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ESG news spillovers across the value chain

Vu Le Tran[1] | **Guillaume Coqueret**[2]

[1]Nord University Business School, Nord University, Bodø, Norway

[2]EMLYON Business School, Ecully, France

Correspondence
Vu Le Tran, Nord University, Norway.
Email: vu.l.tran@nord.no

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Abstract

We document the impact of ESG shocks on the stock returns of suppliers and clients of affected firms. Our empirical analysis of US stocks, along with their global clients and suppliers, reveals that ESG shocks are integrated into prices intradaily and that the cross-effect between shocks and ESG levels is statistically significant. The indirect diffusion of ESG shocks to customers' and suppliers' returns is also significant, but takes more time (a few days) and is less pronounced. Finally, the impact is stronger for small firms and for corporations that benefit from less media coverage. In addition, effects are more pronounced in the recent period (posterior to 2017), possibly due to increased investor attention toward sustainability.

1 | INTRODUCTION

Financial markets react to news flows. The integration of announcements into prices has been a recurring topic in economics for decades. Simply put, stock market participants are likely to update their expectations when they receive new pieces of relevant information. Their positions are then updated, which may shift prices up or down, depending on whether the total demand for an asset is higher or lower than the corresponding supply.[1]

The heterogeneity in drivers of expectations at the stock level is driven by the large spectrum of fields that data providers sell to investors. Recently, sentiment and sustainability have expanded the palette of firm-specific attributes, even if their relevance for predictability and portfolio choice remains an open question. Many contributions find value

[1] Originally, signals consisted of two types mainly: macro-economic news (inflation, GDP, unemployment, consumption, etc.) and firm-specific announcements (earnings, dividends, stock splits). Nowadays, with the advent of so-called alternative data, the sources of signals are diversified and it has been documented that many drivers of mood can shift markets (the weather (Hirshleifer & Shumway, 2003), soccer scores (Edmans et al., 2007), and even music tone (Edmans et al., 2022).

in sentiment,[2] but favorable findings may also be due to the publication bias towards positive results, as is argued in Coqueret (2020), in which sentiment is found to have limited predictive power over future returns, at least at daily frequencies. With regard to sustainability, the debate is at least as rich and also notoriously unsettled.[3]

In the present paper, we analyze the impact of environmental, social, and governance (ESG) shocks not only on firms' stock returns, but also on their *suppliers*' or their *clients'* returns. The rationale is that positive or negative news for a corporation is likely to boost or shrink future sales, or influence the reputation of its suppliers or clients, and thus impact its value chain, its future earnings, and hence, its returns. We test this hypothesis on a sample of US firms that are linked to their most important clients and suppliers worldwide. To this purpose, we run panel regressions that seek to explain firms' returns depending on their own ESG scores, and/or that of their clients or customers. Our empirical contributions can be summarized as follows.

First, we document the significant influence of ESG shocks on firms' returns, on their customers' returns, and on their suppliers' returns, even after controlling for the most common asset pricing factors.[4] A concomitant finding is that the impact of shocks, both direct or stemming from the value chain, is contingent on the original level of the ESG score. We reveal an asymmetric effect: brown firms react more positively to positive news, while green firms are more resilient to negative news.

Second, the impact of a firm's ESG shock on its own return is immediate. The significant coefficients pertain to synchronous terms: firms' returns on a given day are hit by their own ESG news released during that day. There is therefore little predictive power of ESG shocks, at least at the daily frequency. However, we also find that shocks take more time to diffuse along the value chain, as it takes them a few days (two to three) to impact the returns of a firm's main supplier or customer. This spillover effect on the values chain is less pronounced than the direct effect. Importantly, not all measures of ESG are equivalent and we differentiate between standard ESG and materiality-relevant news. A shock related to materialized ESG topics spreads quicker and more potently through the supply chain than a common ESG shock.[5]

In addition, our results are robust, as they also hold when adding customer or supplier returns as control variates. In terms of economic value, we show that building long-short portfolios based on high versus low ESG shocks is able to generate alpha. Depending on time lags, portfolios based on the financially material ESG shocks from customers are associated with alphas between 1% and 8% annually, after controlling for the usual factors.

A third salient conclusion pertains to the cross-section of firms. Our results indicate that most of the effects we document are concentrated within small or medium-sized firms. In addition, attention also plays a role. Media coverage, as measured by the volume of ESG news available for each company, creates discrepancies in the coefficients we report. Indeed, firms with lower coverage are more sensitive to shocks, compared to those with high attention. We interpret this as unexpected bad (or good) surprises from firms for which investors have limited information.

Finally, our estimations show that the impact of ESG shock is more pronounced in recent years: coefficients are more significant after January 2017 (a threshold date for the Paris Accord) than before. We conjecture that this is linked to the rise of investor awareness toward sustainability. It is possible that the push for stricter regulatory disclosure frameworks, as well as the increasing amount of news stemming from social media and real-time reporting,

[2] Results hold for aggregate sentiment (Baker & Wurgler, 2006; Bollen et al., 2011; Da et al., 2015; Fraiberger et al., 2021), or stock-specific sentiment (Chen et al., 2014; Zhang et al., 2016, to cite but a few).

[3] We refer to chapter 4 of Coqueret (2022) for a review on the link between corporate and social responsibility on one hand, and financial performance on the other (see http://www.esgperspectives.com/Perf.htmlhttp://www.esgperspectives.com/Perf.html).

[4] Our baseline panel specification follows from a partial equilibrium model in which sustainability-aware agents trade according to ESG news and shocks therein. The model predicts that returns should be first impacted by ESG shocks. In doing so, we provide a theoretical grounding for the panel regressions similar to those in Serafeim and Yoon (2022b). The model also introduces an interaction term that links these shocks to the current *level* of the sustainability score. This term implies that shocks do not affect all firms in the same manner and that the raw greenness (ex ante) of the firms also matters. The rationale is that a positive or negative shock does not have the same significance for a green or brown firm. An improved version of the model generalizes the first by incorporating the sustainability scores of clients or suppliers into the pricing model of ESG-aware agents.

[5] Though the scope of the study is different, this can be put into perspective with the positive link between materiality disclosure and price informativeness documented in Grewal et al. (2021).

will accelerate the patterns that we document. As ESG becomes mainstream (Edmans, 2023), sustainability-related information will likely be reflected more rapidly in prices.

The remainder of the paper is structured as follows. Section 2 is dedicated to the literature review. Section 3 presents our data set, while Sections 4 and 5.1 detail and discuss our empirical results. Additional robustness checks and cross-sectional analyses are gathered in Section 5. Finally, Section 6 concludes. The theoretical foundation of our estimation models is postponed to Appendix A.

2 | RELATED LITERATURE

Our paper first relates to the studies on the diffusion of news into asset prices, which has been a recurring topic, from the seminal work of Beaver (1968) and Fama et al. (1969), to Dow and Gorton (1993) and Mitchell and Mulherin (1994), and, more recently, to Curtis et al. (2014), Engelberg et al. (2018), Hirshleifer et al. (2021), and Hirshleifer and Sheng (2022). Macroeconomic drivers are for example analyzed in the early contributions of Bodie (1976), Fama (1981), Pearce and Roley (1985), Chen et al. (1986), Jain (1988), and Flannery and Protopapadakis (2002). At more granular levels, stock-specific signals are also exhaustively followed by researchers and practitioners. A longstanding market reaction in the cross-section of stocks is the postearnings announcement drift (see, e.g., Foster et al., 1984; Patell and Wolfson, 1984; Bernard and Thomas, 1989; Dontoh et al., 2003, to cite but a few). Relatedly, the price impact of dividends has also been investigated in Litzenberger and Ramaswamy (1982), Kane et al. (1984), Miller and Rock (1985) and Naranjo et al. (1998). With the advent of text processing, researchers and practitioners have started delving into the impact of individual pieces of news (articles in traditional outlets, posts on social media, earnings conference calls, etc.) on asset prices. We refer to Jeon et al. (2022) and the references therein, as well as to Eccles and Serafeim (2013), Tomlinson et al. (2021), Lanfear et al. (2019), and Ma et al. (2022) for contributions focused on sustainability and climate events.

A second adjacent stream of the literature pertains to the impact of ESG scores and news on financial performance. For instance, Giese et al. (2019) identify three channels through which ESG impacts financial performance: cash flow, risk, and valuation. All three channels are rooted in a discounted cash-flow model. Zeidan and Spitzeck (2015) provide an example of a detailed accounting-based valuation derived from alterations of cash flows and the weighted average cost of capital (WACC). Empirically, Derrien et al. (2021) find that most of the ESG-linked variation in valuation comes from the cash-flow channel and that the discount rates are not much affected by ESG scandals. Capelle-Blancard and Petit (2019), de Franco (2020), Dorfleitner et al. (2020), and Gloßner (2021) also report that ESG incidents do matter and are negatively related to future returns. However, Aouadi and Marsat (2018) document the reverse effect.

In a similar vein, Serafeim and Yoon (2022b) report a positive link between ESG news and price fluctuations. The authors also show that stock prices react to the unexpected part of ESG news. More generally, Bolton and Kacperczyk (2021, 2023) also conclude that carbon risk (a facet of ESG) is priced by markets. Moreover, Serafeim and Yoon (2022b, 2022a) document the mitigating role of disagreement. They find that ESG shocks have an impact on future returns, but this impact is stronger when raters are in unison. Our paper adds another layer to the discussion. We argue that stock prices' reaction to ESG news does not only depend on the ESG news and the current ESG rating but also on the interaction between these two. The role of media and investor attention in the diffusion of sustainability shocks is analyzed in Wong and Zhang (2022) and Zhang et al. (2021). Another adjacent study is that of Adenot et al. (2022), which quantifies the impact of carbon pricing on firm values. They use an input–output model to estimate the effect, on firm earnings, of the introduction of a carbon tax.

The contribution that is closest to ours is the work of Li et al. (2021), who study the propagation of risk information to the stock price of suppliers in China. Our paper departs from their analysis in three important ways. First, we use data from US firms, which results in a somewhat larger sample. Second, our models (both theoretical and empirical) follow the methodology of Serafeim and Yoon (2022b). Third, news in our study stems from sustainability concerns. Another type of signal is considered in Cen et al. (2019), which also analyzes spillover effects, but in the vicinity of earnings announcements.

Lastly, our research also relates to the contributions pertaining to supply chain networks and the spillover effects therein. For example, Oberfield (2018) proposes a theoretical model on the architecture of a firm's input-output and on the choice of optimal suppliers. Interfirm relationships also impact the decision on a firm's capital structure (Banerjee et al., 2008), while bankruptcy fillings can adversely affect other firms in the supply chain (Hertzel et al., 2008). Cohen and Frazzini (2008) show that a firm's price momentum effect can spread to firms that are economically linked to this firm (both customers and suppliers). Barrot and Sauvagnat (2016) and Pankratz and Schiller (2021) both document evidence of spillover effects in the supply chain when a climate shock or disaster occurs. This effect can first adversely impact other firms' sales and operating income but can also break down the production link between firms. Schiller (2018) and Dai et al. (2021) show that environmental and social policies can be transmitted from customers to suppliers firms. Finally, Bose and Pal (2012) prove that announcements related to supply chain management can be drivers of stock prices.

We contribute to these streams of literature by documenting the propagation of ESG shocks alongside the supply chain, from a return standpoint. In contrast to other studies which investigate the impact of low-frequency accounting data, we use daily returns to study the swift market reactions when there are ESG shocks in the value chain. We also predict and confirm that the ESG news propagation effect is nonlinear because it depends both on the magnitude of the shock and on the current ESG rating of the affected firm.

3 | DATA

To investigate the direct and indirect spillover effects of ESG news on stocks' return, we merge three data sets: Truvalue for ESG news data, FactSet Revere for the supply chain relationships, and finally FactSet Price data for prices and returns.

First, we collect daily prices (and returns) and share outstanding of all common stocks traded on NYSE, NASDAQ, and NYSE American (formerly known as AMEX) exchanges, from FactSet Price. Second, we gather the supplier and customer relationship data from FactSet Revere. FactSet Revere provides data on the links between suppliers and customers for public companies worldwide. They also collect the percentage of revenue that a customer firm contributes to the overall revenue of the supplier. FactSet Revere also ranks the importance of each customer (and each supplier) for a firm, based on several factors, such as customer revenue contribution, the company disclosing the relationship, and other metadata. In our study, for tractability, we only focus on the main supplier and the main customer of US firms.

Next, we extract the ESG data for all US firms, as well as the ESG scores of their main supplier, and that of their main customer using TruValue Data. ESG data providers used to resort to companies' annual reports as a main input to derive ESG profiles. In contrast to this practice, TruValue takes an outside-in approach and only uses information that is external to the companies: this decreases the self-reporting bias. In addition, TruValue collects and aggregates unstructured content regarding a company's ESG profile from more than 100,000 sources. The data are both semantic and quantitative for more than a dozen languages. The raw content is usually derived from article news, and reports from nongovernmental organizations (NGOs), watchdog institutions, etc. Then, relevant metrics from the data are analyzed and sorted into 26 categories defined by the Sustainability Accounting Standards Board (SASB). Finally, TruValue normalizes these indicators and generates sustainability performance scores from short-term to long-term.

In our study, we use the *Pulse* score that is a measure of the near-term performance of the companies' sustainability. The Pulse score is disclosed at a daily frequency. It focuses on events of the day and provides a responsive signal when there is a shock to the company's ESG profile. Hence, a shock to the Pulse score will serve as a proxy for what we refer to as Δg in our study.

ESG disagreement is an important issue widely reported in the literature.[6] However, the providers that supply daily scores with no self-reporting bias are scarce, which is why we resort to TruValue data only. For

[6] We refer for instance to Dimson et al. (2020), Gibson Brandon et al. (2021), Avramov et al. (2022), Berg et al. (2022), Christensen et al. (2022), and Serafeim and Yoon (2022a).

example, MSCI, Sustainalytics, and Refinitiv either do not update their fields daily or rely at least partially on company-provided information.

