Sentiment and Environmental Performance*

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Abstract

We identify a novel behavioral driver of environmental performance. An increase in country-level consumer sentiment leads to sustained reduction in emission intensity over a multiyear horizon. Since consumer sentiment increases investment, productivity, energy efficiency, and stock market returns, a plausible explanation is that firms can afford to engage in costly reduction of emissions in a buoyant market. The effect tapers off over time and is stronger in countries where sentiment is a more reliable signal for the state of the economy. Our results suggest that policies boosting economic expectations yield substantial environmental benefits.

JEL classification: E20, G41, Q50, F36, F43.

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1. Introduction

Recent literature identifies several key behavioral drivers of environmental performance, such as a preference for green assets or products (Pástor *et al*. (2021); Zerbib (2022)), political orientation (Edmans and Kacperczyk (2022)), and attention to climate news (Pástor *et al*. (2022); Ardia *et al*. (2023)). In this paper, we explore a novel mechanism. Building on different channels through which sentiment affects macroeconomic outcomes (Akerlof and Shiller (2009); Barsky and Sims (2012); Benhabib *et al*. (2015)), we explore the relation between country-level sentiment and emission intensity.

There are three competing theories about this relation. First, if sentiment merely boosts short-term output without affecting productive capacity (Akerlof and Shiller (2009); Barsky and Sims (2012)), we should observe no change in emission intensity as emissions and GDP would move proportionally. Second, if sentiment enhances productivity and innovation (Benhabib *et al*. (2015); Acharya *et al*. (2021); Constantinides *et al.* (2025)), it should be followed by lower emission intensity as economies become more efficient. Third, if optimistic agents systematically downplay risks (Puri and Robinson (2007); Ben-David *et al*. (2013)), including climate risks (Gifford (2011); Beattie *et al*. (2017)), we should observe higher emissions as economic actors rely more heavily on fossil fuels during optimistic periods.

Using a large cross-country sample from the OECD, we find strong support for the productivity channel. We find that higher country-level sentiment is associated with lower emission intensity, defined as either greenhouse gas emissions or carbon dioxide normalized by a country's GDP. The magnitude is economically meaningful, with a one-standard-deviation increase in sentiment reducing emission intensity by approximately 6-7% within the same year, representing roughly 10% of the sample mean. This relation persists across numerous robustness checks and alternative econometric specifications.

The effect is largest contemporaneously and tapers off gradually over subsequent years. This waning effect is consistent with a genuine sentiment shock, sharply contrasting with the strengthening pattern expected if sentiment merely proxies for anticipated long-run economic fundamentals (*e.g*., Beaudry *et al*. (2011); Colacito *et al*. (2018)). While existing literature attributes environmental performance gains to technological improvement and capital investment (*e.g*., Levinson (2009); Shapiro and Walker (2018)), our paper is the first to show that this structural mechanism is activated through the behavioral channel of sentiment.

We acknowledge that high sentiment may partly reflect past improvements in environmental performance (*e.g*., Levy and Yagi (2011); Heyes *et al.* (2016)). To address this issue, we use an instrumental variables strategy based on national soccer team performance.

Sports outcomes plausibly affect national mood and consumer confidence without directly influencing environmental performance or energy infrastructure decisions. This approach builds on established evidence that sports results affect stock returns (Edmans *et al.* (2007); Kaplanski and Levy (2010); Palomino *et al.* (2009)), economic growth (Berument and Yucel (2005); Falter *et al.* (2008)), and various non-sports decisions (Card and Dahl (2011); Healy *et al.* (2010)), while offering several advantages over alternative instruments like weather patterns (Hirshleifer and Shumway (2003)). Notably, soccer results do not directly affect energy production or usage patterns, and national team performance provides uniform sentiment shocks within countries regardless of their geographical size.

Our first-stage results confirm that soccer sentiment, measured through FIFA world rankings, strongly predicts consumer sentiment, with the F-statistics well above conventional thresholds and the highest Stock-Yogo critical values for instrument strength. The second-stage estimates closely align with our baseline OLS results in both magnitude and significance, suggesting that non-fundamental sentiment genuinely drives environmental outcomes. We further validate this instrument by showing that the effect concentrates in countries where soccer is more popular, consistent with our sports sentiment identification.

We also examine whether local sentiment reflects foreign sentiment to some extent, either global or from the US (Baker *et al.* (2012); Montone and Zwinkels (2020)). In horse race regressions including measures of G7 or OECD sentiment, we find that local sentiment retains its explanatory power while global sentiment measures prove insignificant. We find similar results when we include US sentiment. However, we find evidence of a conditional channel: in countries with stronger US foreign direct investment ties, US sentiment does predict lower local emission intensity in its own right. These results indicate both local and US channels contribute to emission reductions, consistent with recent findings on the international transmission of US sentiment (Baker *et al.* (2012); Montone and Zwinkels (2020)).

We provide additional insights into our results by looking at cross-sectional patterns. Consistent with the view that sentiment effects are stronger in less stable economies, we document two key results. First, the sentiment-emission relation is substantially weaker in the largest advanced economies, identified as G7 countries (Colacito *et al.* (2018); Huo *et al.* (2025)). This aligns with the idea that these countries' policy coordination yields economic stability (Sobel and Stedman (2006); Cormier *et al.* (2024)), thereby dampening the macroeconomic influence of sentiment (Constantinides *et al.* (2025)). Second, we find more persistent effects in countries where sentiment represents a more reliable signal for the state of the economy, namely those with high GDP growth volatility and low sentiment volatility.

We also exploit a breakdown of greenhouse gas emissions into six major industries, provided by the World Resource Institute's Climate Watch database. We find that our aggregate results are driven primarily by the energy sector which accounts for the bulk of global emissions. Within this sector, electricity and heat generation shows the strongest response to sentiment. Other sectors including agriculture, waste, and industrial processes exhibit smaller and less persistent effects. This sectoral pattern points toward energy efficiency gains as the key mechanism, which we test directly in subsequent analysis.

Consistent with this hypothesized channel, we find that high sentiment significantly reduces both primary energy supply and final energy consumption per unit of GDP. The magnitudes—approximately 10% of sample means—closely match our emission intensity results, providing direct evidence that sentiment improves resource utilization efficiency. These gains are robust to controlling for R&D expenditure, indicating that the sentiment effect operates beyond countries' baseline innovation efforts.

We also directly examine green investment. We find that high sentiment increases the share of renewable energy in total final energy consumption, both contemporaneously and in the following year, with the effect dissipating thereafter. Importantly, this relation exhibits substantial heterogeneity across countries. Drawing on the Global Preference Survey (Falk *et al*. (2018)), we show that the sentiment's effect on green investment is both larger and more persistent in countries characterized by greater long-term orientation (patience) and higher willingness to take risks. Since green technologies typically require high upfront investment with distant payoffs and involve substantial technological uncertainty (Sautner *et al.* (2023); Battiston *et al.* (2025)), countries lacking these cultural traits may not channel sentiment-driven optimism toward green investment as effectively.

The overarching mechanism linking sentiment to environmental outcomes should operate through economic growth and productivity. Supporting this channel, we document that high sentiment is associated with large contemporaneous increases in GDP growth, capital formation, consumption, labor productivity, and stock returns, alongside decreases in unemployment. Crucially, the effects on GDP, consumption, and unemployment fully reverse over subsequent years, whereas those on capital formation, productivity, and stock returns show only partial reversals. These persistent gains in productive capacity align with our earlier findings of sustained improvements in energy efficiency and emission intensity.

The remainder of the paper proceeds as follows. Section 2 discusses related literature in detail. Section 3 describes our data construction and provides summary statistics. Section 4 presents baseline results and robustness tests, examining heterogeneity across country groups and industries. Section 5 tests the energy efficiency and economic growth channels underlying our main findings. Section 6 offers concluding remarks and discusses policy implications.

2. Related literature

Our paper connects two main strands of literature. First, it speaks to previous research on sentiment and macroeconomic outcomes. Second, it contributes to the growing literature on green finance. Below, we present a brief overview of each of them.

2.1 Sentiment and macroeconomic outcomes

A central question in macroeconomics concerns whether sentiment represents rational expectations about future fundamentals or, at least in part, reflects non-fundamental beliefs that independently affect economic activity. The latter view dates to Keynes' (1936) notion of animal spirits and has been formalized in models where sentiment affects aggregate demand and resource allocation. Akerlof and Shiller (2009) argue that psychological factors and narratives drive short-term economic fluctuations independently of fundamentals. Barsky and Sims (2012) provide an alternative interpretation, showing that sentiment innovations may reflect information about future productivity rather than non-fundamental beliefs. Their framework suggests sentiment predicts future output because it captures news, not because it causes irrational behavior.

An alternative view is that sentiment can generate genuine and persistent real effects. Benhabib *et al.* (2015) develop a model where sentiment-driven fluctuations arise from self-fulfilling beliefs about aggregate demand, generating business cycles even without fundamental shocks. Acharya *et al.* (2021) extend this framework to show how sentiment affects both the demand and supply sides of the economy, producing persistent effects on output and productivity. These models predict that sentiment shocks should influence not just short-term activity but also capital accumulation and technological adoption.

