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MEASURING FIRM ENVIRONMENTAL PERFORMANCE TO INFORM ASSET MANAGEMENT AND STANDARDIZED DISCLOSURE

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ABSTRACT

Investing according to environmental, social, and governance (ESG) criteria is gaining momentum. Most environmental performance indices focus only on the tonnage of carbon dioxide (CO_2) emissions. This paper proposes an index covering eight pollutants expressed in monetary damage. Inclusion of multiple pollutants reflects a broader range of reputational and regulatory risks. Monetization appropriately weights emissions. CO_2 dominates the mass of other pollutants, yet the marginal damages from other pollutants are larger than CO_2. 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. Dirtier firms exhibit lower share prices and higher forward returns. The effect is twice as large for the multipollutant index compared to CO_2. Analysts' earnings forecasts for dirtier firms systematically undershoot actuals. Earnings errors are between three and five times more sensitive to the multipollutant index than to CO_2. The multipollutant index may suggest new management strategies to financial market participants relative to those based on carbon intensity. ESG disclosure standards based on the new index are more likely to affect financial outcomes, capital allocation decisions, and firm behavior than disclosure of carbon intensity.

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I. Introduction.

This paper develops a monetary index of firm environmental performance. The analysis then tests whether this index can predict several key financial outcomes among publicly traded firms in the United States (U.S.) utility sector. Investors and asset managers may find this new approach useful in guiding their capital allocation decisions. Financial and securities regulators might benefit from using this index to standardize environmental, social, and governance (ESG) [1] disclosure requirements, which is a recently stated goal of the Securities and Exchange Commission[2].

Investing according to ESG criteria has gained considerable momentum in recent years (*New York Times,* 2020; Blackrock, 2020; 2021). Enormous stocks of capital are now managed according to ESG criteria (GSIA, 2018). In response to this demand for ESG investments, numerous products (indices, mutual funds) track aspects of the "E", "S", and "G" of ESG criteria. This paper argues that most prior metrics focusing on the "E" of ESG have mismeasured firm performance. The crux of the misconception of environmental performance stems from a focus on physical emissions rather than the monetary damage of emissions (MSCI, 2019; NUVEEN, 2020; Sustainalytics, 2021). That is, rather than calculate the impacts from discharges of pollution, many existing indices of environmental performance simply tabulate tonnage of pollution discharges. If the goal of ESG indices is to align the behavior of financial market participants with more socially beneficial environmental outcomes, relying on monetary damage is essential.

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[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 .

[2] In 2020, the Securities and Exchange Commission (SEC) argued for a move toward standardized Environmental Social and Governance (ESG) disclosures. "It's time for the SEC to lead a discussion—to bring all interested parties to the table and begin to work through how to get investors the standardized, consistent, reliable, and comparable ESG disclosures they need to protect their investments and allocate capital toward a sustainable economy." https://www.sec.gov/news/public-statement/lee-regulation-s-k-2020-08-26

A related shortcoming is that many major products track only firms' carbon intensity (MSCI, 2019; NUVEEN, 2021). This narrow perspective, in part, stems from the reliance on measuring the mass of emissions. At the margin, damages from different pollution types vary. 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). Clearly, adding up tons of different pollution species overlooks vast differences in "value". Therefore, aggregating tonnage of multiple pollutants into a single ESG index is meaningless. A serious attempt to more comprehensively assess firm environmental performance by including several pollution species simply must have a common unit of account through which various emissions can be weighed. The argument here is akin to assessing the value of a firm that produces a range of goods, or sells its goods in a variety of markets. An accurate estimate of value depends on its cash flows, which reflect the realized market price of each good or service. Applying this approach to measuring environmental performance suggests that each emission should be weighted according to the monetary damage caused. Monetization facilitates aggregation of the impacts from pollution emissions across pollutants, source locations, and across time.

This approach to tabulating damage finds its conceptual basis in the environmental accounting literature (Abraham and Mackie, 2006; Nordhaus, 2006; Muller, Mendelsohn, and Nordhaus, 2011; Muller, 2014). Total damages, computed as the product of marginal damages and emissions, are deducted from macroeconomic aggregates such as Gross Domestic Product (GDP) and Value Added (VA) to align the National Income and Product Accounts (NIPAs) with a measure of economic welfare (Nordhaus and Tobin, 1973). Subtraction of monetary damage from the NIPAs also informs assessments of economy-wide sustainability (Hartwick, 1977). Positive growth rates, accounting for environmental pollution damage and consumption of natural resources, are required for sustainable development. This argument has a direct analog to firm performance.

Building on this macroeconomic foundation, the present paper argues that monetization of pollution damage enables a reconceptualization of firm value that informs assessments of sustainability. Metrics such as book value, operating free cash flow, or market capitalization capture conventional notions of value that hinge on the goods and services firms produce and the assets they own. Investors and other participants in financial markets rely on these (and other) metrics to form expectations over firm performance. Such expectations are, of course, a central determinant of asset prices. 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. Monetization of damages from firms' emissions, and the deduction of such damages from conventional measures of value, provides investors with a more socially comprehensive assessment of firms' worth. This facilitates the alignment of investors' evaluation of firms' performance (and expectations regarding future performance) with a broader measure of firm-level sustainability. And, direct inclusion of pollution damages into a measure of firm value cannot occur without monetization.

Empirically, this paper uses rigorous quantitative 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 excellent information on plant ownership and pollution emissions. Damages are estimated for the years 2014 and 2017 because these years correspond to the most recent nationally comprehensive 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, P/E ratios, earnings per share (EPS), returns, volatility, systemic risk, and idiosyncratic risk.

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 the relative magnitude 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 1/10th 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. Specifically, firms that exhibited especially large increases in pollution intensity between 2014 and 2017 incurred price reductions of about 11 percent. In addition, forward returns were higher for firms that grew more pollution intensive. 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 forward returns are two times more responsive to changes in the multipollutant (Γ) than to changes in carbon intensity. EPS surprises are between three and five times more sensitive to changes in (Γ) than to changes in carbon intensity. These results suggest that the multipollutant (Γ) 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 concentrations. 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). Also, concomitantly accounting for illnesses may result in double counting of damages. GHG damages are computed using recent peer-reviewed estimates of the Social Cost of Carbon (SCC), 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 fine particulate matter ($PM_{2.5}$). 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 tall 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 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 $M_{a,i,y}$.

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

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:

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

In prior applications, AP3 was used to estimate the marginal damage of emissions of SO_2, NO_x, NH_3, VOC, and primary $PM_{2.5}$, by source (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 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).

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

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

Computing the GED in this way finds its conceptual roots in the national income and product accounts (NIPA) and the environmental accounting literature (Abraham and Mackie, 2006; Nordhaus, 2006). That is, 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.

b. Financial Modeling.