We use two main ESG measures in our study. The first is the *All Categories Pulse (ACP)*, which summarizes the ESG scores of all 26 ESG categories following the nomenclature of the SASB. Another one is the *Materiality Pulse (MP)* score, which only summarizes the ESG categories that the SASB considers financially material to that company. We normalize the ESG measures to have a score from 0 to 1. A score of 0.50 means a neutral impact, while values above (*resp*. below) 0.50 correspond to positive (*resp*. negative) news.

Unlike previous studies on the economic and financial ramifications of supply chains that rely on COMPUSTAT data,[7] and hence focus only on the customer firms that are in the United States, our sample is not hindered by such a restriction. For any US company in our sample, we are able to determine its main suppliers and its main customers, either in the United States or abroad. This feature is noteworthy because the supply chain network is increasingly global.

Upon the merger of our three data sets, we obtain three samples. The first sample consists of all US common stocks for which a TruValue score is available. We report the cross-section summary statistics of ACP and MP measures in Panel A of Table 1. The sample has on average around 2800 firms each day. We use this sample to study the direct effect of ESG news shock on stocks' return.

The second sample consists of US firms and their main customers for which ESG scores are available. We report the summary statistics of ACP and MP of the customer firms in Panel B of Table 1. The sample has on average around 1300 pairs each day. We use this sample to investigate the spillover effect of ESG news shocks to US suppliers, from their main customers.

The third sample pertains to US firms and their main suppliers (when they have well-defined ESG scores). We report the summary statistics of ACP and MP of the supplier firms in Panel C, Table 1. The sample has on average around 1000 pairs each day. With this sample, we study the spillover effect of ESG news shocks to US customers from their main suppliers.

All three samples encompass data from January 2007 to May 2021. From the last column in the table, we notice that ESG measures are quite persistent in time: ESG scores only change when there are new shocks or news. This indicator of persistence is very high (above 0.98) for both ACP and MP measures in all three samples. The first difference of the ESG measure ($\Delta g_{t,n}$) captures the ESG shock to company n at time t and is one of the focal quantities in our analysis. By construction, this indicator is much less autocorrelated.

4 | EMPIRICAL METHODS AND RESULTS

4.1 | Empirical methods

As mentioned above, TruValue provides ESG scores based on news that they collect. The ESG score of each company is relatively persistent and only changes if there is new information about this company's ESG profile. In Table 1, the average change in *MP* and *ACP* is small and never greater than 0.07 points in all of the three samples.

Given how changes in ESG scores are small in magnitude, it seems reasonable to assume that their squared value is negligible. Therefore, our empirical test will solely focus on the change in ESG score and ignore the squared value of the change. We thus restrict our study to the following specification:

$$r_{t+1,n} = a_n + b_1 \Delta g_{t+1,n} + b_2 g_t \Delta g_{t+1,n} + e_{t+1,n}.$$

This expression allows us to track the effect of ESG shocks on returns through the two parameters b_1 and b_2. The first coefficient (b_1) links shocks to returns, while the second one (b_2) focuses on the interaction between the shock

[7] See, e.g., Barrot and Sauvagnat (2016), Banerjee et al. (2008), Cohen and Frazzini (2008), and Hertzel et al. (2008)

TABLE 1 Summary statistics of ESG measures for ACP (All Categories Pulse) and MP (Materiality Pulse) after normalization.

	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis	Q0.25	Q0.5	Q0.75	Corr(t, $t-1$)
Panel A: All US firms													
ACP	2795.98	0.53	0.21	0.51	0.01	1.00	0.99	−0.07	−0.34	0.40	0.51	0.68	0.99
MP	2486.27	0.54	0.22	0.52	0.00	1.00	0.99	−0.13	0.01	0.40	0.52	0.69	0.99
$\|\Delta ACP\|$ (when $\neq 0$)	169.92	0.06	0.10	0.02	0.00	0.60	0.60	2.92	10.61	0.01	0.02	0.07	-
$\|\Delta MP\|$ (when $\neq 0$).	114.18	0.07	0.10	0.03	0.00	0.57	0.57	2.73	9.07	0.01	0.03	0.08	-
Panel B: Main customer of US firms													
	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis	Q0.25	Q0.5	Q0.75	Corr(t, $t-1$)
ACP^{Cus}	1248.04	0.53	0.15	0.52	0.03	0.98	0.95	−0.02	0.76	0.44	0.52	0.61	0.98
MP^{Cus}	1227.41	0.53	0.18	0.52	0.02	0.99	0.97	−0.08	0.33	0.43	0.52	0.64	0.98
$\|\Delta ACP\|^{Cus}$ (when $\neq 0$)	488.40	0.02	0.04	0.01	0.00	0.39	0.39	5.68	47.87	0.00	0.01	0.02	-
$\|\Delta MP\|^{Cus}$ (when $\neq 0$)	386.19	0.02	0.04	0.01	0.00	0.39	0.39	5.10	38.52	0.00	0.01	0.02	-
Panel C: Main supplier of US firms													
	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis	Q0.25	Q0.5	Q0.75	Corr(t, $t-1$)
ACP^{Sup}	977.75	0.53	0.17	0.52	0.03	0.98	0.95	−0.07	0.42	0.44	0.52	0.63	0.98
MP^{Sup}	953.62	0.53	0.19	0.53	0.02	0.98	0.96	−0.10	0.06	0.42	0.53	0.66	0.99
$\|\Delta ACP\|^{Sup}$ (when $\neq 0$)	316.90	0.02	0.04	0.01	0.00	0.38	0.38	5.11	37.49	0.00	0.01	0.02	-
$\|\Delta MP\|^{Sup}$ (when $\neq 0$)	248.91	0.03	0.05	0.01	0.00	0.37	0.37	4.62	30.65	0.00	0.01	0.02	-

Note: We do a cross-sectional summary first for each day and then take the average across time. In the table, the abbreviation "SD" means standard deviation. "Q0.25," "Q0.5," and "Q0.75" correspond to the 25%, 50%, and 75% quantiles, respectively. The term Corr(t, $t-1$) refers to the correlation between the measure and its first lag. We also report the summarized statistics of the changes in either ACP or MP in absolute terms, conditionally on the change being nonzero. In Panel A, we use the sample of all US firms and report the summary statistics of ESG measures. In Panel B, we use the sample that consists of the main customers of US firms, while in Panel C, the sample pertains to the main suppliers of US firms. All three samples consist data from January 2007 to May 2021.

and the level of sustainability—and its relationship with returns. A theoretical justification for this particular model can be obtained via an equilibrium approach, and the interested reader is invited to read Appendix A for more details.

The classical empirical approach to studying news impact is to resort to an "event study" à la Fama et al. (1969). Practically, event studies derive the risk-adjusted or abnormal return (AR) return for each stock in the first step. Second, they study the cross-sectional average of AR when computing the cumulative abnormal return (CAR) for days before and after the event day. Usually, a sudden drift in CAR is observed exactly the day the news is reflected in prices. After that day, CAR barely changes. We argue that this method is not best suited for our empirical setting.

First, there is the issue of the identification of the event. In typical financial applications, this would be an announcement day (earning, dividend, M&A). In our framework, events are shocks, but there is no unequivocal way to define an event based on changes in ratings: this requires setting arbitrary thresholds. Second, as is suggested in our theoretical model, the links we study are contingent on the sign of the shocks, the magnitude of the shocks, and the ESG levels of firms that experience the shock. Taking these elements into account would require creating clusters of firms (possibly dynamically), which introduces further degrees of freedom. The multiplication of such discretionary choices for the categorization of firms, shocks, and effects is likely to perturb the quality and reliability of inference.[8]

Instead, we follow both the recommendation from our theoretical framework in Appendix A and the path laid out in Serafeim and Yoon (2022b, 2022a) and also use panel regressions to study ESG news. Formally, we use Equation (1) below to assess the direct impact of ESG news to return, Equation (2) for the spillover effect from customer-to-supplier, and Equation (3) for spillover effect from supplier-to-customer.

$$r_{t,n} - r_f = \gamma_n + \sum_{j=0}^{3} \theta_j \Delta g_{t-j,n} + \sum_{j=0}^{3} \beta_j g_{t-1,n} \times \Delta g_{t-j,n} + \alpha g_{t-1,n} + \delta' Z_t + \varepsilon_{t,n}, \tag{1}$$

$$\begin{aligned} r^{Sup}_{t,n} - r_f = {} & \sum_{j=0}^{3} \theta^{Cus}_j \Delta g^{Cus}_{t-j,n} + \sum_{j=0}^{3} \beta^{Cus}_j g^{Sup}_{t-1,n} \times \Delta g^{Cus}_{t-j,n} + \gamma_n + \delta' Z_t \\ & + \sum_{j=t-3}^{t} \beta^{Sup}_j g^{Sup}_{t-1,n} \times \Delta g^{Sup}_{t-j,n} + \alpha^{Cus} g^{Sup}_{t-1,n} + \sum_{j=0}^{3} \theta^{Sup}_j \Delta g^{Sup}_{t-j,n} + \varepsilon_{t,n}, \end{aligned} \tag{2}$$

$$\begin{aligned} r^{Cus}_{t,n} - r_f = {} & \sum_{j=0}^{3} \theta^{Sup}_j \Delta g^{Sup}_{t-j,n} + \sum_{j=0}^{3} \beta^{Sup}_j g^{Cus}_{t-1,n} \times \Delta g^{Sup}_{t-j,n} + \gamma_n + \delta' Z_t \\ & + \sum_{j=t-3}^{t} \beta^{Cus}_j g^{Cus}_{t-1,n} \times \Delta g^{Cus}_{t-j,n} + \alpha g^{Cus}_{t-1,n} + \sum_{j=0}^{3} \theta^{Cus}_j \Delta g^{Cus}_{t-j,n} + \varepsilon_{t,n}, \end{aligned} \tag{3}$$

where $r_{t,n}$ is the return of the firm n at time t, and r_f the risk-free rate. $g_{t-j,n}$ is the ESG score of firm n, either ACP (All Categories Pulse score) or MP (Materialized Pulse score only), normalized to lie between zero and one. $r^{Sup}_{t,n}$ is the return of the supplier firm. $r^{Cus}_{t,n}$ is the return of the customer firm. $g^{Sup}_{t-j,n}$ is the ESG score of the supplier firm (either ACP (All Categories Pulse score) or MP (Materialized Pulse score only))—after normalization. $g^{Cus}_{t-j,n}$ is the ESG score of the customer firm. Z_t is a vector of control variables: the Fama and French (2015) 5 factors, plus the momentum factor (12 months to prior month return, in line with Jegadeesh and Titman (1993) and Carhart (1997)). γ_n is the fixed effect term. Finally, $\varepsilon_{t,n}$ is the error term.

Panel regressions eliminate the second problem of grouping when we let ESG shocks and ESG levels be continuous and allow interaction between them. Regressions also control the problem of consecutive event days. With the lags approach, we can separate the impact of ESG shocks on one day to return on another day while keeping everything else constant.

[8] For example, we can classify (i) shock to be positive or negative, (ii) shock magnitude into m categories on the interval of [0,1], (iii) ESG level into n categories on the interval of [0,1]. Therefore, the total number of groups is $2 \times m \times n$. The number of groups can explode rapidly with fine slicing (e.g., 50 groups for the arbitrary choice of quintiles, $m = n = 5$), thus shrinking the number of stocks within each group and making results hard to display and interpret.

The inclusion of asset pricing factors in the regression can be thought of as a time effect that reflects current market conditions. In addition, because factor returns are constant for a given date in the cross-section of stocks, their inclusion serves as a chronological fixed effect. Hence, on top of the γ_n, we have in fact fixed effects in both dimensions. In addition, when estimating the spillover effect of ESG news shock from customer-to-supplier, we control for the ESG shock of the supplier itself. The same control applies when we want to estimate the spillover effect of ESG news shock from supplier-to-customer.

The *t*-statistics of all coefficients are computed with errors clustered by date, and firm, as in Thompson (2011). We investigate the impact of ESG news shocks released during the 3 days[9] prior to the return. Implicitly, we assume that news may take time to diffuse into prices, though not *too much* time.

The coefficients in two terms $\sum_{j=0}^{3}\theta_j\Delta g_{t-j,n}$ and $\sum_{j=0}^{3}\beta_j g_{t-1,n}\times\Delta g_{t-j,n}$ show the effect to returns if there is a change in ESG score.

Similarly, the coefficients in $\sum_{j=0}^{3}\theta_j^{Cus}\Delta g_{t-j,n}^{Cus}+\sum_{j=0}^{3}\beta_j^{Cus}g_{t-1,n}^{Sup}\times\Delta g_{t-j,n}^{Cus}$ show the spillover effect from customer-to-supplier, while the coefficients in $\sum_{j=0}^{3}\theta_j^{Sup}\Delta g_{t-j,n}^{Sup}+\sum_{j=0}^{3}\beta_j^{Sup}g_{t-1,n}^{Cus}\times\Delta g_{t-j,n}^{Sup}$ show the spillover effect from supplier-to-customer. With the control settings discussed above, these effects are indeed abnormal returns (AR) related to ESG shocks.

The novelty of our method is the inclusion of the ESG level and the interaction between ESG level and ESG shock in the panel regression. This inclusion arises from our theoretical model that shows heterogeneous reactions to ESG news conditioning on the current ESG level. Other than that, our methods also have minor differences from the one in Serafeim and Yoon (2022b, 2022a). First, we use factors' return in the right-hand side (RHS) rather than using the risk-adjusted return in the left-hand side (LHS) of the regressions. Second, we use multiple RHS variables (lags of ESG shocks) and one LHS variable (return) to study the impact of ESG shock on return at different points in time, rather than one RHS variable (ESG shocks) and different LHS variables (several interval returns). This helps us to get everything compact in one regression rather than doing multiple regressions with multiple LHS variables. Third, we use firm fixed effect rather than industry fixed effect. However, the results are qualitatively similar to the one with industry fixed effect.[10]

4.2 | Direct impact of ESG news shocks to stocks' return

The direct impact of ESG news shocks on stocks' return is in Table 2. For the sake of brevity and clarification, we only report the coefficients of the two terms $\sum_{j=0}^{3}\theta_j\Delta g_{t-j,n}$, and $\sum_{j=0}^{3}\beta_j g_{t-1,n}\times\Delta g_{t-j,n}$ from the Equation (1). These coefficients show the effect on returns if there is a change in the ESG score. We provide two alternative specifications using both ESG measures: ACP (All Categories Pulse) in model (1) and MP (Material Pulse) in model (2).

