.

My core hypothesis centers on PM_{2.5} pollutant for investor and firm levels. However, it is possible that the results are not unique to PM_{2.5} and could be reflected by air quality in general. To test this, I run regressions with other pollutants, like PM₁₀, SO₂ and NO₂, which can help to identify whether those pollutants can explain results. The insignificant coefficients for those pollutants would mean that results are unique for PM_{2.5} pollutant.

The main model assumes that there is a linear-log relationship, but this assumption may not hold if the effect diminishes at higher pollution levels, that is why I test for non-linearity, to ensure that model's functional form is not misspecified, that could lead to biased or misleading conclusions. I augment the main regression model with a quadratic term of the pollution variable

($\ln_pm25_squared$). A statistically insignificant coefficient would support the assumption of linearity,

To visually validate the main model for each level of analysis, I employ the Frisch-Waugh-Lovell (FWL) theorem. This approach allows to produce a partial regression plot that shows the relationship between air pollution and stock returns or profitability ratios after controlling all other variables in the model. This is implemented in three steps. The first step is residualizing the dependent variable, regressing the dependent variable (log returns or profitability ratios), on the full set of control variables and fixed effects, then I save the residuals. Next, I regress the independent variable, which is $\ln(PM2.5_t)$, on the same set of control variables and fixed effects, then I also save these residuals, that represent the variation in pollution that is orthogonal to the controls. And the last step is to plot the residuals; this plot is created by plotting the residuals from the first step against the residuals from the second step.

4. Results and interpretation

1) Investor-level analysis

The results of main regression for investor level analysis in Table 1 reveal that there is a positive relationship with marginal significance between PM2.5 and stock returns in Kazakhstan, where 1% increase in PM2.5 correlates with 0.21% increase in daily stock returns. This finding is not usual for existing studies, which show that there is negative relationship between air pollution and stock returns, for example in studies of China by Zhang et al. (2017) and Chen et al. (2018),

similarly for developed markets in the U.S and Europe.

Kazakhstan is resource-driven country, so the increase of PM2.5 could be a signal of industrial/economic activity, particularly in sectors like energy, oil and gas and mining. Investors may connect high air pollution with activities in these sectors, leading prices to rise.

The regression also shows that there is no effect of air quality on trading volume. This suggests that while pollution influences return expectations, it does not affect market liquidity.

In order to determine the positive relationship between PM2.5 and stock returns visually, Figure 1 provides the residuals of the FWL method of binned data and a scatterplot. The x-axis is the concentration level of PM 2.5, and the y-axis is the predicted log returns. The positive and linear relationship as demonstrated in the upward-sloping trend and the confidence intervals suggest that the regression findings were correct that increased levels of PM2.5 correlate with increased levels of stock returns in Kazakhstan.

Figure 1. Partial regression of PM2.5 and Stock Returns

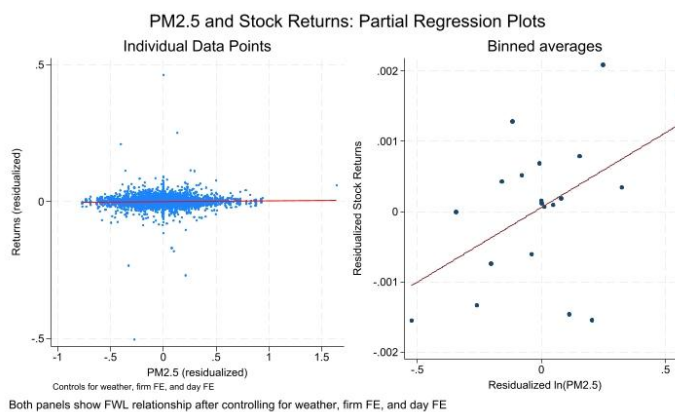


Table 1. Pollution and Stock Returns and Trading Volume

Returns Trading Volume

ln_pm25	0.002125* (0.001167)	0.068604 (0.072609)
temp	-0.000026 (0.000119)	-0.006242 (0.008243)
wind	-0.000138 (0.000580)	0.006827 (0.048955)
O	-0.000237 (0.000257)	-0.025298* (0.014567)
humidity	-0.000025 (0.000039)	-0.007274*** (0.002477)
_cons	-0.005317 (0.006505)	9.048692*** (0.365723)
Weather Controls	Yes	Yes
Firm FE	Yes	Yes
Daily FE	Yes	Yes
R-squared	0.149	0.869
Observations	5042	5004

