One Hundred and Thirty Years of Corporate Responsibility

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Abstract

U.S. history is punctuated by public discourse about the externalities and responsibilities of business in time-varying context. Applying natural language processing (NLP) techniques that account for context evolution in historical news text, we develop a monthly time-series index dating back to the late 19th century that measures public attention to environmental and social issues related to business (ESIX). We explore the properties of ESIX, and relate it to macroeconomic fluctuations, asset prices, and corporate decisions.

Keywords: ESG, ESIX, Natural Language Processing (NLP), Word Embeddings, Big Text Data, Financial History

JEL classifications: C82, E44, G12, G31, G32, M14, N00

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1 Introduction

In recent years, environmental, social, and governance (ESG) concerns have risen in prominence among corporations and investors (see Hartzmark and Sussman, 2019; Krueger, Sautner, and Starks, 2020; Bolton and Kacperczyk, 2021, 2022; Pastor, Stambaugh, and Taylor, 2022). However, the difficulty of measuring the multi-faceted contexts of ESG makes it challenging to understand what drives the demand for ESG and how it affects asset prices and corporate policies (see Berg, Kölbel, and Rigobon, 2022; Berg, Kölbel, Pavlova, and Rigobon, 2023). The contextual richness of ESG also makes it difficult to study long sample periods, despite the fact that public concerns about the externalities of corporate activities and demand for corporate responsibility have punctuated history in various guises.

In this paper, we overcome these challenges by employing advanced natural language processing (NLP) techniques that account for the evolution of environmental and social context in 130 years of historical news text. Specifically, we train a *word embeddings* algorithm, or Word2Vec, on different decades throughout the corpus sample. We then apply a small set of universal and time-invariant seed words that capture environmental and social problems, and use the period-specific language models to generate time-varying ESG dictionaries that contain keywords closely related to these seed words. Applying these dictionaries to articles about business and the economy, we construct a novel text-based time-series index that measures public attention to ESG and corporate responsibility, or ESIX.

The time-series of our ESIX measure and its environmental and social components, EIX and SIX, reflect different aspects of environmental and social concerns that were prevalent at different points in history. Our NLP methodology is able to achieve this without relying on the econometrician's subjective judgement regarding which topics should be included in the index during different periods. The index also enables us to derive stock-month level ESIX exposures from monthly stock returns. Motivated by recent studies that show that shocks to green preferences and the demand for green assets explain the return premium of green over brown assets (see Pastor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and

Pomorski, 2021; Pastor et al., 2022), we use the ESIX exposures as demand-based proxies for corporate ESG profiles. These exposures are free of arbitrary selection of topics that have led to widespread ambiguity and disagreement across contemporary ESG ratings (see Berg, Fabisik, and Sautner, 2021; Berg et al., 2022, 2023).

We explore the properties of ESIX and validate the measure by inspecting its relationships with several macroeconomic variables. We find that public attention to social issues arise amid internal economic and social instability, signified by high levels of SIX during times of high volatility in real GDP growth, high unemployment, frequent recessions, and high wealth inequality. In contrast, attention to environmental issues (i.e., high levels of EIX) are afforded by society during times of relative stability and prosperity, but positively correlated with partisanship and political polarization. Further validating our measure, we find that the EIX component closely tracks a news-based measure of climate policy uncertainty in recent years.

We then apply our ESIX measure to study first-order questions in finance, such as the cross-sectional financial implications of corporate responsibility and the real effects of societal demand for ESG. In our analysis of stock returns, we find no evidence that stocks that are positively exposed to ESIX earn higher returns than stocks that are negatively exposed. If anything, our results suggest that positive exposure stocks cost rather than pay investors when the level of public attention to environmental and social issues are low.

We also examine the impact of public attention and discourse about environmental and social issues on corporate investment and investment efficiency. Our results suggest that heightened public concerns about these issues dampen business activity, indicated by lower capital expenditures. In particular, we find that elevated concerns about social issues such as inequality and discrimination are negatively associated with corporate investment efficiency, implied by weakening links between corporate investment and Tobin's q. These findings cast doubt on the notion that corporate responsibility creates value in the long-run.

By exploiting rich historical time-series, our findings complement the growing literature on the financial market implications of corporate ESG performance. Given the rise of ESG and climate finance as a recent phenomenon, studies that examine investor ESG demand and its relationship with economic conditions have relied on short sample periods around specific events or shocks (see Hartzmark and Sussman, 2019; Döttling and Kim, 2022). Cross-sectional asset pricing studies have also focused on recent sample periods due to the availability of data on environmental performance (see Bolton and Kacperczyk, 2021, 2022; Hsu, Li, and Tsou, 2023; Zhang, 2023). Our study provides a tool to help generalize this line of research to broader sustainability issues and longer sample periods.

Our work also complements recent studies that analyze granular text data to shed light on how companies incorporate stakeholder values into their policies. For example, Rajan, Ramella, and Zingales (2023) analyze corporate letters to shareholders and document that firms have recently been proclaiming environmental and social goals in their purported corporate objectives. Li, Shan, Tang, and Yao (2023) and Sautner, van Lent, Vilkov, and Zhang (2023a,b) apply climate-related dictionaries to earnings call transcripts and construct firm-level measures of climate risk exposures. Rouen, Sachdeva, and Yoon (2023) analyze the evolution of content in corporate ESG reports over the past decade. Our study contributes to this literature along two important dimensions. First, by going back to the late 19th century (or early 20th century for firm-level analysis), we dramatically extend the time-series coverage beyond what the literature has been able to examine. Second, by applying NLP techniques based on *word embeddings* to different time periods, our ESIX measure incorporates a wide variety of contexts related to ESG, endogenously accommodating the historical evolution of public interest in different aspects of corporate responsibility.

Finally, our study contributes to the broader literature that applies natural language processing (NLP) techniques in financial economics. Earlier studies in this area use "bag-of-words" approaches that utilize word count frequencies to measure aggregate uncertainty or firm-level risk exposures (see Baker, Bloom, and Davis, 2016; Loughran and McDonald, 2016; Manela and Moreira, 2017; Hassan, Hollander, Lent, and Tahoun, 2019). With the proliferation of NLP techniques and big text data, the literature has also adopted a variety of topic modeling and prediction-based word embedding techniques to understand rich contexts related to economic sentiment, business cycles, or geopolitical risk (see Binsbergen, Bryzgalova, Mukhopadhyay, and Sharma, 2023; Bybee, Kelly, Manela, and Xiu, 2023; Hirshleifer, Mai, and Pukthuanthong, 2023a,b; Jha, Liu, and Manela, 2023). Recent studies also explore the implications of large language models (LLMs) based on generative AI (e.g., ChatGPT) for asset prices and monetary policy (see Lopez-Lira and Tang, 2023; Hansen and Kazinnik, 2023; Jha, Qian, Weber, and Yang, 2023). Our work adds to this literature by employing a novel time-varying word embedding approach recently adopted in the literature (see Bandyopadhyay, Mai, and Pukthuanthong, 2023a,b), which allows the econometrician to model the historical evolution of context free of subjective judgement.

The paper is organized as follows. In Section 2, we discuss our data and NLP methodology that are used to construct our ESIX measure. In Section 3, we explore and validate ESIX, and use it to examine the financial implications of corporate responsibility and the real effects of public attention to environmental and social externalities. In Section 4, we summarize our findings and conclude.

2 Data and Methodology

2.1 Data

Our primary data source is an extensive text corpus of historical news articles from The Wall Street Journal (WSJ) and The New York Times (NYT) spanning 130 years back to 1890. We obtain digitized copies of these articles from ProQuest TDM Studio. Our initial pre-processing of the raw articles involves removing punctuations, digits, and special characters. We then lemmatize each word by transforming it to its base form based on the word's *part-of-speech*.[1] We further remove all stop words that are frequently used but do

[1]For example, "*faster*" and "*cars*" are transformed into "*fast*" and "*car*", respectively.

not carry substantial meaning by themselves.[2] We also require that within each article, at least 1% of words are related to the seed words, "*business*", "*economy*", or "*corporation*", based on a dictionary generated from *word embeddings* as we describe in more detail below. Lastly, we exclude all articles with fewer than 100 content words, following Hirshleifer et al. (2023a). After pre-processing, we are left with approximately 4 million news articles related to business and the economy.

We inspect several historical macroeconomic variables in our time-series analysis of ESIX. We obtain real GDP growth rates and unemployment rates from the Jordà, Schularick, and Taylor (2016) Macrohistory database, and National Bureau of Economic Research (NBER) recession indicators from the St. Louis Fed. We also obtain wealth inequality, measured as the share of total household wealth held by the top 1% percentile of households, from Piketty, Saez, and Zucman (2018). We use two measures of political frictions: congressional polarization (see Poole and Rosenthal, 1984, and Voteview.com) and news-based partisan conflict (see Azzimonti, 2018). We adopt two additional news-based indices: climate policy uncertainty from Gavriilidis (2021), and geopolitical risk from Caldara and Iacoviello (2022).