This prediction finds increasing empirical support. Constantinides *et al.* (2025) document that consumer sentiment predicts future economic growth and productivity, with particularly strong effects in non-G7 countries where macroeconomic volatility is high and fundamentals are hard to assess. They show these effects persist for multiple years and operate through channels including innovation and capital formation. Constantinides and Montone (2025) further show that sentiment operates through diagnostic expectations—the tendency to overweight recent changes when forming beliefs—producing patterns of initial overreaction and subsequent partial reversal in macroeconomic variables.

In this paper, we provide new evidence on the real effects of sentiment. By documenting sentiment's influence on energy efficiency and emission intensity, we extend beyond traditional macroeconomic outcomes to show that sentiment affects how efficiently economies transform inputs into output. The mechanism we identify, based on sentiment-driven productivity and capital formation, reinforces recent findings that sentiment influences innovation and growth through channels beyond short-term animal spirits.

The investment channel provides a key mechanism linking sentiment to real outcomes. Baker and Wurgler (2006, 2007) show that investor sentiment affects the cross-section of stock returns, with greater impact on securities whose valuations are highly subjective and difficult to arbitrage. Baker *et al.* (2003) find that when managers perceive their equity is overvalued due to high sentiment, they issue more shares and invest more, particularly for equity-dependent firms. Arif and Lee (2014) and Constantinides *et al.* (2025) provide evidence for this mechanism at the aggregate level. This market timing behavior leads to persistent real effects even as sentiment eventually reverts. Our findings align with this mechanism and suggest that sentiment-driven investment has far-reaching implications for the economy, ultimately affecting resource utilization.

2.2 Determinants of environmental performance

A growing literature examines what drives firms and countries to improve their environmental performance. One strand emphasizes preferences. Kitzmueller and Shimshack (2012) survey research on corporate social responsibility, showing that some firms invest in environmental improvements beyond regulatory requirements, potentially due to managerial preferences or stakeholder pressure. Pástor *et al.* (2021) develop a model where investors with green preferences tilt portfolios toward low-emission firms, affecting both asset prices and corporate behavior. Zerbib (2022) shows that sustainable stocks command lower expected returns, consistent with investor preferences for environmental performance. Green preferences then affect environmental outcomes primarily through capital allocation, lowering the cost of capital of low-emission firms and enabling greater investment in clean technologies. This creates market-based incentives for firms to reduce emissions even absent regulation.

Political orientation also affects environmental outcomes. Edmans and Kacperczyk (2022) survey the sustainable finance literature, noting that political preferences influence both regulatory stringency and firm-level environmental choices. The literature documents substantial heterogeneity across countries in environmental policies and outcomes that correlate with political factors. Political orientation affects outcomes through both policy channels—with left-leaning governments implementing stricter environmental regulations—and through corporate responses to stakeholder preferences in politically sensitive contexts.

Attention to climate issues represents another channel. Pástor *et al.* (2022) show that attention to climate news affects green asset pricing, with stronger effects when climate concerns are more salient. Ardia *et al.* (2023) provide evidence that climate change concerns predict the performance differential between green and brown stocks. The attention mechanism operates through salience: when climate issues are prominent in media and public discourse, both investors and managers respond more strongly to climate-related information. This attention-driven mechanism suggests that environmental outcomes may respond to time-varying salience of climate issues, with a correspondingly growing effect in recent years.

A related strand of research examines the link between technological progress and environmental outcomes. Levinson (2009) shows that technological change in US manufacturing substantially reduced pollution intensity, demonstrating that this "technique effect" dominates compositional changes in what is produced. Shapiro and Walker (2018) find that productivity improvements account for a substantial share of emission reductions through cleaner production technologies. Grossman and Krueger (1995) provide earlier evidence for an inverted-U relationship between income and pollution, partly driven by technology adoption. More recent work shows how innovation directs toward clean technologies through policy incentives (Aghion *et al*., 2016) and market forces (Acemoglu *et al*., 2012). Altogether, these papers establish that technological advancement can decouple economic growth from environmental degradation.

Our contribution to this literature is to identify sentiment as a behavioral mechanism that generates cleaner production through productivity-enhancing investments. While factors such as green preferences, political orientation, or climate attention capture specific environmental motivations, we show that broad-based optimism or pessimism about economic prospects influences emission intensity through its effect on productivity and resource utilization efficiency. This channel is important because it speaks to the debate about economic growth and environmental sustainability. The conventional view posits a trade-off between these goals. Our findings challenge this dichotomy, suggesting that policies promoting innovation and productive investment may serve both economic and environmental objectives.

3. Data

Our data consists of a panel of annual observations for 42 countries, covering the period from 1990 to 2018.[1] The main variables used in our analysis are country-level consumer sentiment, retrieved from the OECD database, and several macroeconomic and energy-related indicators, made available by the World Bank. The data on greenhouse gas (GHG) and carbon dioxide (CO2) emission intensity is originally compiled by the World Resource Institute's Climate Watch. The country coverage reflects the availability of country-level consumer sentiment data, whereas the sample period reflects the availability of country-level energy data.

In Table 1, Panel A, we report summary statistics for sentiment and the macroeconomy. Consumer sentiment is measured using the country-level consumer confidence index from the OECD and represents our main independent variable. The sentiment index has a mean of 100.15 and a standard deviation of 1.92, indicating that the series is a relatively stable measure with limited variation around its historical average. The distribution is quite symmetric, with a median value of 100.30 and an interquartile range between 99.09 and 101.34.

Our macroeconomic variables include the growth rates of real GDP, capital formation, and consumption, changes in inflation and unemployment, labor productivity growth, and aggregate real stock returns. To mitigate the influence of outliers, we winsorize capital formation growth and inflation at the 5th and 95th percentiles. The summary statistics reveal that the mean GDP growth is 2.90%, with a median of 2.82%, suggesting a symmetric distribution. The mean and median values of capital formation growth are 3.65% and 3.75%, respectively. For consumption growth, these estimates are respectively equal to 2.81% and 2.60%. Changes in inflation and unemployment have small negative means of -0.27% and -0.09%, respectively. Labor productivity growth has mean 1.23% and median 1.02%. Real stock returns are equal to -0.31% on average, with a median value of 0.18%.

In Table 1, Panel B, we report summary statistics for the energy-related variables. Our primary dependent variables, GHG and CO2 emission intensity, are defined as emissions per unit of real USD GDP. Non-CO2 emissions are expressed in CO2 equivalents (eq.) using 100-year global warming potential values from the IPCC Fourth Assessment Report. CO2 is the largest component of GHG emissions and is often the object of taxation (*e.g.*, Giglio *et al.* (2021)). The other gases that comprise total GHG emissions include methane (CH4), nitrous

[1] The countries in our sample are Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Costa Rica, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Poland, Portugal, Russia, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States.

oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF_6). Average annual GHG emissions are equal to 0.58 kg CO_2 eq. per USD billion, whereas CO_2 emissions exhibit a mean of 0.43. The ratio between CO_2 and GHG emissions is about three quarters and is quite stable over the entire sample period.

Among the energy variables, we also consider total primary energy supply and total final energy consumption, both winsorized at the 5th and 95th percentiles due to the presence of outliers. Their average values are respectively equal to 4.37 and 2.55 exajoules, reflecting the well-known imbalance between energy production and consumption. In our empirical analysis, we scale them by the size of the respective economy and therefore express them as megajoules per USD billion. These two transformed variables represent measures of energy intensity, where a lower ratio indicates less energy is used to produce one unit of economic output. Their mean values in our sample are 7.27 and 4.76, respectively. Finally, we consider the share of renewable energy in total final energy consumption, defined as the energy consumed from all renewable resources including hydro power, solid biofuels, wind, solar, liquid biofuels, biogas, geothermal, marine, and waste. This variable is equal to 16.43% on average, with a median value of 12.32%.

In Table 2, Panel A, we classify GHG emissions into six major industries, also retrieved from the World Resource Institute's Climate Watch database. The industries are agriculture, bunker fuels, energy, industrial processes, land-use change and forestry, and waste. Agriculture emissions cover activities such as livestock and agricultural soils. Bunker fuels emissions are from fuels used for international shipping and aviation. The energy sector represents emissions from energy production and consumption. Industrial processes emissions result from specific industrial processes and product use, such as the chemical reactions needed to produce goods like cement and steel. Land-use change and forestry emissions and removals are a result of human activities like deforestation or reforestation. Finally, the waste sector's emissions are from the treatment and disposal of waste. The largest source of global emissions by far is the energy sector, with a mean value of 0.442 kg CO_2 eq. per USD billion. The second largest is agriculture (0.084), followed by waste (0.027), industrial processes (0.026), bunker fuels (0.016), and land-use change and forestry (-0.013).

The Climate Watch database also provides a further breakdown of the energy sector into its main components, providing a more granular outlook. We report them in Table 2, Panel B. The most polluting subcategory is emissions from the generation of electricity and heat (0.196 kg CO_2 eq. per USD billion, on average). Other categories include emissions from the building sector, which come from fossil fuels used for heating and gases for cooling and refrigeration in both commercial and residential buildings. Fugitive emissions are unintentional releases of gases that occur during the extraction, processing, and transport of fossil fuels. Emissions from manufacturing/construction are a part of the broader industrial sector. Other fuel combustion includes emissions from a variety of sources not captured in other energy categories, and transportation emissions primarily come from the burning of fossil fuels for vehicles, including cars, trucks, ships, trains, and airplanes.

