Measuring Firm Environmental Performance

to Inform ESG Investing.

PRELIMINARY DRAFT: DO NOT QUOTE.

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Abstract

Investing according to environmental, social, and governance criteria is gaining momentum. Most environmental performance indices focus only on the tonnage of carbon dioxide (CO_2) emissions. This paper proposes a new monetary index covering eight pollutants. Inclusion of multiple pollutants reflects a broader range of risks. In the U.S. utility sector from 2014 to 2017, indices which only track CO_2 mischaracterize firms' environmental performance and underestimate its effect on financial outcomes relative to the multipollutant index. Analysts' earnings forecasts for dirtier firms systematically undershoot actuals. The multipollutant index suggests new financial management strategies relative to those based on carbon intensity.

Keywords: ESG investing, air pollution, climate change, utilities, disclosure.

JEL Codes: G11, Q51, Q53, Q54, G41

I. Introduction.

Investing according to environmental, social, and governance (ESG) [1] criteria has gained considerable momentum in recent years, influencing enormous flows of capital (GSIA, 2018; *New York Times,* 2020; Blackrock, 2020; 2021). In response to the rise of ESG-related preferences among market participants, numerous products (indices, mutual funds) track aspects of the "E", "S", and "G" of ESG performance. This paper argues that most prior metrics focusing on the "E" of ESG have mismeasured firm performance in two ways. First, most indices focus on physical emissions instead of the monetary damage of emissions (MSCI, 2019; NUVEEN, 2020; Sustainalytics, 2021). The emphasis on mass likely arises from the perceived difficulty of calculating damages. This paper demonstrates how to connect emissions to monetary cost and how to incorporate these external costs into firm value. The second shortcoming is that many major products track only firms' carbon intensity (MSCI, 2019; NUVEEN, 2021). This narrow perspective, in part, stems from the aforementioned tendency to focus on the mass of emissions. In the United States (U.S.) economy, CO_2 emissions totaled about 5 billion tons in 2019. In contrast, combined emissions of the criteria air pollutants governed by the U.S. Clean Air Act amounted to under 100 million tons in the same year (USEPA, 2021: https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data). Thus, from the perspective of *total emissions*, it would seem that tracking CO_2 sufficiently captures firms' environmental performance.

So, why not just measure carbon intensity in tonnage? First, despite the dominance of CO_2 *emissions*, recent research indicates that air pollution damages significantly exceed those from CO_2 (Muller, Mendelsohn, and Nordhaus, 2011; Muller, 2019; Mohn et al., 2020). Specifically, Mohan et al., (2020)

[1] One of the earliest references to the acronym ESG in reference to financial investment criteria is found in a 2004 joint publication of the United Nations and the Swiss Federal Department of Foreign Affairs: https://d306pr3pise04h.cloudfront.net/docs/issues_doc%2FFinancial_markets%2Fwho_cares_who_wins.pdf .

report that, globally, damages from fine particulate matter (one local air pollutant) range between two and three-times greater than the damages from CO_2 between 1998 and 2018[2]. Only reporting carbon intensity clearly misses important determinants of firms' environmental performance. Therefore, an ESG index defined over multiple pollutants will better align capital allocations with actual firm "E" performance than indices defined strictly in terms of carbon intensity.

Second, in most economies around the world, except for the European Union, CO_2 emissions are unregulated. In contrast, binding regulations exist for air pollution in many developed countries. An ESG index reporting only carbon intensity misses a range of risks specifically tied to impacts from *other pollutants*. These risks may stem from lost profits due to costly compliance measures or from reputational risks associated with publicly announced violations. The key point is that extant policy risk manifests primarily for pollutants other than CO_2, and, therefore, outside the scope of many existing ESG metrics.

Third, monetization of pollution damage enables a reconceptualization of firm value that is needed to correct inefficiencies in financial markets. Metrics such as book value, operating free cash flow, or market capitalization reflect conventional notions of value that hinge on the goods and services firms produce and the assets they own. Participants in financial markets rely on these (and other) metrics to form expectations over firm performance, which drive the allocation of capital. Importantly, absent Pigouvian taxes, these market-based measures do not reflect external costs or benefits stemming from firms' production processes or the subsequent use of their products. While an extensive literature characterizes the nature of environmental market failure in the markets for goods and services (NRC, 2010; Muller, Mendelsohn, and Nordhaus, 2011; Tschofen et al., 2019), this paper contends that

[2] This disparity in damage stems from large differences in the marginal damages from air pollution and CO_2 emissions. For example, the damage per ton of carbon dioxide (CO_2) was recently estimated to be in the neighborhood of $50/ton. An emission of soot in the U.S. induces damages in excess of $100,000/ton (FWG, 2016; Muller and Mendelsohn, 2009; Gilmore et al., 2018).

financial markets also fail to reflect these determinants of firm value and, as a result, inefficiently allocate capital in pollution-intensive industries. A monetary ESG index defined over multiple pollutants will help to mitigate these inefficiencies.

Unifying these three points is the argument that, in order to allocate capital efficiently, financial markets require good information regarding firm value and risks. An environmental performance index based on monetized damages from multiple pollution emissions informs markets in two ways. First, the deduction of damages adjusts commonly relied on metrics of firm value according to the costs emissions impose on society. This provides investors with a more socially comprehensive assessment of firms' worth. Second, a multipollutant index captures a broad range of risks beyond those associated with carbon. Neither function is possible without monetization. Both enhance the information available to market participants focused on ESG investing.

Empirically, this paper uses empirical modeling techniques to compute the monetary damages from five local air pollutants and three primary greenhouse gases (GHGs) produced by firms in the utility sector in the U.S. economy. The focus lies on the utility sector because of a relatively high degree of pollution intensity, excellent information on plant ownership, and pollution emissions. Further, as the U.S. economy increasingly turns to electrification as a means to decarbonize, the environmental performance of this sector will be a crucial determinant of macro-scale environmental outcomes. It is of broad social importance to allocate ESG-managed capital efficiently in this sector.

Damages are estimated for the years 2014 and 2017 because these years correspond to the most recent nationally comprehensive facility-level emission inventories. The calculation of damages relies on the following steps. A text matching algorithm attributes plants to firms and their corporate parents. Next, emissions of eight distinct pollutants from approximately 10,000 facilities are monetized using peer-reviewed integrated assessment models (Muller, Mendelsohn, and Nordhaus, 2011; Muller, 2014;

Tschofen, Azevedo, Muller, 2019; FWG, 2016). These models produce location specific pollution damage estimates. The paper proposes a new index of environmental performance, derived from these damage estimates, which benchmarks each firm's contribution to industry-wide damage and market capitalization. Finally, the analysis explores the association between this index and conventional measures of firms' financial performance including current period and forward share prices, returns, P/E ratios, earnings per share (EPS), and volatility.

The pollutants covered in this paper include fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), nitrogen oxides (NO_x), ammonia (NH_3), volatile organic compounds (VOCs), methane (CH_4), nitrous oxide (N_2O), and carbon dioxide (CO_2). At a national scale, the magnitude of damage from these pollutants are large relative to standard macroeconomic indicators such as GDP and VA (USEPA, 1999; 2011; Muller, Mendelsohn, and Nordhaus, 2011; Muller, 2014; Tschofen, Azevedo, Muller, 2019; Mohan et al., 2020). As such, at the firm level, these elements of "E" performance have the capacity to dramatically affect investors' perceptions of firm value and, hence, the allocation of capital.

This analysis contributes to a large and growing literature on ESG investing. Several recent papers explore the motivation for investors' interest in ESG managed assets (Reidl and Smeets, 2017; Hartzmark and Sussman, 2019; Barber, Morse, and Yasuda, 2020; Krueger, Sautner, and Starks, 2020). Shive and Forster (2019) examine whether corporate governance structures affect environmental performance. Other papers evaluate the performance of ESG funds, broadly defined, relative to benchmark indices (Auer and Schuhmaker, 2015; Friede, Busch, and Bassen, 2015; Halbritter and Dorfleitner, 2015; Verheyden et al., 2016; Winegarden, 2019). The present paper differs from this extant literature in its focus on *how* measurement of environmental performance is executed, rather than an assessment of investors' beliefs or of the financial performance of existing ESG products.

The key empirical results reported herein are the following. This paper proposes a new index of environmental performance. This index, denoted (Γ), is computed as the ratio of each firm's contribution to total utility sector damage to each firm's contribution to total utility market capitalization. Alternatively, (Γ) is a relative measure of how much each firm causes in damage to how much each firm contributes to industry value. This metric reveals considerable variation in the environmental performance of firms in the utility sector. In 2014, the best performing firm exhibited a (Γ) score of under 0.10, implying that its contribution to industry damage comprised $1/10^{th}$ of its contribution to industry market capitalization. On the other end of the spectrum, the dirtiest firm had a (Γ) score of over 5.

From 2014 to 2017 there was appreciable reordering of the (Γ) scores across firms as the use of pollution removal technologies, fuel sources, and asset (power plant) ownership changed. This within-firm variation in (Γ) is significantly associated with several measures of firms' financial performance. Firms that became dirtier exhibited substantial share price reductions. Current returns were higher for firms that grew more pollution intensive, as investors required greater compensation for risks due to holding equity in such enterprises. Future EPS surprises were larger for dirtier firms because analysts systematically *underestimated* future EPS. The empirical analyses also reveal that an important determinant of EPS surprises is the degree to which pollution damage produced by each firm was concentrated at relatively few facilities. A Herfindahl Index for firms' damage is positively associated with EPS surprises, and negatively associated with the noisiness of analysts' EPS estimates. How damages are distributed across firms' plants affects the ease with which analysts and other market participants can ascertain environmental performance. The empirical results suggest that this information transmission mechanism is especially relevant to financial outcomes for CO_2.

Importantly, the new index suggests systematically larger effects of environmental performance on financial outcomes than a measure comprised only of carbon intensity. Current period prices and returns are between two and three times more responsive to changes in the multipollutant (Γ) score than to changes in carbon intensity. EPS surprises are between two and five times more sensitive to changes in (Γ) than to changes in carbon intensity. These results suggest that the multipollutant (Γ) score may provide asset managers, investors, and other market participants with new insights, relative to the standard reliance on carbon intensity, regarding the relationship between environmental performance and financial outcomes. Such insights may inform new capital allocation strategies. From the perspective of ESG disclosure requirements, an index based on the multipollutant measure proposed in this paper is more likely to affect capital allocation decisions than disclosure of carbon intensity. If a goal of standardized ESG disclosure is to affect behavior, (Γ) is clearly superior to previous metrics.

The remainder of the paper is structured as follows. Section II. describes the data sources and empirical methods used in the study. Section III. reports results and IV. concludes.

II. Data Sources and Methods.

a. Estimation of Pollution Damage.

This analysis computes the monetary damages from local air pollution and GHGs. To estimate the damages from local air pollution, the paper focuses on premature mortality due to exposure to fine particulate matter ($PM_{2.5}$) concentrations[3]. Prior research indicates that this damage endpoint comprises as much as 90% of the total damages from air pollution in the U.S. economy (USEPA, 1999; 2011; Muller, Mendelsohn, and Nordhaus, 2011). Concomitantly accounting for illnesses may result in double counting of damages. GHG damages are computed using recent estimates of the Social Cost of Carbon (SCC),

[3] Ambient $PM_{2.5}$ is comprised of multiple subspecies. These result from emissions of the local air pollutants listed below.

which is the present value of the damages from an emission of one ton of carbon dioxide equivalents (CO_2eq), (FWG, 2016). Total GHG damages are the product of emissions and the SCC.