Finally, stock returns (from 1926 and onward) and firm fundamentals (from 1960 and onward) are obtained from CRSP/Compustat.

2.2 Methodology

Our methodology for constructing ESIX follows three stages. The first stage is to generate time-varying language models that can account for the evolution of linguistic context over time. This step is critical for our study as we aim to create an index capturing discourse in issues for which the contexts are in flux and multifaceted. The second stage is to use these language models to generate a time-varying set of dictionaries without infusing our subjective judgement of how those dictionaries ought to change over time. The third stage entails constructing ESIX using these dictionaries.

[2] To identify stop words, we use the "Expanded stop words list" developed by Matthew L. Jockers (https://www.matthewjockers.net/macroanalysisbook/expanded-stopwords-list/).

2.2.1 Time-Varying Language Models (Word2Vec)

To implement the first stage of our methodology, we use the skip-gram implementation of Word2Vec, a widely used NLP technique that relies on prediction-based word embeddings. This algorithm produces vector representations of words and phrases in a corpus by using the co-occurrence of words to predict context words surrounding a target word. Specifically, it solves for an objective function that maximizes the probability that any "context" word in a corpus appears within some radius of a given target word. The byproduct of this optimization is the full vector space of all words and phrases in the corpus, where words with similar contextual meanings have similar vector representations. The distances between these vectors, or "cosine similarities", can be used to measure how similar words are with one another. The key strength of this algorithm compared to traditional "bag-of-words" approaches is that it captures the context in which a word or phrase is used, such that it can identify contextually similar phrases even if they are not used together in proximity.

This algorithm is well-suited for the purpose of our study. Unlike recent studies that rely on pre-trained language models such as BERT or ChatGPT (see Jha et al., 2023; Lopez-Lira and Tang, 2023; Hansen and Kazinnik, 2023), we are interested in the evolution of context over time. Therefore, we train separate Word2Vec models for each decade throughout the sample period (e.g., 1890–1899, 1900–1909, ... , etc.) to generate our own set of time-varying language models. This allows us to capture the historical evolution of context in which the public has been concerned about issues related to what we might call today as "ESG" or "corporate responsibility".

When training our models, we identify bi-grams and tri-grams in our corpus to ensure that the Word2Vec algorithm accounts for contexts in which a word is used as part of a multi-word phrase.[3] As hyperparamaters needed for training the Word2Vec models, we use a vector dimension size of 300 and the standard context radius (i.e., window length) of 10.[4] In

[3]For example, "*new*", "*york*", "*city*" are three separate words, but are frequently used together in the three-gram, "*new_york_city*".

[4]The model output is robust to alternative window lengths of 5 and 15.

addition, we drop words that appear in the corpus less than five times and run the skip-gram algorithm 20 times (instead of 5 times, as in default) to enhance our models' performance.

2.2.2 Subjectivity-Free, Time-Varying Dictionaries

Next, we use these decade-specific language models to generate time-varying dictionaries that contain keywords that are closely related to ESG issues, as semantically used in each decade. To ensure that the time-variation in the dictionaries is not driven by our subjective judgement of which environmental and social issues ought to have been important in different time periods, we start from a "universal", or *time-invariant* set of seed words that we can feed to the Word2Vec models. We choose these initial seed words carefully, such that they not only appear in every decade of our corpus, but can also be unambiguously interpreted as issues pertaining to environmental and social problems. These seed words are *pollution*, *inequality*, and *discrimination*. We then use the Word2Vec models to span time-varying dictionaries by identifying the top 100 words and phrases with the highest cosine similarity scores for each seed word within each decade. To ensure that our dictionaries are not polluted by generic words or phrases that are used often in sentences, we drop keywords that are in the top 50 in terms of frequency of use, but in the bottom 50 in terms of their cosine similarity scores. We use this automated approach to trim the dictionary to minimize the influence of subjective judgement on dictionary context.

Figure 1 illustrates how the dictionary context evolves over time by showing word clouds for select decades. The word clouds visualize the relative frequency of each keyword from our dictionary, weighted by their cosine similarity score to the seed word they are generated from. Panel A to C each show word clouds of keywords generated from the seed word "*pollution*", "*discrimination*", and "*inequality*", respectively, for select decades.

[Insert Figure 1 here]

The word clouds clearly illustrate that our methodology generates evolution in context. For example, pollution-related discourse in business/economy-related news has evolved from focusing on issues related to water pollution in the late 19th and early 20th century, to increasingly discussing air pollution and greenhouse gas emissions in recent decades.

2.2.3 Construction of ESIX

Finally, we use the time-varying dictionaries to construct the public ESG attention index, or ESIX. For each news article, we first count the total number of occurrences of the keywords contained in the dictionary, and divide it by the total word count of the article.[5] ESIX is then computed as the monthly average of this ratio across all news articles in that month. For subsequent analysis, we also construct environmental and social sub-indices, EIX and SIX, based on dictionaries spanned separately from the environmental seed word "*pollution*" or social seed words "*inequality*" and "*discrimination*".

Figure 2 illustrates and summarizes the methodology for constructing our monthly ESIX index that we have discussed in detail above.

[Insert Figure 2 here]

3 Results

3.1 Properties of ESIX

We begin by exploring the properties of ESIX. Figure 3 presents the full monthly time-series of ESIX from January 1889 to March 2023. Panel A shows the overall ESIX measure, and Panel B shows EIX and SIX separately.

[Insert Figure 3 here]

Several notable patterns are observed. Over the past 130 years, there have been several waves of high-ESIX periods. In the first half of the 20th century, long before formalized

[5] To account for the fact that we use *one* environmental seed word, "*pollution*", and *two* social seed words, "*inequality*" and "*discrimination*", we average the word counts of keywords spanned from the two social seed words before aggregating the environmental and social word counts.

concepts of corporate social responsibility (CSR) or ESG, our ESIX measure indicates that there had already been much public discourse about environmental and social issues. Separate plots of EIX and SIX reveal that much of this early concern was driven by social issues related to inequality and discrimination. This period, which includes the 1929–1939 great depression, was indeed marked by poverty, rampant inequality, and labor rights movements. In the post-war era after 1950, SIX subsides while EIX begins to dominate the index. In particular, EIX captures conversations in the mid-1960s about protecting the environment, sharply spiking after the establishment of the U.S. Environmental Protection Agency (EPA) in late 1970. This was also the period when widespread debates on corporate social responsibility began to take hold, marked by the "Friedman (1970) doctrine". During the recent two decades since 2000, there has been a gradual uptick in ESIX, EIX, and SIX, punctuated by a spike in the last few years when ESG, climate change, gender and racial diversity came front and center in public discourse among investors and business leaders alike.

[Insert Table 1 here]

Table 1 describes the time-series properties of ESIX and its components. The mean ESIX value throughout the entire sample period is 0.05, indicating that 5% of the average article's text consists of keywords that belong to our decade-specific ESG dictionary. The components, EIX and SIX, have correspondingly lower means of 0.02 and 0.03, respectively. The median values are similar to the means, indicating that the indices are not significantly skewed, despite their occasional spikes. The standard deviation is 0.02 for the overall index as well as its components, implying that our methodology generates consistent variability across the topics it covers. The minimum and maximum index values are also reported separately for two sub-periods: pre-1970 and post-1970. All of the indices exhibit wide ranges in both periods, consistent with long-run waves of public discourse related to environmental and social issues in business and the economy.

3.2 ESIX and Macroeconomic Conditions

To understand the forces that drive fluctuations in public attention to environmental and social issues related to business and the economy, we start by examining the time-series relationships between our indices and several macroeconomic variables. Figure 4 illustrates how EIX and SIX are associated with real GDP growth (Panel A), unemployment (Panel B), recessions (Panel C), and wealth inequality (Panel D). Columns 1 to 4 of Table 2 present formal time-series regressions of these associations (see Equation 1).

[Insert Figure 4 here]

[Insert Table 2 here]

$$ESIX_t = \alpha + \beta \cdot Macro\ variable_t + \epsilon_t \tag{1}$$

Figure 4 paints a clear picture that helps explain the historical patterns in EIX and SIX. During periods of internal economic strife indicated by high volatility in real GDP growth, high unemployment, frequent recessions, and high wealth inequality, public discourse focuses more on social externalities such as inequality and discrimination (i.e., high SIX), rather than on environmental problems (i.e., low EIX). In particular, SIX very closely tracks wealth inequality measured as the top 1%'s share of total household wealth (see Piketty et al., 2018). In contrast, the stabilization of the economy and society is followed by a shift in public focus to environmental issues, elevating EIX to higher levels.