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 results refute the assumption that the positive correlation between pollution and returns can be explained by stronger returns in high-pollution companies. In case this was the case, then we would see a more pronounced effect in high-pollution industries. The impact is however trivial in high-pollution firms and substantial in low-pollution firms, and this suggests that pollution is an overall economic indicator and not the industry-specific performance indicator.

Table 2. Daily Returns. Industry Heterogeneity

	High-Pollution Industries	Low-Pollution Industries
ln_pm25	0.001789 (0.003694)	0.003087** (0.001392)
temp	-0.000061 (0.000351)	-0.000081 (0.000122)
wind	-0.001233	0.000438

	(0.001414)	(0.000709)
O	0.000456 (0.000845)	-0.000380 (0.000248)
humidity	0.000088 (0.000103)	-0.000074 (0.000045)
_cons	-0.012999 (0.021949)	-0.005334 (0.006359)
Weather Controls	Yes	Yes
Firm FE	Yes	Yes
Daily FE	Yes	Yes
R-squared	0.270	0.218
Observations	1684	3214

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The fact that PM2.5 coefficients are not significant, both in an up and down day in the market (Table 3) questions the premise that pollution is always an industrial indicator or a behavioral stimulus. In the case that pollution is a good economic indicator, we would anticipate a significant impact on the up days; in the case that it is a mood-influencing variable, we may find significant impact on the down days. The lack of either implies that the relationship is spurious or very context specific.

Table 3. Market Condition Heterogeneity

	Market Up Days	Market Down Days
ln_pm25	0.003461 (0.002420)	0.001712 (0.001212)
temp	0.000492** (0.000211)	-0.000307** (0.000125)
wind	-0.000306 (0.001176)	0.000219 (0.000634)
O	0.000223 (0.000511)	-0.000718*** (0.000244)

humidity	0.000182** (0.000071)	-0.000133*** (0.000041)
_cons	-0.030655** (0.013683)	0.006954 (0.005741)
Weather	Yes	Yes
Controls		
Firm FE	Yes	Yes
Daily FE	Yes	Yes
R-squared	0.164	0.141
Observations	1681	3361

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To ensure that results are not driven by other pollutants, I ran regressions with other pollutants, such as NO₂, PM₁₀, SO₂ and table shows that none of them is significant, meaning that only PM_{2.5} can explain results for investor-level. Moreover, Figure 2 reveals that the relationship between returns and air pollution is linear.

Table 4. Daily Returns. Comparison Across Pollutants

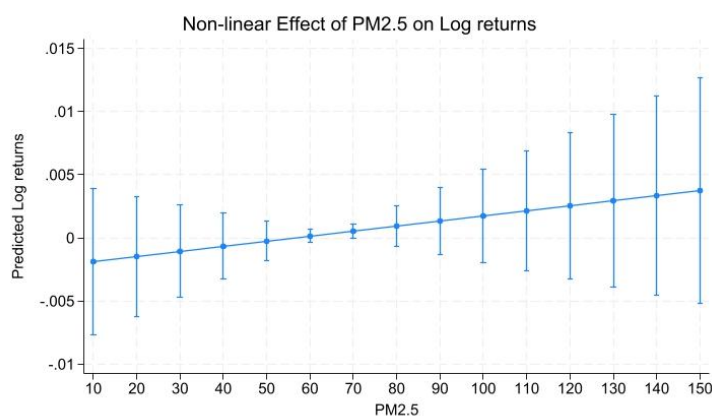
	PM2.5	PM10	SO2	NO2
ln_pm25	0.002125* (0.000970)			
temp	-0.000026 (0.000102)	-0.000088 (0.000087)	-0.000027 (0.000100)	-0.000192 (0.000288)
wind	-0.000138 (0.000408)	-0.000512 (0.000514)	-0.000750 (0.000533)	-0.000373 (0.000900)
cloudiness	-0.000237 (0.000256)	-0.000605*** (0.000188)	-0.000320 (0.000238)	-0.000438 (0.000419)
humidity	-0.000025 (0.000045)	-0.000069* (0.000038)	-0.000002 (0.000038)	-0.000088 (0.000106)
ln_pm10		0.000736 (0.000539)		
ln_so2			0.000093 (0.000799)	
ln_no2				-0.000447