Our results show that the impact of the shock on ESG news is priced instantaneously intraday. The coefficient θ_0 in the terms $\sum_{j=0}^{3}\theta_j\Delta g_{t-j,n}$ is positive and highly significant for both ESG measures. The magnitude of θ_0 is quite similar in both ACP and MP. For ACP, $\theta_0 = 0.012$ (*t*-stat = 6.91) while for MP $\theta_0 = 0.010$ (*t*-stat = 4.91). The positive sign implies that good (*resp.* bad) ESG news shock will push prices up (*resp.* down), after controlling for the traditional asset pricing factors. The coefficient θ_0 is also economically significant. For example, with the ACP measure, an increase of 0.10 points in ESG score[11] will shift the daily return by +0.12%, on average.

However, to assess the total impact of ESG shocks to return, we have to also consider the coefficients of the cross terms, β_0. The latter is negative for both models of *ACP* ($\beta_0 = -0.025$; *t*-stat: –8.02) and *MP* ($\beta_0 = -0.018$; *t*-stat:

[9] The results are qualitatively the same when using lags up to 5 days, and coefficients are not significant beyond 3 days. These additional results are available upon request.

[10] Again, the results are available upon request.

[11] Recall that ESG score is from 0 to 1, with 0.50 being neutral, so to speak.

TABLE 2 Panel regression of the effect of ESG shocks to returns.

Variable \ Model:	(1) $g = ACP$		(2) $g = MP$	
L(Δg,3)	0.001	(0.866)	0.001	(0.815)
L(Δg,2)	0.002*	(2.310)	0.002*	(2.080)
L(Δg,1)	−0.000	(0.066)	0.000	(0.234)
Δg	0.012**	(6.910)	0.010**	(4.910)
L(Δg,3) × L(g,1)	−0.000	(−0.281)	−0.002	(−0.953)
L(Δg,2) × L(g,1)	−0.003*	(−2.010)	−0.004*	(−2.470)
L(Δg,1) × L(g,1)	0.000	(0.225)	0.001	(0.467)
Δg × L(g,1)	−0.025**	(−8.020)	−0.018**	(−5.280)
Fixed effects:				
Firm id	Yes		Yes	
Time via Factors' return	Yes		Yes	
VCOV: clustered	Firm & date		Firm & date	
Observations	10,089,466		8,970,685	
R^2	0.030		0.028	
Within R^2	0.030		0.028	
Signif. codes : **0.01, *0.05				

Note: The model equation is:

$$r_{t,n} - r_f = \sum_{j=0}^{3} \theta_j \Delta g_{t-j,n} + \sum_{j=0}^{3} \beta_j g_{t-1,n} \times \Delta g_{t-j,n} + \alpha g_{t-1,n} + \gamma_n + \delta' Z_t + \varepsilon_{t,n},$$

where $r_{t,n}$ is the return of the firm n; $g_{j,n}$ is the ESG score of firm n (ACP (All Categories Pulse score) or MP (Materialized Pulse score)). γ_n is the fixed effect, Z_t is a vector of control for Fama and French (2015) 5 factors and momentum. ε is the noise term. The t-statistics are computed with the clustered errors by date and firm, as in Thompson (2011). We only report the coefficients in two terms $\sum_{j=0}^{3} \theta_j \Delta g_{t-j,n}$, and $\sum_{j=0}^{3} \beta_j g_{t-1,n} \times \Delta g_{t-j,n}$. $L(x, n)$ is the lag function: $L(x_t, n) = x_{t-n}$. Samples consist of daily data from January 2007 to May 2021.

−5.28). The negative coefficient β_0 will generate a mitigating effect on the impact of ESG shocks on the return, in addition to θ_0.

Given a positive ESG shock with the same magnitude, high ESG profile firms will react less positively (or even negatively), compared to low ESG firms. Depending on the ESG score, there is a different reaction toward the same ESG news shock. This makes sense heuristically: a firm with a high ESG reputation has less to gain from incremental improvement in ratings.

To further illustrate this idea, we plot in Figure 1 the average impact of a *positive* shock of ESG news having magnitude 0.1 onto the firm return, as a function of the ESG score of the firm. This is given by the linear mapping $\tilde{r}_t(g_{t-1}) = (\theta_0 + \beta_0 \times g_{t-1})\Delta g_t$, where $\tilde{r}_t$ is the part of returns due to an ESG shock. Given $\Delta g_t = 0.1$, as well as the θ_0 and β_0 values in Table 2, we plot $\tilde{r}_t$ as an affine function of g_{t-1}, the ESG level. Technically, the average of fixed effects is omitted.

We observe that low ESG firms react very favorably to positive ESG news. This confirms that a positive shock is more valuable for brown firms than it is for green firms. For most green firms, a positive shock in ESG is, surprisingly, even detrimental. Reversely, in the advent of a negative shock, green firms will be more resilient. Indeed, the negative impact from θ_0 is similar to all firms. However, with a negative β_0, green firms will suffer less from negative news than brown firms.

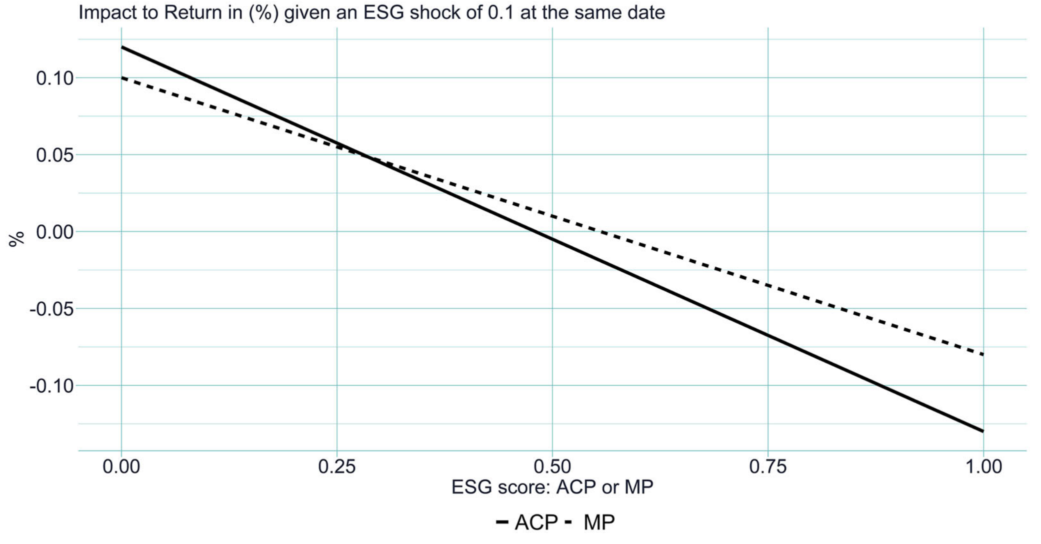

FIGURE 1 Impact to daily return (in %) given an ESG shock (Δg_t) of +0.1 at the same date contingent on different firm's ESG level, g_{t-1}.
Note: The plot shows $\tilde{r}_t(g_{t-1}) = (\theta_0 + \beta_0 \times g_{t-1})\Delta g_t$, with $\Delta g_t = 0.1$, θ_0, and β_0 from Table 2. The ESG measure is either ACP (full line) or MP (dashed line).
[Color figure can be viewed at wileyonlinelibrary.com]

In short, our results reveal that most of the effect of an ESG shock happens at high frequency and then fades away. Low ESG firms benefit from positive shocks more than high ESG firms. However, high ESG firms suffer less from negative ESG shocks than low ESG firms.

4.3 | ESG news shock to suppliers' stock returns

In the previous section, we documented the instantaneous market's reaction to ESG news shocks. An interesting follow-up question is: is there any spillover effect along the supply chain? In this section, we investigate this effect from the main customer firm to the supplier firm.

We want to estimate the spillover effect of ESG news shock from customer-to-supplier while controlling for the ESG shock of the supplier itself and other common factors on the market. We report the coefficients of the two terms $\sum_{j=0}^{3} \theta_j^{Cus} \Delta g_{t-j,n}^{Cus}$ and $\sum_{j=0}^{3} \beta_j^{Cus} g_{t-1,n}^{Sup} \times \Delta g_{t-j,n}^{Cus}$, from the Equation (2), in Table 3. These coefficients show the spillover effect from customer-to-supplier if there is a shock in the ESG score from the customer side.

In Table 3, we observe a faint spillover effect of ESG news from customer-to-supplier. With the ACP measure, the estimate for θ_3^{Cus} is equal to 0.003 (t-stat of 2.09). This effect is thus four times weaker than the direct effect of ESG news' shock to the company return on the same day (0.012 in the previous section).

Therefore, a shock on ACP news from the customer side takes 3 days to diffuse to the supplier's return. For example, an increase of 0.1 points in ACP from the customer firm 3 days ago will increase the present-day return of the supplier firm by 0.03% on average.

However, this spillover effect is mitigated by the coefficient $\beta_3^{Cus} = -0.005$ (t-stat equal to –2.08) in the cross terms. This moderation depends on the ESG profile of the supplier firm, $g_{t-1,n}^{Sup}$: the higher g^{Sup} is, the stronger the mitigation effect is. Equivalently, a high ACP profile firm will be less positively impacted by a positive shock from their customer. In some cases, a high ACP firm even faces a negative impact when there is a positive shock in return from the customer side. The total impact on return from the customer ESG shock depends on the level of ESG of the supplier firm.

TABLE 3 Panel regression of the spillover effect of ESG news from customer-to-supplier.

Variable \ Model	(1) $g = ACP$		(2) $g = MP$	
$L(\Delta g^{Cus},3)$	0.003*	(2.090)	0.003	(1.730)
$L(\Delta g^{Cus},2)$	−0.003	(−1.840)	0.000	(0.069)
$L(\Delta g^{Cus},1)$	−0.001	(−0.458)	−0.005**	(−2.900)
Δg^{Cus}	−0.000	(−0.224)	−0.002	(−1.260)
$L(\Delta g^{Cus},3) \times L(g^{Sup},1)$	−0.005*	(−2.080)	−0.004	(−1.440)
$L(\Delta g^{Cus},2) \times L(g^{Sup},1)$	0.002	(0.651)	−0.001	(−0.284)
$L(\Delta g^{Cus},1) \times L(g^{Sup},1)$	0.001	(0.297)	0.008**	(2.960)
$\Delta g^{Cus} \times L(g^{Sup},1)$	−0.000	(−0.001)	0.003	(1.140)
Fixed effects:				
Supplier ID	Yes		Yes	
Time via Factors' return	Yes		Yes	
Cluster: supplier ID and date	Yes		Yes	
Observations	4 496 060		4 031 087	
R^2	0.149		0.147	
Within R^2	0.148		0.147	
Signif. codes : **0.01, *0.05				

Note: The model equation is

$$r^{Sup}_{t,n} - r_f = \sum_{j=0}^{3} \theta_j^{Cus} \Delta g^{Cus}_{t-j,n} + \sum_{j=0}^{3} \beta_j^{Cus} g^{Sup}_{t-1,n} \times \Delta g^{Cus}_{t-j,n} + \gamma_n + \delta' Z_t +$$

$$\sum_{j=t-3}^{t} \beta_j^{Sup} g^{Sup}_{t-1,n} \times \Delta g^{Sup}_{t-j,n} + \alpha^{Cus} g^{Sup}_{t-1,n} + \sum_{j=0}^{3} \theta_j^{Sup} \Delta g^{Sup}_{t-j,n} + \varepsilon_{t,n},$$

where $r^{Sup}_{t,n}$ is the return of the supplier firm n. $g^{Sup}_{j,n}$ is the variable of the ESG score of supplier n, which can be ACP (All Categories Pulse score) or MP (Materialized Pulse score only) after being normalized to have a value between zero and one. The notation is similar to $g^{Cus}_{j,n}$, which is the main customer of firm n. The term γ_n is the fixed effect, and Z_t is a vector of control for Fama and French (2015) 5 factors and momentum. ε is the noise. The t-statistics are computed with clustered errors by date and firm n. We only report the coefficients in two terms $\sum_{j=0}^{3} \theta_j^{Cus} \Delta g^{Cus}_{t-j,n}$ and $\sum_{j=0}^{3} \beta_j^{Cus} g^{Sup}_{t-1,n} \times \Delta g^{Cus}_{t-j,n}$. Samples consist of daily data from January 2007 to May 2021.

We also find a significant spillover effect from customer-to-supplier when using the MP (Materiality Pulse) measure. Similarly to ACP, the magnitude is less marked, compared to the direct effect. Indeed, $\theta_1^{Cus} = -0.005$ (t-stat: −2.90) is two times smaller in magnitude compared to the effect reported in the previous section (0.010). Importantly, it takes only 1 day for the spillover to materialize with the MP measure. Similarly to the ACP metric, with the MP values, we find a mitigating force on the same day: $\beta_1^{Cus} = 0.008$ (t-stat: 2.96) will pull the effect of $\theta_1^{Cus} = -0.005$ in the opposite direction. Overall, the total effect will depend on the ESG profile of the supplier firm. High MP firms will react more favorably to positive news than low MP firms.

To summarize our findings, we plot average effects in Figure 2 in the same spirit as Figure 1. Given a positive ESG shock of 0.1 ($\Delta g = 0.1$) from the customer side, the horizontal axis features the ESG score (ACP or MP) of the supplier firm, while the vertical axis shows the impact in return, in percentage. Again, the figure shows that the impact of news is contingent on the level of the ESG score, but also, importantly, on the type of measure (ACP versus MP).