Emissions data for the local air pollutants are obtained from the USEPA's National Emissions Inventories (NEI), which are published in three-year intervals (USEPA, 2017; 2020). These data are reported in U.S. short tons per year, by facility and pollution species. Local air pollutants covered include sulfur dioxide (SO_2), nitrogen oxides (NO_x), volatile organic compounds (VOCs), ammonia (NH_3) and primary $PM_{2.5}$. For the 2017 NEI (USEPA, 2020b), the principal greenhouse gases are also reported. These include carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). For 2014, CO_2eq are reported, by facility, in the EGRID database (EPA, 2020b).

Armed with emissions, expressed in U.S. short tons per year, the next step is to convert tonnage to monetary damage. For the local air pollutants, this study relies on the AP3 integrated assessment model, which is an updated version of the AP2 and APEEP models (Muller and Mendelsohn, 2009; Muller, Mendelsohn, and Nordhaus, 2011; NAS NRC, 2010; Muller 2014; Clay et al., 2019; Tschofen, Azevedo, Muller, 2019). AP3 and its predecessors link emissions to monetary damages in five modules: emissions, air quality modeling, exposures, concentration-response, and valuation. Beginning with emissions, in a given data year, say 2017, the AP3 model attributes all emissions reported in the 2017 NEI to source type and physical location. These emissions include all discharges in the U.S. economy, not just those from utilities. So, encompassed in this database are pollution releases from utilities, transportation, households, manufacturers and every other anthropogenic and biogenic source type listed in the NEI. AP3 allocates the emissions to the county that the NEI reports the discharges occurred in. Further, AP3 differentiates between emissions that occur at the ground-level, such as from cars and trucks, versus those that are released from a smokestack, such as from power plants.

With emissions appropriately documented and allocated in the model, AP3 then employs an air quality model to track the dispersion and chemical transformation of emissions. The result of this step is an estimate of the annual average ambient concentrations of $PM_{2.5}$ in every county in the coterminous U.S. Crucial to this step are county-resolved weather data which influence the fate and transport of emissions. Also, a chemistry module in AP3 links emissions of SO_2, VOC, NH_3, and NO_x to the formation of secondary $PM_{2.5}$, as described in Sergi et al., (2020). The accuracy of the predicted concentrations produced by AP3 and its earlier version has been verified (Jaramillo and Muller, 2016; Minnesota Dept. of Commerce, 2016; Sergi et al., 2020).

The next step in modeling premature mortality from $PM_{2.5}$ exposure is to document county populations. These data are provided by the U.S. Census Bureau, by data year in five year age groups. In addition, the Centers for Disease Control and Prevention provide county mortality rate data, also differentiated by age (CDC Wonder, 2020). To estimate the fraction of mortality risk due to exposure to $PM_{2.5}$, AP3 employs concentration-response functions from the peer-reviewed epidemiological literature (Krewski et al., 2009; Lepeule et al., 2012). These functions are widely used in federal policy analyses and the academic literature (USEPA, 1999; 2011; Muller, Mendelsohn, and Nordhaus, 2011; Tschofen, Azevedo, and Muller, 2019). Equation (1) demonstrates the calculation of number of deaths for age group (a), in county (i), in year (y) due to exposure to $PM_{2.5}$, or $M_{a,i,y}$.

$$M_{a,i,y} = Pop_{a,i,y} Rate_{a,i,y} \left(1 - \frac{1}{exp^{\beta PM_{2.5,i,y}}}\right) \tag{1}$$

where: $Pop_{a,I,t}$ = population count of age group (a), in county (i), year (y).
$Rate_{a,I,t}$ = mortality rate of age group (a), in county (i), year (y).
β = statistically estimated parameter from epidemiological study.

Deaths are the product of the attributable risk from pollution exposure (the parenthetical term), times baseline risk, times the size of the exposed population.

The final module in AP3 converts premature deaths to monetary units using the Value of a Statistical Life (VSL) approach that is widely employed in federal policy analyses and academic research (USEPA, 1999; 2011; 2013; Muller, Mendelsohn, and Nordhaus, 2011; Tschofen, Azevedo, and Muller, 2019). The VSL is the marginal rate of substitution between income and mortality risk and it is the benchmark empirical measure of the monetary value of small changes in mortality risk (Cropper, Hammit, Robinson, 2011). Empirical estimates of the VSL primarily stem from two methodological approaches: hedonic wage studies which estimate the wage premium workers require to assume additional mortality risk, and contingent valuation studies that ask people directly about their valuation of risk on surveys. The VSL used herein is the average of studies from both literatures (USEPA, 1999; 2011). Though prior research has varied the VSL based on age of the exposed population (Muller, Mendelsohn, and Nordhaus, 2011), this analysis applies a uniform VSL irrespective of the age of the exposed population, as is done in most policy analyses and applied research (USEPA, 1999; 2011). The VSL does vary with income. Thus, for each year of this analysis, changes in the reported median income level affect the VSL through an elasticity reported in the literature (Kleckner and Neumann, 1999).

The monetary damage from $PM_{2.5}$ exposure in county (i) during year (y) is the sum across age groups of the product of the count of premature deaths and the VSL:

$$D_{a,i,y} = \sum_{a=1}^{A} \left(VSL_y \times M_{a,i,y} \right) \quad (2)$$

AP3 is used to estimate the marginal damage of emissions of SO_2, NO_x, NH_3, VOC, and primary $PM_{2.5}$, by facility (Muller and Mendelsohn, 2009; Muller, Mendelsohn, Nordhaus, 2011). To accomplish this, AP3 is run through with all emissions reported in the NEI to compute total baseline damage. Then, one ton of one emitted pollutant (p) is added to baseline emissions at one source (s) and AP3 is run again. The difference in damage is strictly attributable to the change in emission. This is the damage per ton for pollutant (p) at source (s). To compute total or gross external damage (GED) for source (s) and pollutant (p), the marginal damages are treated as emissions “prices” and the total damage from a source, industry, or sector’s emissions are the product of emission tonnage and marginal damages as shown in (3).

$$GED_{y,s,p} = \left(E_{y,s,p} \times MD_{y,s,p}\right) \qquad (3)$$

Adding up damages across pollutants (p) yields the total GED produced by a given source in year (y). Adding up damages across sources yields total GED attributable to a firm.

Computing the GED in this way finds its conceptual roots in the national income and product accounts (NIPA) in that the gross value of production from industries as reported in the NIPA is computed as the market price of its goods times the volume of goods produced. This approach is used in the environmental accounting literature (Abraham and Mackie, 2006; Nordhaus, 2006; Muller, Mendelsohn, and Nordhaus, 2011; Muller, 2014).

b. Financial Modeling.

While the estimation of pollution damage relies on facility level emissions information, financial modeling occurs at the firm level. As such, linking facilities to firms is an essential step in the present study. Two critical variables in the emissions database enable this exercise. Most facilities are listed in the emissions data by name. This facility name often includes references to the firm owner. Second, most facilities also have an operator, owner, or company name listed in the data. Using both sources of information, a text string matching algorithm links facility or owner names to firm names in the Standard and Poor’s 500 and the Wiltshire 5000. Embedded in this algorithm are numerous crosswalks between parent companies and subsidiaries, the latter of which are often listed either directly in the facility or operator name information in the emissions datasets.

For those plants that are linked to a publicly traded firm, the GED for each firm is compared to reported market capitalization by year (Siblis, 2020). The motivation for doing so is to provide a scale-adjusted measure of pollution damage. This analysis offers a new summary statistic of firms' pollution damage intensity. This statistic, the gamma (Γ), is the ratio of each firm's contribution to total industry GED, to total industry market cap, as shown in (4), where (f) denotes firm and $Cap_{f,y}$ denotes market capitalization in year (y) for firm (f).

$$\Gamma_{f,y} = \frac{\frac{GED_{f,y}}{\sum_{f=1}^{N} GED_{f,y}}}{\frac{Cap_{f,y}}{\sum_{f=1}^{N} Cap_{f,y}}} \tag{4}$$

This statistic expresses the relative share of damage to the relative share of value, for each of the N firms in the industry and it is defined on the $[0, \infty)$ interval. In what follows below, the firm-$\Gamma_{f,t}$ is reported in three ways: for GHGs, $\Gamma_{f,t}^{G}$, for local air pollutants, $\Gamma_{f,t}^{A}$, and for both combined, $\Gamma_{f,t}^{T}$.

This analysis next explores how firms' environmental performance affects standard measures of firms' financial performance. The financial performance measures include prices, trailing price-to-earnings ratios (P/E), returns, volatility in prices and returns, earnings per share (EPS), and Sharpe Ratios[4]. Prices, returns, volatility, P/E ratios, and Sharpe Ratios are resolved at the daily level. Refinitiv® reports EPS quarterly (IBES, 2021).

Expression (5) displays the specification used with prices ($P_{f,y,m}$) as the outcome variable, where (m) denotes month-of-year, (d) denotes day of month. Auto-regressive distributed lag (ADL) models are employed.

$$(P)_{f,y,m,d} = \theta_1 + \theta_2 \Gamma_{f,y}^{T} + \sum_{l=1}^{12} \theta_{3,l} P_{f,y,m,d-l} + \sum_{l=0}^{12} \theta_{4,l} \mathrm{X}_{f,y,m,d-l} + \mu_f + \tau_y + \omega_m + \cdots$$

[4] The financial data is provided by Refinitiv® including the IBES earnings data.

$$+\lambda_w + \beta_a + \varepsilon_{f,y,m,d} \qquad (5)$$

Included in the specification are month-of-year, day-of-week, day-of-month, year, and firm fixed effects $(\omega_m, \lambda_w, \beta_a, \tau_y, \mu_f)$, and the index X, which includes net generation[5], annual dividends and market capitalization, sentiment (Baker and Wurgler, 2006), returns, and volatility in prices and returns. The models include up to 10-day (two trading weeks) lagged values of the dependent variable, returns, and the volatility measures. Due to the relative infrequency with which dividends and market capitalization are reported, these covariates enter (5) annually. (5) is also fitted with returns ($R_{f,t}$), both measures of volatility, P/E ratios, and Sharpe Ratios as the outcome variable. The covariate of interest, $\Gamma^T_{f,y}$, is calculated on an annual basis, by firm. Expression (5) is fit distinctly for each measure of environmental performance ($\Gamma^T_{f,y}$, $\Gamma^G_{f,y}$, $\Gamma^A_{f,y}$) and for each financial outcome variable. A fourth specification includes $\Gamma^G_{f,y}$ and $\Gamma^A_{f,y}$ together in the model.

