Trade Credit Flow along the Supply Chain and Disruptions from ESG Risk

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Abstract: Using an international sample of firms, we provide evidence that there exists an ESG risk in the supply chain: firms receive less trade credit financing following intense negative media exposure to ESG incidents. This effect depends on a firm's position in the supply chain. A closer "distance" to would-be boycotting end-consumers appear to be modulating the negative effect of ESG risk on trade credit usage: unlike upstream firms, downstream (i.e., consumer-adjacent) firms are punished after ESG incidents. While downstream firms are being liquidity-squeezed by suppliers after ESG issues, they do not reduce their own trade-credit extension, making them liquidity providers. This liquidity provision negatively impacts a firm's cash holdings, causing them to invest less. Especially foreign suppliers, and suppliers domiciled in countries with high social norms, are punishing consumer-adjacent and unimportant customers that ESG-misbehave.

JEL codes: A13, G15, G30, G32, L14

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1 Introduction

In the aggregate, trade credit is the most important source of short-term financing for companies (Barrot, 2016; Fisman & Love, 2003; Petersen & Rajan, 1997; Rajan & Zingales, 1995).[1] Prior literature reports that good Environmental, Social, and Governance (ESG) performance, among other factors, can increase a firm's access to trade credit from suppliers (Xu, Wu, & Dao, 2020; M. Zhang, Lijun, Su, & Zhang, 2014; Y. Zhang, Lara, & Tribó, 2020). However, less is known about the effects of ESG incidents on companies' ability to access trade credit. In this paper, we employ a large international sample of firms to investigate whether negative news about a company's ESG practices (the "ESG risk") affect trade credit usage.

An especially compelling reason for focusing on ESG risk rather than good or poor ESG performance — usually interpreted as high or low ESG ratings — is that ESG incidents are largely exogenous shocks to a firm's ESG performance. In contrast, measures of ESG performance often rely on self-reported content by firms, which can lead to "greenwashing" issues. ESG performance is also likely to be endogenous by nature, e.g., more profitable firms may have better access to trade credit, but also be more likely to invest in ESG activities. Furthermore, companies with poor ESG performance (which is the focus of this study) may simply be companies that do not report on ESG activities. Finally, prior literature expresses serious concerns about the validity of ESG ratings (Berg, Kölbel, & Rigobon, 2022; Chatterji, Durand, Levine, & Touboul, 2016). To overcome these concerns, we focus on the severity and reach of negative media coverage of ESG issues, a measure that a company is unlikely to be in control of. Hence, this measure should be a more objective gauge of poor ESG performance by companies (Colak, Hickman,

[1] Trade credit is the single most important source of short-term financing for U.S. firms, (Petersen & Rajan, 1997). Barrot (2016) quantifies this importance: Accounts payable are three times the size of bank loans on U.S. non-financials' balance sheets. In many other countries, where financing opportunities may be scarcer, firms are even more likely to rely heavily on supplier financing in the form of trade credit (Fisman & Love, 2003). Indeed, Rajan and Zingales (1995) report that the average accounts receivable for non-financials in the U.S. is 18% of total assets, with corresponding numbers for France, Germany, and Italy exceeding 25%.

Korkeamäki, & Meyer, 2022; Gantchev, Giannetti, & Li, 2022).

In its essence, inter-firm financing through trade-credit is built upon trust and reputation (Fisman & Love, 2003; Guiso, Sapienza, & Zingales, 2004; Wu, Firth, & Rui, 2014). Although suppliers may have some advantages relative to financial institutions (i.e., banks), for example an information-advantage in assessing the financial situation of the customer (Biais & Gollier, 1997; Burkart & Ellingsen, 2004; Emery, 1987; Giannetti, Burkart, & Ellingsen, 2011; Jain, 2001) or the ability (in the U.S.) to repossess a good within ten days of delivery if sold to an insolvent buyer (Garvin, 1996), credit would not be extended as easily if the supplier's trust in the customer diminished. The junior status of trade debt (Cuñat & Garcia-Appendini, 2012; Jacobson & Von Schedvin, 2015) highlights the importance of trust: As one of the most junior forms of credit in most legislations (Cuñat and Garcia-Appendini), recovery rates are low on unsecured trade credit in bankruptcy procedures that involve liquidation. But what happens to that trust after an ESG incident? If socially responsible engagements can increase a firm's reputation (Cui, Jo, & Na, 2018), thereby increasing its credit worthiness (Xu et al., 2020), we hypothesize that ESG risk could damage the trust between suppliers and customers, thereby adversely affecting a company's ability to access trade credit.