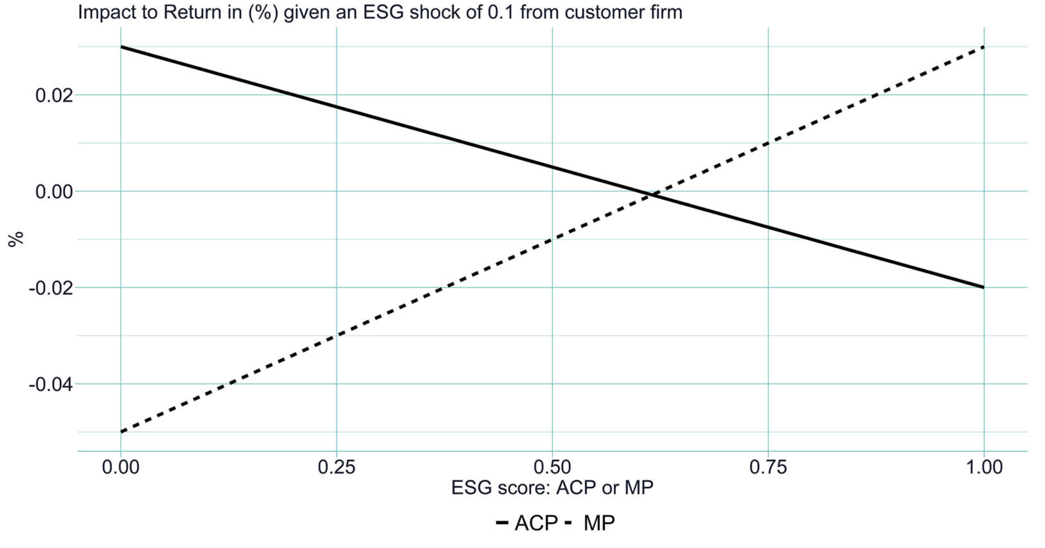

FIGURE 2 Impact to daily firm return (in %), given an ESG shock of +0.1 ($\Delta g^{Cus} = 0.1$) from its customer firm, contingent on the ESG level of the firm.
Note: For the ACP measure (hard line), it is the total effect to return of day 3 after the shock date on the customer side, which includes the significant interaction terms $\Delta g^{Cus} \cdot \theta_3^{Cus}$ and $\Delta g^{Cus} \beta_3^{Cus} \cdot g_{t-1}^{Sup}$. For the MP measure (dashed line), it is the total effect of day 1 after the shock on the customer side, which includes $\Delta g^{Cus} \cdot \theta_1^{Cus}$ and $\Delta g^{Cus} \beta_1^{Cus} \cdot g_{t-1}^{Sup}$. [Color figure can be viewed at wileyonlinelibrary.com]

4.4 | ESG news shock to customers' stock returns

In this subsection, we investigate the reverse effect, that is, from supplier-to-customer, that is, when the ESG shock comes from the supplier side using Equation (3).

In Table 4, we gather the estimated coefficients of the two terms $\sum_{j=0}^{3} \theta_j^{Sup} \Delta g_{t-j,n}^{Sup}$ and $\sum_{j=0}^{3} \beta_j^{Sup} g_{t-1,n}^{Cus} \times \Delta g_{t-j,n}^{Sup}$. When ACP is the ESG indicator, we find a significant spillover effect from supplier-to-customer 3 days after the shock. Surprisingly, $\theta_3^{Sup} = -0.004$ (t-stat = –1.98): the negative sign means that markets react positively to a drop in ACP rating. However, we also need to consider the interaction effect, which has the opposite sign ($\beta_3^{Sup} = 0.005$, (t-stat = 1.72)). The latter will serve as a mitigation force to drag down the ESG shock's impact from θ_2^{Sup}.

We also detect a slow spillover effect when considering MP as an ESG measure. In this case, $\theta_2^{Sup} = 0.004$ (t-stat = 2.38), but again this effect remains smaller than the direct effect (0.012, reported in Section 4.2).

In other words, if there is a shock in the MP score from the supplier side of +0.1 points, the customer's daily stock return will increase 2 days later by 0.04% on average. Nevertheless, this effect is moderated because $\beta_2^{Sup} = -0.008$, (t-stat = –2.73). The dragging force is positively related to the ESG score of the customer. Hence, when there is a positive shock on the supplier side, the brown customer firm is the one that has the most positive spillover impact. In contrast, when there is a negative shock from the supply side, then the green customer firm is the one that suffers less from that effect.

To illustrate this pattern, we plot in Figure 3 the average effect of a +0.1 ($\Delta g^{Sup} = +0.1$) supplier shock on a firm's return, as a function of the firm's ESG score. Again, the type of news (ACP versus MP) has a major impact on the effect.

Our final comment pertains to the speed of diffusion, depending on the type of news. In Tables 3 and 4, the significant coefficients for the ACP variable occur for the maximum lag (3 days). However, the significant ones for the Materiality Pulse score occur are associated with smaller lags. This means that financially material news seems to be priced more rapidly than generic ESG news.

TABLE 4 Panel regression of the spillover effect of ESG news from supplier-to-customer.

Variable \ Model	(1) $g = ACP$		(2) $g = MP$	
L(Δg^{Sup},3)	−0.004*	(−1.980)	−0.004	(−1.430)
L(Δg^{Sup},2)	−0.000	(−0.027)	0.004*	(2.380)
L(Δg^{Sup},1)	−0.000	(−0.074)	−0.000	(−0.015)
Δg^{Sup}	0.003	(1.210)	0.001	(0.402)
L(Δg^{Sup},3) × L(g^{Cus},1)	0.005	(1.720)	0.005	(1.190)
L(Δg^{Sup},2) × L(g^{Cus},1)	0.000	(0.130)	−0.008**	(−2.730)
L(Δg^{Sup},1) × L(g^{Cus},1)	0.001	(0.309)	0.001	(0.369)
Δg^{Sup} × L(g^{Cus},1)	−0.005	(−1.480)	−0.001	(−0.393)
Fixed effects:				
Customer ID	Yes		Yes	
Time via Factors' return	Yes		Yes	
Cluster: Customer ID and date	Yes		Yes	
Observations	3,520,532		3,142,980	
R^2	0.094		0.090	
Within R^2	0.093		0.089	
Signif. codes : **0.01, *0.05				

Note:

$$r_{t,n}^{Cus} - r_f = \sum_{j=0}^{3} \theta_j^{Sup} \Delta g_{t-j,n}^{Sup} + \sum_{j=0}^{3} \beta_j^{Sup} g_{t-1,n}^{Cus} \times \Delta g_{t-j,n}^{Sup} + \gamma_n + \delta' Z_t +$$

$$\sum_{j=t-3}^{t} \beta_j^{Cus} g_{t-1,n}^{Cus} \times \Delta g_{t-j,n}^{Cus} + \alpha g_{t-1,n}^{Cus} + \sum_{j=0}^{3} \theta_j^{Cus} \Delta g_{t-j,n}^{Cus} + \varepsilon_{t,n},$$

where $r_{t,n}^{Cus}$ is the return of the customer firm n. $g_{j,n}^{Sup}$ is the variable of the ESG score of the supplier to firm n, which can be ACP (All Categories Pulse score) or MP (Materialized Pulse score only) after being normalized to have a value between zero and one. The logic is similar with $g_{j,n}^{Cus}$. The term γ_n is the fixed effect, and Z_t is a vector of control for Fama and French (2015) 5 factors and momentum. ε is the noise. The t-statistics are computed with clustered errors by date and firm n. We only report the coefficients in two terms $\sum_{j=0}^{3} \theta_j^{Sup} \Delta g_{t-j,n}^{Sup}$ and $\sum_{j=0}^{3} \beta_j^{Sup} g_{t-1,n}^{Cus} \times \Delta g_{t-j,n}^{Sup}$. These coefficients show the spillover effect from supplier-to-customer if there is a shock/change in ESG score from the supplier side. Samples consist of daily data from January 2007 to May 2021.

4.5 | Economic value of ESG shocks

The above discussion shows that ESG shocks from the supply chain can affect a firm's return. However, to what extent investors should care about that effect? To shed light on this question, we perform a portfolio sorting exercise in order to quantify the economic potential of the ESG spillover effect for investors.

The portfolio sorting process is a standard double-sorting procedure in empirical asset pricing literature.[12] It will use ESG shocks from the supply chain as trading signals while also controlling for the firm's ESG level.

Formally, at the end of the day $t-1$, we sort stocks into 10 equal groups $G1 : G10$ based on their ESG levels. Doing that makes stocks in each group have quite similar ESG levels. For ESG shocks from customers, within each ESG level group, we use shocks from the last 3 days ($t-1$, $t-2$, $t-3$) from both AP and MP measures as signals for portfolio forming. For each signal in each ESG level group, we build a cash-neutral portfolio by going long with stocks having

[12] We relate to Bali et al. (2016) for an overview of the procedure.

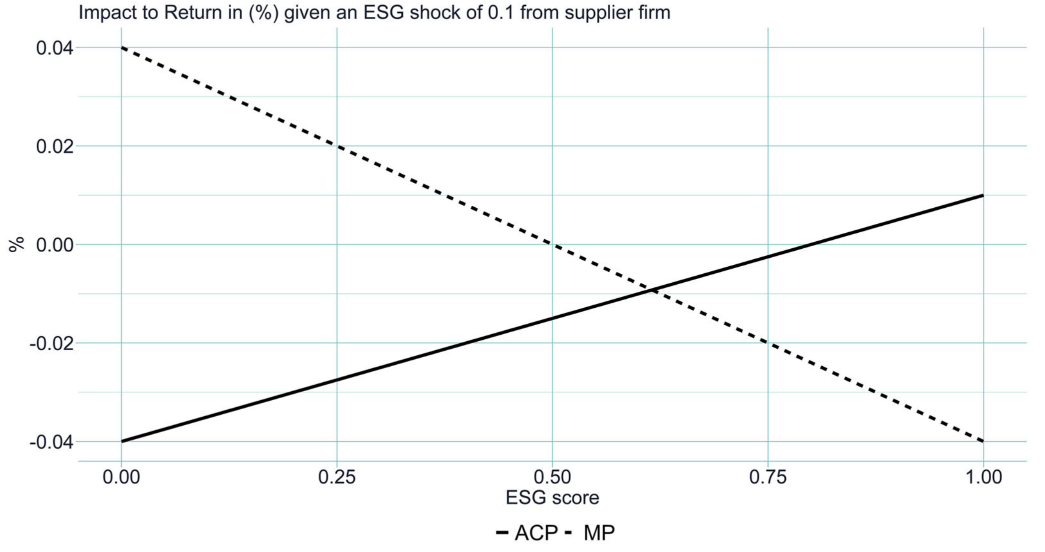

FIGURE 3 Impact to return in (%), given an ESG shock of +0.1 ($\Delta g^{Sup} = +0.1$) from the supplier firm, contingent on the firm's ESG level.
Note: For ACP, it is the combined effect of day 3 after the shock on the supplier side, which includes the significant interaction terms $\Delta g^{Sup} \cdot \theta_3^{Sup}$ and $\Delta g^{Sup} \beta_3^{Sup} \cdot g_{t-1}^{Cus}$. For MP, it is the total effect of day 2 after the shock on the supplier side $\Delta g^{Sup} \cdot \theta_2^{Sup}$ and $\Delta g^{Sup} \beta_2^{Sup} \cdot g_{t-1}^{Cus}$.
[Color figure can be viewed at wileyonlinelibrary.com]

positive ESG shocks from customers and going short with stocks having negative ESG shocks from customers. The initial ESG sorting ensures that the ESG level is controlled and that we only focus on ESG shocks.

We use both equal-weighted and value-weighted schemes for both the long and short legs of the cash-neutral portfolio. After that, we track the return of the cash-neutral portfolio within each ESG level group at the end of the day t. Then we form a new portfolio, named H-L, by averaging all the cash-neutral portfolios in all the 10 ESG level groups as a way to control for ESG level. We repeat the procedure on the day $t + 1$ and collect the return of the H-L portfolio. Finally, we compute the Sharpe Ratio (SR), the α from Fama French 5 factors plus momentum model, and annualized them. We also provide the α t-statistics in parentheses using Newey and West (1987) standard errors with 3 lags. For ESG shocks from suppliers to customers, the procedure is similar. We report results in Table 5 with α in percentage.

Consistent with the regression results in the above sessions, some of the ESG shocks from the supply chain can have an important impact and generate a consistent return for investors. For the ESG shocks from the customer's side, the H-L portfolios using *MP* shocks 3 days in the past ($t - 3$) offer a substantial annualized α of 6.77% (t-stat: 1.98) for the EW scheme portfolio and 8.28% (t-stat: 2.36) for the VW scheme portfolio. The α is both statistically and economically significant. Moreover, the Sharpe Ratio of these mentioned H-L portfolios is also noteworthy at 0.50 for the EW portfolio and 0.59 for the VW portfolio. Similarly, for the ESG shocks from the supplier side, the H-L portfolios using *ACP* shocks 3 days in the past ($t - 3$) offer an economically significant annualized α of –7.1% (t-stat: 2.06) for the EW portfolio. The Sharpe Ratio of this H-L portfolio is –0.59.

In summary, the portfolio sorting exercise also proves that the ESG spillover effect will take days to propagate through the supply chain network. Such a delay creates an opportunity for return capturing via portfolio forming using ESG shocks from the value chain. Some cash-neutral portfolios based on ESG shock signals can offer substantial annual α around 7%–8% and a Sharpe Ratio of 0.5 to 0.6. Therefore, the ESG spillover effect from the supply chain is economically important and could be harvested by investors.

TABLE 5 Double Sorting Portfolios based on ESG shocks from customer/supplier firms while controlling for the firm's ESG level.