The analysis of EPS and environmental performance includes actual EPS, estimated EPS, and the EPS surprises. Expression (6) features EPS surprises as the dependent variable. (Distinct models are fit with actual and estimated EPS as the dependent variables.)

$$EPS^{surprise}_{f,y,m} = \theta_1 + \theta_2\Gamma^T_{f,y} + \theta_3 \mathrm{EPS}^{actual}_{f,y-1,m} + \theta_4 \mathrm{EPS}^{estimate}_{f,y-1,m} + \theta_4 \mathrm{EPS}^{surprise}_{f,y-1,m} + \sum_{l=0}^{12} \theta_{5,l} \mathrm{X}_{f,l} + \mu_f + \tau_y + \omega_m + \varepsilon_{f,y,m} \qquad (6)$$

Included in (6) are one-year lagged values of actual EPS, forecast EPS, and the EPS surprise. Because of the infrequency with which the EPS are reported, only year, month-of-year, and firm fixed effects are included.

[5] Net generation is included as an annual total of the amount of electricity each firm produced in year (y).

The coefficients for the $\Gamma_{f,y}$ statistics are reported in the following results section as these are of primary interest. The full model results are relegated to an online appendix.

In models (5) and (6), the $\Gamma_{f,y}$ statistics are included contemporaneously, by year, with the dependent variables. Each of the above models is also fit with one-year ahead values of the dependent variables. The models retain the ADL specification, with the only difference being that the $\Gamma_{f,y}$ statistics are lagged by one year relative to the dependent variables.

In addition to the analyses discussed above, the full sample of 43 firms is subset according to whether firms are listed on the Standard and Poor's 500 (S&P). The motivation for this subsampling exercise is found in prior work arguing that investors are particularly attuned to firms on the S&P (Yang, Muller, Liang, 2021).

One concern with the above specifications is whether extant air pollution regulations pertinent to utilities influence firm performance through environmental performance. In order to test for such a relationship, the models that feature prices, returns, and P/E ratios include the count of facilities in locations (counties) that are out of attainment with air pollution standards. The results of these specifications are reported in the appendix. The motivation for this approach is that plants in such locations are subject to especially strict controls on emissions[6].

i. Unit Root Tests

The daily firm data on prices, returns, volatility, and Sharpe Ratios are tested for the presence of unit roots. The Augmented Dickey-Fuller Test is used. The test assumes the following form, where, as an example, daily prices are the subject of the test.

[6] Specifically, Title I of the Clean Air Act stipulates limits on ambient concentrations of several air pollutants. Counties that exceed these limits are classified as "non-attainment" areas. States or municipalities then submit detailed plans to reach attainment status, which typically involved costly abatement.

$$(\Delta P)_{f,y,m,d} = \alpha_1 + \alpha_2 P_{f,y,m,d-1} + \alpha_2 \Delta P_{f,y,m,d-1} + \alpha_3 t + \varepsilon_{f,y,m,d} \tag{7}$$

The hypothesis testing centers on the α_2 term. The time series data for each firm is tested individually. Table A.1 in the appendix reports the results. Specifically, the table reports the number of firms (out of 43 total firms) for which the null hypothesis of the presence of a unit root is rejected at the $\alpha < 0.01$ level of significance.

One goal of this paper is to compare how different measures of firms' environmental performance influence financial performance. In light of this, the empirical exploration of the associations between firms' financial performance and the $\Gamma_{f,y}$ statistics is repeated with two gross tonnage of GHGs and local air pollutants, and the $\Gamma_{f,y}$ statistics defined in terms of tonnage rather than the GED as shown in (8).

$$\Gamma_{f,y} = \frac{\frac{GHG_{f,y}}{\sum_{f=1}^{N} GHG_{f,y}}}{\frac{Cap_{f,y}}{\sum_{f=1}^{N} Cap_{f,y}}} \tag{8}$$

Finally, Refinitiv ® provides numerous measures of environmental performance. The analysis compares the sensitivity of financial performance to these alternative measures in the appendix, retaining the same basic ADL specification used above.

III. Results.

a. Firm Environmental Performance.

Table 1 reports the growth in market capitalization, GED, and an adjusted measure of market capitalization that is net of GED. The GED are decomposed according to LAP and GHG. Table 1 reveals that the firms included in this analysis experienced a median annualized growth rate in market capitalization of just over 6 percent (in real terms). Against this trend in market capitalization growth, combined GED fell by about 20 percent, annually. This reduction was primarily due to declining LAP damages. Between 2014 and 2017, LAP GED dropped at a 27 percent annual rate. GHG GED were statistically flat. This simple decomposition of pollution damage indicates that indices which only track GHGs in the utility sector will seriously mischaracterize environmental performance. Subsequent sections of the paper will demonstrate that this has important implications for the relationship between financial outcomes and these measures of environmental performance.

How do firms reduce damage? Firms have several options to reduce pollution damage. They can install pollution control technology such as flue gas desulfurization units and selective catalytic reducers to control SO_2, and NO_x, respectively. Companies may elect to switch fuels, from say coal to natural gas, to reduce SO_2 and CO_2. Both of these approaches maintain output (net generation of kwh) while reducing pollution intensity. Alternatively, firms may close facilities. Of course, this reduces pollution, but it may concomitantly decrease output if other facilities are not acquired or constructed.

The decreasing GED deducted from rising market capitalization results in high annual rates of growth in adjusted, or net, market capitalization; while market cap grew at 6.5 percent, market cap less GED grew by 16 percent, annually. When only the LAP GED are deducted, growth in net market capitalization is 14 percent. And, if only GHG GED are subtracted, growth in adjusted market capitalization is about 8 percent, or about 1.5 percent more rapid than annually growth in conventionally reported market capitalization. This phenomenon of rising within-market measures of growth coupled with falling pollution leading to more rapid pollution-adjusted growth was first documented at the economy-wide and sectoral level (Muller, 2013; 2014). The present paper is the first to examine this at the enterprise level.

While table 1 summarizes firm market capitalization and GED growth rates, table 2 presents the ($\Gamma_{f,y}^{T}$) scores, total GED, and GED per share outstanding for firms listed on the Standard and Poor's 500 in the utility sector. Three themes emerge from this table. First, within year, there is considerable variation in the ($\Gamma_{f,y}^{T}$) scores, from 0.06 to 5.81 in 2014. Second, there is considerable re-ordering of the firms' ($\Gamma_{f,y}^{T}$)

scores between 2014 and 2017. Third, the companies' total GED and their GED per share provide an insightful means for investors and asset managers to relate pollution intensity to intuitive measures of firm value.

In 2014, the ($\Gamma_{f,y}^{T}$) scores ranged between 0.06 and 5.81. Recall that a ($\Gamma_{f,y}^{T}$) score of 0.06 means that American Water Works' combined air pollution and GHG damage share (relative to the industry total) was less than one tenth of its market capitalization share. At the other end of the spectrum, NRG's damage share was almost six times larger than its market capitalization share. Firms like CMS Energy and Edison International exhibited ($\Gamma_{f,y}^{T}$) scores around 1. These firms had relatively equal damage and market capitalization shares. In 2017, the range in ($\Gamma_{f,y}^{T}$) scores was even larger.

The difference in GED per outstanding share also shows the difference in pollution intensity between firms. In 2014, American Water Works produced GED equivalent to just under $1 per share. NRG generated GED of nearly $60 per share. Figure 1 demonstrates the implication of these differences in pollution intensity for net share prices. The top left panel shows American Water Works. The black line traces monthly averaged share prices. The red line nets out GED per share[7]. At $1 per share, the deduction makes very little difference between the observed share price and that which nets out GED. While American Water Works was the cleanest firm in 2014, it dropped to the fifth cleanest in 2017. The company's total GED and GED per share fell slightly over this period. Its ranking fell because other firms became even cleaner.

The top right panel repeats the same exercise for XCEL Energy. For this firm, the GED per share amounted to between one-third and one-fifth of observed prices. What is interesting about XCEL is that the spread between actual and net prices remains roughly constant. Table 2 indicates that the GED per share held at about $8 per share from 2014 to 2017. And, total GED was essentially flat at $4 billion. This

[7] Since the empirical calculation of GED occurs in 2014 and 2017, the GED is interpolated for 2015 and 2016.

constant level of GED, in the context of an industry with GED that fell at an annual rate of 17 percent, results in a $\Gamma_{f,y}^{T}$ score that increased from 0.82 to 1.30. XCEL didn't keep pace with its industry peers.

The bottom left panel of figure 1 focuses on Edison International. This firm exhibited GED per share of about \$17, which amounted to nearly one-third of its share price in 2014. In contrast to XCEL, Edison International's GED per share fell precipitously to just under \$8. This reduction is evident in figure 1. The spread between Edison International's market share price and the GED-adjusted price narrowed appreciably. It's $\Gamma_{f,y}^{T}$ score also dropped from 0.96 to 0.78, and the total GED decreased by about one-half. Finally, the bottom right panel plots the market and adjusted share prices for NRG, the firm with the most pollution intensive $\Gamma_{f,y}^{T}$ score in both 2014 and 2017. First, the horizontal line at zero indicates that deducting the nearly \$60 in GED per share from NRG's observed share price in 2014 results in a negative valuation. This also implies negative market capitalization for NRG. One might ask whether such a magnitude for the GED is plausible. Using 2002 data[8], prior research demonstrated that the fleet of coal-fired power plants produced greater GED than its collective value-added (Muller, Mendelsohn, and Nordhaus, 2011). So, there is precedent for this degree of pollution intensity for utilities in the literature. Despite remaining as the most pollution intensive firm, NRG cleaned up considerably. Its GED per share dropped from about \$60 in 2014 to \$25 in 2017. Total GED produced by the company fell from \$19 billion to \$8 billion in 2017. Yet, its $\Gamma_{f,y}^{T}$ grew from 5.8 in 2014 to 8.3 in 2017. The firm became even more of an outlier in terms of its contribution to industry damage, relative to market capitalization.

The rationale for the comparison between firms' market share price and the GED-adjusted share price is the following. An investor holding a share of a firm has an ownership stake in the firm, which conveys a claim to earnings, the value of liquidated assets and the like. The GED per share thus represents

[8] In 2002, the electric power industry was characterized by much higher levels of pollution intensity and gross emissions than in 2014 (Holland et al., 2019).

investors' ownership of the monetary damage caused by pollution emitted during firms' production processes. Absent regulation, such as a Pigouvian tax that charges firms for the damages caused by their emissions, the GED is not realized by investors in a pecuniary sense. Because, in the U.S. at least, pollution policy does not feature Pigouvian taxation (or the polluter pays principle more broadly), the GED per share may serve an important informational role to investors and asset managers, especially when this metric is directly compared to market share prices.

b. Firm Financial Performance.

Tables 3 and 4 report the empirical results from the ADL regression models. Table 3 examines current period outcomes, table 4 focuses on financial outcomes the year after the ($\Gamma_{f,y}$) scores are calculated. Each financial outcome measure (the dependent variable from each regression) is shown in the row headings, and each environmental performance measure is shown in the column headings. In both tables, column (1) features ($\Gamma_{f,y}^{T}$), whereas columns (3) and (4) include ($\Gamma_{f,y}^{A}$) and ($\Gamma_{f,y}^{G}$), respectively. Column (2) includes ($\Gamma_{f,y}^{A}$) and ($\Gamma_{f,y}^{G}$) as separate covariates together in the same model. Tables 3 and 4 report only the fitted coefficients on the ($\Gamma_{f,y}$) measures. The full regression results are shown in the online appendix.

i. Prices.