				(0.001072)
_cons	-0.005317 (0.004664)	0.006598** (0.003797)	0.002768 (0.003829)	0.011321 (0.009406)
Weather Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Daily FE	Yes	Yes	Yes	Yes
R-squared	0.149	0.158	0.128	0.162
Observations	5042	5255	6094	3958

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2. Linearity check plot



Then I ran causality check to see if returns are changing because of increased air pollution or if it is just correlation. As instrumental variable I used wind direction. Table 5 shows both the OLS and 2SLS. The Kleibergen-Paap F-statistic of the first stage is 9.06 which shows a relevant instrument. Results show that IV results became insignificant, meaning that results are spurious, there could be omitted variables, that are not included in regression. Most likely that this variable is industrial activity, because of results of heterogeneity analysis for industries and market returns. So, overall, for investor-level analysis, in

Kazakhstan it is not behavioral story, but story that linked to a variable, because of what pollution and returns increase together.

Table 5. OLS and IV Results

	(1) OLS	(2) IV (2SLS)
ln_pm25	0.002125* (0.001167)	0.0132 (0.0083)
temp	-0.000026 (0.000119)	-0.0002 (0.0002)
wind	-0.000138 (0.000580)	0.0029 (0.0023)
O	-0.000237 (0.000257)	-0.0006 (0.0004)
humidity	-0.000025 (0.000039)	-0.0001 (0.0001)
Constant	-0.005317 (0.006505)	
Observations	5042	4948
R-squared	0.149	-0.020
Kleibergen-Paap F-stat		9.06

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2) Firm level analysis

The results on the firm level paint a more detailed picture. According to Table 6, PM2.5 has significant negative and significant relationships with ROA at the 5 percent level (-0.017951, SE=0.007640), but not with ROE or gross profit margin. This means that the increased PM2.5 levels are associated with the reduction of asset efficiency, which, perhaps, may be operational disturbances or regulatory

expenses.

Table 6. Air Pollution and Financial Performance

	ROA	ROE	Gross Profit Margin
ln_pm25	-0.017951** (0.007640)	-0.025141 (0.019290)	0.040314 (0.083817)
temp	-0.000190 (0.000721)	-0.002854 (0.001786)	-0.017433 (0.021676)
wind	-0.016797 (0.011884)	-0.032019 (0.018687)	-0.192827 (0.246679)
lev	0.164186 (0.132384)	0.138669 (0.231443)	2.692307 (1.644967)
cash_h	-0.031386 (0.044014)	-0.009397 (0.057781)	0.700193** (0.281795)
ln_size	0.002317 (0.033678)	-0.026214 (0.050883)	0.062040 (0.226207)
sales_growth	0.012619 (0.007246)	0.016590* (0.009125)	0.072507 (0.053576)
ln_firm_age	0.050152 (0.102750)	-0.067429 (0.185099)	1.140007 (0.733347)
_cons	-0.100077 (0.620937)	0.833113 (1.171545)	-4.625681 (5.535227)
Weather	Yes	Yes	Yes
Controls			
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
R-squared	0.642	0.860	0.730
Observations	119	119	119

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 adds an interaction term between high-pollution industry dummy and PM2.5. Interaction coefficient of ROE is negative though non-significant (-0.033491, SE=0.030136): it indicates that there is no differentially greater negative

impact of polluting industries on equity returns.