While the estimation of pollution damage relies on facility level emissions information, financial modeling hinges on firm level information. As such, linking facilities to firms is an essential step in the present study. Two critical variables in the emissions data 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. 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. In addition to simply reporting the ratio of GED to market cap, by firm, in a given year, 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 $Cap_{f,t}$ 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. Broadly, financial performance measures include prices, price-to-earnings ratios (P/E), returns, and three measures of risk[3]. Because of the infrequent emissions reporting data, high frequency analyses are not possible. Thus, daily prices and returns are averaged to the firm-month level. Refinitiv® reports EPS quarterly as are the 12-month forward P/E ratios (IBES, 2021). As shown in (5) below, auto-regressive distributed lag (ADL) models are employed.

Expression (5) displays the specification used with prices ($P_{f,y,m}$) as the outcome variable, where (m) denotes month-of-year.

$$(P)_{f,y,m} = \theta_1 + \theta_2 \Gamma_{f,y}^{T} + \sum_{l=1}^{12} \theta_{3,l} P_{f,l} + \sum_{l=0}^{12} \theta_{4,l} \mathrm{X}_{f,l} + \mu_f + \tau_y + \omega_m + \varepsilon_{f,y,m} \qquad (5)$$

Included in the specification are month, year, and firm fixed effects $(\omega_m, \tau_y, \mu_f)$, the index X, which includes net generation[4], dividends, market capitalization, sentiment (Baker and Wurgler, 2006), returns, and volatility, measured as the monthly standard deviation in returns. The models include up to 12-month lagged values of the dependent variable, returns, and volatility. Due to the relative infrequency with which dividends and market capitalization are reported, these covariates enter (5) annually. (5) is also fitted with returns ($R_{f,t}$) and volatility ($P_{f,t}$) as the outcome variable. The covariate of interest, $\Gamma_{f,y}^{T}$, is calculated on an annual basis, by firm. Expression (5) is fit distinctly for each measure of

[3] The financial data is provided by Refinitiv® including the IBES earnings data.
[4] Net generation is included as an annual total of the amount of electricity each firm produced in year (y).

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.

For P/E ratios, the specification departs from that in (5) because of the infrequency with which EPS are reported.

$$\left(\frac{P}{E}\right)_{f,y,m} = \theta_1 + \theta_2\Gamma^{T}_{f,y} + \sum_{l=0}^{12}\theta_{3,l}\mathrm{X}_{f,l} + \mu_f + \tau_y + \omega_m + \varepsilon_{f,y,m} \qquad (6)$$

In (6), prices, returns, sentiment, and volatility enter as in (5), concurrently and with up to 12-month lagged values. Net generation, dividends, and market capitalization enter annually.

The analysis of EPS and environmental performance includes actual EPS, estimated EPS, and the EPS surprises, the latter of which is shown as the dependent variable in (7). (Distinct models are fit with actual and estimated EPS as the dependent variables.)

$$EPS^{surprise}_{f,y,m} = \theta_1 + \theta_2\Gamma^{T}_{f,y} + \theta_3\mathrm{EPS}^{actual}_{f,y-1,m} + \theta_4\mathrm{EPS}^{estimate}_{f,y-1,m} + \theta_4\mathrm{EPS}^{surprise}_{f,y-1,m} + \sum_{l=0}^{12}\theta_{5,l}\mathrm{X}_{f,l} + \mu_f + \tau_y + \omega_m + \varepsilon_{f,y,m} \qquad (7)$$

Included in (7) are one-year lagged values of actual EPS, forecast EPS, and the EPS surprise. In (7), prices, returns, sentiment, and volatility enter as in (5) and (6), as do net generation, dividends, and market capitalization.

The analysis next explores the association between environmental performance and risk. Three dimensions, or representations, of risk are considered: the monthly standard deviation in returns, the beta from the Capital Asset Pricing Model (CAPM), and the standard deviation of the residual from the CAPM regression, as a proxy for idiosyncratic risk.

To begin, the monthly standard deviation in returns ($\sigma_{f,y,m}$) is regressed on firms' environmental performance.

$$\sigma_{f,y,m} = \theta_5 + \theta_6\Gamma_{f,t}^{T} + \sum_{l=1}^{12}\theta_{7,l}\sigma_{f,l} + \sum_{l=0}^{12}\theta_{8,l}\mathrm{X}_{f,l} + \mu_f + \tau_y + \omega_m + \varepsilon_{f,y,m} \quad (8)$$

As above, a separate specification of (8) is fit to each measure of environmental performance ($\Gamma_{f,y}^{T}$, $\Gamma_{f,y}^{G}$, $\Gamma_{f,y}^{A}$) and a fourth that includes $\Gamma_{f,y}^{G}$ and $\Gamma_{f,y}^{A}$ together. The components in ($X_{f,l}$) are as above, and the model includes firm, year, and month fixed effects.

For each publicly traded firm matched to plants in the emissions data, the CAPM regression equation is fit in order to estimate firm specific beta and alpha values, as shown in (9).

$$R_{f,y,m,d} - \bar{R}_{y,m,d} = \alpha_{f,y} + \beta_{f,y}\left(R_{y,m,d}^{SP} - \bar{R}_{y,m,d}\right) + \varepsilon_{f,y,m,d} \quad (9)$$

Empirically, this procedure relies on daily returns for each utility firm ($R_{f,y,m,d}$), as well as the daily returns on the Standard and Poor's 500, denoted $\left(R_{y,m,d}^{SP}\right)$, in (9), as well as U.S. 10 year treasury yields to proxy for the risk free rate $\left(\bar{R}_{y,m,d}\right)$.

The fitted annual values of $\beta_{f,t}$ are then regressed on measures of firms' environmental performance as shown in (10), including one-year lagged estimates of $\hat{\beta}_{f,y}$.

$$\hat{\beta}_{f,y} = \theta_9 + \theta_{10}\Gamma_{f,y}^{T} + \theta_{11}\mathrm{X}_{f,y} + \mu_f + \tau_y + \varepsilon_{f,y} \quad (10)$$

In (10), ($X_{f,y}$) includes net generation, dividends, and market capitalization, and the firm and year fixed effects are specified as above. In total, four specifications are fit, with $\Gamma_{f,y}^{T}$, $\Gamma_{f,y}^{A}$, $\Gamma_{f,y}^{G}$, and $\Gamma_{f,y}^{A}$ and $\Gamma_{f,y}^{G}$ together.

While $\hat{\beta}_{f,t}$ measures systematic risk exposure, the monthly standard deviation of the residual from the CAPM regression (10), denoted ($\sigma_{f,y,m}^{\varepsilon}$) captures firm-specific, or idiosyncratic risk. This metric is then regressed on the $\Gamma_{f,y}$ statistics in the same manner as total risk, inclusive of net generation, and month, year, and firm fixed effects.

$$\sigma^{\varepsilon}_{f,y,m} = \theta_{13} + \theta_{14}\Gamma^{T}_{f,y} + \sum_{l=1}^{12} \theta_{15,l}\sigma^{\varepsilon}_{f,l} + \sum_{l=0}^{12} \theta_{16,l}\mathrm{X}_{f,l} + \mu_f + \tau_y + \omega_m + \varepsilon_{f,y,m} \quad (11)$$

This model also assumes an ADL specification with up to 12-month lagged values of prices, returns, volatility, sentiment, and the dependent variable along with current measures of net generation, dividends, and market capitalization.