Panel A: From customer-to-supplier								
	A1: $g = ACP$				A2: $g = MP$			
Signal	Portfolio	H-L annualized SR	H-L annualized α		Portfolio	H-L annualized SR	H-L annualized α	
$L(\Delta g^{Cus},1)$	EW	0.44	3.46	(1.55)	EW	0.39	4.40	(1.51)
	VW	0.52	3.92	(1.68)	VW	0.39	4.85	(1.63)
$L(\Delta g^{Cus},2)$	EW	0.09	1.21	(0.49)	EW	0.04	1.11	(0.33)
	VW	0.10	1.24	(0.47)	VW	0.07	1.64	(0.52)
$L(\Delta g^{Cus},3)$	EW	0.17	2.07	(0.80)	EW	0.50	6.77*	(1.98)
	VW	−0.06	−0.31	(−0.11)	VW	0.59	8.28*	(2.36)
Panel B: From supplier-to-customer								
	B1: $g = ACP$				B2: $g = MP$			
Signal	Portfolio	H-L annualized SR	H-L annualized α		Portfolio	H-L annualized SR	H-L annualized α	
$L(\Delta g^{Sup},1)$	EW	0.28	5.00	(1.04)	EW	0.10	0.93	(0.29)
	VW	0.41	8.05	(1.47)	VW	0.30	4.33	(1.03)
$L(\Delta g^{Sup},2)$	EW	0.42	5.65	(1.64)	EW	0.16	2.51	(0.56)
	VW	0.05	0.95	(0.21)	VW	−0.02	−0.72	(−0.14)
$L(\Delta g^{Sup},3)$	EW	−0.59	−7.10*	(−2.06)	EW	0.07	1.31	(0.34)
	VW	−0.38	−5.49	(−1.30)	VW	0.13	1.95	(0.42)
Signif. Codes: **: 0.01, *: 0.05								

Note: At the end of the day $t-1$, we sort stocks into 10 equal groups $G1 : G10$ based on their ESG. For ESG shocks from customers, within each ESG level group, we use shocks from the last 3 days from both *AP* and *MP* measures as signals for portfolio forming. For each signal in each ESG level group, we build a cash-neutral portfolio by going long with stocks having positive ESG shocks from customers and going short with stocks having negative ESG shocks from customers. We use both equal-weighted and value-weighted schemes for both the long and short legs of the cash-neutral portfolio. After that, we track the return of the cash-neutral portfolio within each ESG level group at the end of the day t. Then we form a new portfolio, named H-L, by averaging all the cash-neutral portfolios in all the 10 ESG level groups as a way to control for ESG level. We repeat the procedure on the day $t+1$ and collect the return of the H-L portfolio. Finally, we compute the Sharpe Ratio (SR), the α from Fama French 5 factors plus momentum model, and annualized them. We also provide the α t-statistics in parentheses using Newey and West (1987) standard errors with 3 lags. For ESG shocks from suppliers to customers, the procedure is similar. The α is in percentage.

5 | ROBUSTNESS CHECKS AND SUBSAMPLES ANALYSES

We use this section to perform different robustness and subsamples analyses. We first investigate the spillover effect before and after the Paris Climate Accord. Then, we compare this effect among big stocks versus small stocks and among ESG-attention versus non-ESG-attention stocks. Finally, we distinguish the spillover effect from other non-ESG effects.

5.1 | Chronological splitting: The evolution of investor awareness

The previous section has led us to conclude that ESG news creates an instantaneous impact on stock returns, and spreads to supplier and customer returns in a matter of days. In this section, we investigate if these conclusions have been constant through time by splitting our sample in two, prior and posterior to 2017.

TABLE 6 Chronological subsampling: panel regression of the effect of ESG shocks to returns before and after 2017.

Variable \ Model	Panel A: Before 2017				Panel B: After 2017			
	(1) $g = ACP$		(2) $g = MP$		(3) $g = ACP$		(4) $g = MP$	
L(Δg,3)	0.001	(0.525)	0.001	(0.876)	0.001	(0.554)	0.000	(0.133)
L(Δg,2)	0.002	(1.760)	0.003*	(2.030)	0.002	(1.310)	0.001	(0.809)
L(Δg,1)	0.000	(0.102)	0.001	(0.596)	−0.001	(−0.334)	−0.001	(−0.407)
Δg	0.008**	(4.680)	0.007**	(3.700)	0.018**	(5.280)	0.014**	(3.470)
L(Δg,3) × L(g,1)	−0.000	(−0.089)	−0.001	(−0.531)	−0.000	(−0.162)	−0.002	(−0.739)
L(Δg,2) × L(g,1)	−0.002	(−1.360)	−0.004	(−1.840)	−0.004	(−1.370)	−0.005	(−1.630)
L(Δg,1) × L(g,1)	−0.000	(−0.034)	−0.000	(−0.147)	0.002	(0.498)	0.003	(0.961)
Δg × L(g,1)	−0.018**	(−5.69)	−0.014**	(−3.770)	−0.037**	(−5.930)	−0.024**	(−3.820)
Fixed effects:								
Firm id	Yes		Yes		Yes		Yes	
Time via Factors' return	Yes		Yes		Yes		Yes	
VCOV: Clustered	Firm & date		Firm & date		Firm & date		Firm & date	
Observations	6,307,257		5,461,448		3,775 ,309		3,502,891	
R^2	0.020		0.018		0.125		0.126	
Within R^2	0.020		0.018		0.124		0.125	
Signif. codes **0.01, *0.05								

Note: The model equation is:

$$r_{t,n} - r_f = \sum_{j=0}^{3} \theta_j \Delta g_{t-j,n} + \sum_{j=0}^{3} \beta_j g_{t-1,n} \times \Delta g_{t-j,n} + \alpha g_{t-1,n} + \gamma_n + \delta' Z_t + \varepsilon_{t,n},$$

where $r_{t,n}$ is the return of the firm n; $g_{j,n}$ is the ESG score of firm n (ACP (All Categories Pulse score) or MP (Materialized Pulse score)). γ_n is the fixed effect, Z_t is a vector of control for Fama and French (2015) 5 factors and momentum. ε is the noise term. The t-statistics are computed with the clustered error by date, and firm, as in Thompson (2011). We only report the coefficients in two terms $\sum_{j=0}^{3} \theta_j \Delta g_{t-j,n}$ and $\sum_{j=0}^{3} \beta_j g_{t-1,n} \times \Delta g_{t-j,n}$. $L(x, n)$ are the lag function: $L(x_t, n) = x_{t-n}$. Panel A consists of data from January 2007 to December 2016. Panel B consists of data from January 2017 to May 2021.

Sustainability is increasingly perceived as important by investors (Stroebel & Wurgler, 2021); hence, it is likely that they have paid more attention to ESG news in the most recent period. This, combined with improved telecommunication technologies and the expansion of social media, brings us to hypothesize that the diffusion of news to prices should have accelerated since 2017. The choice of 2017 as the splitting date originates from the enforcement of the Paris Climate Accords in November 2016 (though they were signed in April). Empirically, we consequently re-estimate all our models using pre-2017 and post-2017 samples.

We report the direct influence of ESG news to returns in Table 6. Panel A (left) consists of the results for the pre-2017 sample while panel B (right) contains the estimates of the post-2017 sample. The pricing of ESG shocks is stronger and somewhat quicker intraday after 2017. For example, with the *ACP* measure, before 2017, the impact coefficients are significant at day 0 ($\theta_0 = 0.008$, t-stat = 4.68) and less so at day 2 after the ESG news. The interaction coefficients surpass the threshold at day 0 only ($\beta_0 = -0.018$, t-stat = −5.69). After 2017 however, all the ESG news impact concentrates intraday, and the magnitudes are more pronounced. Indeed, we obtain $\theta_0 = 0.018$ with t-stat = 5.28 post-2017, versus $\theta_0 = 0.008$ pre-2017. Moreover, we have $\beta_0 = -0.037$ with t-stat = −5.93 post-2017 versus $\beta_0 = -0.018$ pre-2017. With the *MP* variable, we report qualitatively similar results.

We perform the same exercise with the customer-to-supplier spillover effect pre-2017 and post-2017 in Panel A, Table 7. In panel A1, we see no effect in the pre-2017 sample for both *ACP* and *MP* measures. After 2017, a shock in the customer's *ACP* takes three days to affect the supplier's return. For the *MP* proxy, after 2017, it takes 2 days for an ESG shock from the customer firm to spread to its supplier's return. The shock's coefficient is $\theta_2 = -0.008$ with *t*-stat = –2.41 and the interaction coefficient is $\beta_2 = 0.012$ with *t*-stat = 2.55. The results of both measures in the post-2017 sample are qualitatively similar to the full sample estimates in Table 3. This means that most of the ESG spillover effect from customer-to-supplier concentrates in the post-2017 period.

Finally, we analyze the contagion of ESG news from supplier-to-customer pre-2017 and post-2017 in Panel B, Table 7. For the *ACP* measure, we observe no spillover effect in the pre-2017 sample. In contrast, after 2017, a shock in supplier's *ACP* news takes 3 days to spread to the customer's return. The impact coefficient is $\theta_3^{Sup} = -0.006$ with *t*-stats= –2.03. This result is qualitatively similar to the full sample estimates in Table 4. Surprisingly, with the *MP* measure, we observe the opposite: the effect is only significant for the first subperiod.

To summarize the findings of this final section, we remark that, in a large majority of the cases, both the direct impact of ESG news on a company's return and the supply-chain spillover effect is more salient after 2017 than before 2017.

5.2 | Small versus large firms

Drempetic et al. (2020) have shown that firm size can be a driver of ESG disclosure because large firms have more means to devote to reporting. Hence, another interesting question pertains to how small versus large firm returns react to ESG shocks. Intuitively, small firms, because they may have a more concentrated basis of customers and suppliers could be more at risk of shocks. To examine this assumption, we split the cross-section of stocks into three equal samples: small, medium, and large capitalization at every point in time and perform the same analyses from Tables 3 and 4. The results are reported in Table 8.

Panel A of Table 8 shows the ESG spillover effect from the main customer firm to the supplier firm. For the *ACP* measure, the effect only exists in the *Medium* size sample. The results in this sample are qualitatively similar to the ones in Table 3. For example, *ACP* shock takes 3 days to transfer from customer-to-supplier. The shock coefficient is 0.004 with a *t*-stat of 1.84 (0.003 with *t*-stat 2.09 in Table 3). The interaction coefficient is –0.007 with *t*-stat –2.18 (–0.005, *t*-stat of –2.08 in Table 3). For the materiality (*MP*) measure, the ESG spillover effect only exists among the *Small* size sample. The *MP* shock needs 1 day to propagate from customer-to-supplier. However, this effect in the *Small* size sample is almost twice stronger than in the full sample. Indeed, the shock coefficient is now –0.013 (*t*-stat –3.17) versus –0.005 (–2.90) in the total cross-section. The interaction coefficient is 0.019 (*t*-stat 2.85), whereas it is 0.008 (2.96) in the full sample.

We have the same *Small* size phenomenon when studying the spillover effect from supplier firm to customer firm. Panel B of Table 8 shows only the effect among the *Small* stocks, with both *ACP* and *MP* measures. We find no spillover effect in the medium group, nor for large stocks. In a nutshell, with regard to the *ACP* variable, it takes 3 days for the shock to spread from supplier-to-customer for small stocks. The coefficient and interaction coefficients in the *Small* size sample are twice larger than the ones in the full sample. For the materiality metric, both types of coefficients in the *Small* size sample are qualitatively similar to the ones in the full sample. Lastly, an interesting insight is that, quite often, the sign of the coefficients reverses when switching from large to small firms. Hence, news can have opposite effects, depending on which group is considered.

Overall, the ESG spillover effect is mostly confirmed for small- to medium-sized firms. Such corporations are more likely to have a poorer diversification of customers and suppliers (compared to large firms); hence, ESG shocks in the value chain may be more impactful for them.

TABLE 7 Chronological subsampling: panel regression of the spillover effect of ESG news from supplier-to-customer, and from customer-to-supplier before and after 2017.

Panel A: From customer-to-supplier								
	Panel A1: Before 2017				**Panel A2: After 2017**			
Variable \ Model	**(1) $g = ACP$**		**(2) $g = MP$**		**(3) $g = ACP$**		**(4) $g = MP$**	
$L(\Delta g^{Cus},3)$	0.002	(1.200)	0.001	(0.654)	0.005	(1.700)	0.005	(1.790)
$L(\Delta g^{Cus},2)$	−0.003	(−1.550)	0.002	(0.889)	−0.003	(−0.924)	−0.002	(−0.863)
$L(\Delta g^{Cus},1)$	0.0003	(0.163)	−0.003	(−1.680)	−0.003	(−0.926)	−0.008*	(−2.410)
Δg^{Cus}	−0.001	(−0.731)	−0.002	(−0.890)	0.001	(0.386)	−0.003	(−1.09)
$L(\Delta g^{Cus},3) \times L(g^{Sup},1)$	−0.003	(−0.886)	−0.000	(−0.129)	−0.010*	(−1.980)	−0.009	(−1.920)
$L(\Delta g^{Cus},2) \times L(g^{Sup},1)$	0.0008	(0.251)	−0.004	(−1.200)	0.003	(0.673)	0.004	(0.841)
$L(\Delta g^{Cus},1) \times L(g^{Sup},1)$	−0.0004	(−0.159)	0.005	(1.630)	0.003	(0.718)	0.012*	(2.550)
$\Delta g^{Cus} \times L(g^{Sup},1)$	0.001	(0.471)	0.003	(0.856)	−0.003	(−0.512)	0.005	(0.927)
Fixed effects:								
Supplier ID	Yes		Yes		Yes		Yes	
Time via Factors' return	Yes		Yes		Yes		Yes	
Cluster: Supplier ID and date	Yes		Yes		Yes		Yes	
Observations	2,763,656		2,415,333		1,729,188		1,612,776	
R^2	0.163		0.160		0.132		0.134	
Within R^2	0.163		0.160		0.131		0.133	
Panel B: From supplier-to-customer								
	Panel A1: Before 2017				**Panel A2: After 2017**			
Variable \ Model	**(1) $g = ACP$**		**(2) $g = MP$**		**(3) $g = ACP$**		**(4) $g = MP$**	
$L(\Delta g^{Sup},3)$	−0.001	(−0.706)	−0.000	(−0.014)	−0.006*	(−2.030)	−0.008	(−1.650)
$L(\Delta g^{Sup},2)$	0.001	(0.522)	0.005*	(2.090)	−0.002	(−0.620)	0.004	(1.270)
$L(\Delta g^{Sup},1)$	0.0003	(0.081)	0.001	(0.181)	−0.001	(−0.353)	−0.001	(−0.321)
Δg^{Sup}	0.004	(1.62)	0.001	(0.339)	0.001	(0.241)	0.001	(0.200)
$L(\Delta g^{Sup},3) \times L(g^{Cus},1)$	0.003	(0.987)	−0.000	(−0.108)	0.008	(1.410)	0.012	(1.470)
$L(\Delta g^{Sup},2) \times L(g^{Cus},1)$	−0.002	(−0.496)	−0.010**	(−2.590)	0.003	(0.769)	−0.005	(−1.180)
$L(\Delta g^{Sup},1) \times L(g^{Cus},1)$	−0.001	(−0.104)	−0.001	(−0.154)	0.004	(0.784)	0.004	(0.887)
$\Delta g^{Sup} \times L(g^{Cus},1)$	−0.007	(−1.860)	0.001	(0.162)	−0.002	(−0.355)	−0.004	(−0.666)
Fixed effects:								
Customer ID	Yes		Yes		Yes		Yes	
Time via Factors' return	Yes		Yes		Yes		Yes	
Cluster: Customer ID and date	Yes		Yes		Yes		Yes	
Observations	1,987,743		1,708,304		1,530,145		1,432,228	
R^2	0.077		0.070		0.124		0.125	
Within R^2	0.076		0.069		0.123		0.124	
Signif. codes : **0.01, *0.05								

Note: We perform the same ESG spillover analyses from customer-to-supplier as in Table 3, and from supplier-to-customer as in Table 4 with two samples: before 2017 and after 2017.

