ESG news spillovers across the value chain*

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Abstract

We document the impact of ESG shocks on the stock returns of suppliers and clients of affected firms. Our equilibrium model suggests that this impact is contingent not only on the sign and magnitude of the shock, but also on the interaction between the shock and the level of the ESG score. An empirical analysis of US stocks, along with their global clients and suppliers, reveals that ESG shocks are integrated into prices intra-daily 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 effects we report are stronger in the recent period, possibly due to increased investor attention towards 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, in relatively inelastic markets (Gabaix and Koijen (2021)), 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 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.

We propose a partial equilibrium model in which sustainability-aware agents trade according to ESG news and shocks therein. The model predicts that returns should be impacted by ESG shocks,[4] but also by 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. Our second model generalizes the first by incorporating the sustainability scores of clients or suppliers into the pricing model of ESG-aware agents. We test our theoretical predictions on a sample of US firms which 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 a 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. Second, the impact of a firm's ESG shock on its own return is immediate. The significant coefficients pertain to

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[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 and Shumway (2003)), soccer scores (Edmans et al., 2007), and even music tone (Edmans et al., 2021).

[2]Results hold for aggregate sentiment (Baker and Wurgler (2006), Bollen et al. (2011), Da et al. (2015), and Fraiberger et al. (2021)), or stock-specific sentiment (Chen et al. (2014) and 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.html).

[4]In doing so, we provide an equilibrium-based theoretical grounding for the panel regressions carried out in Serafeim and Yoon (2022b). Though the model is not exactly the same, it could be altered to match their specification more closely.

synchronous terms: firms' return 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. Third, a shock related to materialized ESG topics spreads quicker through the supply-chain than a common ESG shock.[5] Finally, the impact of ESG shock is more salient in recent years, concomitantly with the rise of investor awareness toward sustainability.

An important empirical confirmation is that the impact of shocks, both direct or stemming from the value chain, is indeed 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. This latter finding is somewhat counter-intuitive, as green firms seem to have more to lose from a negative shock to their reputation.

The remainder of the paper is structured as follows. Section 2 is dedicated to the literature review. The theoretical models are presented in Section 3. Section 4 presents our dataset, while Sections 5 and 6 detail and discuss our empirical results. Finally, Section 7 concludes.

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 a more granular levels, stock-specific signals are also exhaustively followed by researchers and practitioners. A longstanding asset pricing anomaly is the post earnings announcement drift (see, e.g., Foster et al. (1984), Patell and Wolfson (1984), Bernard and Thomas (1989), and 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. (2021) and the references therein, as well as to Eccles and Serafeim (2013); Lanfear et al. (2019); Ma et al. (2022); Tomlinson et al. (2021) 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 channel 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 weighted average cost of capital (WACC). Empirically, Derrien et al. (2021) find that most of the ESG-linked variation

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[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).

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. Moreover, Serafeim and Yoon (2022a,b) document the mitigating role of disagreement. They find that ESG shocks to 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 not only depends 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), who quantify 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), who also analyze 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 firm's input-output and on the choice of optimal suppliers. Inter-firm relationships also impacts the decision on 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 on 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 non-linear because it depends both on the magnitude of the shock and on the current ESG rating of the affected firm.

3 Stylized equilibrium model

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 $g_{t,n}$.[6] The scores are normalized so that, in the cross-section, they always lie in the unit interval, i.e., $g_{t,n} \in [0,1]$: 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.

3.1 Agents and partial equilibrium

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

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

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:

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

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

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

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

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

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[6]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 is out of the scope of the present paper.

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

$$\boldsymbol{r}_{t+1} = \mathrm{diag}(\boldsymbol{p}_t)^{-1}(\boldsymbol{p}_{t+1} - \boldsymbol{p}_t)$$

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

where $\mathrm{diag}(\boldsymbol{v})$ is the diagonal matrix with vector $\boldsymbol{v}$ as diagonal elements. Essentially, supply shocks will be taken as innovations. The terms $\mathrm{diag}(\boldsymbol{p}_t)^{-1}\mathbb{E}_t[\boldsymbol{p}_{t+1}^*]$ and $\mathrm{diag}(\boldsymbol{p}_t)^{-1}\mathbb{E}_{t+1}[\boldsymbol{p}_{t+2}^*]$ 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 Berk and van Binsbergen (2021), the share of green investors is shown to be an important driver of the cost of capital of firms. 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 (3) may be unlikely to affect asset returns. This will also depend on how inelastic the demands can be (see, e.g., Gabaix and Koijen (2021) for the aggregate market). Typically, it may occur that liquidity suppliers be inactive after an important signal, resulting in small magnitude $\boldsymbol{\epsilon}_{t+1}$, whereas the signal is actively used by ESG signal traders.