4. Main findings

We present our main empirical findings as follows. In Subsection 4.1, we show our baseline results with several robustness checks. In Subsection 4.2, we explore which types of sentiment drive our main findings. In Subsection 4.3, we perform sample breakdowns along some dimensions of interest at the country and the industry level.

4.1 Baseline regressions

Our baseline test equation is:

$$y_{i,t+h} = \alpha_i + \beta Sentiment_{i,t} + \delta Controls_{i,t} + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is either GHG or CO2 emission intensity for country i in year t+h, with h = 0, 1, 2, 3, 4, and $Sentiment_{i,t}$ is the country-level consumer confidence index. By regressing the dependent variable at different time horizons on the current sentiment variable, we can observe how the initial impact of sentiment evolves over the years through local projections (*e.g.*, Jordà (2005)). We also use a rich set of controls, including our main five local macro variables (growth in GDP, capital formation, and consumption, and changes in inflation and unemployment), the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009), and unobserved time-invariant country-specific factors through country fixed effects. Standard errors are robust and clustered by year. Below, we also introduce a variety of alternative econometric specifications.

Following established practice in the environmental economics literature, we use emission intensity—emissions per unit of GDP—as our primary outcome variable (*e.g.*, Levinson (2009); Shapiro and Walker (2018)). Emission intensity captures the efficiency with which economies transform inputs into output, isolating technological and organizational improvements from pure scale effects. Since sentiment may affect both output levels and production efficiency, using intensity allows us to test whether sentiment specifically influences how cleanly economies produce, not merely how much they produce.

Using a rich set of US fundamentals as controls is important to capture potentially omitted local fundamentals, given the leading role that the US plays in the world economy (Harvey (1991), Campbell and Hamao (1992), Kwark (1999), Kim (2001), and Lumsdaine and Prasad (2003)). Using country fixed effects allows us to identify the relation between within-country changes in sentiment and emission intensity relative to their long-run means, effectively removing the long-run persistence from our variables of interest. The coefficient of our main regressor (β) represents the average effect of a domestic sentiment shock on emission intensity across all countries in the sample.

Based on the different views of how sentiment affects the macroeconomy, we entertain three priors for the sign of our coefficient of interest. One view is that sentiment only increases short-term output without affecting productivity (*e.g.*, Akerlof and Shiller (2009); Barsky and Sims (2012)). If so, high sentiment should lead to a proportional relation between emissions and GDP, implying $\beta = 0$. Another view is that sentiment leads to increased productivity and innovation (*e.g.*, Benhabib *et al*. (2015); Acharya *et al*. (2021); Constantinides *et al*. (2025)), with capital flowing towards riskier investment opportunities (*e.g.*, Baker and Wurgler (2006), (2007); Baker *et al*. (2012)). In this scenario, high sentiment should lead to greater efficiency in the economy, implying lower emissions per unit of GDP ($\beta < 0$). Finally, optimistic agents may downplay risk (*e.g.*, Puri and Robinson (2007); Ben-David *et al*. (2013)), including climate risk (*e.g.*, Gifford (2011); Beattie *et al*. (2017)). This would lead to a greater reliance on fossil fuel and therefore a corresponding rise in emissions ($\beta > 0$).

Our baseline regression results, reported in Tables 3 and 4, indicate a strong negative relation between consumer sentiment and both GHG and CO2 emission intensity. The effect is also economically meaningful. A one-standard-deviation increase in sentiment is associated with a 6.63% decrease in emission intensity within the same year, 6.04% in the subsequent year, and then 5.41%, 4.52% and 4.26% two to four years ahead, respectively. This represents annual reduction of 7% to 11% relative to the average GHG emissions intensity in our sample. Similarly, a one-standard deviation increase in sentiment is associated with a 4.20% decrease in CO2 emission intensity within the same year, 3.23% one year ahead, and then 2.39%, 1.75% and 1.28% for each of the other time horizons, respectively, which translates to a decrease of 3% to 10% relative to the average CO2 emissions. The consistency across both GHG and CO2 measures reinforces the robustness of our findings.

It is worth noting that the large immediate impact of sentiment on emissions and the slow tapering off is consistent with a genuine sentiment shock. If sentiment merely captured long-run economic news (*e.g.*, Beaudry *et al*. (2011)), the effect would counterfactually become stronger over time. This time pattern is also consistent with the macroeconomic effects of sentiment documented in previous literature (*e.g.*, Arif and Lee (2014)).

In Appendix A, Table A1, we find similar results for a variety of alternative econometric specifications. In Panel A, we estimate OLS regressions with double clustering by country and year, which simultaneously addresses potential serial correlation (over time within a country) and cross-sectional correlation (across countries in the same year). In Panel B, we estimate an even more conservative specification that includes both country and year fixed effects and double clustering by country and year. In Panel C, we estimate Fama-MacBeth regressions, an estimation method that is robust to cross-sectional dependence.[2] In Table A2, we also find similar results when we construct emission intensity normalizing with average country-level GDP over the whole sample period, which allays the concern that the estimates may reflect temporary variations in GDP unrelated to emissions.[3]

Overall, our findings add a new behavioral dimension to the factors that are known to influence environmental performance, such as green or political preferences (Kitzmueller and Shimshack (2012); Pástor *et al*. (2021); Zerbib (2022); Edmans and Kacperczyk (2022)), and attention to climate news (Pástor *et al*. (2022); Ardia *et al*. (2023)).

4.2 Types of sentiment

Next, we shed light on the types of sentiment that drive our results. First, we analyze the effect of sentiment unrelated to economic fundamentals through instrumental variables (IV) regressions. Then we run horse races between local sentiment and several measures of foreign sentiment.

4.2.1 IV regressions

One concern with our results is that high sentiment may partly reflect past improvements in environmental performance (*e.g.*, Levy and Yagi (2011); Heyes *et al.* (2016)). Building on established sports sentiment literature, we identify exogenous changes in consumer confidence

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[2] As pure time series variables, the US macroeconomic indicators are excluded from the text equation when using year fixed effects or when estimating cross-sectional regressions (Fama-MacBeth).

[3] For this test, we cannot use country fixed effects because they would effectively absorb the scaling by mean GDP (which is also country-specific and time invariant). For this reason, we run either OLS regressions with double clustering or Fama-MacBeth regressions.

using the FIFA Men's World Rankings of national soccer teams. The ranking points, which are based on a team's official match results, capture shocks to national morale and public mood associated with the performance of a country's favorite team. Since these ranking changes are driven by sports results and not by economic conditions, they serve as a unique, independent variable that can be used to isolate the effect of sentiment on emission intensity. Also, the soccer games played by national teams are typically evenly spread throughout the year, thereby aligning both conceptually and empirically with our measure of country-specific sentiment, which is calculated as an annual average of monthly values.

The economic mechanism is as follows. When a national soccer team achieves good results in a given year, its FIFA ranking score increases. A higher score, and the corresponding boost in national sentiment, should positively affect country-level consumer confidence given the worldwide popularity of the sport. While previous research uses other sources of exogenous variation in sentiment such as weather patterns (*e.g.*, Hirshleifer and Shumway (2003)), a sports-related approach is better suited here because, unlike the weather, a nation's athletic performance is unlikely to directly affect the performance or selection of energy sources. Also, weather patterns can be heterogeneous within some of the large countries included into our rich sample. By contrast, national soccer results do not suffer from this issue.

The impact of sports results on economic sentiment has already been established in previous literature. For example, the seminal work by Edmans *et al*. (2007) shows significant stock market reactions to soccer outcomes, as losses in World Cup elimination stages are followed by lower next-day returns. Our approach extends this framework in three key ways: we analyze sports sentiment over a longer time horizon (using an annual frequency), we focus on environmental outcomes instead of financial markets, and we propose a continuous measure of sports sentiment (using FIFA ranking scores) rather than relying on discrete win/loss outcomes.

In further research, Kaplanski and Levy (2010) find a spillover effect of soccer sentiment from individual countries to the US equity market. Palomino *et al*. (2009) find further evidence for the impact of soccer sentiment on stock returns at the micro level. The impact of soccer sentiment also extends beyond financial markets to real economic outcomes. Falter *et al*. (2008) find that winning the soccer World Cup boosts a country's consumer demand. Berument and Yucel (2005) provide micro-level evidence that soccer sentiment boosts economic growth. Finally, there are also broader sports-economy connections. Looking at football, Card and Dahl (2011) show how unexpected football losses affect emotional states and behavior, establishing a sports-mood channel. Similarly, Healy *et al*. (2010) find that local football team performance affects voter satisfaction with incumbents, establishing a link between sports sentiment and non-sports decisions. Therefore, our choice of sports outcomes as an exogenous source of sentiment variation is well-grounded in previous research.