Table 3 provides clear evidence that current period share prices fall as firms became more pollution intensive. This holds for each specification. Because the daily price series are non-stationary, as indicated by the results of the Dickey-Fuller test in table A.1, the price series is first-differenced. The interpretation of the coefficient on ($\Gamma_{f,y}^{T}$) is: a one unit increase in ($\Gamma_{f,y}^{T}$) corresponds to a \$0.0148 percent decrease in daily price changes ($p < 0.01$). The average daily price change is \$0.029. So, the estimated effect of a one-unit worsening in ($\Gamma_{f,y}^{T}$) is quite large: about 50 percent of daily price changes.

However, a one-unit change in ($\Gamma^T_{f,y}$) is a very large increase in pollution intensity; the 95th percentile of changes in ($\Gamma^T_{f,y}$) from 2014 to 2017 is 1.4. The average change in ($\Gamma^T_{f,y}$) was about 0.045. The coefficient on ($\Gamma^T_{f,y}$) suggests that an average firm incurred a statistically significant price reduction of 2.3 percent due to changes in ($\Gamma^T_{f,y}$). Recall that these models include firm fixed effects[9]. It is *within firm* changes in pollution intensity from 2014 to 2017 that drive the associated price responses. Within firm variation in ($\Gamma_{f,y}$) reflects repositioning of firms within the utility sector according to their relative pollution intensity of output. So, as firms re-shuffle between 2014 and 2017 according to the ($\Gamma^T_{f,y}$) measure, share prices respond inversely to firms' pollution intensity.

In a theme evident across multiple financial outcomes, the price changes due to pollution intensity is significantly larger when damages from air pollution and GHGs are combined in the ($\Gamma^T_{f,y}$) measure. Column (2) shows that the price effects of ($\Gamma^A_{f,y}$) and ($\Gamma^G_{f,t}$), when these metrics are included together in the same model, are about one-third to one-half the magnitude of ($\Gamma^T_{f,y}$). In columns (3) and (4), LAP intensity and GHG intensity are included in separate models as stand-alone measures of environmental performance. The marginal effect of both measures is about one-half the magnitude of ($\Gamma^T_{f,y}$). Hence, columns (3) and (4) suggest pollution intensity measures that focus on either just air pollution or just GHGs will substantially underestimate the price response to changes in pollution intensity, relative to ($\Gamma^T_{f,y}$). Summarizing, table 3 provides robust evidence that current period prices respond inversely to firms' relative pollution intensity and that the combined, multi-pollutant measure exerts the largest effect. Table 4 indicates that the negative association between the firms' ($\Gamma_{f,y}$) scores and share prices does not persist one year after the firms' ($\Gamma_{f,y}$) scores are calculated. The marginal effect of firms' ($\Gamma_{f,y}$) scores is about the same size as in table 3, but the coefficients are not precisely estimated.

[9] Table A.2 in the appendix reports how the coefficient on ($\Gamma^T_{f,y}$) changes as a function of controlling for different combinations of firm and time fixed effects.

ii. Returns and Risk.

Table 3 provides evidence that investors require greater returns for firms that became dirtier relative to their peers. A one-unit increase in pollution intensity for the combined ($\Gamma_{f,y}^{T}$) score is associated with a 5 percent increase in weekly returns ($p < 0.01$). Given that the average change in ($\Gamma_{f,y}^{T}$) is just 0.045, the estimated coefficient implies an increase in weekly returns of 0.23 percent for an average firm. On an annual basis, this amounts to roughly a 12 percent premium[10]. Bolton and Kacperczyk (2019) report a 2 to 3 percent annual premium on returns for firms with higher total CO_2 emissions[11]. To compare with this result, column (4) indicates that the coefficient for carbon intensity is 0.0295. The average change in ($\Gamma_{f,y}^{G}$) is 0.029. Annualizing the carbon return premium using the coefficient in column (4), for an average firm, yields an estimated premium of 4.5 percent, which is larger than, but comparable to that reported by Bolton and Kacperczyk (2019). Table 4 indicates that the returns one year following the environmental performance measures are also positively associated with the ($\Gamma_{f,y}$) scores. The effect sizes tend to be larger, however, the statistical significance is weaker than for current returns. In accord with the results for share prices, the combined measure of pollution intensity exerts an effect on returns that is about two-times greater than the ($\Gamma_{f,y}^{G}$) or the ($\Gamma_{f,y}^{A}$) scores.

Table 3 includes two measures of risk: volatility in prices and volatility in returns. Price volatility is not significantly related to the environmental performance measures. In contrast, volatility in returns is positively associated with pollution intensity for all of the ($\Gamma_{f,y}$) scores. The coefficient for ($\Gamma_{f,y}^{T}$) is 0.025

[10] The annualized premium is: $(1+0.0023)^{52}$- 1 = 0.12.7.

[11] Similarly, Hsu, Li, and Tsou (2020) find higher returns for firms that are higher emitters of toxic air pollutants (not those covered herein).

($p < 0.05$). The mean volatility for firms in this sample is 1.51: a one unit increase in ($\Gamma^{T}_{f,y}$) is associated with a 1.7 percent increase in (weekly) volatility. Reiterating the pattern observed in prices and returns, the coefficient associated with ($\Gamma^{T}_{f,y}$), the combined measure of pollution intensity, is between 1.5 and 2 times larger than the coefficients for the air pollution and GHG intensity metrics. Table 4 provides suggestive evidence that volatility in returns falls for more pollution intensive firms, one year following when the ($\Gamma_{f,y}$) scores are calculated. This effect is only significant for the ($\Gamma^{A}_{f,y}$) metrics.

The bottom row of table 3 focuses on Sharpe Ratios, defined as the ratio of returns to volatility in returns. Sharpe Ratios are interpreted as a measure of risk-adjusted returns. Beginning with the combined measure of pollution intensity ($\Gamma^{T}_{f,y}$), table 3 indicates that a one unit worsening of ($\Gamma^{T}_{f,y}$) corresponds to a 25 percent reduction in risk-adjusted returns. Again, referencing the firm average change in ($\Gamma^{T}_{f,y}$) of 0.045, a typical firm incurred a small (1.1 percent) decrease in risk-adjusted returns. The effect of pollution intensity on the Sharpe Ratios appears to be driven by local air pollution. The coefficients for the ($\Gamma^{A}_{f,y}$) metric in columns (2) and (3) are about -0.07 ($p < 0.01$). The ($\Gamma^{G}_{f,y}$) score is not significant at conventional levels. Table 4 indicates that the Sharpe Ratios one year after the ($\Gamma_{f,y}$) scores are calculated are not associated with these measures of environmental performance.

iii. Earnings and P/E Ratios.

Table 3 shows that, despite the significant decline in prices associated with each measure of environmental performance, the trailing P/E ratios are positively associated with the ($\Gamma_{f,y}$) scores[12]. This association is largely driven by carbon intensity. In columns (2) and (4) the ($\Gamma^{G}_{f,y}$) score exhibits a positive and significant ($p < 0.05$) effect on the P/E ratios, which enter the regression models in natural log form.

[12] Recall that the trailing P/E ratio features observed prices in 2014 and 2017, relative to analysts' estimated EPS for the preceding 12 month period.

As such, the estimated coefficients for the ($\Gamma_{f,y}^{G}$) scores suggest a 15 percent increase in the P/E ratios for each one-unit change in ($\Gamma_{f,y}^{G}$). The air pollution damage metrics are not significantly associated with the P/E ratios. Repeating an earlier theme, the combined pollution damage measure ($\Gamma_{f,y}^{T}$) displays a larger partial effect on the P/E ratios (0.266; $p < 0.10$) than either the ($\Gamma_{f,y}^{A}$) or the ($\Gamma_{f,y}^{G}$) scores.

The positive effect of pollution intensity on P/E ratios, despite the negative association between the ($\Gamma_{f,y}$) scores and prices, implies that analysts' EPS estimates (which comprise the denominator of the P/E ratios) must also fall with the ($\Gamma_{f,y}$) scores. To test this, analysts' EPS estimates are regressed on each ($\Gamma_{f,y}$) score. The bottom panel of table 5 reports that current period EPS estimates are negatively associated with the ($\Gamma_{f,y}$) scores. A one unit increase in ($\Gamma_{f,y}^{T}$) is associated with a \$0.15 decrease in estimated EPS ($p < 0.01$). The average estimated EPS is \$2.80. The coefficient implies a six percent reduction in EPS for a one-unit change in ($\Gamma_{f,y}^{T}$). Recall that a one-unit increase in ($\Gamma_{f,y}^{T}$) induced a \$0.015 reduction in price changes. So, the \$0.15 reduction in EPS estimates outweighs the price effect. Thus, the P/E ratios rise for firms that became more pollution intensive.

In addition to the combined score, both of the ($\Gamma_{f,y}^{G}$) scores are significantly, negatively associated with the EPS estimates ($p < 0.05$). This is not surprising given that many current ESG indices focus exclusively on carbon intensity. The coefficients for the air pollution scores are also negative, but imprecisely estimated.

In addition to the EPS estimates, the bottom panel of table 5 also reports EPS actuals, and EPS surprises, defined as the difference between the two. While EPS actuals are not systematically associated with the ($\Gamma_{f,y}$) scores, EPS surprises appear to be. Both columns (2) and (4) indicate that carbon intensity ($\Gamma_{f,y}^{G}$) drives larger EPS surprises. The coefficients suggest that a one-unit increase in the ($\Gamma_{f,y}^{G}$) is associated with a 2 percent increase in EPS surprises ($p < 0.05$). EPS surprises are reported by Refinitiv® as the difference between actual and the mean estimated EPS across analysts. Hence, these empirical results suggest that analysts *underestimate* EPS to a greater extent for firms that became relatively more carbon pollution-intensive from 2014 to 2017.

The top panel of table 5 reports the effect of pollution intensity on future EPS actuals, estimates, and surprises. There are two key results from this analysis of future EPS. First, each of the measures of pollution intensity is significantly associated with all of the EPS measures. Second, EPS surprises are robustly, positively associated with pollution intensity. For example, a one-unit increase in ($\Gamma_{f,y}^{T}$) induces a \$0.31 increase in actual EPS ($p < 0.01$) and just a \$0.15 increase in estimated EPS ($p < 0.01$). Accordingly, EPS surprises are 15 percent larger for firms that incur a one-unit increase in ($\Gamma_{f,y}^{T}$). Across the ($\Gamma_{f,y}$) metrics, the partial effect on actual EPS is roughly double that of the estimated EPS. This difference results in the large positive association between EPS surprises and the ($\Gamma_{f,y}$) scores. This means that analysts' errors in estimating EPS stem not from projecting decreases in EPS for dirtier firms. Rather the errors are due to underestimating the degree to which actual EPS increase as a function of pollution intensity. And, repeating a pattern evident in the analysis of prices, returns, and volatility, the combined, multi-pollutant metric ($\Gamma_{f,y}^{T}$) exhibits a larger effect on actual EPS, the estimated EPS, and the EPS surprise than the other measures.