Table 2 shows that these relations are statistically and economically significant. Columns 2 to 4 show that EIX is negatively and significantly associated with unemployment, recession period dummies, and wealth inequality, whereas SIX is positively and significantly associated with all of these variables. Column 1 shows that EIX is negatively associated with real GDP growth, indicating that public concerns regarding the environment rises in a maturing economy and slowing growth.

Figure 5 and Table 2 (Columns 5 to 9) further examine the relationships between ESIX and several sources of political frictions. These results show that political polarization based on congressional votes (both House and Senate) and the news-based partisan conflict index by Azzimonti (2018) are both positively and significantly correlated with EIX. On the other hand, their relationships with SIX are mixed, exhibiting negative associations during the pre-1970 sample but positive associations post-1970. Corroborating the validity of ESIX, our indices closely track a news-based climate policy uncertainty index by Gavriilidis (2021). This is consistent with the idea that the recently positive associations between the EIX/SIX and political frictions may be due to rising contention over environmental and social policy issues.

[Insert Figure 5 here]

Unlike internal political conflicts, external geopolitical risks are not as closely linked to ESIX. Although Column 9 of Table 2 shows that EIX (SIX) is negatively (positively) associated with the news-based geopolitical risk measure by Caldara and Iacoviello (2022), visual inspection of Figure 5 (Panel D) suggests that these statistical associations are mainly driven by World Wars I and II.

3.3 ESIX Exposure and Stock Returns

Armed with a macro-founded validation of ESIX, we next apply our measure to examine the relationship between corporate responsibility and asset prices as a first-order question. We do this by measuring firms' exposures to ESIX, and testing whether firms with higher or lower ESIX exposure earn higher or lower stock returns.

An underlying assumption of this exercise is that a firm is likely to be environmentally and/or socially (ir)responsible if its stock co-moves positively (negatively) with public attention to environmental and social issues in business and the economy. This is motivated by recent studies that theoretically and empirically show that shocks to green preferences – and thus the demand for green assets – explain the return premium of green over brown investments (see Pastor et al., 2021, 2022; Pedersen et al., 2021). If innovations in ESIX can be interpreted as common shocks to ESG preferences, we can interpret their correlation with a stock's returns (i.e., ESIX exposure) as a demand-based proxy for the issuing firm's ESG profile. ESIX exposure not only provides unprecedented time-series coverage, but is also free of arbitrary selection of specific aspects of ESG that result in ambiguity and disagreement that are prevalent across third-party ESG ratings (see Berg et al., 2021, 2022, 2023).

We measure stock-month level ESIX exposure by estimating a five-year rolling window regression of the stock's return in excess of the risk-free rate, on the Fama and French (1993) three-factor model augmented with monthly innovations in ESIX as an additional factor (see Equation 2). The beta coefficient on the ESIX innovation term, or ESIX-beta, as our measure of ESIX exposure.

$$r_{i,t} - rf_t = \alpha_i + \beta_i \cdot \Delta ESIX_t + \gamma_i \cdot [rm_t - rf_t] + \delta_i \cdot SMB_t + \eta_i \cdot HML_t + \epsilon_{i,t} \tag{2}$$

We start by inspecting ESIX exposures in different industries over different time periods. As the context of ESG and corporate responsibility changes over time, so will the universe of firms that are most positively or negatively impacted by changes in public concerns about such issues. We summarize this evolution by tabulating the Fama-French 30 industries that consisted of the most firms in the highest and lowest ESIX exposure decile groups over the past five two-decade periods (i.e., 1930–1949, 1950–1969, ... , 2010–present).[6]

[Insert Table 3 here]

The summary is reported in Table 3, which illustrates how the set of industries affected by public concerns about environmental and social issues have shifted over time. Panel A to C each show the top and bottom three industries in terms of exposures to ESIX, EIX, and SIX, respectively. Panel B, for example, demonstrates that fossil fuel and other greenhouse gas emitting industries have increasingly become negatively exposed to EIX (i.e., their stocks perform poorly when the public is more concerned about environmental issues). Panel C also shows that industries that were at the center of labor disputes and protests in the late 19th

[6]The sample period is restricted to after 1930 due to the availability of stock returns from CRSP.

and early 20th century, such as textiles and steel works, were among the industries most negatively exposed to SIX during those historical periods. Overall, the firm-level exposures derived from our indices produce sensible patterns that successfully capture historical context.

We now examine whether stocks with greater ESIX exposure command higher or lower future returns. We run regressions of monthly stock returns on ESIX exposures, obtained from five-year rolling regressions as detailed above (see Equation 3). ESIX exposure estimated over the five-year window ending month $t-1$ is used to explain returns in month t. The regressions are run on the full sample period from February 1931 to January 2023, and also on subsamples covering the pre-1970 and post-1970 periods. We include a vector of standard control variables, denoted as $\mathbf{X}$, including lagged values of firm size (i.e., market capitalization), lagged monthly returns, past twelve months' returns skipping a month (i.e., momentum), past three year's monthly returns skipping a year (i.e., reversal), idiosyncratic volatility computed from daily residuals from the Fama and French (1993) three-factor model estimated over the previous twelve months, and the average bid-ask spread.[7] We include stock and month fixed effects, and cluster standard errors at the stock level.

$$r_{i,t} = \beta \cdot ESIX\ exposure_{i,t-1} + \gamma' \cdot \mathbf{X}_{i,t-1} + \eta_i + \theta_t + \epsilon_{i,t} \tag{3}$$

[Insert Table 4 here]

The results are reported in Table 4. Panel A uses the raw continuous exposures as explanatory variables, while Panel B uses dummy variables indicating whether exposure is positive. Throughout all sample periods, we find no evidence that positive exposure to the overall ESIX measure is associated with higher future stock returns. If anything, we find that positive exposure hurts stock performance when the index level is low. For example, in the pre-1970 period when the level of EIX is low, stocks with more positive exposure

[7] In untabulated analysis, we also add book-to-market, profitability, asset growth, and accruals, which restricts our sample period to the post-1960 period due to the availability of fundamentals data. The coefficients we obtain for the ESIX exposures remain identical to those from our baseline post-1970 regression.

to EIX tend to perform worse. Similarly, in the post-1970 period when SIX is low, stocks more positively exposed to SIX tend to under-perform. Moreover, this under-performance is not compensated for during times of high index levels: Stocks with positive exposures to EIX (SIX) perform no better than other stocks even when the index level is high during the (pre-) post-1970 period. These results suggest that it costs more than it pays to invest in stocks with positive ESIX-betas: These stocks do poorly when public discourse does not focus on environmental or social issues, and they do not do particularly well even when public concerns on these issues are elevated.

[Insert Figure 6 here]

This is also shown in Figure 6, which plots the cumulative return on a portfolio strategy that, each month, longs the top decile of stocks and shorts the bottom decile of stocks sorted on their previous month's ESIX exposures. The figure illustrates detailed time-series variation in the profitability of such an "ESG investing" strategy. Consistent with the regression results in Table 4, Panel A of Figure 6 shows that the strategy does not deliver positive returns over the very long-run (i.e., entire sample period) nor over the pre-1970 or post-1970 sub-periods. Panel B shows that a EIX-beta long-short strategy has negative cumulative returns in the pre-1970 era, while also failing to generate positive cumulative returns in the post-1970 era. The latter is due to the fact that even long periods of good EIX-beta performance (e.g., decade-long periods in the 1980s or 2000s) are followed by sharp and large reversals (e.g., early 1990s or early 2010s). Panel B also shows that a SIX-beta long-short strategy delivers flat returns before 1970 and performs negatively after 1970.

Overall, a first-pass application of our ESIX methodology casts doubt on the often-debated idea that "companies can do well by doing good, *in the long-run*".

3.4 ESIX and Corporate Investments

An equally important first-order question is whether public concerns about environmental and social externalities have real effects on the decisions of firms. As one of the most important decisions made by firms, we examine corporate investments.

On one hand, heightened public interest in corporate responsibility may require firms to invest more in creating socially equitable organizations or environmentally friendly products, to satisfy investors and customers who exhibit strong ESG preferences or to comply with changing regulatory requirements. However, these areas may not necessarily be where the best growth opportunities reside, meaning that such changes in investments may be inefficient. On the other hand, greater concerns about environmental and social externalities created by businesses may curtail economic activity and therefore suppress investment. For example, recent studies show that environmental regulatory scrutiny impacts firms' resource allocation decisions (see Bartram, Hou, and Kim, 2022).