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 the appendix. The fitted $\hat{\beta}_{f,t}$ estimates from the CAPM regressions are also presented in the appendix.

In models (5) through (11), 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. An example is shown in (12) with prices as the dependent variable.

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

For the models that feature prices as the dependent variable, (12) is extended to include observations of the dependent variables up to two years forward from the year in which the $\Gamma_{f,y}$ statistics are estimated. To obtain a more granular perspective on how environmental performance affects forward prices, these models include interaction terms between the $\Gamma_{f,y}$ statistics and month-forward fixed effects (γ_a) as shown in (13). In this setting, there are 24 forward months of EPS forecast errors, returns, and volatility outcomes and 24 interaction terms.

$$P_{f,y,m,a} = \theta_1 + \theta_2\Gamma^{T}_{f,y} + \sum_{l=1}^{12} \theta_{3,l}P_{f,l} + \sum_{l=0}^{12} \theta_{4,l}\mathrm{X}_{f,l} + \sum_{a=1}^{24} \theta_{5,a}(\Gamma^{T}_{f,y} \times \gamma_a) + \mu_f + \tau_y + \omega_m + \varepsilon_{f,y,m} \quad (13)$$

In (13), the subscript (a) denotes month forward relative to $\Gamma_{f,y}^{T}$. The components of ($\mathrm{X}_{f,l}$) are the same as in (5), and the model includes year, month-of-year, and firm fixed effects.

One goal of this paper is to compare different measures of firms' environmental 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 additional measures of environmental performance: 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 (14).

$$\Gamma_{f,y} = \frac{\frac{GHG_{f,y}}{\sum_{f=1}^{N} GHG_{f,y}}}{\frac{Cap_{f,y}}{\sum_{f=1}^{N} Cap_{f,y}}} \tag{14}$$

These alternative metrics are substituted in for the damage $\Gamma_{f,y}$ statistics in (5) through (13) 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. Indices which only track GHGs in the utility sector will seriously mischaracterize environmental performance. The decline in LAP damages dominates that from GHGs. Subsequent sections of this analysis will demonstrate that this has important implications for the relationship between financial outcomes and these measures of environmental performance.

Firms face several ways 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. Deducting total GED increases apparent growth up to 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 ($\Gamma^T_{f,y}$) 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 ($\Gamma^T_{f,y}$) scores, from 0.06 to 5.81 in 2014. Second, there is considerable re-ordering of the firms' ($\Gamma^T_{f,y}$) 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 ($\Gamma^T_{f,y}$) scores ranged between 0.06 and 5.81. Recall that a ($\Gamma^T_{f,y}$) 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[5]. 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 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

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

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[6], 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 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

[6] 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).

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 reports the empirical results from the ADL regression models of the form shown in (5) through (12). Table 3 examines current period outcomes, table 4 focuses on year ahead outcomes. 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 ($\Gamma^T_{f,y}$), whereas columns (3) and (4) include ($\Gamma^A_{f,y}$) and ($\Gamma^G_{f,y}$), respectively. Column (2) includes ($\Gamma^A_{f,y}$) and ($\Gamma^G_{f,y}$) 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 appendix.

i. Prices.

Table 3 provides clear evidence that current period share prices fall as firms became more pollution intensive. A one unit increase in ($\Gamma^T_{f,y}$) corresponds to a 9 percent decrease in prices ($p < 0.01$). These models include firm fixed effects. 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. There are about 40 firms in the sample. The four firms that exhibited the largest increase in ($\Gamma^T_{f,y}$) from 2014 to 2017 incurred an increase of about 1.3. (These four firms represent those above the 90th percentile in changes to the ($\Gamma^T_{f,y}$) score from 2014 to 2017.) So these firms incurred an 11 percent reduction (1.3 x -0.086) in prices due to their increased ($\Gamma^T_{f,y}$) score. Conversely, the four firms that saw the largest improvement in ($\Gamma^T_{f,y}$), those below the 10th percentile in ($\Gamma^T_{f,y}$) score changes, exhibit a reduction of 0.77, which implies a price increase of 7 percent.

In a theme evident across multiple financial outcomes, the price change relative to pollution intensity is significantly larger when damages from air pollution and GHGs are combined in the ($\Gamma^T_{f,y}$) measure. When air pollution intensity and GHG intensity are measured separately but included together in the regression model, both measures are negatively, significantly associated with share prices. However, column (2) shows that the price effects of ($\Gamma^A_{f,y}$) and ($\Gamma^G_{f,t}$) are about one-half the magnitude of ($\Gamma^T_{f,y}$). In column (3), when ($\Gamma^A_{f,y}$) is included without GHGs, the marginal effect of ($\Gamma^A_{f,y}$) is about 6 percent, ($p < 0.01$). And, in column (4), with only GHG intensity, the marginal effect of ($\Gamma^G_{f,y}$) is also negative (5 percent) and significant ($p < 0.05$). Hence, columns (3) and (4) suggest pollution intensity measures that focus on either just air pollution or just GHGs will underestimate the price response by about 40 percent, relative to ($\Gamma^T_{f,y}$). Indices that only track carbon intensity suggest a significantly smaller price response to changes in environmental performance than ($\Gamma^T_{f,y}$). 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 persists one year forward of when the the firms' ($\Gamma_{f,y}$) scores are calculated. The marginal effect of firms' ($\Gamma_{f,y}$) scores is smaller, about three-fourths the magnitude of the effect on current period prices, and is only significant for ($\Gamma^A_{f,y}$) and ($\Gamma^T_{f,y}$). And, as in table 3, the largest effect on forward prices is observed for the combined, multi-pollutant measure ($\Gamma^T_{f,y}$).

The regression models in tables 3 and 4 force any association between the ($\Gamma_{f,y}$) scores and prices to manifest through a single coefficient. The model in (13) relaxes this restriction by interacting the ($\Gamma_{f,y}$)

scores with the number of months between observed future prices and the ($\Gamma_{f,y}$) scores. Figure 2 reports the coefficients for these interaction terms, by month forward, up to two years after the data used to compute firms' ($\Gamma^T_{f,y}$) scores are available. The lower horizontal line is equal to the coefficient from column (1) of table 4: -0.063 ($p < 0.05$). Initially, prices respond negatively to ($\Gamma^T_{f,y}$). This negative reaction in the first month following ($\Gamma^T_{f,y}$) is indistinguishable from -0.063. However, by two months after the data for the ($\Gamma^T_{f,y}$) scores are reported, the coefficients are statistically zero. By eight months forward, the coefficients are positive and significantly different from zero. These subsequent positive coefficients suggest that market participants respond to new information about pollution intensive firms as the year following ($\Gamma^T_{f,y}$) progresses. Section ii below provides evidence that EPS announcements may induce this price response. The right-hand panel extends the analysis a full two years after the data for the ($\Gamma^T_{f,y}$) scores are reported. Prices rise within the first year, but then cease to respond to the ($\Gamma^T_{f,y}$) scores during the second year.

ii. Earnings and P/E Ratios.