Table 7. Pollution Effects by Industry Type

	ROE	ROA	Gross Profit Margin
ln_pm25	-0.022310 (0.019043)	-0.015394 (0.008749)	0.058919 (0.094865)
1.high_polluti on#c.ln_pm25	-0.033491 (0.030136)	-0.030243 (0.021414)	-0.220072 (0.207270)
temp	-0.003896* (0.001920)	-0.001131 (0.001024)	-0.024284 (0.023882)
wind	-0.029439 (0.019349)	-0.014468 (0.012964)	-0.175875 (0.233122)
lev	0.124647 (0.227950)	0.151524 (0.128742)	2.600167 (1.591365)
sales_growth	0.017876* (0.008454)	0.013780* (0.006757)	0.080955 (0.057442)
ln_size	-0.026912 (0.050999)	0.001686 (0.033819)	0.057455 (0.223414)
cash_h	-0.011924 (0.059317)	-0.033668 (0.045456)	0.683587** (0.274147)
ln_firm_age	-0.063123 (0.181125)	0.054041 (0.099401)	1.168303 (0.709366)
_cons	0.859978 (1.179019)	-0.075818 (0.634393)	-4.449151 (5.268203)
Weather	Yes	Yes	Yes
Controls			
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
R-squared	0.861	0.652	0.736
Observations	119	119	119

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The next step was to check if pollution effect differs for firm size. Results in the Table 8 prove that effect is not affected by firm size, all coefficients are not significant for every financial metric.

Table 8. Pollution Effects by Firm Size

	ROE	ROA	Gross Profit Margin
ln_pm25	-0.020781 (0.023003)	-0.015333 (0.009562)	-0.000872 (0.070759)
1.large_firm#c .ln_pm25	-0.008486 (0.011757)	-0.005095 (0.005897)	0.080164 (0.090274)
temp	-0.002744 (0.001856)	-0.000124 (0.000747)	-0.018470 (0.021924)
wind	-0.032403 (0.018600)	-0.017028 (0.011769)	-0.189199 (0.243886)
lev	0.128851 (0.218325)	0.158291 (0.131329)	2.785045 (1.725692)
sales_growth	0.016404 (0.009442)	0.012507 (0.007427)	0.074267 (0.054307)
ln_size	-0.027119 (0.051060)	0.001773 (0.034398)	0.070594 (0.241491)
cash_h	-0.008362 (0.058683)	-0.030765 (0.044661)	0.690417** (0.281536)
ln_firm_age	-0.071128 (0.180898)	0.047931 (0.102268)	1.174951 (0.761988)
_cons	0.859725 (1.146469)	-0.084098 (0.626992)	-4.877058 (5.905172)
Weather	Yes	Yes	Yes
Controls			
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
R-squared	0.860	0.643	0.733
Observations	119	119	119

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To check if other pollutants can explain movement of profitability metrics, I ran regression with SO₂, PM₁₀ and NO₂. Results reveal SO₂ is positive and significant for both ROA (0.010408) and ROE (0.012894). (Table 9)

SO₂ has a significant and positive impact on ROA (0.020405,

SE=0.009527) and ROE (0.010122, SE=0.004781). The partial regression plot of Figure 4 provides a visual support to this. Since in this case the SO₂ is very much concentrated on the industrial combustion, this finding supports the interpretation that industrial activity, in this case, represented by SO₂, increases the profitability of firms in the short-term.