We first examine whether higher levels of ESIX are associated with greater or smaller corporate investments. To do this, we run regressions of corporate investments, measured as capital expenditures scaled by lagged assets, on lagged values of ESIX and/or its year-to-year innovations (see Equation 4). Alternatively, we regresss investments on the components of ESIX, namely EIX or SIX and/or their innovations. We control for a vector of firm controls, denoted $\mathbf{X}$, including Tobin's q, return on assets (ROA), long-term debt as a fraction of assets, and firm size measured as the log of total assets. We also control for firm and industry-by-*decade* fixed effects. Standard errors are clustered at the firm level.

$$\frac{Capex_{i,t}}{Assets_{i,t-1}} = \beta_1 \cdot ESIX_{t-1} + \beta_2 \cdot \Delta ESIX_{t-1} + \gamma' \cdot \mathbf{X}_{i,t-1} + \eta_i + \theta_{j,[t-10 \to t-1]} + \epsilon_{i,t} \tag{4}$$

[Insert Table 5 here]

The results are reported in Panel A of Table 5. The key takeaway is that higher levels of ESIX are associated with significantly lower investments, and that this is primarily driven by

EIX rather than by SIX. These indicate that heightened environmental concerns are particularly not conducive of business activity. Controlling for Tobin's q and industry-by-decade fixed effects mitigate concerns that the reduction in investments may be driven by worsening investment opportunities, or by the long-run transition from the pre-war to post-war era that coincided with a structural shift in economic stability and prosperity.

Next, we further examine whether increases in ESIX are associated with changes in investment efficiency. To test this, we augment the investment regressions by further interacting ESIX with Tobin's q, while retaining Tobin's q as a standalone control variable (see Equation 5). In these tests, we include more granular fixed effects at the firm and industry-by-*year* levels, the latter subsuming the time-series ESIX variable.

$$
\begin{aligned}
\frac{Capex_{i,t}}{Assets_{i,t-1}} = \beta_1 \cdot ESIX_{t-1} \times Tobin's\ q_{i,t-1} + \beta_2 \cdot \Delta ESIX_{t-1} \times Tobin's\ q_{i,t-1} \\
+ \gamma' \cdot \mathbf{X}_{i,t-1} + \eta_i + \theta_{j,t} + \epsilon_{i,t}
\end{aligned}
\tag{5}
$$

Panel B of Table 5 reports the results. Higher levels of ESIX and greater increases in ESIX are both associated with a decrease in investment efficiency. The negative and significant coefficients on the interaction terms throughout most specifications indicate that the positive link between corporate investments and Tobin's q is substantially weakened. The one exception is the interaction term between the *level* of EIX and q, which has a positive coefficient. This contrasts with the negative coefficient on the interaction term between the *change* in EIX and q. One explanation for this could be that the *level* of EIX reveals information about which investment opportunities are compliant with new regulatory frameworks, whereas *changes* in EIX reflect regulatory uncertainty and confusion about the viability of growth options. Therefore, while greater *changes* in EIX make investments more inefficient, higher *levels* of EIX may result in smaller but more targeted investments.

Overall, these results are consistent with a negative impact of public ESG concerns on corporate investment and investment efficiency.

4 Conclusion

Leveraging recent developments in natural language processing (NLP) techniques and applying them to an extensive corpus of historical news text, we construct a historical time-series index dating back to late 19th century, ESIX, that measures public attention to environmental and social issues related to business and the economy. Our approach incorporates the evolution of linguistic context over time, enabling ESIX to reflect different aspects of environmental and social concerns that were prevalent in different points of time. We also derive stock-month level ESIX exposures that provide demand-based proxies for corporate ESG profiles. Our methodology is inoculated from subjective judgement regarding which topics should be included in the index during different periods, and also free of arbitrary selection of topics that result in widespread ambiguity and disagreement across third-party ESG ratings.

We validate the ESIX measure by relating it to macroeconomic variables and inspecting how industries with high or low ESIX exposures have shifted throughout history. We also use ESIX to study the value implications of ESG, and investigate how changes in public concerns about corporate responsibility impact real firm decisions such as their investments.

We find that public attention to social issues arise during times of internal economic and social instability, whereas attention to environmental issues are afforded during times of relative prosperity. We also find evidence from stock return analysis that casts doubt on the notion that corporate responsibility creates value in the long-run. Finally, our results suggest that heightened environmental and social concerns dampen business activity, and that social concerns in particular erode corporate investment efficiency.

Our findings provide researchers with new tools to study long time-series developments in topics related to ESG. We also shed new light on our understanding of the implications of ESG from a historically informed perspective.

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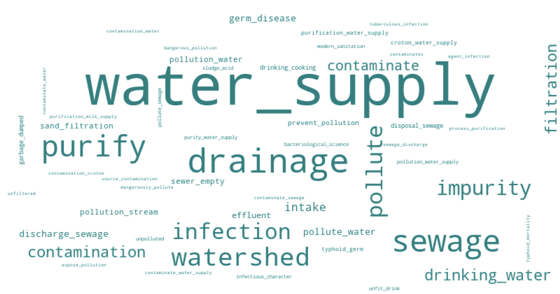
Figure 1. Evolving Context

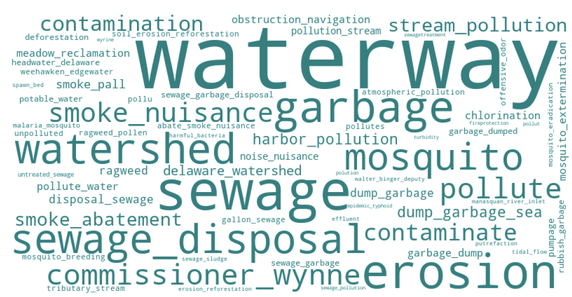
This figure presents decade-specific word clouds of the top 100 keywords generated from the seed words "*Pollution*" (Panel A), "*discrimination*" (Panel B), and "*inequality*" (Panel C) through decade-specific Word2Vec models.

Panel A. Keywords related to "*Pollution*"

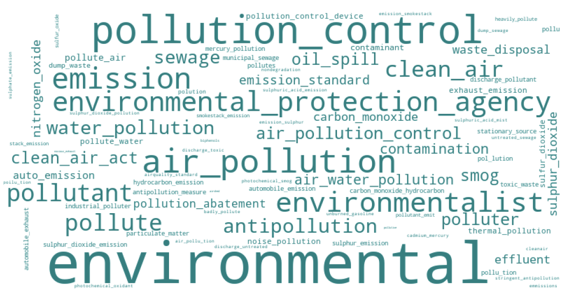
1890-1899



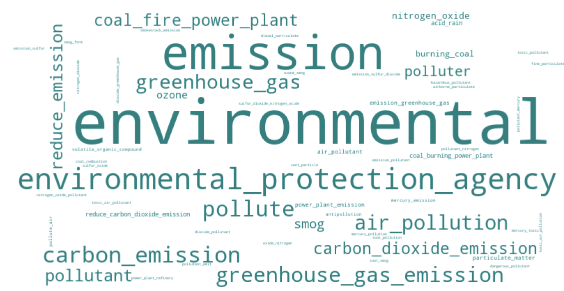
1930-1939



1970-1979



2010-2019



Panel B. Keywords related to "*Discrimination*"

1890-1899

1930-1939

1970-1979

2010-2019

Figure 1. Evolving Context (continued)

Panel C. Keywords related to "*Inequality*"

1890-1899

1930-1939

1970-1979

2010-2019

Figure 2. Methodology

This figure illustrates our methodology of constructing the ESIX measure by training decade-specific Word2Vec models on historical news text from the Wall Street Journal (WSJ) and New York Times (NYT), and using the models to span time-varying ESG dictionaries from time-invariant seed words.