The systematic EPS errors for dirtier firms suggest that a careful portfolio manager could exploit the findings reported herein to achieve a period of overperformance relative to a strategy based on the reported EPS estimates. Suppose a manager employs the mean EPS estimates to determine their capital allocations within the utility sector. This tack would down-weight dirtier firms in the portfolio as expected earnings are lower than for cleaner firms. Because the EPS forecasts are biased down for pollution intensive firms, a manager informed by the results in table 5 could capitalize on this bias to generate superior returns relative to a strategy strictly adherent to the mean EPS forecast. Further, a manager focusing on the multipollutant index would stand to roughly double the returns to this approach relative to a strategy based solely on carbon intensity.

Table A.3 explores how the distribution of damages, across facilities owned by the same firm, affects the future EPS surprises. A motivation for exploring the intra-firm distribution of damage is the following. Emissions (and damages) that emanate from fewer plants makes ascertaining firm's environmental performance easier. This would matter for regulators as well as other market participants (including analysts) using real time surveillance or otherwise trying to glean environmental performance by observational means. To measure the firm-level concentration of damages, a Herfindahl Index is computed as shown in (9):

$$\mathrm{H}_{f,y} = \sum_{p=1}^{P} \left(\frac{GED_{f,p,y}}{\sum_{p=1}^{P} GED_{f,p,y}} \right)^2 \tag{9}$$

where p = facility.

This index characterizes the degree to which firms' damages are concentrated in relatively few facilities, akin to how a typical application of the Herfindahl Index conveys the concentration of market shares across firms within an industry. One would expect the Herfindahl Index in (9) to increase the EPS surprise, because analysts would more readily assess environmental performance, thereby enhancing their tendency to underestimate EPS for pollution intensive firms.

Table A.3 reports the resulting from running the same regressions as reported in table 5 (with EPS surprises as the dependent variable) with the Herfindahl Index added as an independent variable. Table A.3 confirms the hypothesis above, especially for CO_2. A 1 percent increase in the Herfindahl Index for CO_2 exerts a 7 percent increase in the EPS surprise ($p < 0.01$). Also, the coefficient for ($\Gamma_{f,y}^{G}$) increases from 4.5 in table 5 to 9.3 in table A.3 upon inclusion of the Herfindahl Index. In column (3), which also includes ($\Gamma_{f,y}^{A}$) and the Herfindahl Index for air pollution, the Herfindahl Index for CO_2 retains its significance. The magnitude of its effect on the EPS surprise attenuates only slightly, relative to column (1). These results indicate that analysts' EPS are less accurate for companies whose CO_2 damages emanate from relatively few sources. As argued above, one explanation for this result is that the information about emissions and damages required for analysts to judge environmental performance is less costly to acquire for firms with higher Herfindahl scores. Adding a Herfindahl index for air pollution does not significantly affect EPS surprises.

Table A.4 explores the standard deviation across analysts' EPS estimates, by firm. The bottom panel focuses on the standard deviations for current period estimates. There is suggestive evidence that dispersion in analysts' estimates is higher for firms that become more carbon-intensive. However, the coefficient of variation does not systematically vary with the ($\Gamma_{f,y}$) scores. This implies that the standard deviations vary in proportion to the mean EPS estimates. The top panel of table A.3 examines the dispersion of year ahead EPS estimates. In the year ahead context there is more consistent evidence that analysts' estimates become noisier as firms grow more pollution intensive. A one unit increase in the ($\Gamma_{f,y}^{T}$) score is associated with a \$0.01 increase in the standard deviation of analysts' estimates ($p < 0.10$). The effect is also evident in the ($\Gamma_{f,y}^{A}$) scores. While pollution intensity increases the standard deviation of EPS estimates, it reduces the coefficient of variation. A one unit increase in the ($\Gamma_{f,y}^{T}$) score is associated with a \$0.01 decrease in the coefficient of variation in analysts' estimates ($p < 0.01$). Table 5 shows why this is the case. The (mean) EPS estimates increase by \$0.15 ($p < 0.01$) for each unit increase in the ($\Gamma_{f,y}^{T}$) score. Because this effect is so much larger than that for the standard deviation (\$0.01 $p < 0.10$), the coefficient of variation falls. So, not only do analysts overreact to firms' pollution intensity, but, collectively, there appears to be less disagreement in the estimates, according to the coefficient of variation. Analysts coalesce around biased EPS estimates.

Table A.5 reports the results from regressing measures of dispersion in analysts' EPS estimates on the Herfindahl Indices. The key finding is that the coefficient of variation in the EPS estimates falls as firms have higher CO_2 Herfindahl scores, as observed in columns (1) and (5). Information regarding firms' CO_2 environmental performance is easier to obtain for firms with higher Herfindahl scores. If the information is easier to access, it is more likely that a plurality of analysts share the same, or similar, information. This facilitates greater agreement among analysts, and, in turn, less dispersion in their EPS estimates. The Herfindahl indices for air pollution do not affect the dispersion in EPS estimates.

Tables A.3 and A.5 suggest that, at the margin, increasingly concentrated damages among facilities owned by the same firm induces greater EPS surprises and less noisy EPS estimates for more carbon-intensive firms than for firms that grew more air pollution intensive. Why would this effect manifest for more carbon-intensive firms?

One explanation hinges on a version of Keynes' beauty contest. Analysts expect investors and other market participants to react to news about carbon intensive firms because the current offering of environmental performance metrics in the market emphasize carbon intensity, not air pollution (MSCI, 2019; NUVEEN, 2021; Sustainalytics; 2021). Higher Herfindahl Index scores make it easier for both those developing the environmental performance metrics and market participants to ascertain CO_2 performance. So, analysts may believe that highly concentrated, carbon-intensive firms bear additional reputation risk in light of the fact that environmental performance metrics guiding ESG allocations emphasize carbon and that the transmission of information regarding their performance is facilitated by the concentrated nature of damages for these firms.

A second explanation for the importance of the Herfindahl Index is that market participants might consider future regulatory risk for concentrated, carbon-intensive firms. Efforts to manage environmental pollution often focus on the largest sources first. As governments increasingly focus on limiting GHG emissions from the utilities sector, regulatory constraints may bind first for companies with large plants. These are the firms with higher Herfindahl scores. Of course, increased costs of compliance with environmental policy would adversely affect profits, and EPS.

The absence of an effect of the Herfindahl Index for air pollution damage reflects the information channel outlined above. Information regarding air pollution emissions has been gathered by federal regulators and made available to the public for decades. Some of the local air pollutants covered in the ($\Gamma_{f,t}^{A}$) measure have been regulated since the 1970s. Since air pollution emissions have been extensively monitored for many years, the degree of concentration in damages does not appreciably affect the EPS surprises because information regarding environmental performance in this dimension is already accessible to market participants. Further, since extant ESG metrics largely ignore local air pollution, the degree of concentration in air pollution damage is likely irrelevant to market participants and index developers.

iv. The Standard and Poor's 500.

Table 6 reports the results of regressing measures of current financial performance on two subsamples of firms: those listed on the S&P 500 and the rest. The central insight from this exercise is that financial outcomes for firms on the S&P tend to be more sensitive to the ($\Gamma_{f,t}$) scores than the firms not on the S&P. For the combined ($\Gamma_{f,t}$) score, prices, returns, volatility in returns, and the Sharpe Ratios are significantly affected by ($\Gamma_{f,t}^{T}$) for firms on the S&P. These outcomes are not significantly associated with ($\Gamma_{f,t}^{T}$) for firms not on the S&P. P/E ratios, in contrast, are significantly associated with ($\Gamma_{f,t}^{T}$) across both subsamples of firms. One argument for the strong association between environmental performance and financial outcomes for firms on the S&P is the degree of exposure to various stakeholders for these firms. That is, the S&P is a widely employed gauge of financial markets. Because of this, market participants are *more likely* to follow environmental performance (and other dimensions of performance) for this subset of firms, relative to other publicly traded enterprises. Though this analysis cannot precisely test this mechanism, prior authors have made similar claims (Yang, Muller, Liang, 2021).

v. Air Pollution Regulations.

Table A.6 in the appendix explores the role of extant air pollution regulations on prices, returns, and P/E ratios. The count of facilities, by firm, that are located in non-attainment areas (denoted NA Count in table A.6) enters in levels and it is interacted with the ($\Gamma_{f,t}^{T}$) score. The top panel employs current financial outcomes. The parameter estimates from tables 3 and 4 are reported alongside the specification including the non-attainment measure. There are two results in table A.6 emphasized here.

First, for current returns, including the controls for non-attainment reduces the coefficient on ($\Gamma_{f,t}^{T}$) by about 40 percent. The smaller coefficient on ($\Gamma_{f,t}^{T}$) suggests that investors command a smaller premium on returns for firms that grow dirtier without owning any plants in non-attainment counties. This implies that about 60 percent of the premium reported in table 3 is not due to extant regulatory risk for air pollution. And, while the count of facilities in non-attainment areas entering in levels is not significant, the interaction term with ($\Gamma_{f,t}^{T}$) is -0.0034 ($p < 0.01$).

The other notable result in table A.6 pertains to future P/E ratios. Recall from table 5 that, without the non-attainment covariates, future P/E ratios fell by about 20 percent for a one-unit increase in ($\Gamma_{f,t}^{T}$). Now, for firms without any plants in non-attainment areas, the negative effect on P/E ratios is much larger, about 30 percent ($p < 0.05$). The detailed analysis of EPS estimates revealed that ($\Gamma_{f,t}^{T}$) positively influences analysts future EPS estimates, which, all else equal, reduces the P/E ratio. Thus, comparing tables 5 and A.6 suggests that analysts may be more optimistic about EPS for firms that grow dirtier, but that do not own plants in non-attainment areas.

Why would analysts' EPS estimates manifest in this way? Consider that firms may become dirtier relative to their peers by using dirtier fuels which tend to be cheaper than cleaner burning fuels. Alternatively, if some firms elected to invest in costly abatement technology, those that do not would become more pollution intensive according to the ($\Gamma^{T}_{f,t}$) metric. In either case, dirtier firms may expect to lower costs and earn higher profits. The drawback to becoming dirtier, of course, is reputation and regulatory risk. Risk due to environmental policy is limited for firms without plants in nonattainment areas. Therefore, one reason analysts are more optimistic about EPS for dirty firms without plants in non-attainment areas might be the absence of regulatory risk, coupled with the apparent benefits of becoming more pollution intensive. Had reputation risk dominated the formulation of EPS estimates, one would not expect to see the larger effect on P/E ratios due to ($\Gamma^{T}_{f,t}$) for firms without plants in non-attainment areas.

c. Comparing Alternative Measures of Environmental Performance.

Table A.7 in the appendix compares environmental performance scores and metrics published by Refinitiv® to those developed in this paper, and the associations of each with prices, returns, and EPS surprises. The top panel of table A.7 focuses on current period outcomes, the bottom panel reports results for future period financial outcomes. Summarizing the top panel, seven out of nine coefficients corresponding to the ($\Gamma_{f,t}$) scores are significantly associated with financial outcomes. Just four out of twelve coefficients for the Refinitiv® measures are significant determinants of financial outcomes. In the bottom panel of table A.7, again, seven out of nine coefficients corresponding to the ($\Gamma_{f,t}$) scores are significantly associated with financial outcomes. Only three out of twelve environmental performance measures from Refinitiv® significantly affect future financial outcomes. From this comparison, the conclusion is clear that the ($\Gamma_{f,t}$) scores are systematically stronger determinants of financial outcomes than the Refinitiv® measures for the firms and time periods covered in this study.