The data on Historical Men FIFA Rankings is from Ismael Gómez Schmidt's website.[4] While multiple scores are available per year, we use annual averages for consistency with the data frequency of our analysis. It is worth noting that the ranking system has undergone significant changes over time. Major methodological shifts were introduced in 1999, 2006, and 2018. To account for these regime shifts and their potential influence on country-level scores, we estimate additional specifications introducing a dummy variable for each of these transition years in our first-stage regressions. The intuition is that within a country-fixed effects framework, the only problematic observations are those where methodological changes could create artificial jumps or drops in the rankings. In additional tests, we either drop these years altogether or consider a three-year moving average score.

The first-stage regression results, presented in Table A3, show that FIFA ranking scores serve as a highly effective instrument for consumer sentiment. The coefficient for the FIFA score is large and statistically significant, indicating that a one-standard-deviation increase in the score is associated with an increase in local consumer sentiment between 0.39 and 0.49. The inclusion of country fixed effects is critical, as it allows us to identify the within-country changes in both FIFA ranking scores and sentiment, thereby controlling for time-invariant country-specific factors.

In all specifications, the FIFA score's coefficient exhibits an F-statistic well above the conventional threshold of 10 and the highest Stock-Yogo critical value of 16.38. This confirms that our instrument is quite strong. Additionally, the partial R-squared of the FIFA score is approximately 2% across specifications. Therefore, it explains additional, non-trivial variation in consumer sentiment beyond what is accounted for by US and local macroeconomic fundamentals.

It is also important to note that the exclusion restriction appears plausible, as FIFA rankings should affect environmental outcomes exclusively through their influence on general mood and sentiment, not through direct economic channels. While one could argue that better soccer results might affect environmental performance through increased sports infrastructure spending or tourism, both channels should lead to more emissions—which is the opposite of the effect we find in our regressions.

[4] https://www.datofutbol.cl/blog/ranking-fifa-last-en/index.html.

The second-stage results, presented in Table A4, confirm the effectiveness of our instrument. The coefficient of the instrumented sentiment is negative and significant across all specifications and time horizons. Moreover, its economic magnitude is similar to the coefficient from our baseline specifications, providing further support to our initial findings. This suggests that the impact of sentiment on environmental outcomes is robust and unlikely to simply reflect other unobserved factors.

Although soccer is popular worldwide, its appeal varies across countries and time. Our results should then be stronger for countries where soccer is more popular. To identify such countries, we calculate the median FIFA score for each year in the sample and divide countries into those with below- and above-median scores, respectively. The intuition is that countries with higher scores should also be those where the sport is more popular, not only because of their success on the pitch but also because of the grassroots support that soccer needs to produce successful players. In Table A5, we separately repeat the second-stage regressions for countries with low and high soccer popularity, respectively. Consistent with our expectations, we find that the results are confined to the latter group of countries. These additional findings confirm that our IV results reflect genuine soccer-related sentiment.

4.2.2 Foreign sentiment

In additional tests, we check whether the results are only driven by local sentiment or also reflect, to some degree, the level of sentiment among global or US investors (Baker *et al*. (2012); Montone and Zwinkels (2020)). To address this point, we run horse races with several measures of foreign sentiment. In Table A6, we consider global sentiment, alternatively defined as the average level of consumer sentiment across G7 countries (Panel A) or OECD countries (Panel B). Reassuringly, the results show that our coefficient of interest is virtually unaffected, whereas the coefficient of either definition of global sentiment is close to zero in both magnitude and significance.

We acknowledge that sentiment among US investors may also play a potential role in our setup, as the US plays a leading role both in the world economy and financial markets (Albuquerque *et al*. (2005); Rapach *et al*. (2013)), also through a sentiment channel (Montone and Zwinkels (2020); Constantinides and Montone (2025)). In light of this, we run a horse race between local and US consumer sentiment. The results, reported in Table A7, Panel A, are similar to those from Table A6, indicating again that the effect of local sentiment is robust to the inclusion of foreign sentiment and the coefficient of US sentiment is insignificant.

We also estimate an alternative specification where we interact US sentiment with a variable that represents foreign direct investments (FDIs) from the US scaled by local GDP. The idea is that countries with stronger ties to the US should also be more sensitive to US sentiment (*e.g.*, Montone and Zwinkels (2020)). The results, reported in Table A7, Panel B, lend support to this conjecture. However, the effect of local sentiment is again negative, large, and statistically significant. These findings suggest that the US and the local channel of sentiment transmission may in fact overlap, as each of them seems to contribute to a reduction in country-level emission intensity.[5]

4.3 Sample breakdown

Next, we separately re-estimate our baseline regressions in a few subsamples of interest. First, we look at the breakdown into G7 and non-G7 countries. Second, we consider measures of GDP and sentiment volatility. Third, we perform an industry breakdown.

4.3.1 G7 versus non-G7

Previous research shows that the effect of sentiment on economic growth and productivity is more pronounced among non-G7 countries. The intuition is as follows. The G7 countries represent the largest advanced economies (Colacito *et al.* (2018); Huo *et al.* (2025)), which commit to the implementation of common policies with the ultimate goal of increasing economic stability (Sobel and Stedman (2006); Cormier *et al.* (2024)), leading to lower macroeconomic volatility and a correspondingly weaker effect of sentiment on macroeconomic outcomes (Constantinides *et al.,* (2025)).

In light of these previous findings, we expect the effect of sentiment on emission intensity to be stronger in non-G7 countries. Our empirical results, reported in Table 5, are consistent with this prediction. The initial effect of sentiment on emission intensity is more than three times larger for non-G7 countries (6.89% v 2.04%), followed by a steeper decline over time. More generally, these results suggest that sentiment may affect emission intensity through its impact on economic growth and productivity. Below we provide more direct evidence for this channel.

[5] This finding is also consistent with Constantinides and Montone (2025), who show that both local and US sentiment simultaneously play an important role in the transmission of sentiment to the macroeconomy.

4.3.2 GDP and sentiment volatility

Constantinides and Montone (2025) study the effect of sentiment as a signal for future economic growth. They show that the sensitivity of macroeconomic growth to sentiment is stronger for economies characterized by higher GDP growth volatility and lower sentiment volatility. The intuition is that sentiment may be used as a signal for the state of the economy by economic agents, and the reliance on the signal increases with its precision and with the uncertainty surrounding the state of the economy. We should then find stronger results for countries characterized by volatile GDP growth and stable sentiment.

To identify these countries, we separately estimate the standard deviation of GDP growth and consumer sentiment for each country over the entire sample period, then we respectively rank countries into those that exhibit above- and below-median volatility. Our findings, reported in Table 6, align with our conjecture. In our first breakdown (Panels A and B), we show that the results are confined to countries with above-median GDP growth volatility, indicating that the effect of sentiment on emission intensity only takes place in economies with less predictable fundamentals. In our second breakdown (Panels C and D), we find that the effect of sentiment is most persistent when sentiment itself is less volatile. Conversely, when sentiment is noisier and therefore represents a less reliable signal, the effect on emission intensity tapers off more quickly.

4.3.3 Industry breakdown

Finally, we re-estimate our baseline regressions using the industry breakdown introduced in Table 2. The results are in Table 7. The overall findings from the full sample are mostly driven by the energy sector (the most polluting one), whereas the impact of sentiment on emission intensity in other industries is substantially smaller and exhibits a flatter pattern over time (Panel A). Within the energy sector, the effect is mostly driven by the generation of electricity and heat (Panel B). Altogether, these findings suggest that sentiment may decrease emissions through an increase in energy efficiency. We test this prediction below.

5. Testing the channel

In the final part of our analysis, we provide further evidence on the economic channels underlying our results. In Subsection 5.1, we carry out a direct test of the energy efficiency channel. In Subsection 5.2, we explore the role of sentiment-driven economic growth and productivity.

5.1 Energy efficiency

If sentiment decreases emission intensity through a more efficient utilization of resources, then high sentiment should lead to greater energy efficiency gains. This is the analysis we turn to next, alternatively using our two energy intensity measures as dependent variables. For these analyses, we control for R&D expenditures (scaled by GDP). The intuition is that investment in innovation (R&D) can improve energy efficiency in its own right, so including it as a control variable helps us isolate the specific impact of sentiment on energy efficiency. By removing the effect of a country's baseline innovation effort, we make sure that the sentiment effect does not spuriously reflect differences in research and development across countries.

The results are reported in Table 8. Consistent with our arguments, we find that high sentiment reduces energy intensity both on the supply side (Panel A) and the consumption side (Panel B), indicating that less energy is needed to produce a unit of GDP when sentiment is high. The time patterns of our coefficient of interests mirror those of emission intensity, with an initial spike and then tapering off over time. Crucially, the magnitude of the effect starts out at about 10% of the sample mean for energy intensity on both the supply and the consumption side (-0.5486 and -0.3834, respectively), which matches the magnitude of the effect from our emission intensity regressions. Taken together with the industry-level results, these findings strongly indicate that the mechanism underlying the reduction in emission intensity is a sentiment-driven increase in energy efficiency.