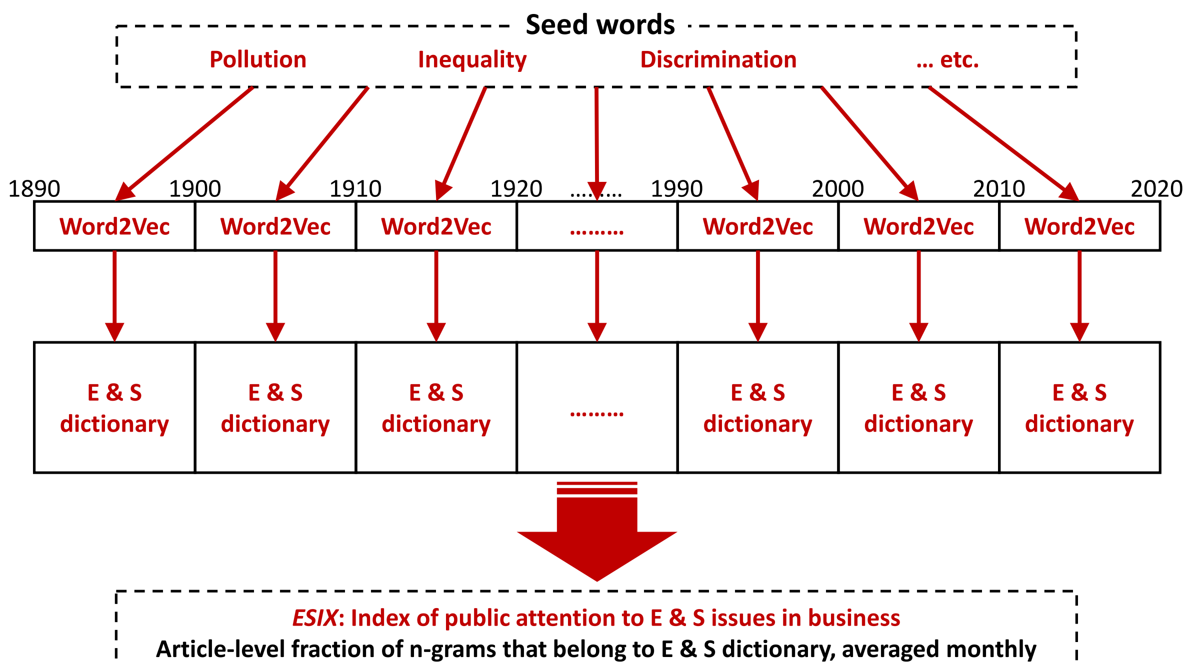
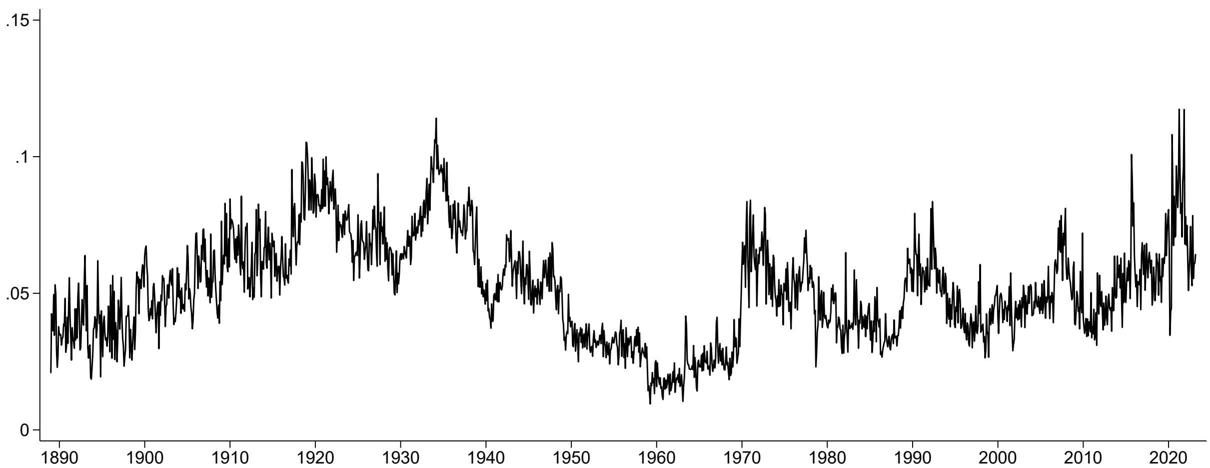


Figure 3. The ESIX Measure

This figure plots the historical monthly time-series of ESIX (Panel A) and its components, EIX and SIX (Panel B).

Panel A. Overall ESIX



Panel B. EIX and SIX

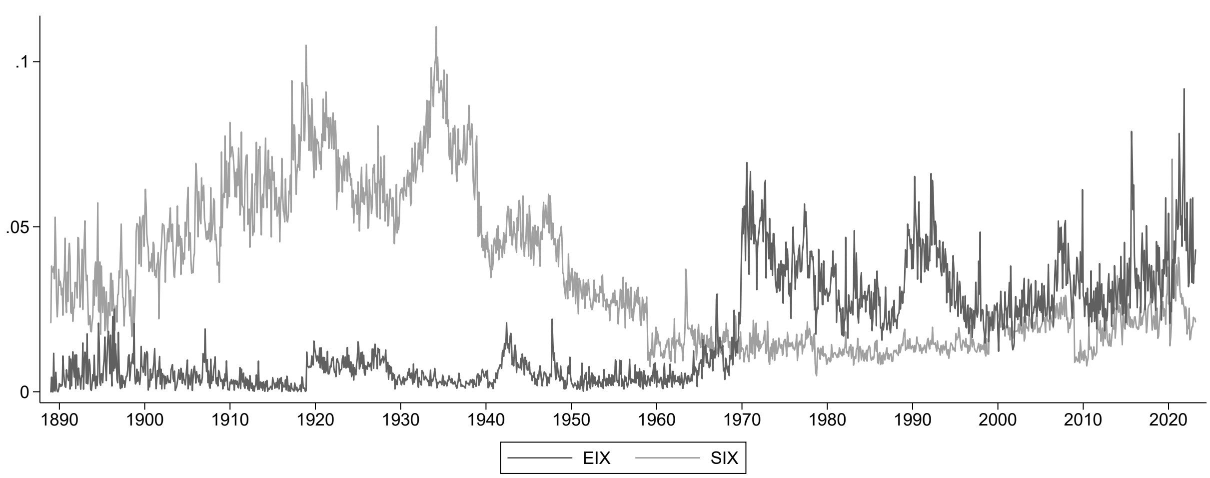
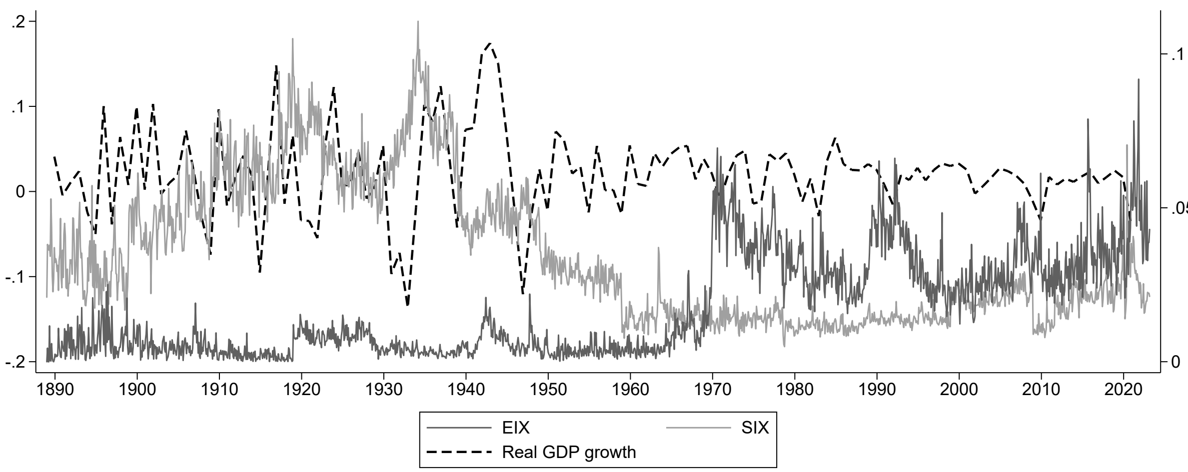


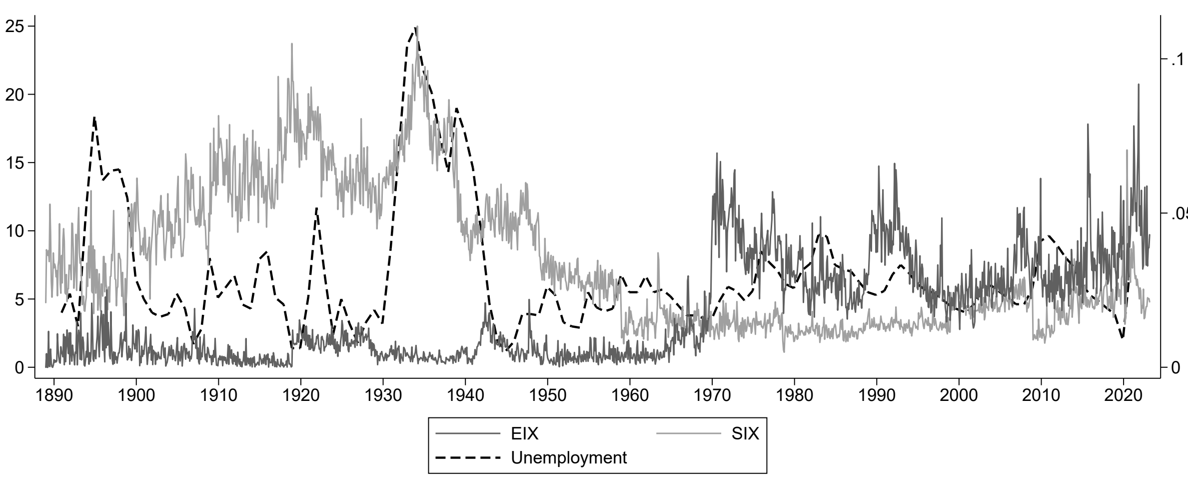
Figure 4. ESIX and Macroeconomic Conditions

This figure plots the historical monthly time-series of EIX and SIX, together with annual real GDP growth (Panel A), unemployment (Panel B), NBER recession dummies (Panel C), and wealth inequality (Panel D).