Table A.8 in the appendix reports how current period financial outcomes vary with the ($\Gamma_{f,t}$) scores defined in terms of emissions, rather than damages. The key insight in this table is that GHG emissions dominate LAP emissions because of the large difference in emissions tonnage. Therefore, multi-pollutant environmental performance scores expressed in terms of emissions mimic CO_2. This underscores the importance of monetizing multi-pollutant indices. Table A.9 in the appendix regresses current period financial outcomes on raw tonnage. Here the results reveal very little evidence of any significant relationship between tonnage and financial outcomes.

IV. Conclusions.

This analysis offers a new approach to the measurement of firms' environmental performance. In contrast to existing metrics, which often focus exclusively on CO_2 emissions, the present paper computes the monetary damage from eight pollutants and devises a summary statistic that relates relative pollution damage to relative firm value. Monetization is essential to the measurement of firms' environmental performance for two reasons. First, monetization enables aggregation of multiple pollutants by converting emissions into a common metric – money. Simply adding up tons doesn't work because CO_2 emissions are so abundant relative to other pollution species. Second, monetization facilitates adjustments to firm value reflecting the external (monetary) cost from emissions. This direct reconfiguration of firm value is not possible with emissions measured in tons.

The paper estimates this new statistic in the context of the U.S. utility industry from 2014 to 2017. This is both a data rich and pollution intensive setting. The environmental performance in this sector will be a crucial determinant of macro-scale environmental outcomes. As such, it is of broad social importance to allocate ESG-managed capital efficiently in the utility sector.

While market capitalization among these firms grew, pollution damages fell sharply. Importantly, LAP damages constitute the bulk of these declines, with GHG emissions and damages essentially flat from

2014 to 2017 (Holland et al., 2020). Hence, only focusing on CO_2 would fundamentally mischaracterize environmental performance in this sector. Within utility firms traded on the S&P 500, there is significant variation in environmental performance. Consolidated Edison's combined air pollution and GHG damage share (relative to the industry total) was one tenth of its market capitalization share. At the other end of the spectrum, NRG's combined air pollution and GHG damage share was over five-times larger than its market capitalization share.

The analysis explores the relationship between this new performance measure and a host of financial outcomes. These include current and future prices, P/E ratios, returns, earnings, and volatility. Key results include the following. Current prices fall and returns rise when firms' pollution damage intensity increases. Analysts tend to systematically underestimate future EPS for firms that grew more pollution intensive between 2014 and 2017. The analysis shows that the intrafirm distribution of damage matters for financial outcomes. The EPS surprises are larger for firms with CO_2 damages produced by relatively few sources. Further, EPS estimates are less noisy (across analysts producing estimates for the same firm) for firms with more concentrated CO_2 damages. Information regarding firms' CO_2 environmental performance is easier to obtain for firms whose damage emanates from fewer, larger plants. And, if the information is easier to access, it is more likely that analysts share the same information about emissions and environmental performance. This facilitates greater agreement among analysts, and, in turn, less dispersion in their EPS estimates.

A primary goal of the paper is a comparison of the new performance measure to existing metrics, those based only on GHGs, and only on emissions. These comparisons reveal three important insights. First, the (Γ) scores developed here are consistently stronger determinants of key financial outcomes than those offered by Refinitiv ® a leading financial data provider. Second, pollution intensity measured by adding up tons is dominated by GHGs. This stems from the fact that the volume of GHG emissions is orders of magnitude larger than local air pollution. Yet, in the U.S. utility sector, the monetary damages from LAPs are on par with GHGs (Holland et al., 2020). Adding up tons ignores the vast difference in the value of LAP tons and GHG tons at the margin. If a goal of ESG indices is to align the behavior of financial market participants with more socially beneficial environmental outcomes, monetization is essential.

Third, the financial outcomes modeled in this paper are considerably more responsive to the monetized multipollutant (Γ) scores than to indices based on GHGs, either monetized or calculated from emissions mass. Recall that prices and returns are about twice as sensitive to the combined (Γ) score. EPS surprises are between three and five times more responsive. There are two important implications of this. One, financial market participants who rely on the multipollutant (Γ) scores could exploit this heightened sensitivity to bolster returns on ESG-oriented capital allocation strategies. Why? Because if the majority of ESG-oriented portfolio managers focus only on carbon intensity, they will underestimate the systematic EPS forecast errors by as much as a factor of five. And two, standardized ESG disclosure requirements would benefit from the multipollutant (Γ) scores because it is a more effective driver of essential financial market outcomes (prices, returns, EPS) than an index relying on tonnage or focusing strictly on GHGs. This position is predicated on the idea that standardized ESG disclosure is intended to affect both firm behavior and that of financial market participants in a manner that nudges outcomes in financial markets and in the real economy toward a more socially beneficial allocation of resources.

This paper suggests new research in a number of areas. While the U.S. utility sector is a natural starting point, it reflects a small segment of the investible market. In the U.S., the data exist to apply this new measure of environmental performance to other sectors. Likely candidates include industrials, consumer staples, and the energy sectors. Subsequent analyses focusing on these segments of the economy will determine whether the relationships between pollution intensity and financial outcomes reported here manifest in other sectors. This will matter to asset managers, investors, and analysts as diversified ESG strategies must include firms outside of the utility sector. Additionally, estimation of the (Γ) scores in other sectors facilities firm rankings beyond the “best in class” scores presented herein. Further, explicit consideration of portfolios and investment strategies, only hinted at herein, is enabled by the present analysis. And, finally, future work might consider whether the new measure of environmental performance varies across private and public firms, as prior research indicates ownership matters for environmental outcomes.

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Tables and Figures.

Table 1: Growth in Market Capitalization and Pollution Damages.

	No Pollution	**GHGs + LAP**	**LAP**	**GHG**
Market Cap	0.065[A] (0.051,0.112)			
GED		-0.203 (-0.268,-0.140)	-0.270 (-0.377,-0.199)	-0.069 (-0.156,0.004)
Market Cap – GED		0.165 (0.103,0.187)	0.142 (0.080,0.174)	0.087 (0.063,0.131)

A = median annualized growth rate between 2014 and 2017. 0.065 = 6.5% annualized growth.
B = 95% confidence interval for estimated median.

Table 2: Environmental Performance of the Utility Firms Listed on the Standard and Poor's 500.

2014				2017			
Firm	(Γ)[A]	GED/ Share[B]	GED[C]	Firm	(Γ)	GED/ Share	GED
American Water Works	0.06	0.99	0.18	Eversource Energy	0.00	0.03	0.01
Consolidated Edison	0.09	1.56	0.46	Sempra Energy	0.02	0.37	0.09
PG&E Corp	0.10	1.58	0.70	Exelon	0.05	0.27	0.25
Pub. Service Ent. Group	0.13	1.58	0.80	PG&E Corp	0.07	0.48	0.24
Eversource Energy	0.16	2.40	0.76	Consolidated Edison	0.07	0.77	0.23
NextEra Energy	0.19	1.51	2.57	American Water Works	0.08	0.86	0.15
Exelon	0.30	3.31	2.85	Pub. Service Ent. Group	0.15	0.92	0.47
Dominion Resources	0.39	8.77	5.08	NextEra Energy	0.27	1.32	2.47
Sempra Energy	0.56	17.62	4.39	CenterPoint Energy	0.31	1.17	0.51
Pinnacle West Capital	0.58	10.42	1.15	Pinnacle West Capital	0.50	5.65	0.63
NiSource	0.64	7.81	2.45	Dominion Resources	0.51	5.49	3.39
CenterPoint Energy	0.75	5.56	2.40	CMS Energy Corp	0.66	4.12	1.15
Xcel Energy	0.82	8.27	4.11	WEC Energy Group	0.66	5.58	1.77
WEC Energy Group	0.85	12.14	2.79	Edison International	0.78	7.75	2.56
Edison International	0.96	17.27	5.68	NiSource	0.89	3.09	1.00
CMS Energy	1.09	10.45	2.84	PPL	0.96	4.73	3.23
Southern Co	1.17	16.73	14.67	Southern Co	1.17	8.16	7.69
DTE Energy	1.26	30.87	5.40	Xcel Energy	1.30	8.07	4.11
Entergy	1.34	32.60	5.82	Duke Energy	1.57	17.84	12.33
Duke Energy	1.36	31.90	22.52	DTE Energy	1.87	26.67	4.77
PPL	1.37	14.15	9.39	Entergy	2.15	22.57	4.04
Evergy	2.09	24.40	3.11	AEP	2.19	20.67	10.17
Ameren	2.12	26.96	6.59	Evergy	2.64	18.55	2.64
AES	2.73	11.70	8.75	Ameren	2.66	20.16	4.91
FirstEnergy	2.88	31.34	13.13	FirstEnergy	2.83	12.14	5.17
AEP	3.24	54.75	26.66	AES	3.01	4.45	2.94
NRG Energy	5.81	58.50	18.90	NRG Energy	8.30	25.12	7.94

A = the ratio of each firm's contribution to total industry GED, relative to the firm's contribution to total industry market cap.
B = GED (nominal dollars) per outstanding share.
C = GED (nominal billions of dollars).

Table 3: Firm Current Financial Performance and Pollution Damage Gammas.

Dependent Variable	(1) GHG + LAP[A]	(2) LAP	(2) GHG	(3) LAP	(4) GHG
Prices	-0.0148***[B]	-0.00677***	-0.00538*	-0.00864***	-0.00785**
	(0.00449)[C]	(0.00230)	(0.00296)	(0.00263)	(0.00295)
Returns	0.0505***	0.0266***	0.0198**	0.0335***	0.0295***
	(0.0173)	(0.00974)	(0.00833)	(0.0119)	(0.0103)
Forward P/E[D]	0.266*	0.0428	0.155**	0.0404	0.155**
	(0.138)	(0.0609)	(0.0737)	(0.0752)	(0.0721)
Volatility[E] (Prices)	-0.000215	-0.000383	0.000205	-0.000311	0.0000658
	(0.000344)	(0.000275)	(0.000256)	(0.000224)	(0.000242)
Volatility[F] (Returns)	0.0251**	0.0115**	0.0114**	0.0153**	0.0155**
	(0.00997)	(0.00500)	(0.00518)	(0.00670)	(0.00624)
Sharpe Ratios	-0.0801*	-0.0707***	0.00757	-0.0681***	-0.0183
	(0.0398)	(0.0227)	(0.0314)	(0.0166)	(0.0327)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table 3 is a fitted OLS parameter estimate from distinct regression model of the form in (5). The full results for each of the regression models supporting table 3 are reported in the online appendix.
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = weekly standard deviation in price.
F = weekly standard deviation in returns.
Column (1) combines LAP and GHG damages. Column (2) includes both LAP and GHG damages separately in the same regression model. Column (3) and (4) feature each in separate regression models. Prices and volatility are first-differenced, P/E ratios enter in natural log form. The other dependent variables enter in levels.
* p<0.10 ** p<0.05 *** p<0.01

Table 4: Firm Forward Financial Performance and Pollution Damage Gammas.