3.2 Price expectations

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

$$p_n^*(g_n) = \frac{c_n}{r_n(g_n) - \delta_n(g_n)}(1 + \kappa_n(g_n)), \qquad (4)$$

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 κ_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 $\kappa_n = 0$. Technically, this simplification could also be circumvented by considering that κ_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.[7] The rationale is the following. In a world with environmentally-aware customers, news on

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[7]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.

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 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 (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

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

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

$$p'(g) = -c(1 + \kappa)\frac{r'(g) - \delta'(g)}{(r(g) - \delta(g))^2} = -p(g) \times \frac{r'(g) - \delta'(g)}{r(g) - \delta(g)}$$

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

$$= -p(g) \times \left[\frac{(r''(g) - \delta''(g))(r(g) - \delta(g)) - 2(r'(g) - \delta'(g))^2}{(r(g) - \delta(g))^2}\right].$$

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

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

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 3.3 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 non-monotonic. The first and second order sensitivities are then

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

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

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

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

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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 (3) can be written as

$$r_{t+1,n} = a_n + b_1 \Delta g_{t+1,n} + b_2 g_{t,n} \Delta g_{t+1,n} + e_{t+1,n}, \quad \text{(first order), or} \tag{10}$$

$$r_{t+1,n} = a_n + b_1 \Delta g_{t+1,n} + b_2 g_{t,n} \Delta g_{t+1,n} \qquad \text{(second order)} \tag{11}$$
$$+ d_0 (\Delta g_{t+1,n})^2 + d_1 g_{t,n} (\Delta g_{t+1,n})^2 + d_2 g_{t,n}^2 (\Delta g_{t+1,n})^2 + e_{t+1,n},$$

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 (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 that 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 (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., Hou et al. (2015), Harvey et al. (2016), Green et al. (2017), Kelly et al. (2019), and Hou et al. (2020)) 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. (2017)), 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.

3.3 Comments

We now spend some time commenting on the terms in Equations (4), (5) and (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 over valuation. While most studies assume linear impacts in panel models, this stylized property of non-linearity 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 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 (6)
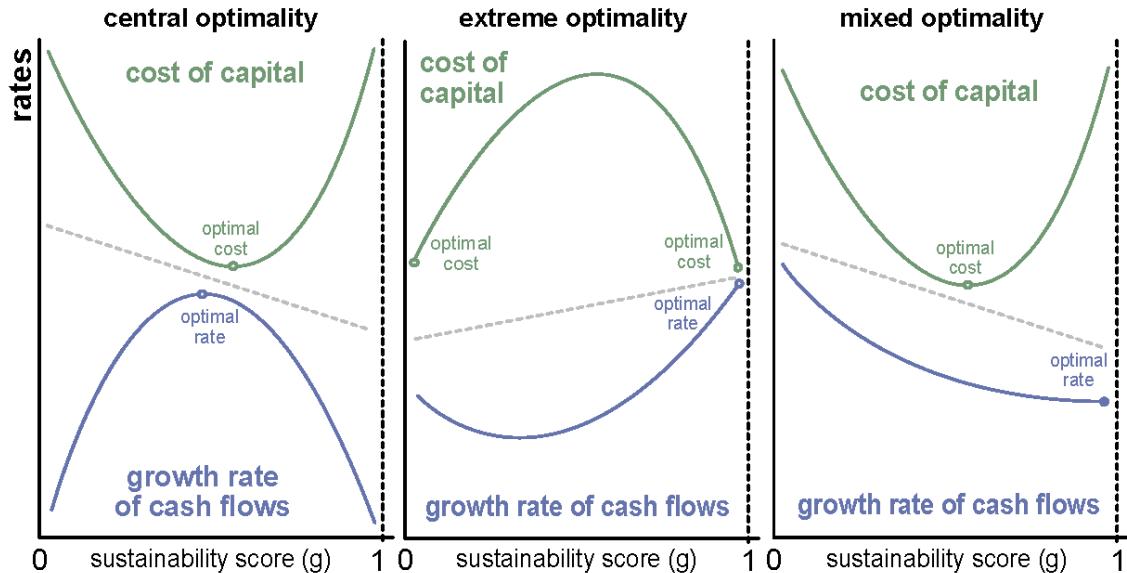

Figure 1: **Impact of sustainability on the components (r and δ) of the discounted dividend-growth model**. Depending on the configuration, the optimal price is reached for very different sustainability scores.

A key point in Equation (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 be performed on returns, as is suggested in Equation (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.

3.4   Indirect impacts: clientele and supply chain

Heuristically, a negative ESG shock for a firm is likely to cascade to its clients (Hartmann and Moeller (2014)), but also potentially to its suppliers. Reversely, being cautious with regard to the supply chain may prove beneficial (Sancha et al. (2015), Yawar and Seuring (2018), Subramaniam et al. (2020), and de Bodt et al. (2022)). 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 (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

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

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 firms own ESG score.