Panel A. Real GDP growth



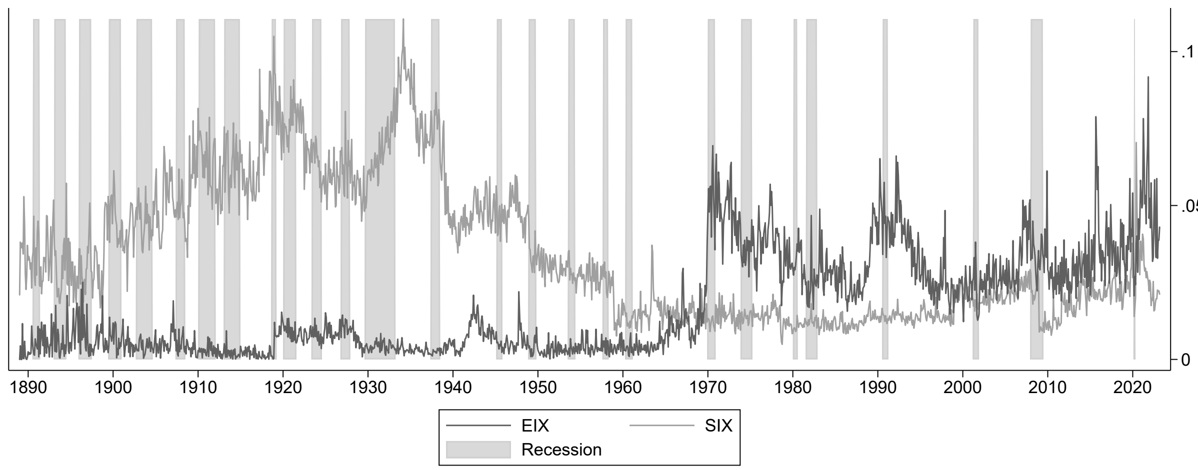
Panel B. Unemployment



(continued)

Figure 4. ESIX and Macroeconomic Conditions (continued)

Panel C. Recessions



Panel D. Wealth inequality

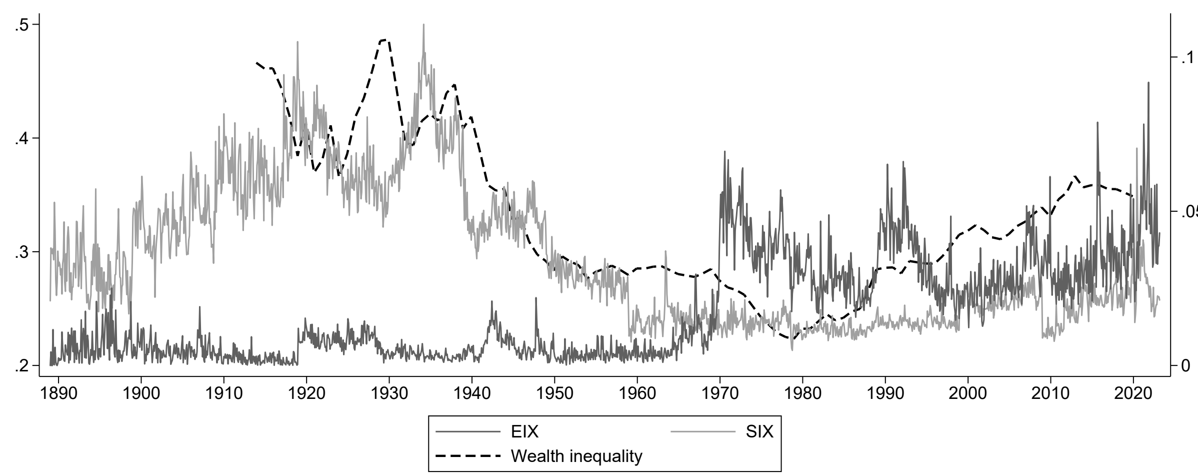
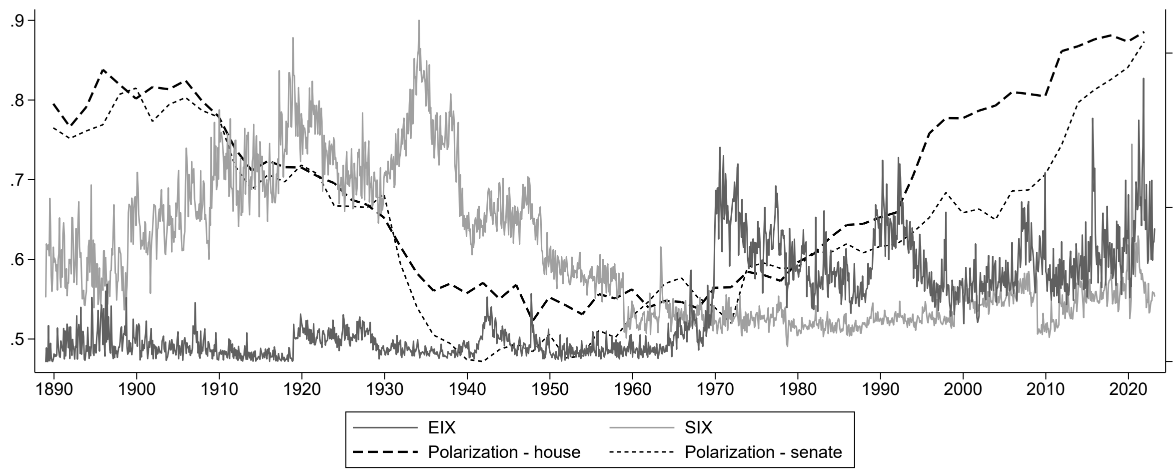


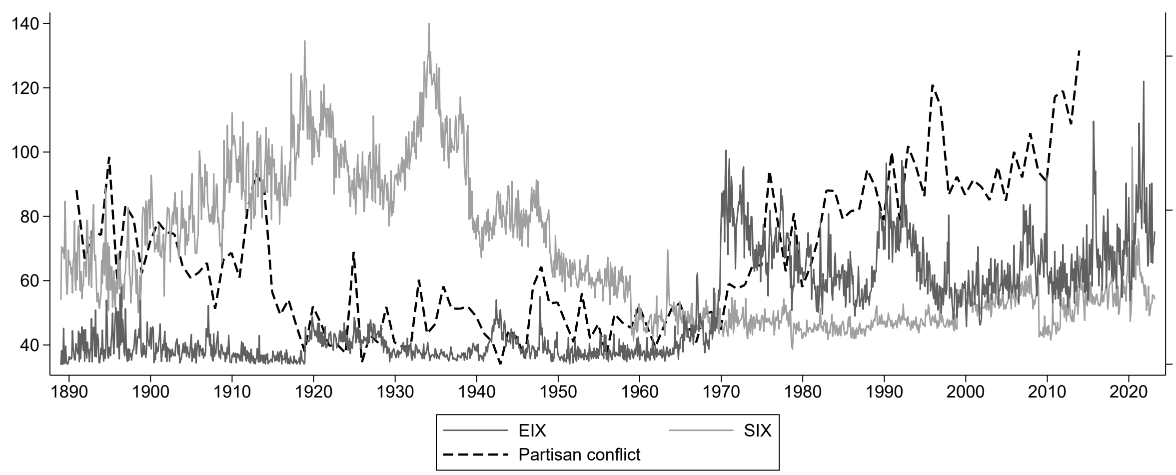
Figure 5. ESIX and Political Frictions

This figure plots the historical monthly time-series of EIX and SIX, together with congressional political polarization (Panel A), partisan conflict (Panel B), climate policy uncertainty (Panel C), and geopolitical risk (Panel D).