Table 3 shows that, despite the significant decline in prices associated with each measure of environmental performance, the forward P/E ratios do not systematically vary with the ($\Gamma_{f,y}$) scores[7]. This 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, reflecting expectations over the following 12 months, are negatively associated with the ($\Gamma_{f,y}$) scores. A one unit increase in ($\Gamma^T_{f,y}$) is associated with a \$0.21 decrease in estimated EPS ($p < 0.01$). The average estimated EPS is \$2.69. So the coefficient implies an eight percent reaction to a one unit change in ($\Gamma^T_{f,y}$). Thus, EPS estimates decline in

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

proportion to prices. This explains why the current period P/E ratios do not systematically respond to ($\Gamma^{T}_{f,y}$). Both of the ($\Gamma^{G}_{f,y}$) scores are significantly, negatively associated with the EPS estimates ($p < 0.01$). 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. The bottom panel of table 5 also indicates that actual EPS decline with the ($\Gamma^{G}_{f,y}$) scores and that EPS surprises are therefore not associated with the ($\Gamma_{f,y}$).

Table 4 shows that future EPS surprises are sensitive to environmental performance[8]. A one unit increase in ($\Gamma^{T}_{f,y}$) is associated with a 14% increase in the EPS surprise ($p < 0.01$). Table 4 further reports that each of the ($\Gamma_{f,y}$) measures is positively and significantly associated with the EPS surprises. As observed for prices, the marginal effect of the combined, multipollutant ($\Gamma^{T}_{f,y}$) score is much larger than the effects of either the air pollution or GHG score. Specifically, ($\Gamma^{T}_{f,y}$) exerts a positive effect on the EPS surprise that is nearly twice as large as air pollution intensity and three to seven-times larger than the effect of GHG intensity.

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* future EPS to a greater extent for firms that became relatively more pollution-intensive from 2014 to 2017. Analysts are overly pessimistic with respect to the future EPS of pollution intensive firms[9].

[8] The future EPS estimates are made by analysts in 2015 and 2018, one year after the environmental performance measures are tabulated.

[9] In light of analysts' apparent systematic errors, a natural question is whether analysts are acting rationally. Table A.1 in the appendix tests whether analysts' forecasts are rational using the regression-based approach in Keane and Runkle (1998). Two measures of realized EPS are used, the actual EPS and reported EPS are regressed on contemporaneous forecast EPS. Keane and Runkle (1998) claim that analysts are rational if the intercept from this model is zero and the coefficient on estimated EPS is equal to unity. The top panel employs actual EPS. In all four specifications, a Wald test of the null hypothesis that the coefficient on estimated EPS is equal to unity is rejected at conventional levels. In all columns, the intercept is significantly different from zero. This evidence suggests analysts' forecasts are not rational. In contrast, the bottom panel of table A.1 regresses reported EPS on the estimated. Here, the null hypothesis that the coefficient on estimated EPS is equal to unity cannot be rejected at

To explore analysts' behavior in greater depth, the top panel of table 5 decomposes forward EPS surprises into actuals and estimates, and it also reports the EPS surprises. The central insight is that actual EPS (reported in the year after the ($\Gamma_{f,y}$) scores are estimated) increase more for firms that become relatively dirtier than do the estimated EPS. For example, a one-unit increase in ($\Gamma^{T}_{f,y}$) induces a \$0.31 increase in actual EPS ($p < 0.01$) and just a \$0.15 increase in estimated EPS ($p < 0.01$). 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. Summarizing the top panel of table 5, 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.

Repeating a pattern evident in the analysis of current period outcomes, the combined, multi-pollutant metric ($\Gamma^{T}_{f,y}$) exhibits a larger effect on actual EPS, the estimated EPS, and the EPS surprise than the other measures. For the actual EPS, ($\Gamma^{T}_{f,y}$) exerts an effect roughly two to three times larger than either ($\Gamma^{A}_{f,y}$) or ($\Gamma^{G}_{f,y}$). For estimated EPS, the difference in effect size is on the order of 50 percent to a factor of two.

Finally, the forward EPS results inform inferences about the future pricing patterns evident in figure 2. (Recall that after an initial sharp decline, future prices rebound and react positively to increased pollution intensity between eight and twelve months after the ($\Gamma_{f,y}$) scores.) Market participants could be responding to the actual EPS for firms that become dirtier, which table 5 shows outpace estimated

conventional levels. Further, except for the OLS specification in column (1), the intercept is not significantly different from zero. This provides strong evidence that analysts' forecasts are rational. This decidedly mixed evidence implies that irrationality in analysts' forecasts cannot be ruled out as an explanation for persistently underestimating the EPS for more pollution intensive firms.

EPS. This news (actual EPS in excess of estimated EPS) would drive share prices higher as investors update their expectations about such firms' future earnings.

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 6 takes an additional look at the EPS data by exploring the standard deviation across analysts' 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 6 examines the dispersion of year ahead EPS estimates. In the year ahead context there is more consistent evidence that analysts' estimates become more noisy 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 concentrated in the ($\Gamma_{f,y}^{A}$) scores. There is also evidence of an association between pollution intensity and 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 ($p < 0.01$). Note that while the standard deviation increases with pollution intensity, the coefficient of variation falls. Table 5 shows why this is the case; year ahead 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. Analysts coalesce around biased EPS estimates.

Tables 4 and 5 indicate that analysts' estimates are sensitive to firms' overall pollution intensity. Table A.3 takes a more granular approach. It explores how the distribution of damages, across facilities owned by the same firm, affects the forward EPS surprises. A motivation for exploring the intra-firm distribution of damage is the following. Concentrated damage would make ascertaining firm's environmental performance easier because damages then come from fewer plants. 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. Empirically, a Herfindahl Index is computed as shown in (15):

$$\mathrm{H}_{f,y} = \sum_{p=1}^{P} \left(\frac{GED_{f,p,y}}{\sum_{p=1}^{P} GED_{f,p,y}} \right)^2 \qquad (15)$$

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. Based on the information transmission argument above, one would expect the Herfindahl Index in (15) 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 distinction that the Herfindahl Index is 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 4.4 in table 5 to 9.3 in table A.3 upon inclusion of the Herfindahl Index. This coefficient is statistically indistinguishable from the 9.63 corresponding to ($\Gamma_{f,y}^{A}$) in table 4. Thus, controlling for how concentrated damages are across facilities owned by the same firm renders the partial effect of GHG intensity equivalent to air pollution intensity. 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 that companies whose CO_2 damages emanate from relatively few sources. As argued above, one explanation for this result is that the information on emissions and damages required for analysts to judge environmental performance is less costly to acquire for firms with higher Herfindahl scores.