Table 9. Robustness Check. Alternative Pollutants on Firm Profitability

	(1) PM10 ROA	(2) PM10 ROE	(3) SO ₂ ROA	(4) SO ₂ ROE	(5) NO ₂ ROA	(6) NO ₂ ROE
PM10	-0.012499 (0.015684)	-0.008898 (0.012447)				
SO ₂			0.020405* (0.009527)	0.010122* (0.004781)		
NO ₂					-0.021300 (0.011323)	-0.008092 (0.008131)
Observations	121	121	125	125	116	116
R-squared	0.876	0.638	0.861	0.640	0.862	0.623

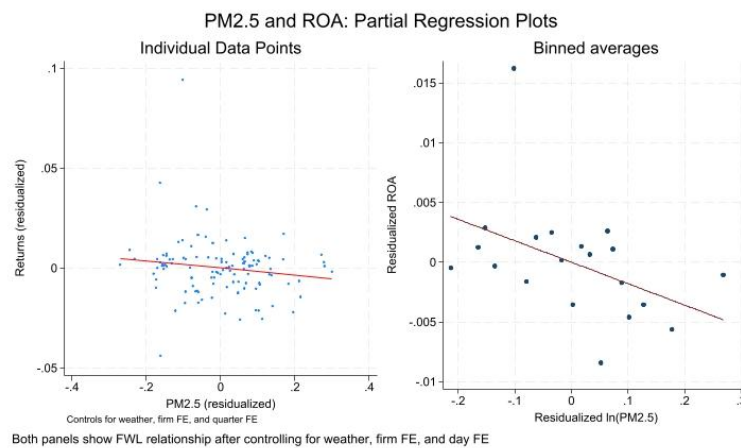
Notes: Robust standard errors in parentheses. All specifications include firm fixed effects, quarterly fixed effects weather and firm controls.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The figure shows biased regression plot that shows the relationship between log-transformed PM_{2.5} concentrations (ln_pm25) and Return on Assets (ROA) when weather conditions, firm characteristics, and time and firm fixed effects are held constant. Individual firm-quarter residuals are displayed in the left panel, and binned averages are given in the right panel to make visual representation possible. The negative slope in both panels is also aligned with the negative coefficient of Table 6 (-0.017951) that indicates that high levels of PM_{2.5} are linked to low

profitability, in terms of ROA. Nevertheless, the overall tendency of the visuals downwardly, the large distribution of the observations, and the small slope value show that this relationship is not highly deterministic in the sample, although it has a negative direction. This is consistent with this interpretation; PM2.5 could be an indicator of operational inefficiency or regulations instead of being a good industrial indicator of firm performance.

Figure 3. Partial regression plot of PM2.5 and ROA



The positive trend line in Figure 4 visually supports the positive and important relationship that was found in the regression analysis (Table 9). According to the model, a one percent change in SO₂ is related to a statistically significant gain in ROA of 2.04 percentage points ($p < 0.10$). SO₂, the pollutant that is mostly caused by the burning of fossil energy during the industrial processes, therefore, serves as a proxy of industrial activity that impacts positively

on company profitability in this instance.

Figure 4. Partial residual plots of SO2 and ROA

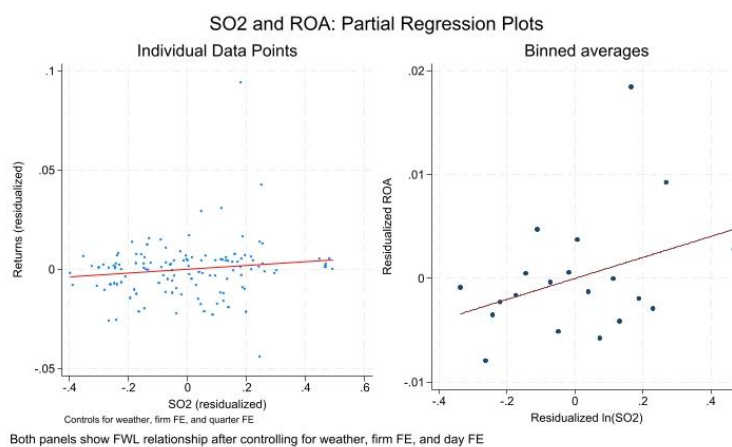


Table 10 results of regression on firm size indicates a positive and statistically significant result of SO2 on both ROA and ROE. The terms of interaction with firm size are both negative and statistically non-significant, which suggests that the effect of industrial activity on profitability, which is enhanced by SO2, is not significantly different when it comes to large and small firms. This implies that industrial growth does not favor large firms over small businesses, but instead it favors firms of every size.