In addition to energy efficiency gains, it is possible that high sentiment also reduces emissions through an increase in green investment. The intuition is as follows. Previous research shows that sentiment leads to more innovation (*e.g.*, Constantinides *et al*. (2025)), and greater investment in more speculative projects (*e.g.*, Baker and Wurgler, 2006). Since green technologies are both innovative and more speculative in nature (*e.g.*, Sautner *et al*. (2023); Battiston *et al*. (2025)), these mechanisms may apply to green investment. To test for this, we analyze the relation between sentiment and the green share of total final energy consumption. The results, reported in Table 9, Panel A, indeed indicate a positive relation. A one-standard-deviation increase in sentiment is associated with an increase in the green share of energy consumption of 0.49% in the same year and 0.44% in the subsequent year, whereas the effect is insignificant for longer time horizons.

However, we acknowledge that there could be cross-sectional differences in the impact of sentiment on country-level green investment, such as cultural traits. To explore this possibility, we consider the traits of long-term orientation (patience) and willingness to take risks measured through the Global Preference Survey (GPS), a large-scale, globally representative survey data set developed and validated by Falk *et al*. (2018). The measure of long-term orientation is constructed from the GPS's time preference module, with a higher score indicating greater patience in making intertemporal trade-offs. This patience is crucial for green investment, which typically requires high upfront capital and offers delayed, long-horizon returns. Similarly, the willingness to take risks measure is derived from the GPS's risk preference module, capturing an individual's general propensity for risk-taking. Given that many green technologies are innovative, unproven, and highly speculative, a higher country-level risk tolerance is a necessary ingredient for aggregate green investment to flourish.

In light of these considerations, we expect the effect of sentiment on green investment to be stronger for countries that exhibit greater long-term orientation and willingness to take risks. In Table 9, Panels B and C, we find evidence consistent with this conjecture. Following high sentiment, country-level green investment increases substantially and lasts longer (up to four years) for countries that score high on these two cultural dimensions. These findings are important for two reasons. First, cultural traits seem to play a primary role in mediating sentiment shocks. Second, policymakers should take these cultural traits into account in devising optimal green policies.

5.2 Economic growth

The overarching channel for our results should be a sentiment-driven increase in economic growth and productivity, leading to a more efficient utilization of resources. We provide a direct test of this mechanism in the analysis that follows, studying the effect of sentiment on GDP, capital formation, consumption, unemployment, labor productivity, and stock returns.

The results are in Table 10. We find that sentiment is associated with a large contemporaneous increase in the rate of growth of GDP, capital formation, consumption, a decrease in unemployment, and an increase in labor productivity and real stock returns. Crucially, these effects completely revert over time for GDP, consumption, and unemployment, whereas the reversals are only partial for capital, productivity, and stock returns. These partial reversals are consistent with managerial market timing, as managers rationally take advantage of high stock prices, and a correspondingly lower cost of equity, by timing their investments or issuing new shares (Morck *et al*. (1990); Stein (1996); Baker and Wurgler (2000, 2002); Baker *et al*. (2003); Polk and Sapienza (2009); Arif and Lee (2014); McLean and Zhao (2014)).

The persistent increase in capital and productivity aligns with the sustained improvement in energy efficiency and emission intensity from our previous tests, providing evidence for the hypothesized economic mechanism underlying our baseline results.

6. Concluding remarks

In this paper, we introduce sentiment as a novel channel that affects sustainability outcomes. We find a negative and statistically significant relation between country-level consumer sentiment and emission intensity, measured both contemporaneously and over a time window of up to four years ahead. Our results are also economically large, as a one-standard-deviation increase in sentiment is associated with a decrease in emission intensity of approximately 10% of its sample mean. This finding is robust to a variety of alternative econometric specifications, including instrumental variable regressions leveraging country-specific sports sentiment.

Our results suggest that sentiment-driven optimism leads to better environmental outcomes through a more efficient utilization of resources. We show that higher sentiment is followed by sustained improvements in energy efficiency on both the supply and consumption sides. Our findings also indicate that sentiment is associated with a large contemporaneous increase in capital formation, labor productivity, and real stock returns. Importantly, while the sentiment effect on other macroeconomic variables such as GDP, consumption, and unemployment completely reverts over time, the gains in capital, productivity, and stock returns are only partially reversed. The resulting persistent increase in efficiency aligns with the sustained reduction in emission intensity we document in our baseline regressions.

Our findings also contribute to the literature in two additional ways. First, we are the first to show that market-wide sentiment, through its effect on resource utilization, affects sustainability outcomes in its own right. This adds a new behavioral dimension to the factors that are known to influence environmental performance, such as green preferences, political affiliation, and attention to climate news. Second, we provide a new kind of confirmation that sentiment can have a strong effect on macroeconomic growth and productivity.

The findings of this paper also have policy implications. They challenge the general idea that there is a trade-off between economic and sustainable outcomes, suggesting instead that these goals can be jointly pursued. Our results indicate that policies aimed at boosting productivity and economic expectations could lead to substantial reductions in emission intensity. Furthermore, our analysis suggests that green initiatives can be optimally timed to periods of high sentiment, which leads to greater green adoption, especially among countries with green-friendly cultural values.

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Table 1. Summary statistics

Annual summary statistics for the main variables in our sample. In Panel A, the variables include country-level sentiment, defined as the OECD consumer confidence index, the real rates of growth of GDP, capital formation, and consumption, changes in inflation and unemployment, the rate of growth of labor productivity, defined as total value added per worker, and real stock returns, all expressed in percentage points. In Panel B, we include measures of country-level emission intensity, defined as the ratio between greenhouse gas (GHG) or carbon dioxide (CO2) emissions and local GDP (expressed in kg CO2 equivalent per USD billion), total primary energy supply and final energy consumption (expressed in exajoules), energy efficiency, defined as the ratio between energy supply or consumption and local GDP (expressed in megajoules per USD billion), and the share of renewables in total final energy consumption (expressed in percentage points). Sentiment data is from the OECD; macro and energy data are from the World Bank. Capital formation growth, inflation, energy supply, and energy consumption are winsorized (5%, 95%) due to outliers. The sample includes 42 countries from the OECD database. The sample period is from 1990 to 2018.

Panel A. Economy	Mean	SD	P25	Median	P75
Sentiment	100.1548	1.9245	99.0918	100.2962	101.3444
GDP growth (%)	2.8957	3.2212	1.4130	2.8215	4.3085
Capital growth (%)	3.6462	9.3264	-0.8712	3.7468	8.1613
Consumption growth (%)	2.8149	3.2224	1.3179	2.6009	4.1978
Δ Inflation (%)	-0.2683	2.2456	-0.9869	-0.1140	0.7224
Δ Unemployment (%)	-0.0893	1.2838	-0.6800	-0.1500	0.3800
Labor productivity growth (%)	1.2260	2.5808	-0.2077	1.0152	2.4673
Stock returns (%)	-0.3144	3.7646	-2.0549	0.1757	1.7798

Panel B. Energy	Mean	SD	P25	Median	P75
GHG to GDP (kg CO2 eq. per USD billion)	0.5818	0.5131	0.2710	0.4029	0.7099
CO2 to GDP (kg per USD billion)	0.4269	0.3549	0.2269	0.3048	0.4575
Total primary energy supply (EJ)	4.3702	4.0082	0.9066	2.2021	8.3786
Total final energy consumption (EJ)	2.5520	2.1888	0.6310	1.4290	5.4318
Energy supply to GDP (MJ per USD billion)	7.2728	4.7606	4.2417	5.8201	8.5410
Energy cons. to GDP (MJ per USD billion)	4.7594	3.0335	2.9594	3.7400	5.5005
Renewable energy consumption (% total)	16.4313	12.4757	6.3000	12.3234	25.6795

Table 2. Summary statistics: GHG emissions by industry

Annual summary statistics for country-level emission intensity in our sample, defined as the ratio between greenhouse gas (GHG) emissions and local GDP (expressed in kg CO2 equivalent per USD billion), broken down by industry. In Panel A, we consider the six major industries from the World Resource Institute's Climate Watch database. In Panel B, we include a breakdown of the GHG emissions from the energy sector into its subcomponents. The data is from the World Bank and the sample includes the 42 countries from the OECD database. The sample period is from 1990 to 2018.