Table A.4 reports the results from regressing measures of dispersion in analysts' EPS estimates on the Herfindahl Indices. The key finding is that the noise in the EPS estimates falls as firms have higher CO_2 Herfindahl scores. Columns (1), (2), (5), and (6) indicate that both the standard deviations and coefficients of variation are lower for firms that have more concentrated damages. The effect on the coefficients of variation are significant at conventional levels. The essential argument undergirding this result is very much in line with that made above. 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.

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 environmental performance metrics largely ignore local air pollution, the degree of concentration in air pollution damage is likely irrelevant to market participants and index developers.

iii. Returns.

Table 3 presents little consistent evidence that pollution intensity is associated with current period returns. Only the ($\Gamma^{T}_{f,y}$) and ($\Gamma^{A}_{f,y}$) scores are marginally significantly associated with current returns. All of the coefficients are positive. The sign of these coefficients is in agreement with Bolton and Kacperczyk (2019) who report higher returns for firms with higher total CO_2 emissions. However, in light of Bolton and Kacperczyk's (2019) results, the lack of statistical significance in table 3 raises the question of why returns are not significantly higher for more pollution intensive firms. One possible explanation is that Bolton and Kacperczyk (2019) analyze CO_2 emissions across a larger sample of firms in multiple industries. It could be the case that utilities, the focus of the present study, may not command such a large carbon emission premium[10]. Table A.2 in the appendix explores how the returns premium varies according to model specification. The top panel focuses on current period returns. It shows no systematic evidence of a carbon intensity premium.

Table 4, which focuses on future financial outcomes, offers more conclusive evidence of a pollution intensity premium on returns. A one-unit increase in the ($\Gamma^{T}_{f,y}$) score is associated with a 1.2 percent increase in returns ($p < 0.01$). The other ($\Gamma_{f,y}$) scores exhibit positive coefficients with varying degrees of significance. The effect sizes range between 0.4 and 0.8 percent. Here again, the largest coefficient is associated with the multi-pollutant ($\Gamma^{T}_{f,y}$) scores. Returning to the findings of Bolton and Kacperczyk

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

(2019), the bottom panel of table A.2 reports systematic evidence of a carbon premium on future returns. Depending on model specification, the carbon premium ranges between 0.3 and 1 percent.

iv. Risk.

Table 3 provides suggestive evidence that measures of current period risk are associated with the ($\Gamma_{f,t}$) statistics. For example, volatility (defined as the standard deviation in returns) is higher for more pollution intensive firms according to the ($\Gamma_{f,t}^{T}$) and ($\Gamma_{f,t}^{G}$) scores. The coefficient for ($\Gamma_{f,t}^{T}$) is 0.234 ($p < 0.10$). The mean volatility for firms in this sample is 1.77: a one unit increase in ($\Gamma_{f,t}^{T}$) is associated with a 13 percent increase in volatility. Greater volatility in returns may stem from the significant reductions in current prices (reported in table 3) and the reductions in analysts' EPS estimates (in the bottom panel of table 5). Additionally, firms' betas from the CAPM regressions are also positively associated with the ($\Gamma_{f,t}^{G}$) statistics. The average beta for firms in this sample is 0.48 in 2014 and 2017. As such the coefficients on ($\Gamma_{f,t}^{G}$) in columns (2) and (4) suggest a 15 percent increase in firms' beta for a one-unit increase in CO_2 intensity.

c. Comparing Measures of Financial Performance: Tons and Damages.

While tables 3 and 4 focus on the ($\Gamma_{f,t}$) statistics computed using monetized damages, the question of how investors responded to other measures of environmental performance is addressed here. Tables A.5 through A.8 in the appendix systematically examine how the financial outcomes modeled in tables 3 and 4 respond to multiple alternative environmental performance metrics. There are two themes worth summarizing here. First, functional form matters; the ($\Gamma_{f,t}$) statistics computed using emissions rather than damages exhibit many of the same patterns as damages, whereas raw emissions are, in general, less significant determinants of financial outcomes. Second, 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.5 indicates that the outcomes that were significantly associated with the ($\Gamma_{f,t}$) damage statistics in table 3 tend to also be significantly associated with the ($\Gamma_{f,t}$) emission statistics. Specifically, prices are negatively associated with emissions. However, the magnitudes of the coefficients are quite different. While a one-unit increase in the monetary damage ($\Gamma_{f,t}^{T}$) induces an 8 percent reduction in prices, the tonnage ($\Gamma_{f,t}^{T}$) is associated with a 5 percent reduction in prices. For prices, the combined emissions (shown in column 1) display an effect that is nearly identical to GHGs alone, as shown in column 4. This occurs because the magnitude of GHG emissions, in mass, dwarfs that of the LAPs combined. Table A.5 also indicates that results for volatility and firms' betas from the CAPM regressions are similar to those for damages.

Table A.6 covers forward financial outcomes. Like tables 3 and A.5, the comparison of tables 4 and A.6 reveals strong commonality between the emission and damage ($\Gamma_{f,t}$) scores. Forward prices are negatively associated with the emissions ($\Gamma_{f,t}$) scores. The marginal effect of the combined emission score is much smaller than the combined damage score. The EPS surprises are consistently associated with the emissions ($\Gamma_{f,t}$) scores. The magnitudes of the coefficients are smaller than those in table 4. Again the coefficients for ($\Gamma_{f,t}^{T}$) mimic those for ($\Gamma_{f,t}^{G}$) in column (4).

Table A.7 focuses on raw tonnage, rather than the ($\Gamma_{f,t}^{T}$) statistics. Here the results are different. The signs for the ($\Gamma_{f,t}$) scores in the price regressions are not robust. P/E ratios are positively associated with tonnage. Some points of commonality with the ($\Gamma_{f,t}$) scores are evident. Volatility and firms' betas from the CAPM regressions are positively associated with combined GHG and LAP emissions and GHG emissions alone. Table A.8 indicates that EPS surprises are increasing in both GHG emissions and combined emissions. Tables A.7 and A.8 also make clear that GHG emissions dominate LAP emissions because of the large difference in emissions tonnage. Multi-pollutant environmental performance scores expressed in terms of emissions mimic CO_2.

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 enables multi-pollutant assessments of environmental performance. Without monetization, CO_2 dominates environmental performance because emissions are so abundant relative to other pollution species.

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. 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. 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 three measures of risk. Current prices fall when within firms' pollution damage intensity rises. 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 damage information. 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 those based only on GHGs and only on emissions. These comparisons reveal two important insights. First, without monetization, pollution intensity measured by adding up tons of the eight pollutants covered herein is dominated by GHGs. This stems from the fact that the volume of GHG emissions is orders of magnitude larger than the LAP. 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.