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

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

The specification in Equation (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).

4   Data

To investigate the direct and indirect spillover effects of ESG news to 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, NYSE American (formerly known as AMEX) exchange, from FactSet Price. Second, we gather the supplier and customer relationship data from FactSet Revere.

FactSet Revere provides data on the links between supplier and customer 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 meta data. 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 on 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 contents regarding a company's ESG profile from more than 100,000 sources. This data is both semantic and quantitative for more than a dozen languages. The raw content is usually derived from article news, and reports from non-governmental organizations (NGOs), watchdog institutions, etc. Then, relevant metrics from this data is 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 which is a measure of 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 proxy for what we refer to Δg in the theoretical model.

ESG disagreement is an important issue widely reported in the literature.[8] However, the providers that supply daily scores with no self-reporting bias are scarce, which is why we resort to TruValue data only. For 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 summarize the ESG scores of all 26 ESG categories following the nomenclature of the SASB. Another one is the *Materiality Pulse (MP)* score, which only summaries the ESG categories that the SASB considers financially material to that company. We standardize the ESG measures in the cross-section 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,[9] and hence focus only on the customer firms that are in the US, 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 US, 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

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[8]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).

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

around 2800 firms each day. We use this sample to study the direct effect of ESG news shock to stocks' return.

Table 1: **Summary statistics of ESG measures** for ACP (All Categories Pulse) and MP (Materiality Pulse) after normalization. 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 non-zero. In Panel A, we use the sample of of all US firms and report the summary statistics of ESG measures. In Panel B, we use the sample that consists of main customers of US firms, while in Panel C, the sample pertains to main suppliers of US firms. All three samples consist data from January-2007 to May-2021.

Panel A: All US firms

	N	mean	sd	median	min	max	range	skew	kurtosis	Q0.25	Q0.5	Q0.75	Corr$(t, t-1)$
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	-

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 1,300 pairs each day. We use this sample to investigate the spillover effect of ESG news shocks to US suppliers, from their main customer.

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 1,000 pairs each day. With this sample, we study the spillover effect of ESG news shocks to US customers from their main supplier.

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.

5 Empirical methods and results

5.1 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 point 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 first order terms of the Taylor expansion in Equation (10) and we 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 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 and the level of sustainability - and its relationship with returns. A model that encompasses the second order terms was also tested but did not yield additional insights. The results are available upon request.

The classical empirical approach to study 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 into 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 to set arbitrary thresholds. Second, as is suggested in our theoretical model, the links we study are contingent to the sign of the shocks, to the magnitude of the shocks, and to the ESG levels of firms that experience the shock. Taking these elements into account would require to create 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.[10]

Instead, we follow both the recommendation from our theoretical framework and the path laid out in Serafeim and Yoon (2022a,b) who also use panel regressions to study ESG news. Formally, we use Equation (14) below to assess the direct impact of ESG news to return, Equation (15) for the spill-over effect from customer to supplier, and Equation (16) for spill-over effect from supplier to customer.

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[10]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.

$$r_{t,n} - r_f = \gamma_n + \sum_{j=0}^{3} \theta_j \Delta g_{t-j,n} + \sum_{j=0}^{3} \beta_j g_{t-1,n} \times \Delta g_{t-j,n} + \alpha g_{t-1,n} + \delta' Z_t + \varepsilon_{t,n}, \qquad (14)$$

$$r_{t,n}^{Sup} - r_f = \sum_{j=0}^{3} \theta_j^{Cus} \Delta g_{t-j,n}^{Cus} + \sum_{j=0}^{3} \beta_j^{Cus} g_{t-1,n}^{Sup} \times \Delta g_{t-j,n}^{Cus} + \gamma_n + \delta' Z_t +$$
$$\sum_{j=t-3}^{t} \beta_j^{Sup} g_{t-1,n}^{Sup} \times \Delta g_{t-j,n}^{Sup} + \alpha^{Cus} g_{t-1,n}^{Sup} + \sum_{j=0}^{3} \theta_j^{Sup} \Delta g_{t-j,n}^{Sup} + \varepsilon_{t,n}, \qquad (15)$$

$$r_{t,n}^{Cus} - r_f = \sum_{j=0}^{3} \theta_j^{Sup} \Delta g_{t-j,n}^{Sup} + \sum_{j=0}^{3} \beta_j^{Sup} g_{t-1,n}^{Cus} \times \Delta g_{t-j,n}^{Sup} + \gamma_n + \delta' Z_t +$$
$$\sum_{j=t-3}^{t} \beta_j^{Cus} g_{t-1,n}^{Cus} \times \Delta g_{t-j,n}^{Cus} + \alpha g_{t-1,n}^{Cus} + \sum_{j=0}^{3} \theta_j^{Cus} \Delta g_{t-j,n}^{Cus} + \varepsilon_{t,n}, \qquad (16)$$