Panel A. Political polarization



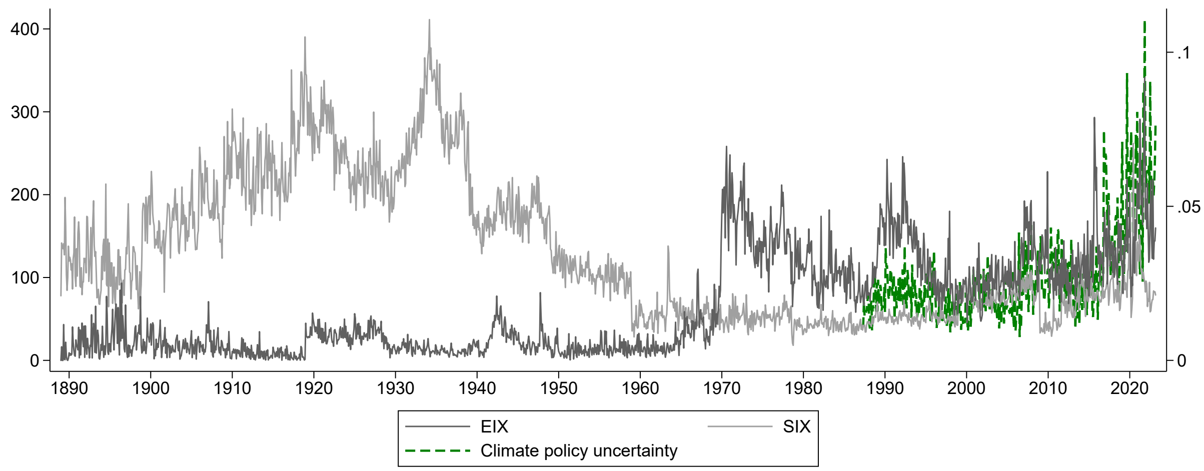
Panel B. Partisan conflict



(continued)

Figure 5. ESIX and Political Frictions (continued)

Panel C. Climate policy uncertainty



Panel D. Geopolitical risk

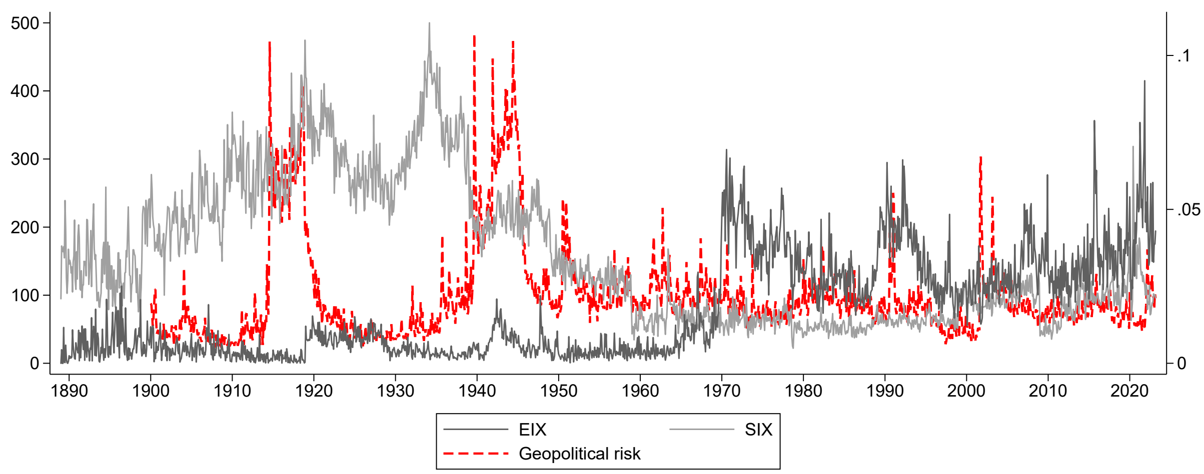
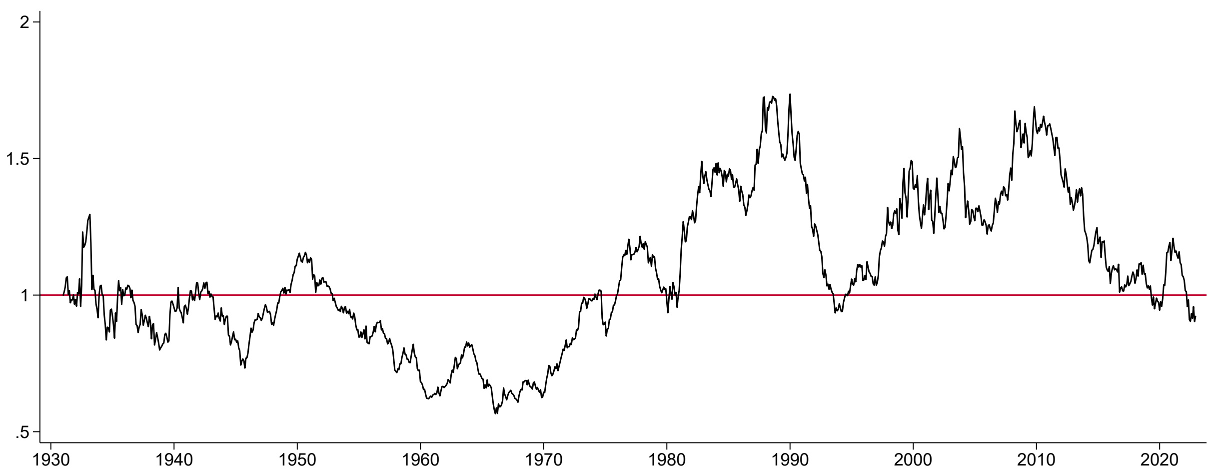


Figure 6. The Value of Exposure to ESIX

This figure plots the cumulative return on a portfolio strategy that, each month, longs the top decile of stocks and shorts the bottom decile of stocks sorted on their previous month's ESIX exposures. Stock-month level ESIX exposure is the ESIX-beta computed from five-year rolling window regressions of the stock's return in excess of the risk-free rate, on the Fama and French (1993) three-factor model augmented with monthly innovations in ESIX as an additional factor.

Panel A. Overall ESIX



Panel B. EIX and SIX

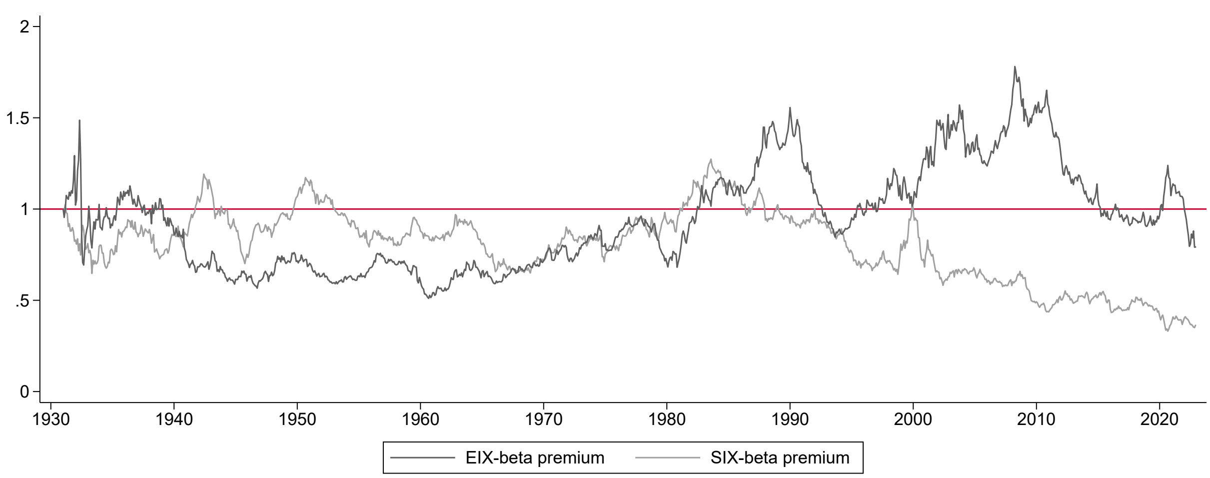


Table 1. Summary Statistics

This table presents time-series summary statistics (i.e., Mean, standard deviation, minimum, 25th percentile, median, 75th percentile, maximum) of ESIX, EIX, and SIX. The table also presents minimum and maximum values of ESIX, EIX, and SIX for the pre-1970 and post-1970 subperiods.

								Pre-1970		Post-1970	
	Mean	Std.dev.	Min	25th	Median	75th	Max	Min	Max	Min	Max
ESIX	0.05	0.02	0.01	0.04	0.05	0.06	0.12	0.01	0.11	0.02	0.12
EIX	0.02	0.02	0.00	0.00	0.01	0.03	0.09	0.00	0.04	0.01	0.09
SIX	0.03	0.02	0.00	0.02	0.03	0.05	0.11	0.01	0.11	0.00	0.07

Table 2. ESIX and Macroeconomic Conditions

This table presents results from time-series regressions of ESIX (Panel A), EIX (Panel B), and SIX (Panel C) on macroeconomic and political variables. These variables include real GDP growth, unemployment, NBER recession dummies, wealth inequality, congressional polarization at the House and Senate, partisan conflict, climate policy uncertainty, and geopolitical risk. Heteroskedasticity-robust standard errors are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

	Real GDP growth	Unemployment	Recession	Wealth inequality	Polarization		Partisan conflict	Climate policy uncertainty	Geopolitical risk
					House	Senate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Dependent variable: ESIX									
Macro variable	-0.020**	0.001***	0.006***	0.172***	0.029***	0.033***	-0.000***	0.000***	-0.000
	(0.010)	(0.000)	(0.001)	(0.007)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)
Adj R^2	0.002	0.054	0.017	0.360	0.029	0.036	0.024	0.267	-0.001
Panel B. Dependent variable: EIX									
Macro variable	-0.016**	-0.000***	-0.007***	-0.109***	0.035***	0.027***	0.000***	0.000***	-0.000***
	(0.006)	(0.000)	(0.001)	(0.004)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)
Adj R^2	0.002	0.016	0.035	0.211	0.059	0.032	0.282	0.193	0.027
Panel C. Dependent variable: SIX									
Macro variable	-0.004	0.001***	0.013***	0.281***	-0.006	0.006	-0.000***	0.000***	0.000***
	(0.013)	(0.000)	(0.001)	(0.006)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)
Adj R^2	-0.001	0.075	0.058	0.623	0.000	0.000	0.219	0.122	0.011
Observations	1,584	1,572	1,611	1,284	804	804	1,488	432	1,479

Table 3. Which Industries are Most Exposed to ESIX?