Second, 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 twice as sensitive. 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 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	GHG	(3) LAP	(4) GHG
Prices	-0.0862***[B]	-0.0483***	-0.0422**	-0.0565***	-0.0503**
	(0.0276)[C]	(0.0131)	(0.0192)	(0.0187)	(0.0203)
Forward P/E[D]	-0.00219	-0.0233*	0.00901	-0.0216	0.00522
	(0.0298)	(0.0129)	(0.0225)	(0.0131)	(0.0227)
EPS Surprise[G]	-0.494	-1.320	0.350	-1.306	0.324
	(1.362)	(1.380)	(0.835)	(1.396)	(0.837)
Returns	0.644*	0.436*	0.281	0.493	0.357
	(0.362)	(0.258)	(0.200)	(0.297)	(0.213)
Volatility[E]	0.234*	0.124	0.129*	0.149	0.150*
	(0.117)	(0.0740)	(0.0761)	(0.0919)	(0.0764)
Beta	0.0201	-0.0391	0.0701*	-0.0250	0.0635*
	(0.0814)	(0.0610)	(0.0371)	(0.0632)	(0.0324)
SD Residual[F]	-0.0387**	-0.0202**	-0.00572	-0.0218**	-0.0135
Return	(0.0150)	(0.00826)	(0.0109)	(0.00893)	(0.0111)

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 (8). The full results for each of the regression models supporting table 3 are reported in the appendix.
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = monthly standard deviation in returns.
F = monthly standard deviation of residual from CAPM regression.
G = (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 models. Prices, P/E ratios, and SD residuals 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	-0.0626**[B]	-0.0282	-0.0167	-0.0317*	-0.0230
	(0.0243)[C]	(0.0193)	(0.0218)	(0.0167)	(0.0191)
Forward P/E[D]	-0.00702	-0.0303**	0.0139	-0.0284**	0.0102
	(0.0315)	(0.0133)	(0.0219)	(0.0134)	(0.0228)
EPS Surprise[G]	14.42***	9.187***	2.663*	9.634***	4.437**
	(2.550)	(1.636)	(1.471)	(1.750)	(2.048)
Returns	1.210***	0.472*	0.664	0.610**	0.770**
	(0.401)	(0.278)	(0.413)	(0.301)	(0.375)
Volatility[E]	0.0160	-0.0559	0.105	-0.0352	0.0936
	(0.125)	(0.0789)	(0.0825)	(0.0781)	(0.0757)
Beta	0.0241	0.0206	0.00659	0.0231*	0.0163
	(0.0263)	(0.0137)	(0.0213)	(0.0122)	(0.0213)
SD Residual[F]	0.0158	0.000320	0.0111	0.00329	0.0112
Return	(0.0150)	(0.00689)	(0.00998)	(0.00699)	(0.0106)

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 (8). The full results for each of the regression models supporting table 4 are reported in the appendix.
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = monthly standard deviation in returns.
F = monthly standard deviation of residual from CAPM regression.
G = (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 models. Prices, P/E ratios, and SD residuals 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	0.314***[B]	0.164***	0.102**	0.181***	0.133**
	(0.0605)[C]	(0.0354)	(0.0459)	(0.0457)	(0.0649)
Estimate	0.151***	0.0930***	0.0591	0.103***	0.0770**
	(0.0499)	(0.0254)	(0.0355)	(0.0279)	(0.0379)
Surprise[D]	14.42***	9.187***	2.663*	9.634***	4.437**
	(2.550)	(1.636)	(1.471)	(1.750)	(2.048)
Current Earnings	**(1) GHG & LAP**	**(2) LAP**	**GHG**	**(3) LAP**	**(4) GHG**
Actual	-0.115	-0.00730	-0.0794*	-0.0105	-0.0796*
	(0.0718)	(0.0616)	(0.0426)	(0.0598)	(0.0422)
Estimate	-0.213***	-0.0424	-0.116***	-0.0469	-0.116***
	(0.0597)	(0.0391)	(0.0337)	(0.0487)	(0.0338)
Surprise	-0.494	-1.320	0.350	-1.306	0.324
	(1.362)	(1.380)	(0.835)	(1.396)	(0.837)

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 (8). Since EPS enter the models in levels, the coefficients are in nominal $.
C = Robust standard errors in parenthesis.
D = (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

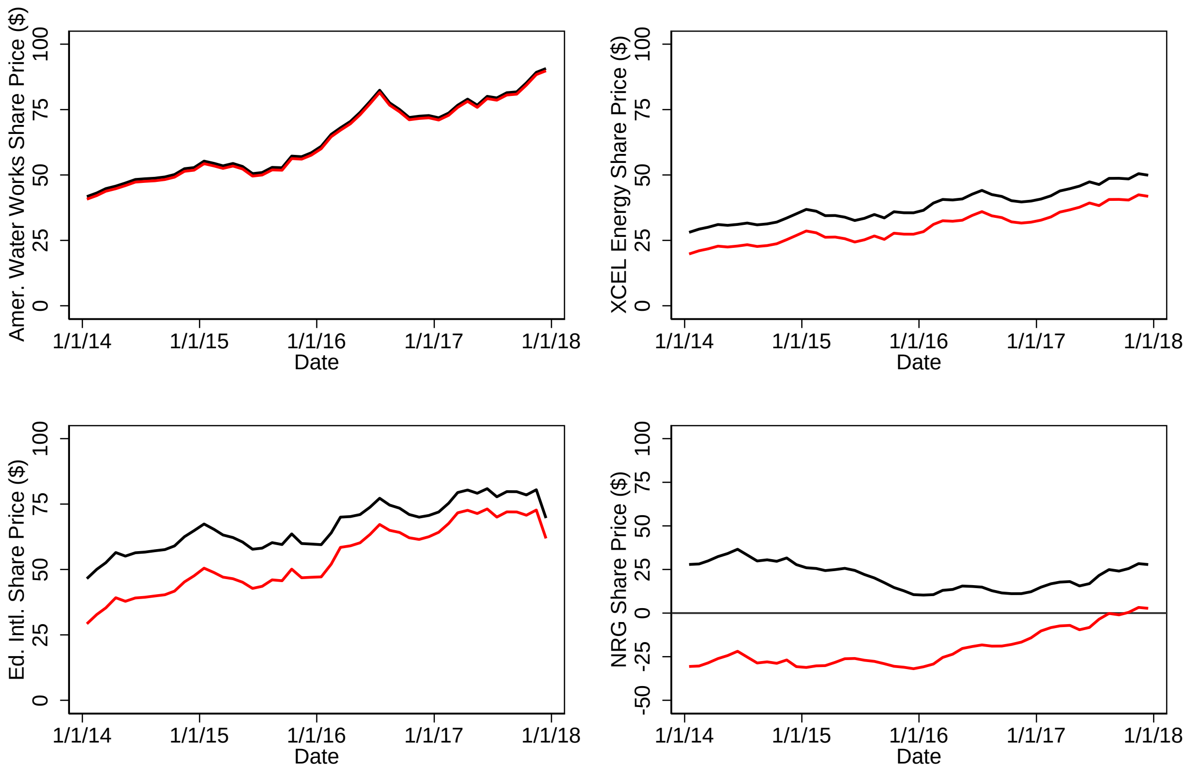
Table 6: Dispersion of Analysts' EPS Estimates.