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.
- $r_{t,n}^{Sup}$ is the return of the supplier firm.
- $r_{t,n}^{Cus}$ is the return of the customer firm.
- $g_{t-j,n}^{Sup}$ is the ESG score of supplier firm (either ACP (All Categories Pulse score) or MP (Materialized Pulse score only)) - after normalization.
- $g_{t-j,n}^{Cus}$ is the ESG score of the customer firm.
- Z_t is a vector of control variables: the Fama and French (2015) 5 factors, plus momentum (12 months to prior month return, in line with Jegadeesh and Titman (1993)).
- 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 level being continuous and allow interaction between them. Regressions also control the first problem of consecutive event days. With lags approach, we can separate the impact of ESG shocks on one day to return on another day while keeping everything else constant.

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 spill-over effect of ESG news shock from customer to supplier, we control for the ESG shock of supplier itself. The same control applies when we want to estimate the spill-over effect of ESG news shock from supplier to customer.

The t-statistics of all coefficients are computed with errors clustered by date, firm, as in Thompson (2011). We investigate the impact of ESG news shocks released during the 3 days[11] 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 spill-over 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 spill-over effect from supplier to customer. With the control settings discussed above, these effects are indeed abnormal return (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 which 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 (2022a,b). 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 point in time, rather than one RHS variable (ESG shocks) and different LHS variables (several interval return). 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 with the one with industry fixed effect.[12]

5.2 Direct impact of ESG news shocks to stocks' return

The direct impact of ESG news shocks to 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 14. These coefficients show the effect to returns if there is a change in ESG score. We provide two alternative specifications using both ESG measures which are ACP (All Categories Pulse) in model (1) and MP (Material Pulse) in model (2).

Our results show that the impact of shock on ESG news is priced instantaneously intra-day. 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 in 0.10 points in ESG score[13] 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 ($\beta_0 = -0.025$;

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

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

[13]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**. 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 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 $\sum_{j=0}^{3} \beta_j g_{t-1,n} \times \Delta g_{t-j,n}$. $L(x,n)$ is the lag function: $L(x_t,n) = x_{t-n}$. Samples consist of daily data from January-2007 to May-2021.

Variable \ Model:	(1) $g = ACP$	(2) $g = MP$
L(Δ g,3)	0.0008 (0.866)	0.0009 (0.815)
L(Δ g,2)	0.002* (2.31)	0.002* (2.08)
L(Δ g,1)	-7.88e-5 (-0.066)	0.0003 (0.234)
Δ g	0.012** (6.91)	0.010** (4.91)
L(Δ g,3) × L(g,1)	-0.0004 (-0.281)	-0.002 (-0.953)
L(Δ g,2) × L(g,1)	-0.003* (-2.01)	-0.004* (-2.47)
L(Δ g,1) × L(g,1)	0.0004 (0.225)	0.0009 (0.467)
Δ g × L(g,1)	-0.025** (-8.02)	-0.018** (-5.28)
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
R2	0.03003	0.02804
Within R2	0.02961	0.02761
Signif. Codes : **: 0.01, *: 0.05		

t-stat: -8.02) , and MP ($\beta_0 = -0.018$; t-stat: -5.28). The negative coefficient β_0 will generate a mitigating effect on the impact of ESG shocks to 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 a same ESG news shock. This makes sense heuristically: a firm with high ESG reputation has less to gain from incremental improvement in ratings.

To further illustrate this idea, we plot in Figure 2 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 return 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
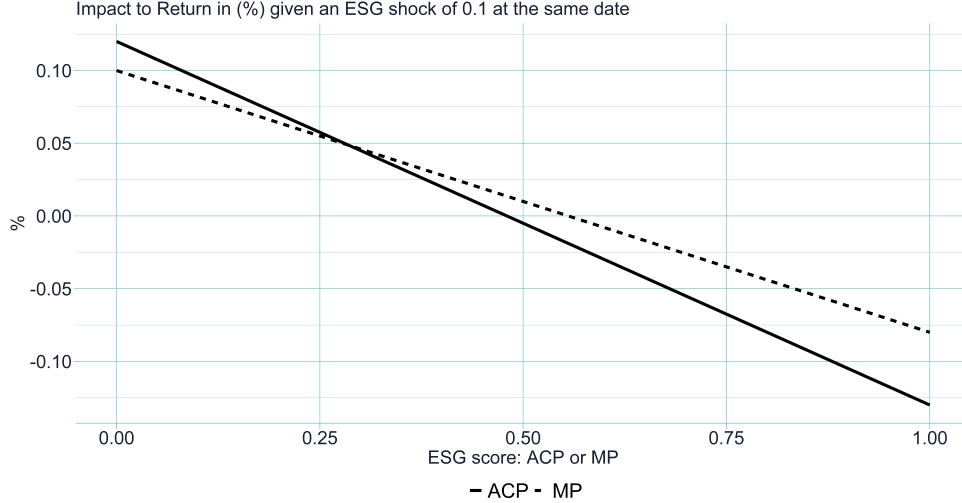
Figure 2: Impact to daily return (in %) given an ESG shock (Δg_t) of +0.1 at the same date contingent on different firm's ESG level, g_{t-1}. The plot shows $\tilde{r}_t(g_{t-1}) = (\theta_0 + \beta_0 \times g_{t-1})\Delta g_t$, with $\Delta g_t = 0.1$, θ_0, and β_0 from Table 2. The ESG measure is either ACP (full line) or MP (dashed line).