Panel A. All industries	Mean	SD	P25	Median	P75
Agriculture	0.0838	0.0951	0.0254	0.0429	0.0976
Bunker fuels	0.0157	0.0085	0.0093	0.0137	0.0198
Energy	0.4420	0.3915	0.2254	0.3083	0.4597
Industrial processes	0.0264	0.0214	0.0124	0.0199	0.0337
Land-use change and forestry	-0.0134	0.2441	-0.0591	-0.0137	0.0016
Waste	0.0274	0.0391	0.0090	0.0184	0.0331

Panel B. Energy industry breakdown	Mean	SD	P25	Median	P75
Building	0.0456	0.0388	0.0221	0.0357	0.0563
Electricity / Heat	0.1975	0.2222	0.0717	0.1236	0.2134
Fugitive emissions	0.0254	0.0809	0.0012	0.0048	0.0190
Manufacturing / Construction	0.0673	0.0774	0.0301	0.0455	0.0665
Other fuel combustion	0.0180	0.0186	0.0083	0.0136	0.0213
Transportation	0.0882	0.0368	0.0606	0.0860	0.1080

Table 3. Sentiment and GHG emissions

Panel regressions of country-level emission intensity, defined as the ratio between greenhouse gas (GHG) emissions and local GDP (expressed in kg CO2 equivalent per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0663***	-0.0604***	-0.0541***	-0.0452***	-0.0426***
	-6.49	-6.18	-7.07	-6.48	-6.38
GDP growth	0.0584*	-0.0091	0.0083	-0.0234	0.0050
	1.83	-0.28	0.34	-0.89	0.18
Capital growth	0.0065	0.0390	0.0017	0.0290	-0.0070
	0.35	1.62	0.10	1.31	-0.39
Cons. growth	-0.0013	0.0211	0.0255	0.0083	0.0172
	-0.04	0.81	1.17	0.30	0.70
Δ Inflation	-0.0123	0.0134	-0.0231	-0.0099	-0.0165
	-0.59	0.63	-1.53	-0.53	-1.31
Δ Unemployment	-0.0090*	-0.0021	-0.0068	-0.0060	-0.0057
	-1.71	-0.47	-1.54	-1.25	-1.64
F1	-0.0798***	-0.0739***	-0.0707***	-0.0634***	-0.0651***
	-4.80	-4.65	-3.99	-3.89	-3.89
F2	-0.0281	-0.0298	-0.0338	-0.0009	0.0096
	-1.09	-1.12	-1.37	-0.04	0.34
F3	0.0661**	0.0676**	0.0658**	0.0247	0.0057
	2.26	2.27	2.52	1.11	0.20
F4	0.0002	-0.0003	-0.0044	-0.0089	0.0006
	0.01	-0.01	-0.14	-0.31	0.02
F5	0.0944***	0.0899***	0.0829***	0.0692***	0.0554***
	6.56	7.00	6.59	5.41	2.88
F6	0.0896***	0.0923***	0.0730***	0.0603**	0.0534**
	3.73	3.88	2.66	2.32	2.12
F7	-0.0217***	-0.0198**	-0.0261***	-0.0273***	-0.0289***
	-2.70	-2.41	-3.12	-3.20	-4.23
F8	0.0008	-0.0047	-0.0009	-0.0144**	-0.0238**
	0.08	-0.59	-0.12	-2.00	-2.44
Observations	911	871	831	791	751
R-squared	0.3468	0.3506	0.3341	0.3221	0.3116

Table 4. Sentiment and CO2 emissions

Panel regressions of country-level emission intensity, defined as the ratio between carbon dioxide (CO2) emissions and local GDP (expressed as kg per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dep. variable: CO2 to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0420***	-0.0323***	-0.0239***	-0.0175***	-0.0128**
	-6.00	-5.21	-4.04	-2.92	-2.14
GDP growth	0.0395*	0.0246	0.0203	0.0138	0.0195
	1.83	1.33	1.09	0.82	1.01
Capital growth	0.0087	0.0122**	0.0126*	0.0104	0.0056
	1.19	1.97	1.93	1.63	0.85
Cons. growth	0.0375	0.0242	0.0123	0.0142	0.0068
	1.46	1.13	0.56	0.71	0.33
Δ Inflation	-0.0081	-0.0067	-0.0010	0.0061	0.0027
	-0.68	-0.62	-0.10	0.69	0.35
Δ Unemployment	0.0059*	0.0076**	0.0077**	0.0090***	0.0090***
	1.67	2.23	2.11	2.65	2.89
F1	-0.0503***	-0.0484***	-0.0443***	-0.0412***	-0.0361***
	-5.12	-4.97	-4.02	-3.77	-3.26
F2	-0.0254	-0.0235	-0.0280	-0.0087	0.0021
	-1.30	-1.21	-1.39	-0.47	0.10
F3	0.0549**	0.0513**	0.0543**	0.0281	0.0102
	2.54	2.44	2.51	1.58	0.45
F4	-0.0029	-0.0005	0.0028	-0.0013	0.0018
	-0.19	-0.03	0.14	-0.07	0.10
F5	0.0713***	0.0678***	0.0658***	0.0564***	0.0415***
	6.62	6.93	6.26	5.39	3.10
F6	0.0610***	0.0594***	0.0609***	0.0490***	0.0440***
	4.43	3.99	3.58	3.03	2.65
F7	-0.0138**	-0.0147***	-0.0147**	-0.0163***	-0.0140**
	-2.12	-2.60	-2.31	-2.76	-2.22
F8	-0.0023	-0.0012	-0.0025	-0.0085	-0.0161**
	-0.36	-0.20	-0.41	-1.41	-2.19
Observations	911	871	831	791	751
R-squared	0.4652	0.4546	0.4346	0.4355	0.4258

Table 5. Sentiment and GHG emissions: G7 breakdown

Panel regressions of country-level emission intensity, defined as the ratio between greenhouse gas (GHG) emissions and local GDP (expressed in kg CO2 equivalent per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). In Panel A, we consider the subsample of G7 countries only. In Panel B, we re-estimate our results in the subsample of non-G7 countries. The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. G7 countries

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0204**	-0.0182**	-0.0172**	-0.0154*	-0.0108
	-2.39	-2.18	-1.99	-1.75	-1.29
GDP growth	0.0507	0.0764*	0.0623	0.0579	0.0350
	1.25	1.70	1.42	1.34	0.76
Capital growth	0.0438**	0.0261	0.0287	0.0069	0.0019
	2.07	1.14	1.19	0.28	0.08
Cons. growth	0.0349	0.0212	0.0199	-0.0035	0.0175
	0.82	0.55	0.59	-0.08	0.43
Δ Inflation	-0.0238	-0.0283	-0.0198	-0.0024	0.0049
	-0.87	-1.04	-0.71	-0.09	0.16
Δ Unemployment	0.0223**	0.0195**	0.0138	0.0043	0.0027
	2.51	2.31	1.53	0.39	0.24
Observations	183	176	169	162	155
R-squared	0.5472	0.5116	0.4816	0.4628	0.4499

Panel B. Non-G7 countries

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0689***	-0.0632***	-0.0571***	-0.0474***	-0.0451***
	-6.12	-5.87	-6.86	-6.28	-6.12
GDP growth	0.0553*	-0.0159	0.0033	-0.0287	0.0010
	1.76	-0.49	0.14	-1.04	0.04
Capital growth	0.0046	0.0388	-0.0003	0.0291	-0.0080
	0.24	1.58	-0.02	1.27	-0.43
Cons. growth	-0.0017	0.0246	0.0301	0.0123	0.0222
	-0.06	0.94	1.37	0.43	0.92
Δ Inflation	-0.0108	0.0157	-0.0226	-0.0099	-0.0170
	-0.51	0.74	-1.51	-0.51	-1.34
Δ Unemployment	-0.0104*	-0.0032	-0.0076*	-0.0063	-0.0056
	-1.88	-0.65	-1.69	-1.28	-1.56
Observations	728	695	662	629	596
R-squared	0.3522	0.3580	0.3397	0.3233	0.3131

Table 6. Sentiment and GHG emissions: Volatility breakdown

Panel regressions of country-level emission intensity, defined as the ratio between greenhouse gas (GHG) emissions and local GDP (expressed in kg CO2 equivalent per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). We estimate our regressions into four separate subsamples of interest based on the volatility of GDP growth and sentiment, separately estimated over the entire sample period for each country. Countries with high (low) volatility are countries whose volatility is above (below) the median value. The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Low GDP growth volatility

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0157	-0.0061	-0.0005	0.0045	0.0048
	-1.35	-0.71	-0.07	0.67	0.63
Observations	461	442	423	404	385
R-squared	0.4650	0.4524	0.4327	0.4271	0.4186

Panel B. High GDP growth volatility

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0829***	-0.0799***	-0.0741***	-0.0658***	-0.0623***
	-6.68	-6.25	-7.22	-6.79	-7.14
Observations	450	429	408	387	366
R-squared	0.3828	0.4045	0.3794	0.3547	0.3435

Panel C. Low sentiment volatility

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0702***	-0.0688***	-0.0694***	-0.0691***	-0.0723***
	-3.94	-5.57	-4.59	-6.73	-5.34
Observations	458	439	420	401	382
R-squared	0.2994	0.3466	0.3119	0.3290	0.3213

Panel D. High sentiment volatility

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0673***	-0.0589***	-0.0521***	-0.0381***	-0.0345***
	-5.21	-4.82	-4.88	-4.15	-4.32
Observations	453	432	411	390	369
R-squared	0.4201	0.4063	0.4071	0.3742	0.3621

Table 7. Sentiment and GHG emissions: Industry breakdown

Panel regressions of country-level emission intensity, defined as the ratio between greenhouse gas (GHG) emissions and local GDP (expressed in kg CO2 equivalent per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). In Panel A, we consider the six major industries from the World Resource Institute's Climate Watch database. In Panel B, we include a breakdown of the GHG emissions from the energy sector into its subcomponents. Each row represents a separate industry-specific regression output. The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. All industries