There are several reasons to believe that firms care about their ESG risk. First, ESG-related corporate misbehavior has been linked to consumer boycotts (Bénabou & Tirole, 2010)[2], to higher expected returns and higher cost of debt (Chava, 2014), to shareholder engagement especially by institutional investors (Gantchev et al., 2022; Krüger, Sautner, & Starks, 2020), and to negative investor reactions to negative news about ESG indicents (Krüger, 2015). Second, Dai, Liang, and Ng (2021) document that firms are not insulated from ESG incidents that occur at companies with which they have close business ties, but rather there is a spillover effect whereby an ESG incident can lead to

[2] Nestlé, for example, was the subject of a worldwide boycott campaign in the 1970s following the so-called "baby milk scandal" (Financial Times (FT) article, 2011; FT article, 2018). More recently, there have also been calls for a boycott against Nestlé over its decision to continue operating in Russia after the invasion of Ukraine (FT article, 2022).

negative media coverage of a company's corporate customers and its suppliers. Furthermore, Darendeli, Fiechter, Hitz, and Lehmann (2022) find that low ESG ratings translates into a lower number of new contracts and corporate customers.

Over and above possible "greenwashing" efforts or incentives to comply with regulations, the threat of a boycott is a significant driver of corporate environmentalism (Innes & Sam, 2008). Given the propensity of consumer boycotts, a downstream — i.e, a consumer-facing — position inevitably seems riskier in terms of possible backlash following corporate irresponsibility. Consumer boycotts are not a new phenomenon: For instance, Innes (2006) reports that between years 1988–1995, over 200 companies and over a thousand products were subject to organised boycotts in the U.S. Hence, the trust and reputation channel of trade credit could be especially important for consumer-facing firms. We therefore expect trade credit usage of downstream firms to be more negatively affected by ESG incidents than the trade credit of upstream firms.

To test these hypotheses, we allocate firms in the supply chain into upstream, intermediate, and downstream groups, respectively, based on their distance to the end-consumer. Each group represents a "chain" in the supply chain of goods and services. To achieve the latter, we rely on U.S. benchmark Input-Output Accounts of the Bureau of Economic Analysis and the data described in Delgado and Mills (2020) who calculate how much of an industry's output that is sold to households. Assuming that firms in the same industry outside of the U.S. has similar sales to households is reasonable since Antràs, Chor, Fally, and Hillberry (2012) provide evidence on how industry "upstreamness" is consistent between the U.S. and Europe, and also between countries in the latter.

Our main data on ESG risk come from the RepRisk database. RepRisk covers 214,753 private and public companies (as of October 2022) from 2007 onwards, and tracks daily ESG incidents of these companies in the news, in many different languages. Assessing the severity, reach, and novelty of each risk incident, RepRisk compiles its monthly RepRisk Index (RRI). The RRI shows the overall risk exposure to ESG issues of a firm in a month, and it is an integer value that ranges between 0 and 100. In our sample, we focus on roughly 14,000 of the largest public companies in the world, which are part of RepRisk's standard package in Wharton Research Data Services (WRDS). We convert the monthly RepRisk data into quarterly data by focusing on the highest RRI value in the previous quarter relative to a firm-year-quarter observation. We then construct an indicator for "high ESG risk" — which takes the value of one for firm-year-quarters with RRI values equal to or greater than 60, and zero otherwise — and employ this as our variable of interest. After merging with other databases, our final sample is comprised of roughly 181,000 firm-year-quarter observations for 5,709 firms in 70 countries.

Using this sample, we estimate panel data regressions where the dependent variable is trade credit measured as *Net Trade Credit*, calculated as accounts payable (AP) minus accounts receivable (AR), scaled by sales (El Ghoul & Zheng, 2016; Love, Preve, & Sarria-Allende, 2007; McGuinness, Hogan, & Powell, 2018). Following Garcia-Appendini and Montoriol-Garriga (2013); Gonçalves, Schiozer, and Sheng (2018); Love et al. (2007), we also, separately, look at the two drivers of this ratio by using *Credit Received* (AP scaled by COGS) and *Credit Extended* (AR scaled by sales). The main independent variable in the regressions is the indicator for RRI values of 60 or above (*High ESG Risk*), and we include control variables from the extant literature on trade credit usage, and firm-fixed effects as well as year-quarter interacted with industry-fixed effects.

We show that after negative ESG incidents, suppliers can "wield the stick" by reducing access to trade credit. Furthermore, a firm's vulnerability to this ESG risk depends on its position in the supply chain: the negative effect on (net) credit received is strongest (both statistically and economically) for downstream firms. We argue that the punishment may be stronger for these consumer-adjacent customer firms since, due to the boycotting behaviour of end-consumers, they could be regarded as riskier and it could be more important for suppliers to distance themselves from such ESG-misbehaving firms.

Having established *who* (i.e., what type of firms) that are being punished for ESG-misbehavior), we then focus on the *consequences* of being punished. We find that being liquidity-squeezed by suppliers erodes the cash holdings of an ESG-misbehaving firm.

Especially detrimental, in the long-term, could be the decrease in investments. Investing less in, e.g., property, plant, and equipment (PPE) or selling off prior investments could be a short-term solution with damaging long-term consequences.