to all firms. However, with a negative β_0, green firms will suffer less from negative news than brown firms.

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 shock more than high ESG firms. However, counter-intuitively, high ESG firms suffer less from negative ESG shocks than low ESG firms.

5.3 ESG news shock to suppliers' stock returns

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

We want to estimate the spillover effect of ESG news shock from customer to supplier, while controlling for the ESG shock of 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 15, in Table 3. These coefficients show the spillover effect from customer to supplier if there is a shock in 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 2.11). This effect is thus 4 times weaker than the direct effect of ESG news' shock to the company return at 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 supplier-firm by 0.03% on average.

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Table 3: **Panel regression of the spillover effect of ESG news from customer to supplier**. The model equation is

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

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

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

Variable \ Model:	(1)	(2)
	$g = ACP$	$g = MP$
L(Δg^{Cus},3)	0.003* (2.09)	0.003 (1.73)
L(Δg^{Cus},2)	-0.003 (-1.84)	0.0001 (0.069)
L(Δg^{Cus},1)	-0.0007 (-0.458)	-0.005** (-2.90)
Δg^{Cus}	-0.0004 (-0.224)	-0.002 (-1.26)
L(Δg^{Cus},3) $\times$ L(g^{Sup},1)	-0.005* (-2.08)	-0.004 (-1.44)
L(Δg^{Cus},2) $\times$ L(g^{Sup},1)	0.002 (0.651)	-0.0007 (-0.284)
L(Δg^{Cus},1) $\times$ L(g^{Sup},1)	0.0007 (0.297)	0.008** (2.96)
$\Delta g^{Cus} \times$ L(g^{Sup},1)	-2.61e-6 (-0.0010)	0.003 (1.14)
Fixed-Effects:		
Supplier ID	Yes	Yes
Time via Factors' return	Yes	Yes
Cluster	Supplier ID and Date	Supplier ID and Date
Observations	4 496 060	4 031 087
R2	0.1487	0.14712
Within R2	0.14818	0.1465
*Signif. Codes : **: 0.01, *: 0.05*		

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.

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 one 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 firm will react more favorably to positive news than low MP firm.

To summarize our findings, we plot average effects in Figure 3 in the same spirit as Figure 2. 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 in the level of the ESG score, but also, importantly, on the type of measure (ACP versus MP).
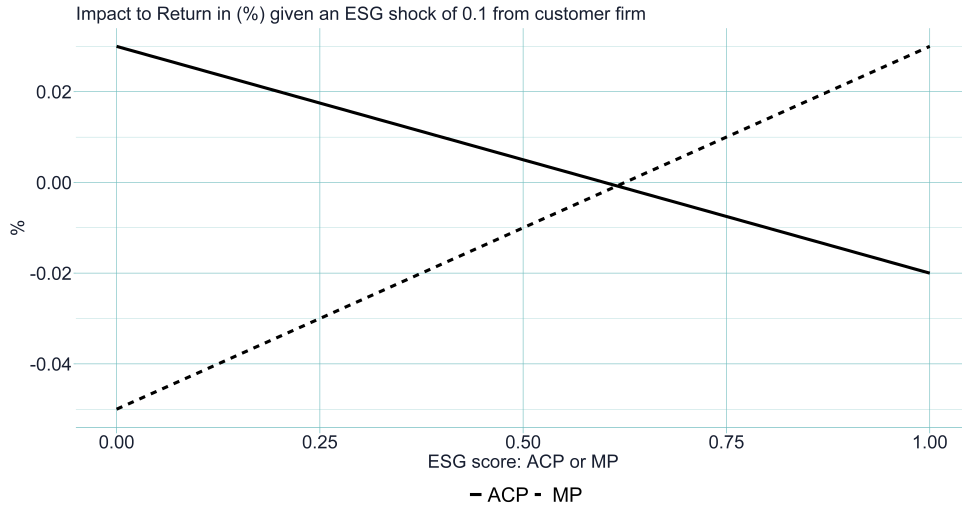

Figure 3: Impact to daily firm return (in %), given an ESG shock of +0.1 ($\Delta g^{Cus} = 0.1$) from its customer firm, contingent on the ESG level of the firm. For the ACP measure (hard line), it is the total effect to return of day 3 after the shock date on customer side, which includes the significant 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 $\Delta g^{Cus} \beta_1^{Cus} \cdot g_{t-1}^{Sup}$.