TABLE 8 Impact of firm size: panel regression of the spillover effect of ESG news from the supplier firm, and from the customer firm.

Panel A: From customer-to-supplier												
	A1: $g = ACP$						A2: $g = MP$					
Size:	*Big*		*Medium*		*Small*		*Big*		*Medium*		*Small*	
$L(\Delta g^{Cus},3)$	0.000	(0.142)	0.004	(1.840)	0.005	(1.450)	−0.000	(0.039)	0.002	(1.170)	0.007	(1.940)
$L(\Delta g^{Cus},2)$	0.001	(0.486)	−0.003	(−1.330)	−0.006	(−1.780)	0.001	(0.755)	−0.001	(−0.498)	−0.000	(0.119)
$L(\Delta g^{Cus},1)$	0.001	(0.653)	−0.000	(−0.008)	−0.003	(−0.925)	−0.000	(−0.251)	0.000	(0.042)	−0.013**	(−3.170)
Δg^{Cus}	−0.000	(−0.045)	0.001	(0.724)	−0.003	(−0.736)	−0.000	(−0.240)	−0.001	(−0.301)	−0.006	(−1.590)
$L(\Delta g^{Cus},3) \times L(g^{Sup},1)$	0.001	(0.153)	−0.007*	(−2.180)	−0.009	(−1.550)	−0.000	(−0.127)	−0.003	(−0.987)	−0.011	(−1.720)
$L(\Delta g^{Cus},2) \times L(g^{Sup},1)$	−0.004	(−1.140)	0.000	(0.095)	0.007	(1.220)	−0.002	(−0.641)	−0.001	(−0.264)	0.001	(0.164)
$L(\Delta g^{Cus},1) \times L(g^{Sup},1)$	−0.002	(−0.580)	0.002	(0.562)	0.002	(0.348)	0.000	(0.141)	0.002	(0.709)	0.019**	(2.850)
$\Delta g^{Cus} \times L(g^{Sup},1)$	0.002	(0.613)	−0.001	(−0.393)	0.000	(0.045)	0.000	(0.050)	0.003	(0.728)	0.008	(1.210)
Fixed effects:												
Supplier ID	Yes		Yes		Yes		Yes		Yes		Yes	
Time via Factors' return	Yes		Yes		Yes		Yes		Yes		Yes	
VCOV-clustered: Supplier ID and date	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1,485,798		1,465,607		1,478,265		1,413,476		1,295,119		1,262,904	
R^2	0.326		0.259		0.083		0.324		0.252		0.081	
Within R^2	0.325		0.258		0.082		0.323		0.250		0.080	
Panel B: From supplier-to-customer												
	B1: $g = ACP$						B2: $g = MP$					
Size:	*Big*		*Medium*		*Small*		*Big*		*Medium*		*Small*	
$L(\Delta g^{Sup},3)$	0.001	(0.490)	−0.000	(0.123)	−0.010*	(−2.330)	0.002	(1.080)	0.001	(0.268)	−0.013	(−1.780)
$L(\Delta g^{Sup},2)$	0.001	(0.648)	0.000	(0.122)	−0.001	(−0.152)	0.002	(1.160)	0.003	(1.280)	0.006	(1.620)
$L(\Delta g^{Sup},1)$	−0.003	(−1.800)	0.001	(0.363)	0.002	(0.357)	−0.002	(−0.934)	0.001	(0.422)	0.002	(0.383)
Δg^{Sup}	0.002	(1.290)	0.000	(0.036)	0.006	(1.120)	0.001	(0.408)	−0.000	(−0.166)	0.003	(0.561)

(Continues)

TABLE 8 (Continued)

	Panel B: From supplier-to-customer											
	B1: $g = ACP$						B2: $g = MP$					
Size:	*Big*		*Medium*		*Small*		*Big*		*Medium*		*Small*	
$L(\Delta g^{Sup},3) \times L(g^{Cus},1)$	−0.002	(−0.598)	−0.001	(−0.131)	0.017*	(2.380)	−0.004	(−1.110)	−0.001	(−0.290)	0.018	(1.600)
$L(\Delta g^{Sup},2) \times L(g^{Cus},1)$	−0.003	(−0.981)	0.000	(0.112)	0.003	(0.533)	−0.004	(−1.550)	−0.005	(−1.180)	−0.012	(−1.790)
$L(\Delta g^{Sup},1) \times L(g^{Cus},1)$	0.005	(1.570)	−0.002	(−0.441)	−0.002	(−0.221)	0.001	(0.443)	0.000	(0.023)	−0.002	(−0.172)
$\Delta g^{Sup} \times L(g^{Cus},1)$	−0.004	(−1.280)	−0.001	(−0.192)	−0.010	(−1.310)	−0.000	(−0.065)	−0.002	(−0.556)	−0.002	(−0.237)
Fixed effects:												
Customer ID	Yes		Yes		Yes		Yes		Yes		Yes	
Time via Factors' return	Yes		Yes		Yes		Yes		Yes		Yes	
VCOV-clustered: Customer ID and date	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1,161,937		1,146,655		1,157,861		1,108,788		1,014,609		971,288	
R^2	0.302		0.245		0.045		0.301		0.240		0.041	
Within R^2	0.300		0.244		0.044		0.299		0.238		0.040	
Signif. codes : **0.01, *0.05												

Note: We first split the cross-section of stocks into three equal samples: small, neutral, and big market-size stocks at every point in time. We then perform the same ESG spillover analyses from the customer as in Table 3, and from the supplier as in Table 4 on these subsamples.

5.3 | The moderating role of attention

Our next batch of results is intended to assess the degree to which ESG attention in the cross-section may condition the spillover effect across the supply chain. Heuristically, if investors are aware of the ESG risk from a firm's supply chain, then the stock price already reflects that risk. Hence, an ESG shock from the value chain will have a smaller impact on the company's return. In contrast, if investors do not pay attention to the firm's ESG risk from the supply chain, then an ESG shock from the customer or supplier will be considered a surprise, thereby having a more substantial impact on the variation of the firm's stock price.

To verify this hypothesis, we use the total volume of ESG news articles about the firm in the last twelve months provided by TruValue as a measure of total ESG attention toward the firm. We then split the cross-section of stocks into three equal samples: *High*, *Neutral*, and *Low* ESG-attention stocks at every point in time. Finally, we perform the same analyses as those in Tables 3 and 4 on these subsamples. Results are reported in Table 9: Panel A shows the effect from the main customer, while Panel B shows the effect from the main supplier.

For the *ACP* measure, the ESG spillover effect from both customer and supplier is not significant in any attention subgroup. However, for the *MP* measure, we see that the ESG spillover effect from the main customer to the firm exists only when that firm belongs to the *Neutral* or *Low* ESG-attention sample. The ESG shock coefficients and interaction coefficients are quasi-similar to the ones in Table 3. Similarly, in Panel B of Table 9, the *MP* shock from a main supplier to a firm is only significant when that firm is in the *Low* ESG-attention sample.

To summarize our findings, ESG attention can be an important factor in the value chain spillover effect. When there is an ESG shock from the customers or suppliers, firms that benefit from lower analyst and media coverage are expected to experience a stronger shift in their prices. This may be because the ESG shock from the supply chain is considered an unknown surprise for the underscrutinized firm, and investors subsequently readjust their assessment of the company's valuation. We however underline that this conditionality of the effect may be linked to the one based on size because small firms may be less covered by the media.

5.4 | Controlling for non-ESG-related propagation

Another interesting question that we want to address is the extent to which the ESG spillover effect relates to other non-ESG variables. Is the ESG spillover different from other spillover types? To answer this question we perform the same ESG spillover analyses as in Tables 3 and 4 but when adding the customer's return (or supplier's return) of the same day and of the last 3 days, so as to control for short-term momentum influences from the value chain. To perform this additional check, we need data that is updated every day, hence the choice of returns. Other fundamental fields are usually updated quarterly which is not suitable here.

If there is a relevant non-ESG (i.e., momentum, reversal, etc.) shock from the supplier or customer firm, then that shock should move the supplier's or customer's return. Therefore, we can use the return as a proxy for these non-ESG shocks from the supply chain. Using return as a proxy for fundamental shocks we follow the Cohen and Frazzini (2008)'s approach wherein it is shown that customer return can predict the supplier return. Combining both ESG shocks and return in one regression, we can distinguish between the ESG and non-ESG spillover effects from the value chain.[13] We report the results of these exercises in Table 10. Panel A reports the results from customer-to-supplier while Panel B shows the results from supplier-to-customer.

We quickly confirm that the ESG spillover effect after controlling for other non-ESG spillover is qualitatively similar to the one in Table 3, and Table 4. This is true for both *AP* and *MP* measures, and for both directions from customer-

[13] Obviously as shown in Table 2, ESG shocks from customers/suppliers firms can also push their own returns. Therefore, putting both ESG shocks and returns from the supply chain firms in one common regression will help us to disintegrate the ESG spillover effect from the other non-ESG spillover effect. The coefficient on ESG shocks will capture the ESG spillover effect, while the coefficient of returns will capture other shocks, which are orthogonal to ESG.

TABLE 9 Impact of ESG attention: panel regression of the spillover effect of ESG news from supplier-to-customer, and vice-versa.

Panel A: From customer-to-supplier												
	A1: $g = ACP$						A2: $g = MP$					
ESG attention:	*High*		*Neutral*		*Low*		*High*		*Neutral*		*Low*	
$L(\Delta g^{Cus},3)$	0.001	(0.308)	0.005	(1.850)	0.003	(1.400)	−0.001	(−0.280)	0.005	(1.580)	0.005	(1.830)
$L(\Delta g^{Cus},2)$	−0.001	(−0.444)	−0.003	(−1.010)	−0.005	(−1.760)	0.001	(0.627)	0.000	(0.017)	−0.001	(−0.541)
$L(\Delta g^{Cus},1)$	0.003	(1.090)	−0.001	(−0.439)	−0.003	(−1.250)	0.000	(0.153)	−0.009*	(−2.140)	−0.007**	(−2.760)
Δg^{Cus}	−0.001	(−0.434)	−0.003	(−1.140)	0.002	(0.878)	−0.001	(−0.584)	−0.007*	(−2.240)	0.002	(0.755)
$L(\Delta g^{Cus},3) \times L(g^{Sup},1)$	−0.002	(−0.451)	−0.007	(−1.420)	−0.006	(−1.560)	−0.001	(−0.156)	−0.004	(−0.790)	−0.008	(−1.830)
$L(\Delta g^{Cus},2) \times L(g^{Sup},1)$	−0.002	(−0.497)	0.003	(0.601)	0.004	(0.956)	−0.003	(−0.876)	−0.000	(−0.012)	0.002	(0.381)
$L(\Delta g^{Cus},1) \times L(g^{Sup},1)$	−0.004	(−0.867)	−0.000	(−0.022)	0.005	(1.240)	0.001	(0.230)	0.012	(1.920)	0.012**	(2.790)
$\Delta g^{Cus} \times L(g^{Sup},1)$	0.003	(0.606)	0.003	(0.521)	−0.004	(−0.920)	0.001	(0.243)	0.011	(1.880)	−0.003	(−0.495)
Fixed effects:												
Supplier ID	Yes		Yes		Yes		Yes		Yes		Yes	
Time via Factors' return	Yes		Yes		Yes		Yes		Yes		Yes	
VCOV-clustered: Supplier and date	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1,529,876		1,315,832		1,575,506		1,496,288		1,117,404		1,349,222	
R^2	0.206		0.125		0.141		0.204		0.124		0.136	
Within R^2	0.205		0.123		0.140		0.203		0.122		0.134	
Signif. codes: **0.01, *0.05												

Panel B: From supplier-to-customer												
	B1: $g = ACP$						B2: $g = MP$					
ESG attention:	*High*		*Neutral*		*Low*		*High*		*Neutral*		*Low*	
$L(\Delta g^{Sup},3)$	−0.004	(−1.660)	−0.003	(−0.740)	−0.004	(−1.510)	0.001	(0.452)	−0.005	(−0.680)	−0.007*	(−2.020)
$L(\Delta g^{Sup},2)$	−0.003	(−0.980)	0.003	(0.993)	0.001	(0.171)	0.000	(0.171)	0.006	(1.660)	0.007*	(2.170)
$L(\Delta g^{Sup},1)$	−0.000	(−0.141)	−0.002	(−0.742)	0.001	(0.279)	−0.002	(−0.740)	0.001	(0.165)	0.001	(0.181)
Δg^{Sup}	0.004	(1.600)	−0.001	(−0.158)	0.004	(1.060)	0.000	(0.138)	−0.003	(−0.698)	0.004	(1.210)

(Continues)

TABLE 9 (Continued)

Panel B: From supplier-to-customer												
	B1: g = *ACP*						B2: g = *MP*					
ESG attention:	*High*		*Neutral*		*Low*		*High*		*Neutral*		*Low*	
$L(\Delta g^{Sup},3) \times L(g^{Cus},1)$	0.008	(1.780)	0.006	(0.892)	0.003	(0.704)	−0.002	(−0.568)	0.005	(0.402)	0.012*	(2.310)
$L(\Delta g^{Sup},2) \times L(g^{Cus},1)$	0.003	(0.656)	−0.003	(−0.630)	0.000	(0.064)	−0.003	(−0.736)	−0.009	(−1.530)	−0.012*	(−2.320)
$L(\Delta g^{Sup},1) \times L(g^{Cus},1)$	0.003	(0.595)	0.006	(1.010)	−0.004	(−0.732)	0.003	(0.765)	0.001	(0.154)	0.000	(0.038)
$\Delta g^{Sup} \times L(g^{Cus},1)$	−0.009	(−1.680)	−0.000	(−0.040)	−0.007	(−1.270)	−0.000	(−0.068)	0.006	(0.896)	−0.009	(−1.650)
Fixed effects:												
Customer ID	Yes		Yes		Yes		Yes		Yes		Yes	
Time via Factors' return	Yes		Yes		Yes		Yes		Yes		Yes	
VCOV-clustered: Customer and date	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1,193,103		1,040,028		1,225,571		1,157,236		883,519		1,045,591	
R^2	0.191		0.055		0.118		0.189		0.051		0.111	
Within R^2	0.190		0.052		0.117		0.188		0.048		0.110	
Signif. codes : **0.01, *0.05												

Note: We first split the cross-section of stocks into three equal samples: low, neutral, and high ESG-attention stocks at every point in time. We then perform the same ESG spillover analyses from the main customer as in Table 3, and from the main supplier in Table 4 on these subsamples.