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 6 is a fitted OLS parameter estimate from distinct regression model of the form in (8). The coefficients for the Coefficient of Variation are expressed as a fraction of EPS, those for Standard Deviation are in nominal $.
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

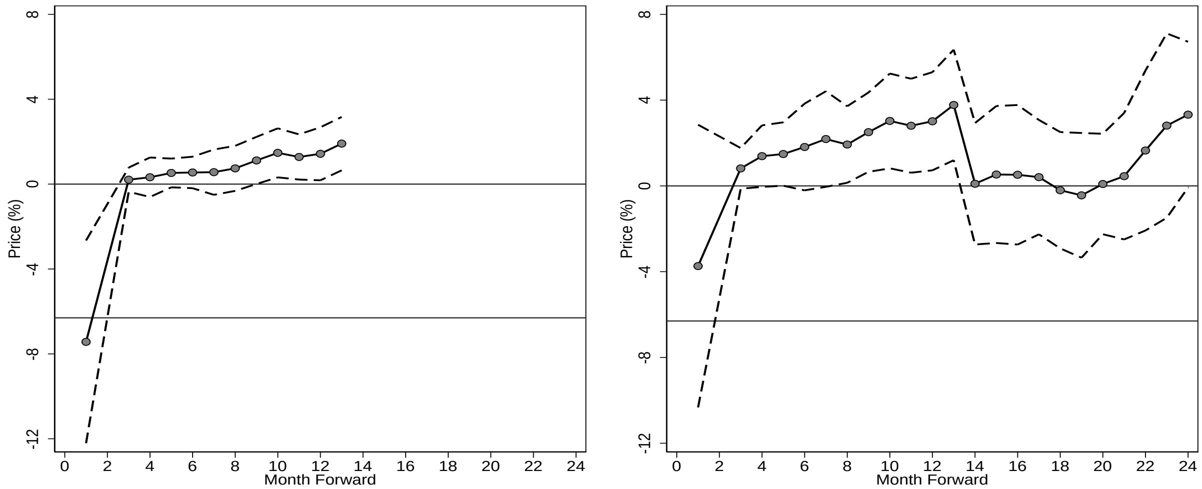
Figures.

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.

Figure 2: Prices and Environmental Performance by Month Forward.



This figure displays the partial effect of $(\Gamma^{T}_{f,y})$ on forward prices in current dollars.
Left column: regression model includes interaction terms between $(\Gamma^{T}_{f,y})$ and month fixed effects up to one year after environmental performance period.
Right column: regression model includes interaction terms between $(\Gamma^{T}_{f,y})$ and month fixed effects up to two years after environmental performance period.
Bottom horizontal line in each panel = -6.3 percent. This is the point estimate of the effect of the $(\Gamma^{T}_{f,t})$ score on prices from table 4.
Dashed lines represent 95 percent confidence intervals.

Appendix:

Table A.1: Test of Rational Earnings Forecasts.

Dep Variable: Actual EPS	**(1)**	**(2)**	**(3)**	**(4)**
Earnings (EPS)	1.065***	1.065***	1.071***	0.856***
Estimate	(0.00733)	(0.0102)	(0.00986)	(0.0819)
Constant	-0.157***	-0.157***	-0.115***	0.376*
	(0.0225)	(0.0274)	(0.0425)	(0.190)
adj. R^2	0.940	0.940	0.942	0.742
N	1345	1345	1345	1345
Firm Fixed Effects				Y
Year Fixed Effects			Y	Y
Month Fixed Effects			Y	Y
Robust SE		Y	Y	Y
Wald Test	78.21***[A]	40.46***	51.29***	3.08*
EPS = 1	(0.000)[B]	(0.000)	(0.000)	(0.086)
Dep. Variable: Reported EPS	**(1)**	**(2)**	**(3)**	**(4)**
Earnings (EPS)	0.982***	0.982***	0.983***	1.161***
Estimate	(0.00841)	(0.0194)	(0.0194)	(0.146)
Constant	0.0137	0.0137	0.0462	-0.404
	(0.0258)	(0.0488)	(0.0498)	(0.350)
adj. R^2	0.910	0.910	0.911	0.668
N	1345	1345	1345	1345
Firm Fixed Effects				Y
Year Fixed Effects			Y	Y
Month Fixed Effects			Y	Y
Robust SE		Y	Y	Y
Wald Test	4.81**[A]	0.91	0.78	1.22
EPS = 1	(0.029)[B]	(0.341)	(0.377)	(0.275)

A = F-statistic

B = p-value

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

Table A.2: Carbon Premiums.

Current Returns	(1)	(2)	(3)	(4)
GHGs	0.175[A]	0.202	0.904**	0.357
	(0.182)[B]	(0.162)	(0.362)	(0.213)
Constant	1.627	1.059	1.122	-38.53***
	(1.024)	(1.224)	(1.624)	(14.27)
Adj. R^2	-0.002	0.203	0.264	0.848
N	925	925	925	925
Forward Returns	**(1)**	**(2)**	**(3)**	**(4)**
GHGs	0.361**	0.336**	0.933**	0.770**
	(0.167)	(0.147)	(0.361)	(0.375)
Constant	3.196***	1.069	0.372	-210.6***
	(0.447)	(0.796)	(2.130)	(30.17)
Adj. R^2	0.132	0.349	0.378	0.679
N	914	914	914	914
Firm Fixed Effects	N	N	Y	Y
Month Fixed Effects	N	Y	Y	Y
Year Fixed Effects	N	Y	Y	Y
ADL	N	N	N	Y

A = each entry is a fitted OLS parameter estimate from a regression of returns on ($\Gamma^{G}_{f,y}$).

B = Robust standard errors in parenthesis.

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

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 (12) 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 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 (12) with EPS Surprise as the dependent variable.
B = Robust standard errors in parenthesis.
* p<0.10 ** p<0.05 *** p<0.01

Table A.5: Current Period Firm Financial Performance and Emission Tonnage Gammas.

Dependent Variable	(1) GHG + LAP[A]	(2) LAP	(2) GHG	(3) LAP	(4) GHG
Prices	-0.0501**[B]	-0.0274	-0.0468**	-0.0386**	-0.0500**
	(0.0204)[C]	(0.0180)	(0.0203)	(0.0158)	(0.0203)
Forward P/E[D]	0.00541	-0.00435	0.00591	-0.00296	0.00541
	(0.0228)	(0.0211)	(0.0229)	(0.0222)	(0.0227)
EPS Surprise[G]	-0.494	-0.268	0.344	-0.174	0.310
	(1.362)	(1.231)	(0.908)	(1.145)	(0.836)
Returns	0.357	0.115	0.342	0.198	0.356
	(0.213)	(0.175)	(0.209)	(0.213)	(0.213)
Volatility[E]	0.150*	-0.0678	0.158**	-0.0310	0.150*
	(0.0763)	(0.0641)	(0.0768)	(0.0517)	(0.0761)
Beta	0.0641*	-0.0589	0.0620*	-0.0626	0.0641*
	(0.0324)	(0.0631)	(0.0316)	(0.0671)	(0.0323)
SD Residual[F]	-0.0136	-0.0239**	-0.00990	-0.0260**	-0.0135
Return	(0.0111)	(0.0114)	(0.0106)	(0.0121)	(0.0111)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table A.5 is a fitted OLS parameter estimate from distinct regression model of the form in (8). The full results for each of the regression models supporting table A.5 are reported in the appendix.
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = monthly standard deviation in returns.
F = monthly standard deviation of residual from CAPM regression.
G = (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 models. Prices, P/E ratios, and SD residuals enter in natural log form. The other dependent variables enter in levels.
* p<0.10 ** p<0.05 *** p<0.01

Table A.6: Future Period Firm Financial Performance and Emission Tonnage Gammas.