5.4 ESG news shock to customers' stock returns

In this last subsection, we investigate the reverse effect, that is, from supplier to customer, i.e., when the ESG shock comes from the supplier side using the Equation 16.

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 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 5.2).

In other words, if there is a shock in 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 with 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 green customer-firm is the one that suffers less from that effect.

To illustrate this pattern, we plot in Figure 4 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.
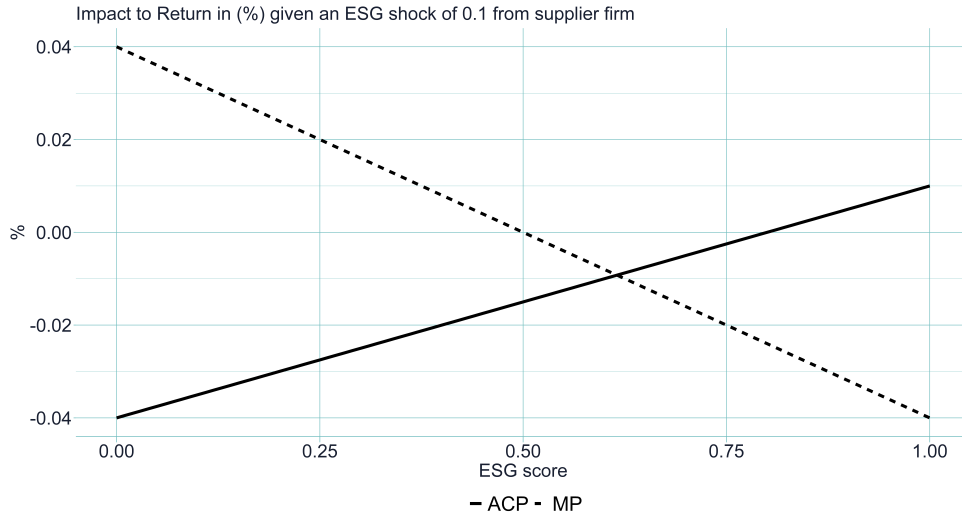

Figure 4: Impact to return in (%), given an ESG shock of +0.1 ($\Delta g^{Sup} = +0.1$) from the supplier firm, contingent on the firm's ESG level. For ACP, it is the combined effect of day 3 after the shock on the supplier side, which includes the significant interaction terms $\Delta g^{Sup} \cdot \theta_3^{Sup}$ 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 $\Delta g^{Sup} \beta_2^{Sup} \cdot g_{t-1}^{Cus}$.

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

Table 4: **Panel regression of the spillover effect of ESG news from supplier to customer**.

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

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

Where $r_{t,n}^{Cus}$ is the return of the customer firm n. $g_{j,n}^{Sup}$ is the variable of ESG score of supplier to firm n which can be ACP (All Categories Pulse score) or MP (Materialized Pulse score only) after being normalized to have value between zero and one. The logic is similar with $g_{j,n}^{Cus}$. The term 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. 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 daily data from January-2007 to May-2021.

Model:	(1)	(2)
	$g = ACP$	$g = MP$
L(Δg^{Sup},3)	-0.004* (-1.98)	-0.004 (-1.43)
L(Δg^{Sup},2)	-4.43e-5 (-0.027)	0.004* (2.38)
L(Δg^{Sup},1)	-0.0002 (-0.074)	-3.37e-5 (-0.015)
Δg^{Sup}	0.003 (1.21)	0.0008 (0.402)
L(Δg^{Sup},3) × L(g^{Cus},1)	0.005 (1.72)	0.005 (1.19)
L(Δg^{Sup},2) × L(g^{Cus},1)	0.0004 (0.130)	-0.008** (-2.73)
L(Δg^{Sup},1) × L(g^{Cus},1)	0.001 (0.309)	0.001 (0.369)
Δg^{Sup} × L(g^{Cus},1)	-0.005 (-1.48)	-0.001 (-0.393)
Fixed-Effects:		
Customer ID	Yes	Yes
Time via Factors' return	Yes	Yes
Cluster	Customer ID and Date	Customer ID and Date
Observations	3 520 532	3 142 980
R2	0.09405	0.08975
Within R2	0.09326	0.0889

Signif. Codes : **: 0.01, *: 0.05

smaller lags. This means that financially material news seem to be priced-in more rapidly than synthetic ESG news.