This table reports the three Fama-French 30 industries with the highest and lowest average ESIX exposures over five two-decade sub-periods throughout our sample (i.e., 1930–1949, 1950–1969, ... , 2010–present).

	1930-1949	1950-1969	1970-1989	1990-2009	2010-present
Panel A. ESIX exposure					
Positive 1	Restaurants, hotels, motels	Coal	Restaurants, hotels, motels	Metals & non-metallic mining	Beer & liquor
Positive 2	Transportation	Banking & finance	Automobiles & trucks	Automobiles & trucks	Communication
Positive 3	Personal & business services	Textiles	Wholesale	Personal & business services	Business equipment
⋮	⋮	⋮	⋮	⋮	⋮
Negative 3	Textiles	Food	Tobacco	Tobacco	Textiles
Negative 2	Business supplies & containers	Aircraft, ships, & railroad	Coal	Healthcare	Tobacco
Negative 1	Healthcare	Printing & publishing	Beer & liquor	Coal	Coal
Panel B. EIX exposure					
Positive 1	Coal	Restaurants, hotels, motels	Wholesale	Restaurants, hotels, motels	Beer & liquor
Positive 2	Recreation	Communication	Restaurants, hotels, motels	Metals & non-metallic mining	Communication
Positive 3	Utilities	Metals & non-metallic mining	Automobiles & trucks	Recreation	Business equipment
⋮	⋮	⋮	⋮	⋮	⋮
Negative 3	Retail	Printing & publishing	Beer & liquor	Electrical equipment	Steel works
Negative 2	Business supplies & containers	Coal	Coal	Healthcare	Tobacco
Negative 1	Beer & liquor	Business equipment	Tobacco	Coal	Coal
Panel C. SIX exposure					
Positive 1	Restaurants, hotels, motels	Coal	Petroleum & natural gas	Beer & liquor	Tobacco
Positive 2	Transportation	Banking & finance	Restaurants, hotels, motels	Textiles	Healthcare
Positive 3	Personal & business services	Electrical equipment	Metals & non-metallic mining	Communication	Printing & publishing
⋮	⋮	⋮	⋮	⋮	⋮
Negative 3	Business supplies & containers	Steel works	Beer & liquor	Construction	Apparel
Negative 2	Textiles	Food	Banking & finance	Tobacco	Food
Negative 1	Healthcare	Aircraft, ships, & railroad	Communication	Coal	Textiles

Table 4. ESIX and Stock Returns

This table presents results from regressions of monthly stock returns on lagged values of ESIX/EIX/SIX exposures. Exposures are obtained from five-year rolling regressions of the stock's return in excess of the risk-free rate, on the Fama and French (1993) three-factor model augmented with monthly innovations in ESIX as an additional factor. Panel A uses the raw exposures as continuous explanatory variables. Panel B uses dummy variables indicating whether exposure is positive as explanatory variables. Regressions are estimated on the full sample period from February 1931 to January 2023, and also on separate subsamples for the pre-1970 and post-1970 periods. Standard control variables are included, including lagged values of firm size (i.e., market capitalization), lagged monthly stock return, past twelve months' returns skipping a month, past three year's monthly returns skipping a year, idiosyncratic volatility computed from daily residuals of the Fama and French (1993) three-factor model estimated over the previous twelve months, and the average bid-ask spread. Stock and month fixed effects are included. Standard errors are clustered at the stock level (*** p<0.01, ** p<0.05, * p<0.1).

Panel A. Continuous exposures

	Dependent variable: Monthly stock return					
	Full sample period		Pre-1970		Post-1970	
	(1)	(2)	(3)	(4)	(5)	(6)
ESIX exposure	-0.002		-0.001		-0.002	
	(0.002)		(0.003)		(0.003)	
EIX exposure		-0.000		-0.063***		0.001
		(0.003)		(0.018)		(0.003)
SIX exposure		-0.007***		0.001		-0.009***
		(0.002)		(0.003)		(0.002)
Observations	1,817,883	1,817,883	246,322	246,322	1,571,559	1,571,559
Stock FE	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y
Stock controls	Y	Y	Y	Y	Y	Y
Adj R^2	0.136	0.136	0.390	0.390	0.109	0.109

Panel B. Positive exposure dummies

	Dependent variable: Monthly stock return					
	Full sample period		Pre-1970		Post-1970	
	(1)	(2)	(3)	(4)	(5)	(6)
I(*ESIX* exposure>0)	-0.000		-0.000		-0.000	
	(0.000)		(0.001)		(0.000)	
I(*EIX* exposure>0)		-0.000		-0.002***		-0.000
		(0.000)		(0.001)		(0.000)
I(*SIX* exposure>0)		-0.001**		0.000		-0.001**
		(0.000)		(0.001)		(0.000)
Observations	1,818,367	1,818,367	246,806	246,806	1,571,559	1,571,559
Stock FE	Y	Y	Y	Y	Y	Y
Year-by-month FE	Y	Y	Y	Y	Y	Y
Stock controls	Y	Y	Y	Y	Y	Y
Adj R^2	0.136	0.136	0.390	0.390	0.109	0.109

Table 5. ESIX and Corporate Investments

This table presents results from firm-year panel regressions of corporate investments (i.e., capital expenditures scaled by lagged assets). In Panel A, investments are regressed on lagged values of yearly average ESIX, EIX, SIX, and the yearly changes (denoted by Δ) in ESIX, EIX, and SIX. Control variables include lagged values of Tobin's q, return on assets (ROA), long-term debt over assets (Debt), log of total assets (Size), as well as firm and industry-by-decade fixed effects. In Panel B, ESIX, EIX, SIX, ΔESIX, ΔEIX, and ΔSIX are interacted with lagged Tobin's q, and industry-by-decade fixed effects are replaced by industry-by-year fixed effects. Standard errors are clustered at the firm level (*** p<0.01, ** p<0.05, * p<0.1).

Panel A. ESIX and corporate investments

	Dependent variable: Capital expenditures$_t$/Assets$_{t-1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
ESIX	-0.085***				-0.081***	
	(0.025)				(0.025)	
Δ*ESIX*		-0.027*			-0.018	
		(0.017)			(0.017)	
EIX			-0.098***			-0.096***
			(0.029)			(0.030)
SIX			-0.015			-0.004
			(0.084)			(0.090)
Δ*EIX*				-0.028*		-0.015
				(0.017)		(0.017)
Δ*SIX*				-0.026		-0.033
				(0.033)		(0.036)
Tobin's q	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Debt	-0.031***	-0.032***	-0.031***	-0.032***	-0.031***	-0.031***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Size	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	202,664	202,664	202,664	202,664	202,664	202,664
Firm FE	Y	Y	Y	Y	Y	Y
Industry-by-decade FE	Y	Y	Y	Y	Y	Y
Adj R^2	0.420	0.420	0.420	0.420	0.420	0.420

(continued)

Table 5. ESIX and Corporate Investments (continued)

Panel B. ESIX and investment-q sensitivity

	Dependent variable: Capital expenditures$_t$/Assets$_{t-1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
ESIX × Tobin's q	-0.085***				-0.070***	
	(0.018)				(0.018)	
Δ*ESIX* × Tobin's q		-0.073***			-0.058**	
		(0.027)			(0.027)	
EIX × Tobin's q			0.072**			0.094***
			(0.030)			(0.032)
SIX × Tobin's q			-0.517***			-0.543***
			(0.057)			(0.077)
Δ*EIX* × Tobin's q				-0.066**		-0.057**
				(0.026)		(0.026)
Δ*SIX* × Tobin's q				-0.096**		0.056
				(0.040)		(0.055)
Tobin's q	0.018***	0.014***	0.021***	0.014***	0.017***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.021***	0.021***	0.021***	0.021***	0.021***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Debt	-0.028***	-0.028***	-0.027***	-0.028***	-0.028***	-0.027***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Size	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	202,657	202,657	202,657	202,657	202,657	202,657
Firm FE	Y	Y	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y	Y	Y
Adj R^2	0.437	0.437	0.437	0.437	0.437	0.437