Coefficient: Sentiment	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Agriculture	-0.0046***	-0.0040***	-0.0037***	-0.0035***	-0.0032**
	-3.08	-3.05	-2.80	-2.64	-2.41
Bunker fuels	-0.0005**	-0.0003	-0.0002	-0.0001	-0.0001
	-2.26	-1.58	-0.79	-0.48	-0.55
Energy	-0.0459***	-0.0355***	-0.0268***	-0.0207***	-0.0162**
	-5.92	-5.15	-4.15	-3.10	-2.35
Industrial processes	-0.0019***	-0.0018***	-0.0015***	-0.0012***	-0.0009**
	-5.64	-5.61	-4.80	-3.50	-2.31
Land use / Forestry	-0.0103	-0.0162***	-0.0198***	-0.0180**	-0.0210***
	-1.60	-2.60	-2.98	-2.53	-2.70
Waste	-0.0031***	-0.0027***	-0.0021***	-0.0017***	-0.0013**
	-4.31	-3.77	-3.22	-2.70	-2.27

Panel B. Energy industry breakdown

Coefficient: Sentiment	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Building	-0.0047***	-0.0039***	-0.0030***	-0.0021***	-0.0016**
	-5.31	-4.72	-3.54	-2.86	-2.50
Electricity / Heat	-0.0282***	-0.0220***	-0.0177***	-0.0142***	-0.0111**
	-5.38	-4.52	-3.99	-3.21	-2.49
Fugitive emissions	-0.0036***	-0.0028***	-0.0025***	-0.0028***	-0.0032***
	-4.40	-4.31	-4.14	-3.94	-3.66
Manufacturing / Constr.	-0.0059***	-0.0045***	-0.0024***	-0.0009	0.0004
	-4.98	-4.96	-2.84	-1.04	0.41
Other fuel combustion	-0.0013***	-0.0008**	-0.0005	-0.0003	-0.0002
	-4.33	-2.49	-1.40	-0.81	-0.76
Transportation	-0.0022***	-0.0014**	-0.0008	-0.0003	-0.0003
	-3.51	-2.38	-1.34	-0.59	-0.59

Table 8. Sentiment and energy efficiency gains

Panel regressions of country-level energy efficiency, defined as the ratio between either total primary energy supply (Panel A) or total final energy consumption (Panel B) and local GDP (expressed as megajoules per USD billion), on sentiment, defined as the country-level consumer confidence index from the OECD, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Energy supply / GDP

	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.5486***	-0.5388***	-0.4368***	-0.3282***	-0.2400**
	-5.90	-5.07	-4.47	-3.36	-2.57
Observations	714	702	686	668	649
R-squared	0.5295	0.5094	0.5013	0.4991	0.5079

Panel B. Energy consumption / GDP

	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.3834***	-0.3315***	-0.2405***	-0.1954**	-0.1669**
	-4.03	-3.77	-2.95	-2.45	-2.20
Observations	649	610	573	534	496
R-squared	0.4338	0.4417	0.4460	0.4460	0.4703

Table 9. Sentiment and the green energy consumption share

Panel regressions of the country-level green energy consumption share, defined as the share of renewables in total final energy consumption, on sentiment, defined as the country-level consumer confidence index from the OECD, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). In Panel A, we estimate our baseline specifications. In Panels B and C, we respectively introduce interaction terms with patience, defined as country-level long-term orientation, and risk taking, defined as a country's willingness to take risks, both retrieved from Falk *et al.* (2018). All independent variables are standardized to ease the interpretation of the results. The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Green energy consumption share

	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	0.4863***	0.4366***	0.2384	0.1641	0.1044
	3.41	2.80	1.34	0.88	0.58
Observations	803	765	727	687	649
R-squared	0.3432	0.3463	0.3639	0.3874	0.4191

Panel B. Green energy consumption share and patience

	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	0.3695**	0.2290	0.0445	-0.0731	-0.1778
	2.25	1.24	0.22	-0.34	-0.94
Sentiment	0.4217***	0.6223***	0.6453***	0.4833***	0.4017***
x Patience	2.70	5.54	5.34	4.02	3.21
Observations	638	608	577	545	514
R-squared	0.3052	0.3216	0.3454	0.3633	0.3957

Panel C. Green energy consumption share and risk taking

	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	0.6929***	0.6251***	0.4595**	0.2799	0.0954
	4.56	3.78	2.17	1.17	0.41
Sentiment	0.5132***	0.5625***	0.6132***	0.5339***	0.3602**
x Risk taking	3.21	3.83	4.59	3.90	2.50
Observations	638	608	577	545	514
R-squared	0.3083	0.3179	0.3427	0.3653	0.3937

Table 10. Sentiment and economic growth

Panel regressions of country-level economic growth on sentiment, defined as the country-level consumer confidence index from the OECD, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The dependent variable is alternatively the real rate of growth of GDP (Panel A), capital formation (Panel B), or consumption (Panel C), the change in unemployment (Panel D), labor productivity growth (Panel E), and real stock returns (Panel F). The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). Local macro variables are lagged in column (1) due to collinearity. The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. GDP growth

	(1)	(2)	(3)	(4)	(5)
	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment	1.2359***	-0.1963	-0.6320**	-0.4358**	-0.1719
	6.02	-0.99	-2.14	-2.05	-0.90

Panel B. Capital formation growth

	(1)	(2)	(3)	(4)	(5)
	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment	3.2545***	-0.2544	-1.1942*	-0.2528	-0.2196
	5.93	-0.48	-1.83	-0.36	-0.43

Panel C. Consumption growth

	(1)	(2)	(3)	(4)	(5)
	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment	1.4653***	-0.2386	-0.7867**	-0.6547**	-0.2538
	5.88	-0.81	-2.05	-2.48	-1.36

Panel D. Change in unemployment

	(1)	(2)	(3)	(4)	(5)
	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment	-0.4604***	0.1068	0.2534***	0.1992**	0.1431
	-4.73	1.62	3.02	2.33	1.50

Panel E. Labor productivity growth

	(1)	(2)	(3)	(4)	(5)
	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment	0.4851***	-0.0052	-0.2373*	-0.1850	-0.0346
	3.62	-0.05	-1.83	-1.09	-0.27

Panel F. Stock returns

	(1)	(2)	(3)	(4)	(5)
	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment	1.5779***	-0.0020	-0.6451*	-0.5306*	-0.3358
	5.71	-0.01	-1.78	-1.91	-1.28

Appendix A

Table A1. Baseline regressions: Alternative econometric specifications

Regressions of country-level emission intensity, defined as the ratio between carbon dioxide (CO_2) emissions and local GDP (expressed as kg per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, and a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment. In Panel A, we estimate OLS regressions with double clustering by country and year and further include a vector of US macroeconomic indicators, defined as the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). In Panel B, we estimate panel regressions with country and year fixed effects and double clustering by country and year. In Panel C, we estimate Fama-MacBeth regressions. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. OLS with double clustering

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.1818***	-0.1820***	-0.1733***	-0.1646***	-0.1530***
	-3.20	-3.33	-3.35	-3.23	-3.20
Observations	911	871	831	791	751
R-squared	0.1975	0.1861	0.1824	0.1716	0.1814

Panel B. Double FE with double clustering

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0632***	-0.0581***	-0.0528***	-0.0433**	-0.0417**
	-3.01	-2.99	-3.11	-2.57	-2.51
Observations	911	871	831	791	751
R-squared	0.9389	0.9427	0.9488	0.9506	0.9542

Panel C. Fama-MacBeth

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.1636***	-0.1701***	-0.1528***	-0.1473***	-0.1412***
	-3.47	-3.59	-3.36	-3.16	-3.32
Observations	911	871	831	791	751
R-squared	0.4553	0.4462	0.4401	0.4397	0.4396

Table A2. Baseline regressions: Scaling by average GDP

Regressions of country-level emission intensity, defined as the ratio between carbon dioxide (CO_2) emissions and local GDP (expressed as kg per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, and a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment. The dependent variable is constructed using average GDP, calculated separately for each country over the entire sample period. In Panel A, we estimate OLS regressions with double clustering by country and year and further include a vector of US macroeconomic indicators, defined as the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). In Panel B, we estimate Fama-MacBeth regressions. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. OLS with double clustering

Dep. variable:	(1)	(2)	(3)	(4)	(5)
GHG to GDP	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment	-0.1311***	-0.1466***	-0.1541***	-0.1573***	-0.1578***
	-3.37	-3.80	-3.65	-3.55	-3.69
Observations	911	871	831	791	751
R-squared	0.1752	0.1769	0.1845	0.1833	0.2023

Panel B. Fama-MacBeth

Dep. variable:	(1)	(2)	(3)	(4)	(5)
GHG to GDP	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment	-0.1250***	-0.1395***	-0.1300***	-0.1327***	-0.1359***
	-3.67	-3.94	-3.74	-3.50	-3.72
Observations	911	871	831	791	751
R-squared	0.4445	0.4398	0.4374	0.4417	0.4468