TABLE 10 Impact of other non-ESG spillover versus ESG spillover.

Panel A: From customer-to-supplier					Panel B: From supplier-to-customer				
Model:	(1) $g = ACP$		(2) $g = MP$			(3) $g = ACP$		(4) $g = MP$	
L(Δg^{Cus},3)	0.003*	(2.070)	0.003	(1.740)	L(Δg^{Sup},3)	−0.003	(−1.890)	−0.004	(−1.440)
L(Δg^{Cus},2)	−0.003	(−1.830)	0.000	(0.066)	L(Δg^{Sup},2)	−0.000	(−0.078)	0.004*	(2.310)
L(Δg^{Cus},1)	−0.001	(−0.440)	−0.005**	(−2.910)	L(Δg^{Sup},1)	−0.000	(−0.188)	−0.001	(−0.206)
Δg^{Cus}	−0.000	(−0.202)	−0.002	(−1.260)	Δg^{Sup}	0.002	(1.050)	0.001	(0.483)
L(Δg^{Cus},3) × L(g^{Sup},1)	−0.005*	(−2.060)	−0.004	(−1.450)	L(Δg^{Sup},3) × L(g^{Cus},1)	0.005	(1.690)	0.005	(1.190)
L(Δg^{Cus},2) × L(g^{Sup},1)	0.002	(0.642)	−0.001	(−0.282)	L(Δg^{Sup},2) × L(g^{Cus},1)	0.000	(0.129)	−0.008**	(−2.660)
L(Δg^{Cus},1) × L(g^{Sup},1)	0.001	(0.276)	0.008**	(2.970)	L(Δg^{Sup},1) × L(g^{Cus},1)	0.001	(0.415)	0.002	(0.556)
Δg^{Cus} × L(g^{Sup},1)	−0.000	(0.002)	0.003	(1.150)	Δg^{Sup} × L(g^{Cus},1)	−0.004	(−1.350)	−0.001	(−0.399)
L(RET^{Cus},3)	−0.000	(0.675)	−0.000	(0.374)	L(RET^{Sup},3)	0.001	(0.440)	0.001	(0.508)
L(RET^{Cus},2)	0.000	(1.680)	0.001	(1.530)	L(RET^{Sup},2)	0.005*	(2.010)	0.005	(1.690)
L(RET^{Cus},1)	0.001	(1.470)	0.001	(1.250)	L(RET^{Sup},1)	0.019**	(6.870)	0.019**	(6.500)
RET^{Cus}	0.003	(1.520)	0.006	(1.230)	RET^{Sup}	0.100**	(19.300)	0.104**	(18.800)
Fixed effects					Fixed effects				
Supplier ID	Yes		Yes		Customer ID	Yes		Yes	
Time via Factors' return	Yes		Yes		Time via Factors' return	Yes		Yes	
VCOV-clustered: Supplier ID and date	Yes		Yes		VCOV-Clustered: Customer ID and date	Yes		Yes	
Observations	4,492,021		4,027,515		Observations	3,513,024		3,137,011	
R^2	0.149		0.147		R^2	0.097		0.093	
Within R^2	0.148		0.147		Within R^2	0.097		0.092	
Signif. codes : **0.01, *0.05									

Note: We perform the same ESG spillover analyses from customer-to-supplier as in Table 3, and from supplier-to-customer as in Table 4. We add the customer's return (supplier's return) of the same day and of the last 3 days to control any other fundamental non-ESG propagation from customer-to-supplier (supplier-to-customer).

to-supplier, and vice-versa. Interestingly, we do not see any significant non-ESG spillover effect from customers to suppliers when using customer returns. In contrast, supplier returns have a significant impact on customer returns. Indeed, this non-ESG effect propagates strongly intraday from the supplier to the customer with a coefficient of around 0.1. Thus, 10% of supplier returns can spread to customer returns on the same day. This non-ESG spillover fades out quickly in 2 days with a coefficient of 0.019 on a subsequent day.

In short, adding returns to control for other non-ESG spillover effects does not alter our baseline results and conclusions: the ESG propagation effect along the value chain remains consistently compelling.

6 | CONCLUSION

In this paper, we estimate panel models in which changes in ESG ratings affect firms' returns, as in Serafeim and Yoon (2022b). This can be justified by a stylized theoretical model that puts the emphasis on two key quantities: the variation in rating, as well as this variation, in conjunction with the *level* of the rating. One important assumption (which is verified empirically) is that updates in sustainability scores are not expected to impact returns uniformly in the cross-section of stocks.

Because we are agnostic with respect to the speed of diffusion of news, our empirical model incorporates lagged changes up to 3 days prior to the return. Our results, based on US firms, show that this is not useful in our baseline model, because updates in ratings are almost immediately priced in the markets. Indeed, the only coefficients that are significant are the ones that are synchronous with the returns, meaning that prices react to shocks intradaily. Whether this can be interpreted as a confirmation of market efficiency remains an open question.

The second stage of the study is to consider economic links between firms. If a firm faces an ESG incident, it may propagate to its clients and to its suppliers. Heuristically, for the clients, the issue is that of reputation, whereas, for suppliers, the risk is a reduction of future sales. Our second batch of results pertains to US firms and to their potential international clients and suppliers. They show that there is some predictability between ESG shocks and subsequent returns for suppliers and clients, but effect sizes and t-statistics are smaller, compared to the direct effect. The speed of propagation is slower in this case, as responses only materialize 2–3 days after the shock. In addition, financially material ESG news diffuses to the supply chain quicker and more potently than common ESG news.

Another key contribution is the confirmation of the mitigating effect of the level of sustainability. In most cases, one cross-term is indeed statistically significant, meaning that changes in ESG ratings do not affect firms uniformly in the cross-section of stocks. In particular, we find that positive shocks are much more beneficial to brown firms, whereas green stocks are, surprisingly, less sensitive to negative shocks. Overall, and in spite of minor differences, our results are relatively robust with respect to the choice of ESG indicator (raw score versus materiality-focused score). Moreover, long-short portfolios built on financially material ESG shocks from customers deliver several percent (between 1% and 8%) in annual alpha, after controlling for the usual asset pricing factors.

A series of additional analyses reveals that the diffusion of ESG shocks is not uniform within the cross-section of firms, beyond their ESG levels. Most of the effects we document are concentrated in the smaller half of our samples, i.e., within corporations with below median capitalization. In addition, the effect is also more significant for firms that are subject to less media coverage.

Lastly, chronological subsampling supports our intuition that the impact of ESG news on stocks' returns is more salient in the most recent years. With the advent of new reporting regulations and the increase in the speed of information diffusion, spillover effects will likely occur even faster in the coming years. This will have to be confirmed by future research.

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APPENDIX A: STYLIZED EQUILIBRIUM MODEL

This section presents the theoretical justification for our panel estimation approach.

Time is discrete and there are N firms (risky assets) indexed by n in which agents can invest at any time t to gain some random time $(t+1)$ payoff. The price of shares is denoted with $p_{t,n}$, or, equivalently, $\boldsymbol{p}_t$ in column vector form when stacking all time-t prices. For simplicity, we will assume that the payoff is the time $(t+1)$ price plus the dividends received between time t and time $t+1$. The payoff for firm n is thus $p^*_{t+1,n} = p_{t+1,n} + d_{t+1,n}$.

All firms are publicly ranked by a third-party agency according to some sustainability criterion, which we denote with $g_{t,n}$.[14] The scores are normalized so that, in the cross-section, they always lie in the unit interval, that is, $g_{t,n} \in [0,1]$: a zero score pertains to a brown firm while a unit value signals firms with the highest sustainability standards. In addition, we assume that a risk-free asset is available in unlimited supply and pays a fixed payoff of $r > 0$ at each period.

A.1 | Agents and partial equilibrium

There are two types of agents in the economy. The first type is *signal* traders who seek to maximize their expected utility over future wealth W_{t+1} via their portfolio allocation $\boldsymbol{x}_t$:

$$U(\boldsymbol{x}_t) = \mathbb{E}_t[W_{t+1}] - \frac{\gamma}{2}\mathbb{V}_t[W_{t+1}], \quad \text{with} \quad W_{t+1} = r\left(W_t - \boldsymbol{x}_t'\boldsymbol{p}_t\right) + \boldsymbol{x}_t'\boldsymbol{p}^*_{t+1}, \tag{A.1}$$

where $\mathbb{E}_t[\cdot]$ and $\mathbb{V}_t[\cdot]$ are the agents' conditional expectation and variance operators and $\boldsymbol{x}'$ is the transpose of vector $\boldsymbol{x}$. This formulation follows that of Admati (1985) and Kacperczyk et al. (2019) closely and reads, in more compact form:

$$U(\boldsymbol{x}_t) = r\left(W_t - \boldsymbol{x}_t'\boldsymbol{p}_t\right) + \boldsymbol{x}_t'\mathbb{E}_t[\boldsymbol{p}^*_{t+1}] - \frac{\gamma}{2}\boldsymbol{x}_t'\boldsymbol{\Sigma}_z\boldsymbol{x}_t,$$

where $\boldsymbol{\Sigma}$ is the (conditional) covariance matrix of the payoffs $\boldsymbol{p}^*_{t+1}$. For simplicity, we assume that it is constant in time. The first-order conditions imply that optimal allocations are

$$\boldsymbol{x}^*_t = \gamma^{-1}\boldsymbol{\Sigma}^{-1}(\mathbb{E}_t[\boldsymbol{p}^*_{t+1}] - r\boldsymbol{p}_t).$$

The signal traders, who represent a share μ of the market, form their expectations $\mathbb{E}_t[\boldsymbol{z}_{t+1}]$ based on sustainability signals (e.g., ESG scores or carbon emissions), which they observe in a fashion we will detail subsequently. The second type of agents are liquidity providers who serve as market makers. Equivalently, they can be considered investors who trade based on information that is orthogonal to the signal mentioned above. They make for $1-\mu$ of the market and their only purpose in the model is to supply shares to the signal traders for reasons that are unrelated to the signal. We

[14] A unique company-specific ESG score is unlikely in practice, see Dimson et al. (2020) and Avramov et al. (2022). Nevertheless, the subtleties in sustainability ratings are out of the scope of the present paper.

write $\boldsymbol{\nu}_t$ for the vector of this supply. Thus, the market clearing condition imposes $\mu \boldsymbol{x}_t^* = (1-\mu)\boldsymbol{\nu}_t$, that is,

$$\boldsymbol{p}_t = r^{-1}\left(\mathbb{E}_t[\boldsymbol{p}_{t+1}^*] - \gamma \frac{(1-\mu)}{\mu}\boldsymbol{\Sigma}\boldsymbol{\nu}_t\right). \tag{A.2}$$

This implies that the equilibrium return vector of all assets can be decomposed as

$$\boldsymbol{r}_{t+1} = \text{diag}(\boldsymbol{p}_t)^{-1}(\boldsymbol{p}_{t+1} - \boldsymbol{p}_t) \tag{A.3}$$

$$= r^{-1}\left(\overbrace{\text{diag}(\boldsymbol{p}_t)^{-1}(\mathbb{E}_{t+1}[\boldsymbol{p}_{t+2}^*] - \mathbb{E}_t[\boldsymbol{p}_{t+1}^*])}^{\text{update in (relative) expectations}} - \gamma \frac{(1-\mu)}{\mu}\text{diag}(\boldsymbol{p}_t)^{-1}\boldsymbol{\Sigma}\overbrace{(\boldsymbol{\nu}_{t+1} - \boldsymbol{\nu}_t)}^{\text{supply shock}}\right), \tag{A.3}$$

where diag($\boldsymbol{v}$) is the diagonal matrix with vector $\boldsymbol{v}$ as diagonal elements. Essentially, supply shocks will be taken as innovations. The terms $\text{diag}(\boldsymbol{p}_t)^{-1}\mathbb{E}_t[\boldsymbol{p}_{t+1}^*]$ and $\text{diag}(\boldsymbol{p}_t)^{-1}\mathbb{E}_{t+1}[\boldsymbol{p}_{t+2}^*]$ are the one period-ahead and two period-ahead expected payoffs, relative to the current price level. The difference between the two is at the center of our model, as it will reflect how traders view ESG news both as signals and shocks. The next subsection is dedicated to this topic.

Naturally, one very important quantity in the above equation is μ. In Heinkel et al. (2001), the share of green investors is shown to be an important driver of the incentive for brown firms to change their policies. In our model, if μ is very small and ESG traders are scarce, they will not have sufficient impact to substantially move prices. In this case, the update in expectations in Equation (A.3) may be unlikely to affect asset returns. This will also depend on how inelastic the demands can be (see, e.g., Gabaix & Koijen, 2021, for the aggregate market). Typically, it may occur that liquidity suppliers be inactive after an important signal, resulting in small magnitude $\boldsymbol{\varepsilon}_{t+1}$, whereas the signal is actively used by ESG signal traders.