Dependent Variable	(1) GHG + LAP[A]	(2) LAP	(2) GHG	(3) LAP	(4) GHG
Prices	-0.0156[B]	-0.00518	-0.0130	-0.00938	-0.0146*
	(0.0119)[C]	(0.00613)	(0.00804)	(0.00769)	(0.00761)
Returns	0.0775*	0.0316	0.0443*	0.0459*	0.0543**
	(0.0391)	(0.0192)	(0.0234)	(0.0267)	(0.0246)
Forward P/E[D]	-0.205*	-0.0811	-0.130**	-0.0592	-0.119*
	(0.110)	(0.0515)	(0.0607)	(0.0616)	(0.0651)
Volatility[E]	0.000371	0.000552*	-0.000486	0.000443	-0.000187
(Prices)	(0.000709)	(0.000283)	(0.000605)	(0.000303)	(0.000587)
Volatility[F]	-0.0159	-0.0150**	0.000518	-0.0149**	-0.00418
(Returns)	(0.0121)	(0.00724)	(0.00717)	(0.00690)	(0.00928)
Sharpe	0.000563	-0.00336	0.00128	-0.00295	0.000215
Ratios	(0.0345)	(0.0157)	(0.0236)	(0.0141)	(0.0219)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table 4 is a fitted OLS parameter estimate from distinct regression model of the form in (5). The full results for each of the regression models supporting table 4 are reported in the online appendix.
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = weekly standard deviation in price.
F = weekly standard deviation in returns.
Column (1) combines LAP and GHG damages. Column (2) includes both LAP and GHG damages separately in the same regression model. Column (3) and (4) feature each in separate regression models. Prices and volatility are first-differenced, P/E ratios enter in natural log form. The other dependent variables enter in levels.
* p<0.10 ** p<0.05 *** p<0.01

Table 5: Decomposition of Earnings per Share Error.

Forward Earnings	(1) GHG & LAP[A]	(2) LAP	GHG	(3) LAP	(4) GHG
Actual[D]	0.309***[B]	0.161***	0.103**	0.178***	0.133*
	(0.0642)[C]	(0.0379)	(0.0476)	(0.0478)	(0.0658)
Estimate	0.151***	0.0922***	0.0608*	0.102***	0.0778**
	(0.0493)	(0.0248)	(0.0350)	(0.0275)	(0.0371)
Surprise[E]	14.58***	9.201***	2.823*	9.657***	4.517**
	(2.581)	(1.642)	(1.491)	(1.771)	(2.019)
Current Earnings	**(1) GHG & LAP**	**(2) LAP**	**GHG**	**(3) LAP**	**(4) GHG**
Actual	-0.0122	0.0226	-0.0383	0.0232	-0.0386
	(0.0634)	(0.0457)	(0.0339)	(0.0426)	(0.0336)
Estimate	-0.154**	-0.0300	-0.106**	-0.0283	-0.106**
	(0.0738)	(0.0428)	(0.0429)	(0.0460)	(0.0428)
Surprise	0.751	-1.164	2.151**	-1.198	2.167**
	(1.630)	(1.119)	(0.994)	(1.237)	(1.035)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table 5 is a fitted OLS parameter estimate from distinct regression model of the form in (6).
C = Robust standard errors in parenthesis.
D = Actual and estimated EPS reported in nominal USD.
E = (Actual EPS – EPS Estimate)/Actual EPS, expressed in % of Actual EPS.
Column (1) combines LAP and GHG damages. Column (2) includes both LAP and GHG damages separately in the same regression model. Column (3) and (4) feature each in separate regression model.
* p<0.10 ** p<0.05 *** p<0.01

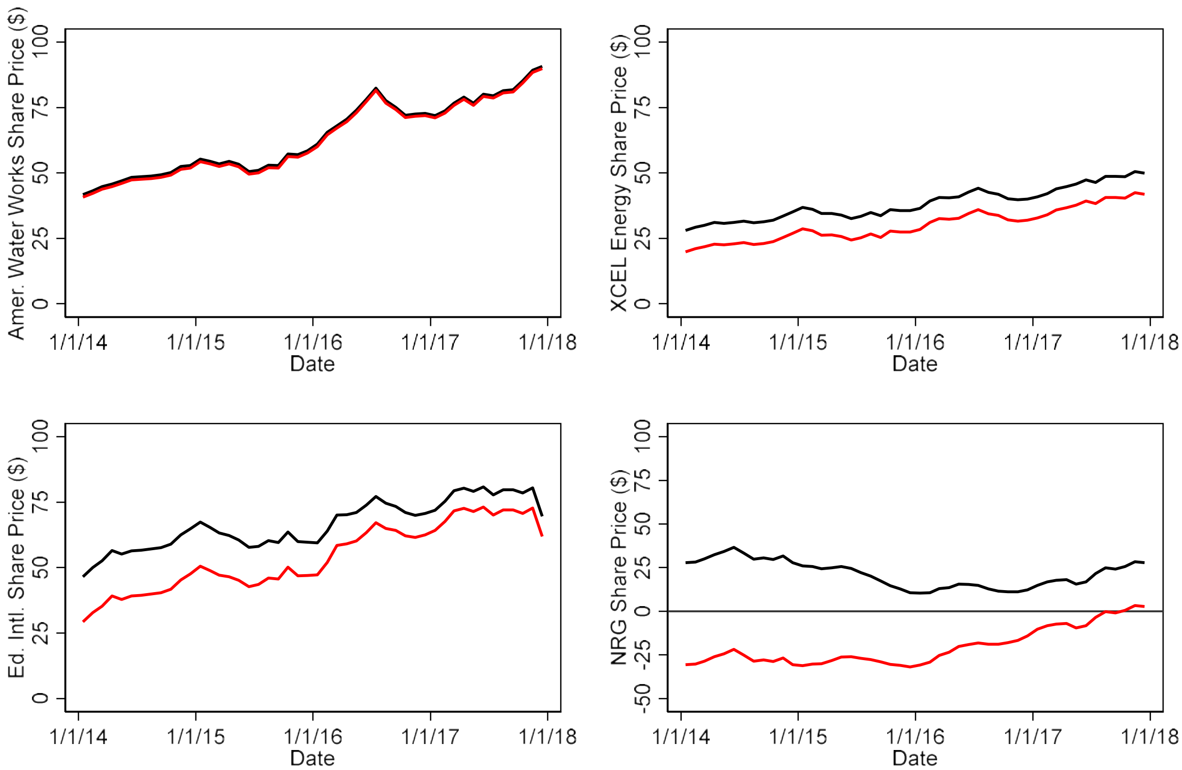
Table 6: Current Firm Financial Performance and Membership in the S&P 500.

	GHGs & LAP[A]		LAP		GHGs		LAP		GHGs	
	S&P	**Not S&P**	**S&P**	**Not S&P**	**S&P**	**Not S&P**	**S&P**	**Not S&P**	**S&P**	**Not S&P**
Prices	-0.02***[B]	-0.00557*	-0.0137**	-0.0043***	-0.00116	-0.014**	-0.015***	-0.00146	-0.009**	-0.0086*
	(0.00554)[C]	(0.00278)	(0.00517)	(0.00128)	(0.00390)	(0.00510)	(0.00439)	(0.00125)	(0.00357)	(0.00413)
Returns	0.078***	0.00702	0.049***	0.00431	0.00939	-0.0009	0.054***	0.00450	0.037***	-0.00605
	(0.0160)	(0.0104)	(0.0127)	(0.00744)	(0.0128)	(0.0258)	(0.00794)	(0.00507)	(0.0129)	(0.0195)
Forward[D] P/E	0.297	6.933***	0.0219	16.16***	0.178**	3.68***	-0.00641	-22.40***	0.176**	2.14***
	(0.203)	(0.317)	(0.0680)	(3.506)	(0.0836)	(0.311)	(0.0684)	(1.025)	(0.0790)	(0.0977)
Volatility[E] Prices	-0.000318	0.000608	-0.0006**	0.000574**	0.000458*	0.00294*	-0.000304	-0.00004	0.000126	0.00226
	(0.000484)	(0.000520)	(0.000245)	(0.000226)	(0.000265)	(0.00143)	(0.000244)	(0.000327)	(0.000295)	(0.00139)
Volatility[F] Returns	0.041***	0.00308	0.0126**	-0.00146	0.017***	-0.0195	0.023***	0.00259	0.024***	-0.0177
	(0.00663)	(0.0134)	(0.00595)	(0.00767)	(0.00502)	(0.0206)	(0.00559)	(0.00628)	(0.00385)	(0.0150)
Sharpe Ratios	-0.116***	0.0173	-0.0279	0.0302	-0.0483*	0.133	-0.0577**	0.00241	-0.064***	0.0973
	(0.0343)	(0.0789)	(0.0302)	(0.0447)	(0.0276)	(0.178)	(0.0231)	(0.0440)	(0.0173)	(0.150)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table 6 is a fitted OLS parameter estimate from distinct regression model of the form in (5).
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = weekly standard deviation in price.
F = weekly standard deviation in returns.
Column (1) combines LAP and GHG damages. Column (2) includes both LAP and GHG damages separately in the same regression model. Column (3) and (4) feature each in separate regression models.
Prices and volatility are first-differenced, P/E ratios enter in natural log form. The other dependent variables enter in levels.
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Figures.

Figure 1: Comparison of Firms' Share Prices and Pollution-Adjusted Share Prices.



Black line: Monthly average share price reported by Refinitiv®.
Red line: Monthly average share price – GED per outstanding share.
All values in nominal USD.

Appendix:

Table A.1: Unit Root Tests.

Year	2014		2015		2017		2018	
Time Series Variable	**Raw Data**	**First Differences**	**Raw Data**	**First Differences**	**Raw Data**	**First Differences**	**Raw Data**	**First Differences**
Prices	2[A]	43	0	43	1	43	5	43
Returns	43	43	43	43	43	43	43	43
Volatility Prices	0	43	0	43	0	43	0	43
Volatility Returns	1	43	1	43	1	43	0	43
Sharpe Ratios	43	43	43	43	43	43	43	43

A = Number of firms for which the null hypothesis of a unit root is rejected at 0.01 level of significance using the Augmented Dickey-Fuller test with MacKinnon p-values. There are 43 firms in the sample.

Table A.2: Fixed Effects Specifications, Current Period Prices, and Firm Environmental Performance.

	(1)	(2)	(3)	(4)	(5)	(6)
GHGs & LAP[A]	-0.00431[B]	-0.0134***	-0.0149***	-0.0149***	-0.0148***	-0.0148***
	(0.00315)[C]	(0.00410)	(0.00450)	(0.00456)	(0.00449)	(0.00449)
Constant	0.0205**	0.0351*	0.0747***	0.166	-0.0512	-0.0915
	(0.0102)	(0.0175)	(0.0214)	(0.255)	(0.250)	(0.248)
adj. R^2	0.644	0.644	0.644	0.646	0.656	0.657
N	18785	18785	18785	18785	18785	18785
Firm FE	N	Y	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y	Y
Month of Year FE	N	N	N	Y	Y	Y
Day of Month FE	N	N	N	N	Y	Y
Day of Week FE	N	N	N	N	N	Y

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)

B = each entry in table A.2 is a fitted OLS parameter estimate from distinct regression model of the form in (5).

C = Robust standard errors in parenthesis.