Table A3. IV stage-1 regressions

Panel regressions of sentiment, defined as the country-level consumer confidence index from the OECD, the FIFA Men's World Rankings score for national soccer teams, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. In column (1), we estimate our baseline regressions. In column (2), we introduce a dummy for each of the years in which the FIFA score system changed (1999, 2006, 2018). In column (3), we exclude those years from the analysis. In column (4), we include the full sample but estimate the FIFA score as a three-year moving average. The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dep. variable: Sentiment	(1) Baseline	(2) Year dummies	(3) Year gaps	(4) Moving average
FIFA score	0.4549***	0.3898***	0.3915***	0.4861***
	4.35	4.59	4.74	4.65
GDP growth	0.3595	0.4455	0.6464**	0.2792
	1.23	1.57	2.37	0.99
Capital growth	0.0483	0.0476	-0.0506	0.0685
	0.38	0.39	-0.44	0.52
Cons. growth	2.1742***	2.1971***	1.9100***	2.2242***
	6.27	6.18	5.71	6.19
Δ Inflation	0.1037	0.1557	0.1706	0.1047
	0.74	1.14	1.10	0.74
Δ Unemployment	-0.3962***	-0.3789***	-0.3716***	-0.4097***
	-4.86	-4.72	-4.46	-4.71
F1	-0.2046	-0.2034	-0.2079	-0.1163
	-1.24	-1.23	-1.31	-0.80
F2	0.3124	0.4160**	0.3904**	0.2980
	1.55	2.44	2.34	1.46
F3	-0.3784*	-0.3852	-0.3866	-0.5032**
	-1.65	-1.57	-1.61	-2.19
F4	-0.1647	-0.2298	-0.2093	-0.2359
	-0.70	-1.08	-0.99	-1.00
F5	-0.0725	-0.0133	-0.0158	-0.0503
	-0.43	-0.08	-0.10	-0.30
F6	0.0051	0.0420	0.0521	-0.0759
	0.02	0.23	0.29	-0.39
F7	0.0180	0.0243	0.0288	0.0465
	0.24	0.34	0.41	0.69
F8	-0.0175	-0.0659	-0.0546	0.0037
	-0.17	-0.61	-0.51	0.04
Observations	721	721	642	688
R-squared	0.4611	0.4767	0.4463	0.4608
F-statistic (FIFA score)	18.96	21.03	22.50	21.62

Table A4. IV stage-2 regressions

Panel regressions of emission intensity, defined as the ratio between carbon dioxide (CO_2) emissions and local GDP (expressed as kg per USD billion), on sentiment, defined as the country-level consumer confidence index from the OECD, and instrumented using the FIFA Men's World Rankings score for national soccer teams, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are bootstrapped using 1,000 repetitions. The independent variables are standardized to ease the interpretation of the results. In Panel A, we estimate our baseline regressions. In Panel B, we introduce a dummy for each of the years in which the FIFA score system changed (1999, 2006, 2018). In Panel C, we exclude those years from the analysis. In Panel D, we include the full sample but estimate the FIFA score as a three-year moving average. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Baseline

Dep. variable:	(1)	(2)	(3)	(4)	(5)
GHG to GDP	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment IV	-0.0457***	-0.0383***	-0.0445***	-0.0435***	-0.0490***
	-3.43	-2.58	-3.42	-3.07	-3.74
Observations	661	631	601	571	541
R-squared	0.2962	0.3055	0.2966	0.2981	0.2918

Panel B. Year dummies

Dep. variable:	(1)	(2)	(3)	(4)	(5)
GHG to GDP	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment IV	-0.0457***	-0.0383***	-0.0445***	-0.0435***	-0.0490***
	-3.29	-2.66	-3.33	-3.16	-3.74
Observations	661	631	601	571	541
R-squared	0.2962	0.3055	0.2966	0.2981	0.2918

Panel C. Year gaps

Dep. variable:	(1)	(2)	(3)	(4)	(5)
GHG to GDP	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment IV	-0.0470***	-0.0433***	-0.0522***	-0.0505***	-0.0578***
	-3.03	-2.63	-3.52	-3.37	-4.11
Observations	582	582	552	522	492
R-squared	0.2966	0.3066	0.2950	0.3000	0.2968

Panel D. Moving average

Dep. variable:	(1)	(2)	(3)	(4)	(5)
GHG to GDP	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment IV	-0.0422**	-0.0416**	-0.0485***	-0.0473***	-0.0541***
	-2.56	-2.33	-3.19	-2.94	-3.65
Observations	628	598	568	538	508
R-squared	0.2969	0.3040	0.3066	0.3047	0.3040

Table A5. IV stage-2 regressions: soccer popularity breakdown

Panel regressions of emission intensity, defined as the ratio between carbon dioxide (CO_2) emissions and local GDP (expressed as kg per USD billion), on sentiment, defined as the country-level consumer confidence index from the OECD, and instrumented using the FIFA Men's World Rankings score for national soccer teams, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are bootstrapped using 1,000 repetitions. The independent variables are standardized to ease the interpretation of the results. For each year, we calculate the median FIFA score in the sample, divide countries into those with scores that respectively lie below (Panel A) or above (Panel B) the median value, and refer to them as countries with low and high soccer popularity. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Low popularity

Dep. variable:	(1)	(2)	(3)	(4)	(5)
GHG to GDP	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment IV	-0.0475	0.0023	-0.0265	-0.0396	-0.0581*
	-1.43	0.06	-0.78	-1.04	-1.82
Observations	322	306	291	276	261
R-squared	0.2402	0.2724	0.2529	0.2613	0.2413

Panel B. High popularity

Dep. variable:	(1)	(2)	(3)	(4)	(5)
GHG to GDP	Year t	Year t+1	Year t+2	Year t+3	Year t+4
Sentiment IV	-0.0666***	-0.0712***	-0.0714***	-0.0657***	-0.0691***
	-4.18	-4.36	-4.79	-4.83	-4.62
Observations	339	325	310	295	280
R-squared	0.3925	0.4061	0.4241	0.4424	0.4390

Table A6. GHG emissions: local and global sentiment

Panel regressions of country-level emission intensity, defined as the ratio between carbon dioxide (CO_2) emissions and local GDP (expressed as kg per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, global sentiment, defined as the average country-level consumer confidence index for G7 countries (Panel A) or OECD countries (Panel B) a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Global sentiment: G7

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0652***	-0.0603***	-0.0546***	-0.0457***	-0.0436***
	-6.15	-6.03	-7.03	-6.39	-6.40
G7 sentiment	-0.0080	-0.0012	0.0090	0.0073	0.0211
	-0.65	-0.10	0.53	0.39	1.25
Observations	911	871	831	791	751
R-squared	0.3474	0.3506	0.3348	0.3226	0.3154

Panel B. Global sentiment: OECD

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0656***	-0.0606***	-0.0548***	-0.0458***	-0.0437***
	-6.20	-6.08	-7.08	-6.44	-6.41
OECD sentiment	-0.0058	0.0014	0.0126	0.0094	0.0212
	-0.42	0.11	0.72	0.50	1.24
Observations	911	871	831	791	751
R-squared	0.3471	0.3506	0.3353	0.3229	0.3155

Table A7. GHG emissions: local and US sentiment

Panel regressions of country-level emission intensity, defined as the ratio between carbon dioxide (CO_2) emissions and local GDP (expressed as kg per USD billion), sentiment, defined as the country-level consumer confidence index from the OECD, US sentiment, defined as the consumer confidence index for the US, a vector of local macroeconomic variables, including the real rates of growth of GDP, capital formation, and consumption, and changes in inflation and unemployment, and a vector of US macroeconomic indicators, including the eight principal components of 132 US macroeconomic variables from Ludvigson and Ng (2009). In Panel B, we also include US flows, defined as the annual foreign direct investment received by a given country from the US, and an interaction between US flows and US sentiment. All specifications include country fixed effects, and standard errors are clustered by year. The independent variables are standardized to ease the interpretation of the results. The dependent variable is observed in the same year in column (1), and up to four years into the future in columns (2) through (5). The US is excluded from the analysis in both panels. The sample period is from 1990 to 2018. *t*-statistics are reported below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Unconditional effect

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0646***	-0.0598***	-0.0543***	-0.0454***	-0.0437***
	-6.01	-5.87	-6.85	-6.30	-6.32
US sentiment	-0.0130	-0.0087	-0.0012	0.0001	0.0098
	-1.23	-0.89	-0.09	0.01	0.71
Observations	884	845	806	767	728
R-squared	0.3465	0.3496	0.3323	0.3199	0.3106

Panel B. Conditional effect

Dep. variable: GHG to GDP	(1) Year t	(2) Year t+1	(3) Year t+2	(4) Year t+3	(5) Year t+4
Sentiment	-0.0490***	-0.0476***	-0.0398***	-0.0328***	-0.0330***
	-5.01	-4.85	-6.95	-5.17	-5.74
US sentiment	0.0024	0.0073	0.0116	0.0131	0.0189*
	0.27	1.00	1.36	1.13	1.68
US flows	-0.1329***	-0.1274***	-0.1425***	-0.1022***	-0.0861***
	-4.63	-4.40	-5.73	-2.86	-2.86
Sentiment	0.0147	0.0134	0.0111	0.0018	-0.0009
x US flows	1.07	1.16	1.21	0.48	-0.24
US sentiment	-0.0351***	-0.0285***	-0.0178**	-0.0101**	-0.0087**
x US flows	-3.04	-3.32	-2.19	-2.46	-2.25
Observations	853	814	775	736	697
R-squared	0.4160	0.4026	0.4318	0.3705	0.3679