A.2 | Price expectations

Signal traders form their expectations on ESG ratings via the following dividend growth model over the whole payoff (price plus dividend):

$$p_n^*(g_n) = \frac{c_n}{r_n(g_n) - \delta_n(g_n)}(1 + \varkappa_n(g_n)), \tag{A.4}$$

where c_n is the cash-flow of firm n, $\delta_n(g_n)$ its growth rate, and $r_n(g_n)$ the cost of capital. We omit the time index for notational convenience. The last term of the equation pertains to expected dividends and $\varkappa_n$ is the dividend yield of firm n (dividend divided by price).

There are reasons to believe that the dividend yield does indeed depend on the level of sustainability of firms. For instance, Giese et al. (2019) and Cheung et al. (2018) show that dividend yields are increasing with ESG scores or CSR policy. Nevertheless, in our framework, what matters is the *local* shock to ESG scores, which occurs at high frequency (daily, in our empirical study). It is unlikely that dividend news be released concomitantly with ESG scores, meaning that, in practice, signal traders will only focus on the latter. Consequently, we will henceforth overlook the dividend issue in our model and equate payoffs with prices ($p = p^*$), or, equivalently, set $\varkappa_n = 0$. Technically, this simplification could also be circumvented by considering that $\varkappa_n$ does not depend on g_n and acts as a scaling constant in the expression of payoffs.

Simply put, signal traders view sustainability scores as the only drivers of expected returns.[15] The rationale is the following. In a world with environmentally aware customers, news on sustainability are likely to affect the propensity of the public to purchase a firm's goods or services. For instance, a negative signal (e.g., a severe downgrade in ESG

[15] Naturally, this assumption is overly simplistic. The number of indicators tracked by analysts and asset managers is virtually impossible to measure. The focus of the present paper is ESG concerns, which is why we stick to this unique signal.

rating linked to a scandal on emissions, $\Delta g \ll 0$) may lead clients to boycott the firm. Reversely, positive news, like pledges to Sustainable Development Goals, may incite new customers to buy products from the firm.

Both rates in Equation (A.4) are functions of the sustainability score g_n and are assumed to be C^∞ over their respective domains, which is the unit interval. As is customary, these rates are of course such that the price remains strictly positive.

If we further omit the firm index and resort to a second-order application of the Taylor expansion, we have that a payoff subject to an ESG shock Δg satisfies

$$p(g + \Delta g) = p(g) + p'(g)\Delta g + \frac{p''(g)}{2}(\Delta g)^2 + R, \tag{A.5}$$

where R is the residual of the expansion (third-order and higher-order terms). Because $g \in [0, 1]$, shocks to g can also only lie in the unit interval, so that powers of Δg become infinitesimally small. We have removed the star superscript * so that it does not interfere with the differential notation: henceforth, p will stand for payoffs or price, interchangeably. Furthermore, we have

$$\begin{aligned} p'(g) &= -c(1+\kappa)\frac{r'(g) - \delta'(g)}{(r(g) - \delta(g))^2} = -p(g) \times \frac{r'(g) - \delta'(g)}{r(g) - \delta(g)} \\ p''(g) &= -c(1+\kappa)\left[\frac{(r''(g) - \delta''(g))(r(g) - \delta(g)) - 2(r'(g) - \delta'(g))^2}{(r(g) - \delta(g))^3}\right] \\ &= -p(g) \times \left[\frac{(r''(g) - \delta''(g))(r(g) - \delta(g)) - 2(r'(g) - \delta'(g))^2}{(r(g) - \delta(g))^2}\right]. \end{aligned}$$

We now make an analytical assumption. We posit a payoff model for signal traders such that payoffs in Equation (A.4) have the following form:

$$p = ce^{ag^2 + bg}. \tag{A.6}$$

The rationale for this choice is that it satisfies several desirable properties. First, it ensures positive payoffs. Second, the function can be both increasing or decreasing in g, just as it can be convex or concave. Hence it is relatively flexible. Finally, it is highly tractable and easily differentiated. Because this parametrization is crucial for our model, we discuss its implications in more detail in Subsection A.3 below.

We do not impose any sign on the parameters in order to leave room for payoffs that can be concave or convex and increasing or decreasing in g, and even nonmonotonic. The first and second-order sensitivities are then

$$p'(g) = (2ag + b) \times p(g), \tag{A.7}$$

$$p''(g) = (4a^2g^2 + 4abg + 2a + b^2) \times p(g). \tag{A.8}$$

Plugging these expressions into Equation (A.5), we get that traders expect relative changes to have the following shape:

$$\frac{p(g + \Delta g) - p(g)}{p(g)} = (2ag + b)\Delta g + \frac{1}{2}(4a^2g^2 + 4abg + 2a + b^2) \times (\Delta g)^2 + R. \tag{A.9}$$

The above equation is very important because it implies that the reaction of payoffs to shocks in sustainability (Δg) is contingent on the initial level of sustainability, g. If we focus on the first-order term only, it is plain that depending on the sign of $2ag + b$, the impact of the shock may change from positive to negative, or vice-versa.

Now, we can choose the level of approximation in the Taylor series. We consider two cases: either ignore the terms beyond the first-order term or ignore the residual term R only. Then, if we allow for nonzero idiosyncratic supply shocks, the equilibrium relationship in Equation (A.3) can be written as

$$r_{t+1,n} = a_n + b_1\Delta g_{t+1,n} + b_2 g_{t,n}\Delta g_{t+1,n} + e_{t+1,n}, \quad (\mathit{firstorder}),\ or \tag{A.10}$$

$$r_{t+1,n} = a_n + b_1\Delta g_{t+1,n} + b_2 g_{t,n}\Delta g_{t+1,n} \quad (\mathit{secondorder}) \tag{A.11}$$

$$+\, d_0(\Delta g_{t+1,n})^2 + d_1 g_{t,n}(\Delta g_{t+1,n})^2 + d_2 g_{t,n}^2(\Delta g_{t+1,n})^2 + e_{t+1,n}, \tag{A.11}$$

where $e_{t+1,n}$ encompasses the demeaned supply shocks of stock n and a_n equals their means.

The fact that expectations are positively linked to ESG shocks (i.e., $b_1 > 0$) is not straightforward. For instance, Pástor et al. (2021) propose a model in which expected returns are a decreasing function of sustainable scores. Avramov et al. (2022) contend that this argument can be mitigated by risk or ambiguity when ESG ratings are subject to measurement uncertainty.

One very important novelty in Equation (A.10) is the inclusion of the interaction term between the level g and the change Δg. This implies that a shock to the sustainable score will heterogeneously impact firms, depending on their original rating. This makes sense: a firm with outstanding ESG credentials is much more at risk with respect to ESG scandals than a firm with an already brown reputation.

Technically, the model predicts that the errors, or innovations, in the model be correlated because of the links in the payoffs (via the covariance matrix $\mathbf{\Sigma}$ in Equation (A.3)). In order to mitigate this issue, we will propose two solutions in our empirical study. First, we will include control variables in the panel models to take into account the correlation arising from systematic risk. Indeed, we add the Fama and French (2015) factors, as well as the momentum factor to the models. Several papers (e.g., Green et al., 2017; Harvey et al., 2016; Hou et al., 2015, 2020; Kelly et al., 2019) argue that a handful of characteristics-based factors (i.e. size, value, profitability, momentum, etc.) suffice to capture the variety of the cross-section of stocks returns. Moreover, Barillas and Shanken (2018) show that a family of 6 such factors is superior to other models in explaining cross-sectional returns. These are also the most common factors used in the literature. In addition to the control variables, to account for the correlation that may not be captured by the systematic factors, our second solution involves the clustering of errors in the computation of standard errors, by firms and by dates, as is advocated by Thompson (2011). Clustering standard errors is often useful (see for example, Abadie et al., 2022), and helps reduce bias in standard errors when dealing with a large enough number of clusters of each dimension (Petersen, 2009)—which will be the case in our sample. The combination of clustered errors and control variables is expected to improve the quality of inference in our results.

A.3 | Comments

We now spend some time commenting on the terms in Equations (A.4), (A.5), and (A.6). First, in the first two, we have not specified any shape for the cost of capital function r nor for the growth rate of cash flows δ. Let us now assume, for simplicity, that they are either convex or concave on the unit interval. This implies that the traders anticipate a non-linear impact of g overvaluation. While most studies assume linear impacts in panel models, this stylized property of nonlinearity has been documented in the literature in relationship to various proxies of financial performance, notably in Barnett and Salomon (2006), Brammer and Millington (2008), Harjoto et al. (2017), and Gerged et al. (2021).

However, as is shown in Figure A.1, this leaves room for several combinations, depending on where r and δ reach their optimal values. In some cases, 'average' values of g may be optimal for prices (left panel): cost of capital is low and growth rate is high. In other configurations, extreme sustainability (or brownness) will be rewarded (center figure). Finally, intermediate combinations are also possible (right plot). We recall that these curves model the (shared) beliefs of the signal traders. With respect to financial performance, it is reasonable to assume that the net impact of both rates can be U-shaped, meaning that extremes perform better. Brown businesses (sin stocks) benefit from lucrative activities, while green firms are more resilient and have loyal customers and more stable cash flows. All these options are feasible, given the form (A.6)

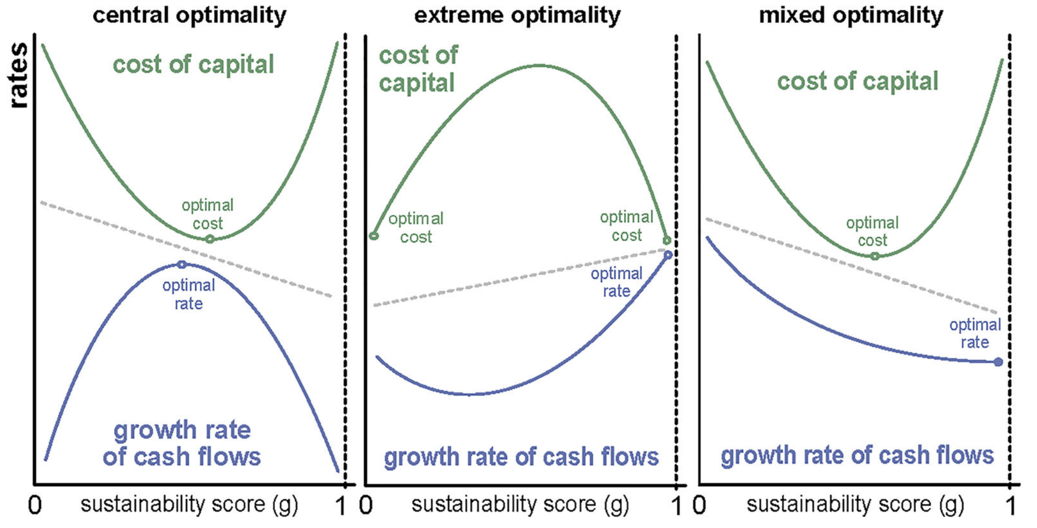

FIGURE A.1 Impact of sustainability on the components (r and δ) of the discounted dividend-growth model.
Note: Depending on the configuration, the optimal price is reached for very different sustainability scores.
[Color figure can be viewed at wileyonlinelibrary.com]

A key point in Equation (A.6) is that of the estimation of coefficients. For instance, there are at least two ways to exploit the links therein. First, in the specification $p_{t,n} = c_n e^{a_n g_{t,n}^2 + b_n g_{t,n}}$ time-series for fixed n can be used to estimate the firm-specific coefficients a_n, b_n, and c_n—on the log-prices. This could be troublesome if $g_{t,n}$ is released at very low frequencies (e.g., annually), thereby implying very small samples. More straightforwardly, the estimation could be directly performed on returns, as is suggested in Equation (A.10) for instance.

In a second specification, the coefficients would be kept constant in the cross-section of firms ($p_{t,n} = c^{a g_{t,n}^2 + b g_{t,n}}$), and a panel model would estimate an average exposure to the g and g^2 scores. This is the route we take in this paper but with returns as dependent variables.

A.4 | Indirect impacts: clientele and supply chain

Heuristically, a negative ESG shock for a firm is likely to cascade to its clients (Hartmann & Moeller, 2014), but also potentially to its suppliers. Reversely, being cautious with regard to the supply chain may prove beneficial (de Bodt et al., 2022; Sancha et al., 2015; Subramaniam et al., 2020; and Yawar & Seuring, 2018;). In the cash-flow channel, lower sales for a firm (because of negative news coverage) may engender higher product stocks and thus lower purchases in the near future for its providers. This may trigger a diminished activity for the supply chain of the firm.

In this subsection, we propose a model that links the ESG shock of a given firm to the returns of its customers or suppliers. To this purpose, we generalize Equation (A.4) by assuming that growth and discounting rates depend not only on the sustainability score of the firm but also on those of its suppliers or clients. This assumption is not too far-fetched. Propagation effects related to reputation in supply chains have been documented in Czinkota et al. (2014), Hoejmose et al. (2014), and Mani and Gunasekaran (2021). We can now consider discount and growth rates such that

$$r\left(g_n + \sum_{i \in S_n} \eta_i g_i\right), \quad \textit{and} \quad \delta\left(g_n + \sum_{i \in S_n} \eta_i g_i\right), \tag{A.12}$$

where S_n is the set of indices of the suppliers (or, alternatively, of the clients) of firm n, and the η_i are scalars that code the heterogeneity in the importance of each supplier for the firm. Typically, we would suppose $|\eta_i| < 1$ because shocks propagating from the supply chain should be less influential than shocks to the firm's own ESG score.

Under the same assumptions as above, the first-order impact of a shock to the sustainability rating in Equation (A.10) then becomes:

$$r_{t+1,n} = a_n + b_1 \left(\Delta g_{t+1,n} + \sum_{i \in S_n} \eta_i \Delta g_{t+1,i} \right) + b_2 g_{t,n} \left(\Delta g_{t+1,n} + \sum_{i \in S_n} \zeta_i \Delta g_{t+1,i} \right) + e_{t+1,n}. \tag{A.13}$$

The specification in Equation (A.13) is the one, up to coefficient names, that we will use in our empirical study. Given that updates in ESG scores are relatively rare, for one given date, the set of nonzero Δg_i often consists of only one firm (client or supplier).