Table A.3: Earnings Surprise and Firms' Herfindahl Indices.

	(1)	(2)	(3)
GHGs	9.255***[A]		6.688***
	(2.336)[B]		(1.844)
ln(Herfindahl CO_2)	6.772***		5.286***
	(2.187)		(1.861)
LAP		9.674***	8.830***
		(1.769)	(1.380)
ln(Herfindahl LAP)		0.250	-0.238
		(2.409)	(3.512)
Constant	37.85**	19.53	22.07**
	(18.47)	(13.93)	(10.32)
Adj. R^2	0.936	0.963	0.977
N	212	213	205

A = each entry is a fitted OLS parameter estimate from a regression of the form in (6) with EPS Surprise as the dependent variable.
B = Robust standard errors in parenthesis.
* p<0.10 ** p<0.05 *** p<0.01

Table A.4: Dispersion of Analysts' EPS Estimates.

Forward Earnings	(1) GHG & LAP[A]	(2) LAP	GHG	(3) LAP	(4) GHG
Coefficient[D] of Variation	-0.00881**[B]	-0.00743***	-0.00121	-0.00766***	-0.00269
	(0.00417)[C]	(0.00246)	(0.00290)	(0.00229)	(0.00303)
Standard[E] Deviation	0.0144*	0.00984**	0.00143	0.0101**	0.00340
	(0.00744)	(0.00415)	(0.00671)	(0.00392)	(0.00652)
Current Earnings	**(1) GHG & LAP**	**(2) LAP**	**GHG**	**(3) LAP**	**(4) GHG**
Coefficient of Variation	0.0157	-0.00243	0.0140	-0.00187	0.0140*
	(0.0156)	(0.0109)	(0.00838)	(0.0130)	(0.00824)
Standard Deviation	0.0221*	0.00478	0.0157*	0.00541	0.0158*
	(0.0126)	(0.00732)	(0.00789)	(0.00990)	(0.00805)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table A.4 is a fitted OLS parameter estimate from distinct regression model of the form in (6). The coefficients for the Coefficient of Variation are expressed as a fraction of EPS, those for Standard Deviation are in nominal USD.
C = Robust standard errors in parenthesis.
D = standard deviation of analysts' EPS estimate/mean EPS estimate
E = standard deviation of analysts' EPS estimate
Column (1) combines LAP and GHG damages. Column (2) includes both LAP and GHG damages separately in the same regression model. Column (3) and (4) feature each in separate regression model.
* p<0.10 ** p<0.05 *** p<0.01

Table A.5: Dispersion of Analysts' EPS Estimates and Firms' Herfindahl Indices.

	CV EPS Estimate (1)	SD EPS Estimate (2)	CV EPS Estimate (3)	SD EPS Estimate (4)	CV EPS Estimate (5)	SD EPS Estimate (6)
GHGs	-0.00998**	-0.0000989			-0.00736	-0.00363
	(0.00427)	(0.00978)			(0.00455)	(0.0107)
ln(Herfindahl CO_2)	-0.0271***	-0.0136			-0.0251**	-0.0164
	(0.00942)	(0.0282)			(0.0105)	(0.0261)
LAP			-0.00786***	0.0105***	-0.00739***	0.0109**
			(0.00270)	(0.00387)	(0.00189)	(0.00459)
ln(Herfindahl LAP)			-0.00579	0.0202	-0.0173	0.0200
			(0.0122)	(0.0266)	(0.0132)	(0.0600)
Constant	-0.0360	-0.0436	-0.0189	-0.0599	-0.0226	-0.0550
	(0.0309)	(0.0879)	(0.0291)	(0.0570)	(0.0304)	(0.0857)
adj. R-sq	0.775	0.373	0.771	0.397	0.785	0.379
N	253	253	251	251	243	243

A = each entry is a fitted OLS parameter estimate from a regression of the form in (6) with EPS Surprise as the dependent variable.
B = Robust standard errors in parenthesis.
* p<0.10 ** p<0.05 *** p<0.01

Table A.6: NAAQS Non-Attainment and Firm Financial Performance

	Current Prices		Current Returns		Current P/E	
GHG & LAP[A]	-0.0148***[B]	-0.00952*	0.0505***	0.0285*	0.266*	0.243
	(0.00449)[C]	(0.00512)	(0.0173)	(0.0143)	(0.138)	(0.151)
NA Count[D]		0.000580		0.00120		-0.00671
		(0.000773)		(0.00178)		(0.00773)
(GHG & LAP) x NA		0.000386		-0.0034***		0.00520
		(0.000436)		(0.000893)		(0.00762)
	Forward Prices		**Forward Returns**		**Forward P/E**	
GHG & LAP	-0.0156	-0.000434	0.0775*	0.0275	-0.205*	-0.317**
		(0.00993)	(0.0391)	(0.0280)	(0.110)	(0.118)
NA Count		-0.000465		-0.00102		-0.0242***
		(0.000896)		(0.00257)		(0.00823)
(GHG & LAP) x NA		0.00212***		-0.0057***		0.0230***
		(0.000507)		(0.00136)		(0.00802)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table A.6 is a fitted OLS parameter estimate from distinct regression model of the form in (5).
C = Robust standard errors in parenthesis.
D = Number of plants in counties that are out of attainment with any National Ambient Air Quality Standard established by the Clean Air Act.

Table A.7: Comparison Between Refinitiv® Performance Measures and Firm Gamma Scores.

Current	LAP & GHG	Refinitiv Env. Score[A]	LAP	Refinitiv NO_X Total[B]	Refinitiv SO_2 Total[C]	GHG	Refinitiv CO_2 Score[D]
Prices	-0.0148***[E]	-0.000231	-0.00864***	-0.00000107***	8.71e-08	-0.00785**	-0.469
	(0.00449)[F]	(0.000289)	(0.00263)	(0.000000348)	(8.09e-08)	(0.00295)	(0.673)
Returns	0.0505***	0.000334	0.0335***	0.00000255*	-0.000000336	0.0295***	2.432*
	(0.0173)	(0.000699)	(0.0119)	(0.00000129)	(0.000000222)	(0.0103)	(1.135)
EPS	0.751	-0.0636	-1.198	0.0000202	-0.0000155	2.167**	-0.117***
Surprise	(1.630)	(0.0677)	(1.237)	(0.0000382)	(0.00000965)	(1.035)	(0.00140)

Forward	LAP & GHG	Refinitiv Env. Score	LAP	Refinitiv NO_X Total	Refinitiv SO_2 Total	GHG	Refinitiv CO_2 Score
Prices	-0.0156	-0.000356	-0.00938	-0.000000831	0.000000269	-0.0146*	-2.101**
	(0.0119)	(0.000547)	(0.00769)	(0.000000798)	(0.000000270)	(0.00761)	(0.675)
Returns	0.0775*	0.000272	0.0459*	0.00000335	-0.000000943	0.0543**	2.403
	(0.0391)	(0.00169)	(0.0267)	(0.00000263)	(0.000000713)	(0.0246)	(1.403)
EPS	14.58***	0.224*	9.657***	0.000194	0.0000324*	4.517**	0.804
Surprise	(2.581)	(0.129)	(1.771)	(0.000178)	(0.0000157)	(2.019)	(.)

A = Refinitiv environmental performance score.
B = Refinitiv NO_x emissions by firm, reported.
C = Refinitiv SO_2 emissions by firm, reported.
D = Refinitiv CO_2 emissions by firm, reported.
E = each entry in table A.7 is a fitted OLS parameter estimate from distinct regression model of the form in (5).
F = Robust standard errors in parenthesis.

Table A.8: Current Period Firm Financial Performance and Emission Tonnage Gammas.

Dependent Variable	(1) GHG + LAP[A]	(2) LAP	GHG	(3) LAP	(4) GHG
Prices	-0.00786**[B]	-0.00473	-0.00733**	-0.00661	-0.00784**
	(0.00296)[C]	(0.00535)	(0.00289)	(0.00551)	(0.00295)
Returns	0.0296***	0.0115	0.0283***	0.0188	0.0295***
	(0.0103)	(0.00999)	(0.0100)	(0.0129)	(0.00999)
Trailing P/E[D]	0.153**	0.0424	0.150**	0.0573	0.153**
	(0.0721)	(0.0651)	(0.0701)	(0.0831)	(0.0719)
Volatility[E] (Prices)	0.0000657	-0.000765*	0.000149	-0.000727*	0.0000658
	(0.000242)	(0.000406)	(0.000244)	(0.000362)	(0.000242)
Volatility[F] (Returns)	0.0155**	-0.00534	0.0161**	-0.00120	0.0155**
	(0.00624)	(0.00488)	(0.00626)	(0.00544)	(0.00622)
Sharpe Ratios	-0.0183	0.000634	-0.0183	-0.00407	-0.0183
	(0.0326)	(0.0400)	(0.0332)	(0.0381)	(0.0325)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table A.8 is a fitted OLS parameter estimate from distinct regression model of the form in (5).
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = weekly standard deviation in price.
F = weekly standard deviation in returns.
Column (1) combines LAP and GHG damages. Column (2) includes both LAP and GHG damages separately in the same regression model. Column (3) and (4) feature each in separate regression models. Prices and volatility are first-differenced, P/E ratios enter in natural log form. The other dependent variables enter in levels.
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table A.9: Current Period Firm Financial Performance and Emission Tonnage.

Dependent Variable	(1) GHG + LAP[A]	(2) LAP	GHG	(3) LAP	(4) GHG
Prices	-1.57e-10[B]	0.000000116	-1.54e-10	0.000000118	-1.57e-10
	(1.55e-10)[C]	(7.86e-08)	(1.58e-10)	(8.63e-08)	(1.55e-10)
Returns	5.13e-10	-0.000000390**	5.04e-10	-0.000000396*	5.14e-10
	(4.57e-10)	(0.000000189)	(4.37e-10)	(0.000000218)	(0.000000189)
Trailing P/E[D]	3.64e-09	-0.000000518	3.77e-09	-0.000000262	3.65e-09
	(2.45e-09)	(0.00000131)	(2.38e-09)	(0.00000121)	(2.45e-09)
Volatility[E]	7.16e-12	6.96e-09	7.33e-12	6.89e-09	7.15e-12
(Prices)	(1.24e-11)	(8.47e-09)	(1.18e-11)	(8.45e-09)	(1.24e-11)
Volatility[F]	4.14e-10*	-0.000000140	4.11e-10*	-0.000000143	4.14e-10*
(Returns)	(2.39e-10)	(0.000000103)	(2.30e-10)	(0.000000106)	(2.39e-10)
Sharpe	6.01e-11	0.00000105*	8.56e-11	0.00000105*	5.74e-11
Ratios	(1.34e-09)	(0.000000528)	(1.23e-09)	(0.000000527)	(1.34e-09)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table A.9 is a fitted OLS parameter estimate from distinct regression model of the form in (5).
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = weekly standard deviation in price.
F = weekly standard deviation in returns.
Column (1) combines LAP and GHG damages. Column (2) includes both LAP and GHG damages separately in the same regression model. Column (3) and (4) feature each in separate regression models. Prices and volatility are first-differenced, P/E ratios enter in natural log form. The other dependent variables enter in levels.
* p<0.10 ** p<0.05 *** p<0.01