Dependent Variable	(1) GHG + LAP[A]	(2) LAP	GHG	(3) LAP	(4) GHG
Prices	-0.0231[B]	-0.0495*	-0.0221	-0.0503*	-0.0230
	(0.0190)[C]	(0.0278)	(0.0190)	(0.0291)	(0.0190)
Forward P/E[D]	0.0104	-0.0145	0.0117	-0.0125	0.0104
	(0.0228)	(0.0208)	(0.0227)	(0.0228)	(0.0228)
EPS Surprise[G]	4.475**	7.992**	3.012	8.870**	4.453**
	(2.036)	(3.775)	(1.790)	(3.893)	(2.031)
Returns	0.772**	0.881***	0.751*	0.911***	0.769**
	(0.375)	(0.272)	(0.381)	(0.322)	(0.374)
Volatility[E]	0.0926	0.0821	0.0914	0.0842	0.0924
	(0.0758)	(0.118)	(0.0748)	(0.113)	(0.0756)
Beta	0.0161	-0.00299	0.0163	-0.000381	0.0160
	(0.0215)	(0.0227)	(0.0214)	(0.0215)	(0.0214)
SD Residual[F]	1.54e-10	-0.000000418*	5.62e-11	-0.000000425*	1.55e-10
Return	(3.83e-10)	(0.000000230)	(3.68e-10)	(0.000000223)	(3.83e-10)

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 (8). The full results for each of the regression models supporting table A.6 are reported in the appendix.
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = monthly standard deviation in returns.
F = monthly standard deviation of residual from CAPM regression.
G = (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 models. Prices, P/E ratios, and SD residuals enter in natural log form. The other dependent variables enter in levels.
* p<0.10 ** p<0.05 *** p<0.01

Table A.7: Current Period Firm Financial Performance and Emission Tonnage.

Dependent Variable	(1) GHG + LAP[A]	(2) LAP	GHG	(3) LAP	(4) GHG
Prices	-7.59e-10[B]	0.00000132**	-6.29e-10	0.00000135**	-7.62e-10
	(7.18e-10)[C]	(0.000000530)	(6.03e-10)	(0.000000578)	(7.18e-10)
Forward P/E[D]	3.25e-10	0.000000932*	4.15e-10	0.000000914*	3.23e-10
	(5.70e-10)	(0.000000494)	(4.61e-10)	(0.000000479)	(5.71e-10)
EPS Surprise[G]	2.02e-09	-0.0000129	9.89e-10	-0.0000129	2.05e-09
	(2.08e-08)	(0.0000114)	(2.09e-08)	(0.0000115)	(2.08e-08)
Returns	6.88e-09	0.000000404	6.92e-09	0.000000111	6.88e-09
	(7.92e-09)	(0.00000398)	(7.94e-09)	(0.00000446)	(7.92e-09)
Volatility[E]	4.92e-09*	-0.000000883	4.83e-09*	-0.00000110	4.92e-09*
	(2.53e-09)	(0.00000152)	(2.51e-09)	(0.00000131)	(2.53e-09)
Beta	2.34e-09**	0.000000934	2.48e-09***	0.000000751	2.33e-09**
	(9.37e-10)	(0.000000824)	(9.13e-10)	(0.000000788)	(9.37e-10)
SD Residual[F]	-6.94e-10***	8.81e-08	-6.93e-10***	9.34e-08	-6.95e-10***
Return	(2.47e-10)	(0.000000191)	(2.46e-10)	(0.000000206)	(2.47e-10)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table A.7 is a fitted OLS parameter estimate from distinct regression model of the form in (8). The full results for each of the regression models supporting table A.7 are reported in the appendix.
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = monthly standard deviation in returns.
F = monthly standard deviation of residual from CAPM regression.
G = (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 models. Prices, P/E ratios, and SD residuals enter in natural log form. The other dependent variables enter in levels.
* p<0.10 ** p<0.05 *** p<0.01

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

Dependent Variable	(1) GHG + LAP[A]	(2) LAP	GHG	(3) LAP	(4) GHG
Prices	3.94e-10[B]	0.00000116**	7.04e-10	0.00000107**	3.92e-10
	(5.34e-10)[C]	(0.000000458)	(5.49e-10)	(0.000000404)	(5.34e-10)
Forward P/E[D]	6.75e-10	0.000000714	8.54e-10	0.000000617	6.74e-10
	(5.71e-10)	(0.000000443)	(5.26e-10)	(0.000000414)	(5.71e-10)
EPS Surprise[G]	0.000000134*	0.000105**	0.000000173**	0.0000737*	0.000000134*
	(7.30e-08)	(0.0000410)	(7.58e-08)	(0.0000415)	(7.29e-08)
Returns	2.97e-09	-0.0000123	-5.15e-10	-0.0000123	3.00e-09
	(8.62e-09)	(0.0000118)	(9.37e-09)	(0.0000114)	(8.63e-09)
Volatility[E]	2.18e-09	0.00000134	2.55e-09	0.000000970	2.17e-09
	(2.21e-09)	(0.00000212)	(2.21e-09)	(0.00000226)	(2.21e-09)
Beta	2.91e-11	-0.000000589	-1.30e-10	-0.000000575	3.05e-11
	(4.87e-10)	(0.000000493)	(4.46e-10)	(0.000000477)	(4.87e-10)
SD Residual[F]	1.54e-10	-0.000000418*	5.62e-11	-0.000000425*	1.55e-10
Return	(3.83e-10)	(0.000000230)	(3.68e-10)	(0.000000223)	(3.83e-10)

A = LAP stands for local air pollutants (SO_2, NO_x, $PM_{2.5}$, VOC, NH_3)
B = each entry in table A.7 is a fitted OLS parameter estimate from distinct regression model of the form in (8). The full results for each of the regression models supporting table A.7 are reported in the appendix.
C = Robust standard errors in parenthesis.
D = the forward P/E is current period share prices over estimated earnings per share (EPS).
E = monthly standard deviation in returns.
F = monthly standard deviation of residual from CAPM regression.
G = (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 models. Prices, P/E ratios, and SD residuals enter in natural log form. The other dependent variables enter in levels.
* p<0.10 ** p<0.05 *** p<0.01