Table 10. SO2 Effects on Firm Performance. Size Heterogeneity

	ROE	ROA
	b/se	b/se
ln(SO2)	0.025356*	0.012075**
	0.013119	0.005507
ln(SO2) × Large Firm	-0.008995	-0.003550
	0.011979	0.008560
Weather Controls	Yes	Yes
Firm controls	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	125	125
R-squared	0.863	0.641

Standard errors clustered at firm level in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Results in Table 11 show that relationship between ROA and SO2 for low-polluted industries is significant and positive, the difference is not significant as well as for high pollution sectors. While the relationship between SO2 and ROE is not significant.

Table 11. SO2 Effects on Firm Performance. Industry Heterogeneity

	ROE	ROA
	b/se	b/se
ln(SO2)	0.019049	0.009372**
	0.011390	0.004253
ln(SO2) × High Pollution	0.003224	0.001782
	0.010631	0.007876
Controls	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	125	125
Adj. R-squared	0.861	0.640

Standard errors clustered at firm level in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 12 is a report of IV estimates of PM 2.5 and SO2. Weak instruments is less than 1 (0.73 PM 2.5, 0.28 SO2) KLeibergen-Paap F-statistics. The IV coefficients, in their turn, are not statistically significant. It implies that the correlations found on the firm level may also be endogeneously biased and cause statements cannot be diluted by the available instrument.

Table 12. IV Results for Firm-Level Profitability

	(1) ROA (PM2.5)	(2) ROE (PM2.5)	(3) ROA (SO2)	(4) ROE (SO2)
ln_pm25	0.007 (0.056)	0.004 (0.052)		
(mean) temp	-0.001 (0.003)	-0.004 (0.003)	-0.002 (0.012)	-0.005 (0.010)

(mean) wind	-0.007 (0.015)	-0.021 (0.013)	-0.019 (0.072)	-0.028 (0.066)
lev	0.128 (0.111)	0.097 (0.232)	0.132 (0.109)	0.104 (0.226)
cash_h	-0.023 (0.043)	-0.000 (0.051)	-0.024 (0.043)	-0.002 (0.048)
ln_size	0.000 (0.029)	-0.029 (0.049)	-0.001 (0.024)	-0.028 (0.049)
sales_growth	0.012* (0.007)	0.016 (0.009)	0.011* (0.006)	0.015 (0.009)
ln_firm_age	0.030 (0.104)	-0.091 (0.184)	0.049 (0.148)	-0.083 (0.172)
ln_so2			-0.007 (0.057)	-0.004 (0.049)
Observations	119	119	125	125
K-P F-stat	0.73	0.73	0.28	0.28

Standard errors clustered by quarter in parentheses. Kleibergen-Paap (K-P) F-statistics below 1 indicate weak instruments. All specifications include firm and quarter fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3) Discussion of results.

The work offers empirical data to prove that the correlation between air pollution and financial performance in Kazakhstan is not only intricate but also context-specific and radically opposes the trends in the developed markets. Unlike the behavioral channel, which has been reported in the literature about China and western economies, where in both cases the pollution rates affect the cognitive capability as well as cause risk aversion, our results indicate that air pollution serves as an industrial cue in a resource-intensive economy such as Kazakhstan. The positive (though insignificant) correlation between PM2.5 and stock returns of a day at the investor level is consistent with the factor that the investors assume