6 Subsample analysis: the evolution of investor awareness

The previous section has led us to conclude that ESG news create 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.

Sustainability is increasingly perceived as important by investors, hence it is likely that they have paid more attention to ESG news in the most recent period. This, combined to improved telecommunication technologies and to 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 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 the direct influence of ESG news to returns in Table 5. 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 in 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- and post-2017 in Table 6. In panel A, we see no effect in the pre-2017 sample for both ACP and MP measures. After 2017, a shock in customer's ACP takes three days to affect the supplier's return. For the MP proxy, after 2017, it takes two days for an ESG shock from 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 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's return pre- and post-2017 in 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 day 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 sub-period.

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

Table 5: **Panel regression of the effect of ESG shocks to returns before and afer 2017**. 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 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 $\sum_{j=0}^{3} \beta_j g_{t-1,n} \times \Delta g_{t-j,n}$. $L(x,n)$ is the lag function: $L(x_t, n) = x_{t-n}$. Panel A consists data from January-2007 to Dec-2016. Panel B consists data from January-2017 to May-2021.

	Panel A: Before 2017		Panel B: After 2017	
Model	(1) $g = ACP$	(2) $g = MP$	(3) $g = ACP$	(4) $g = MP$
L(Δ g,3)	0.0006 (0.525)	0.001 (0.876)	0.0008 (0.554)	0.0002 (0.133)
L(Δ g,2)	0.002 (1.76)	0.003* (2.03)	0.002 (1.31)	0.001 (0.809)
L(Δ g,1)	0.0001 (0.102)	0.0010 (0.596)	-0.0007 (-0.334)	-0.0009 (-0.407)
Δ g	0.008** (4.68)	0.007** (3.70)	0.018** (5.28)	0.014** (3.47)
L(Δ g,3) $\times$ L(g,1)	-0.0002 (-0.089)	-0.001 (-0.531)	-0.0004 (-0.162)	-0.002 (-0.739)
L(Δ g,2) $\times$ L(g,1)	-0.002 (-1.36)	-0.004 (-1.84)	-0.004 (-1.37)	-0.005 (-1.63)
L(Δ g,1) $\times$ L(g,1)	-7.39e-5 (-0.034)	-0.0004 (-0.147)	0.002 (0.498)	0.003 (0.961)
Δ g $\times$ L(g,1)	-0.018** (-5.69)	-0.014** (-3.77)	-0.037** (-5.93)	-0.024** (-3.82)
Fixed-Effects:				
Firm id	Yes	Yes	Yes	Yes
Time via Factors' return	Yes	Yes	Yes	Yes
Cluster	Firm ID and Date	Firm ID and Date	Firm ID and Date	Firm ID and Date
Observations	6 307 257	5 461 448	3 775 309	3 502 891
R2	0.0203	0.0182	0.12465	0.12582
Within R2	0.0196	0.01749	0.12394	0.12504

*Signif. Codes **: 0.01, *: 0.05*

7 Conclusion

In this paper, we first propose an equilibrium-based model in which changes in ESG ratings affect firms' returns, thereby theoretically justifying ex-post panel regressions such as those employed in Serafeim and Yoon (2022b). The baseline model relies on two key quantities: the variation in rating, as well as this variation, in conjunction with the *level* of the rating. This implies 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 three 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

Table 6: **Panel regression of the spillover effect of ESG news from customer to supplier before and after 2017**. The model equation is

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

$$\sum_{j=t-5}^{t} \beta_j^{Sup} g_{t-1,n}^{Sup} \times \Delta g_{t-j,n}^{Sup} + \alpha^{Cus} g_{t-1,n}^{Sup} + \sum_{0-5}^{t} \theta_j^{Sup} \Delta g_{t-j,n}^{Sup} + \varepsilon_{t,n},$$

where $r_{t,n}^{Sup}$ is the return of the supplier firm n. $g_{j,n}^{Sup}$ is the variable of ESG score of supplier n which can be ACP (All Categories Pulse score) or MP (Materialized Pulse score only) after being normalized to have value between zero and one. The notation is similar with $g_{j,n}^{Cus}$ which is the main customer of firm n. The term 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. The t-statistics are computed with clustered errors by date and firm n. We only report the coefficients in two terms $\sum_{j=0}^{3} \theta_j^{Cus} \Delta g_{t-j,n}^{Cus}$, and $\sum_{j=0}^{3} \beta_j^{Cus} g_{t-1,n}^{Sup} \times \Delta g_{t-j,n}^{Cus}$. Panel A consists data from January-2007 to Dec-2016. Panel B consists data from January-2017 to May-2021.

	Panel A: Before 2017		Panel B: After 2017	
Model	(1) $g = ACP$	(2) $g = MP$	(3) $g = ACP$	(4) $g = MP$
L(Δ g^{Cus},3)	0.002 (1.20)	0.001 (0.654)	0.005 (1.70)	0.005 (1.79)
L(Δ g^{Cus},2)	-0.003 (-1.55)	0.002 (0.889)	-0.003 (-0.924)	-0.002 (-0.863)
L(Δ g^{Cus},1)	0.0003 (0.163)	-0.003 (-1.68)	-0.003 (-0.926)	-0.008* (-2.41)
Δ g^{Cus}	-0.001 (-0.731)	-0.002 (-0.890)	0.001 (0.386)	-0.003 (-1.09)
L(Δ g^{Cus},3) $\times$ L(g^{Sup},1)	-0.003 (-0.886)	-0.0004 (-0.129)	-0.01* (-1.98)	-0.009 (-1.92)
L(Δ g^{Cus},2) $\times$ L(g^{Sup},1)	0.0008 (0.251)	-0.004 (-1.20)	0.003 (0.673)	0.004 (0.841)
L(Δ g^{Cus},1) $\times$ L(g^{Sup},1)	-0.0004 (-0.159)	0.005 (1.63)	0.003 (0.718)	0.012* (2.55)
Δ 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	Supplier ID and Date	Supplier ID and Date	Supplier ID and Date
Observations	2 763 656	2 415 333	1 729 188	1 612 776
R2	0.16342	0.16001	0.1324	0.13404
Within R2	0.16289	0.15949	0.13128	0.13274

*Signif. Codes **: 0.01, *: 0.05*

Table 7: **Panel regression of the spillover effect of ESG news from supplier to customer before and after 2017**.

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

$$\sum_{j=t-5}^{t} \beta_j^{Cus} g_{t-1,n}^{Cus} \times \Delta g_{t-j,n}^{Cus} + \alpha g_{t-1,n}^{Cus} + \sum_{0-5}^{t} \theta_j^{Cus} \Delta g_{t-j,n}^{Cus} + \varepsilon_{t,n}$$

Where $r_{t,n}^{Cus}$ is the return of the customer firm n. $g_{j,n}^{Sup}$ is the variable of ESG score of supplier to firm n which can be ACP (All Categories Pulse score) or MP (Materialized Pulse score only) after being normalized to have value between zero and one. The logic is similar with $g_{j,n}^{Cus}$. The term 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. 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. Panel A consists data from January-2007 to Dec-2016. Panel B consists data from January-2017 to May-2021.

Model	Panel A: Before 2017		Panel B: After 2017	
	(1) $g = ACP$	(2) $g = MP$	(3) $g = ACP$	(4) $g = MP$
L(Δ g^{Sup},3)	-0.001 (-0.706)	-3.27e-5 (-0.014)	-0.006* (-2.03)	-0.008 (-1.65)
L(Δ g^{Sup},2)	0.001 (0.522)	0.005* (2.09)	-0.002 (-0.620)	0.004 (1.27)
L(Δ g^{Sup},1)	0.0003 (0.081)	0.0006 (0.181)	-0.0009 (-0.353)	-0.0009 (-0.321)
Δ g^{Sup}	0.004 (1.62)	0.0008 (0.339)	0.0010 (0.241)	0.0007 (0.200)
L(Δ g^{Sup},3) $\times$ L(g^{Cus},1)	0.003 (0.987)	-0.0004 (-0.108)	0.008 (1.41)	0.012 (1.47)
L(Δ g^{Sup},2) $\times$ L(g^{Cus},1)	-0.002 (-0.496)	-0.010** (-2.59)	0.003 (0.769)	-0.005 (-1.18)
L(Δ g^{Sup},1) $\times$ L(g^{Cus},1)	-0.0005 (-0.104)	-0.0009 (-0.154)	0.004 (0.784)	0.004 (0.887)
Δ g^{Sup} $\times$ L(g^{Cus},1)	-0.007 (-1.86)	0.0006 (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	Customer ID and Date	Customer ID and Date	Customer ID and Date
Observations	1 987 743	1 708 304	1 530 145	1 432 228
R2	0.07738	0.06983	0.12395	0.12478
Within R2	0.07623	0.06859	0.12268	0.1235

*Signif. Codes : **: 0.01, *: 0.05*

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 intra-daily. Whether this can be interpreted as a confirmation of market efficiency remains an open question.

The second stage of the model 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 potentially 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 two to three days after the shock. In addition, financially material ESG news diffuse to the supply chain quicker than common ESG news.

Another key finding of our study 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).

Our last batch of results 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 speed of information diffusion, it is likely that spillover effects will occur even faster in the coming years. This will have to be confirmed by future research.

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