pollution to be a measure of increased industrial activity. The fact that heterogeneity analysis supports this point as the effect is significant only in low-pollution industries, but not in high-pollution sectors. It implies that the investors are not necessarily rewarding polluting companies, but are simply seeing pollution as an indicator of a wide-based economic growth benefiting companies in the market in general. But this statistically insignificant result on both up and down days in the market, and the fact that the instrumental variable method fails to prove causality, all point to the possibility that such a relationship is as a result of omitted variables, most probably underlying industrial output, and not necessarily a direct causal impact of pollution on returns. At the company level, there is a duality of pollutants. Whereas PM_{2.5} exhibits a negative correlation with Return on Assets, and this may be an indication of operational inefficiencies, regulatory expenses or even health-related productivity costs, sulfur dioxide (SO₂) is a strong positive predictor of both ROA and ROE. Since industrial combustion is the largest source of SO₂ emissions, this result offers polluting level confirmation of the industrial signal hypothesis: production related emissions have a positive correlation with firm profitability. It is interesting to note, though, that this relationship is not strongly dependent on the size and type of a firm, which can be interpreted as an indication that the benefits of profitability of industrial activity are widely distributed, not chased by large or traditionally polluting companies.

The results of the instrumental variable analysis at the investor and firm level did not provide conclusive results, resulting in weak instruments and negligible

second-stage coefficient results. This highlights the key finding of identification: in the economy where the processes of pollution and industrial production are closely linked, it is empirically challenging to separate pollution as the cause and pollution as the byproduct of the two economic phenomena. I have therefore indicated in findings the endogeneity of the studies of pollution-performance, especially in resource-dependent settings. These findings add to the increasing body of literature on environmental finance as they indicate that not all countries use an economic interpretation of pollution, but one that is dependent on the economic structure of the country. In Kazakhstan, which is a country where the extractive and heavy industries play the most significant role, pollution may serve as both a short-term market indicator and a composite indicator of company performance, depending on the type of pollutant and the financial indicator under analysis.

5. Conclusion

This paper looked at the effects of air pollution in financial decision making in Kazakhstan which is an emerging market that depends on resources. In contrast to the findings in the developed economies, we observe a positive correlation between PM_{2.5} and stock returns on daily basis, which is in line with pollution being an industrial signal and not a behavioral disturber. This indicator seems to be a reflection of general economic action, and not firm-specific performance because the impact of the indicator is only significant in low-pollution industries, and does not vary strongly with market conditions. The situation is more detailed at the firm level. PM_{2.5} is negatively correlated with ROA implying possible efficiency

expenses and SO₂ which is a direct byproduct of industrial combustion has a positive correlation with profitability. This duality in respect of this pollutant points to the fact that not every emission has the same economic implication: some can be the indicator of productive capacity whereas some can be the source of operational costs. Causal claims are limited despite such correlations. Weak instruments undermined the instrumental variable analyses, and the difficulty with isolation of exogenous variation of pollution in an economy with a strongly interwoven industrial and environmental cycle. The consequences to the stakeholders are dual. To resource-based market investors, pollution data can provide a short-run measure of the economic momentum albeit with caution due to the endogeneity issues. To the policymakers, the findings indicate the two-sidedness of pollution as it is an indicator of industrial health, as well as a possible source of firm-level inefficiency, and as such, a reason why regulations need to be balanced in both promoting economic growth and encouraging cleaner production. Future studies would aim at addressing the weaknesses in this study by including the direct measurement of industrial output, diversifying the sample in terms of regions and time, and creating more robust tools of causal identification. With the increase in global demands to be environmentally sustainable, the adaptability of the markets and firms in resource-rich economies and how the industrial signal of pollution is changing will continue to constitute an important direction in inquiry.

6. Limitations

There are a number of limitations that are associated with the study and need to be taken into account when drawing a conclusion on the research. The geographical range is limited to Almaty and Astana as there are data of pollution and this limits the generalization of results to other areas in Kazakhstan. Moreover, the study is limited by a comparatively short time series and a limited sample of only 11 liquid companies, which is primarily relevant to large, high-traded firms in large cities, as opposed to the market, in general. Although there is circumstantial and theoretical support to the use of pollution as a proxy of industrial activity, due to the lack of a direct and high-frequency measure of industrial output, this mechanism can not be positively assessed. Lastly, the instrumental variable method is a theoretically good method but assumes the un-testable hypothesis that the wind direction can only affect the stock returns through its effects on air pollution. To further confirm these results, a study with a more extended time frame, wider geographical range, and direct indicators of economic activity would be beneficial in the future.

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