Finally, by using data from FactSet with information on supplier-customer relationships, we are able to trace the *suppliers* that are *doing the punishing* subsequent to high ESG risk of customer-firms. We cannot, in the data, trace relationship-specific trade credit between firms. However, we can trace the relationship-specific supplier-ranking of the importance of the firm-pair connection. Using this ranking as the dependent variable, we find that foreign suppliers and suppliers domiciled in countries that score high on environmental (E) and social (S) norms are punishing consumer-adjacent customers with high ESG risk by ranking them lower. This drop in ranking for a misbehaving (i.e., ESG-riskier) customer happens immediately (same year-quarter), and is sustained for a period of at least a year. Using a customer's low importance as a dummy variable (*Unimportant*), we find that the interaction of *Customer High ESG Risk* and *Customer Unimportant* results in a significant drop in a (supplier) firm's aggregate level of trade credit extended for especially foreign and high-S-country domiciled suppliers.[3]

In the literature, socially responsible activities have been shown to improve a firm's reputation (Cui et al., 2018) and credit worthiness: access to equity (Breuer, Müller, Rosenbach, & Salzmann, 2018), bank loans (Cheung, Tan, & Wang, 2018), as well as trade credit from suppliers (Xu et al., 2020; Y. Zhang et al., 2020) are increased. We contribute by showing that socially *irresponsible* corporate behavior has a negative effect on trade finance, depending on a firm's position in the supply chain. Furthermore, we look at the consequences of being punished, in terms of cash holdings and its components, as well as what type of supplier that is doing the punishing.

[3] While suppliers domiciled in High-E countries also decrease their credit extended following high ESG risk of an unimportant customer, this effect is not as statistically (10% level for High E) nor economically significant as it is for suppliers in High-S countries.

2 Literature Review and Hypotheses Development

Following the global financial crisis of 2008, the literature on trade credit has expanded exponentially (Pattnaik, Hassan, Kumar, & Paul, 2020). According to Pattnaik et al., 69% of the literature on trade credit has been published after the financial crisis of 2008, with *financial crisis* being one of the top themes in this research. In this paper, our identification does not utilize an exogenous, market-wide shock such as the global financial crisis or the COVID-19 pandemic. Instead, we utilize information on shocks to a firm's ESG performance by investigating the impact of firm-specific ESG violations on trade credit usage, allowing for differences between a firm's position in the supply chain.

Generally, more corporate disclosure reduces the cost of equity and debt (Francis, Khurana, & Pereira, 2005; Lopes & de Alencar, 2010). ESG disclosure (not necessarily the same as ESG performance) has the same effect on the cost of capital — the cost of debt (Eliwa, Aboud, & Saleh, 2021) as well as the cost of equity (Dhaliwal, Li, Tsang, & Yang, 2011, 2014) is lowered. These findings are consistent with an increased transparency and the associated alleviation of agency costs (Cheng, Ioannou, & Serafeim, 2014; Cui et al., 2018); markets and lending institutions are more easily approached when firms become less opaque.

If socially *responsible* corporate behavior can "act as a carrot" in terms of increased access to trade credit from suppliers (Xu et al., 2020; M. Zhang et al., 2014; Y. Zhang et al., 2020), then one would expect that suppliers can also "wield the stick" following socially *irresponsible* corporate behavior. In a closely related paper, Darendeli et al. (2022) exploit an exogenous shock to CSR reporting — namely the expansion of CSR-rating coverage for firms belonging to the Russell 2000 index in year 2017 — and provide evidence that firms with low ESG ratings have a lower numbers of new contracts and clients after 2017 than comparable firms. The authors argue that this is due to two mechanisms: corporate customers benchmarking suppliers according to their ESG performance, and public pressure leading them to "green" their supply chains. We focus especially on the public pressure mechanism, whereby an exogenous shock to a firm's ESG risk (the intense negative media attention to ESG issues) would be expected to affect the access to trade credit negatively. More precisely, we hypothesize that negative ESG incidents have an adverse impact on firms' ability to access trade credit from suppliers:

H1: ESG risk reduces access to trade credit around the world, all else equal

While downstream firms have a closer "distance" to would-be boycotting end-consumers, upstream firms are not in a risk-free position themselves. On the one hand, if an upstream firm experiences a negative ESG event, it may be willing to grant concessions to its customer firms, in fear that they may otherwise be inclined to distance themselves from this supplier in an effort to manage their own reputation. On the other hand, if a customer firm has ESG violations — thereby (possibly) increasing its business risk — then this firm's supplier (i.e., an upstream firm) can suffer increased business risk itself.[4]

Corporate bankruptcy has been shown to propagate from debtor to creditor, with demand shrinkage and credit losses spreading through the supply chain (Jacobson & Von Schedvin, 2015). However, for suppliers, the desire to distance themselves from a customer firm that is violating ESG virtues may compete with the equity-stakes channel: firms upstream have implicit equity-stakes in customer firms downstream (Casey & O'Toole, 2014; Cuñat, 2007; Huang, Shi, & Zhang, 2011; Ng, Smith, & Smith, 1999; Petersen & Rajan, 1997; Wilner, 2000), and therefore suppliers may be more willing to extend credit in order to keep their businesses running smoothly, as per the operational flexibility motive as described in Emery (1984). An increase in sales or market share is after all the foremost financial benefit of trade credit extension by a seller (Box, Davis, Hill, & Lawrey, 2018).

The net effect of these conflicting mechanisms should only be negative if the trust and reputation channel outweigh the equity stakes channel, i.e., the negative effect of a break of trust and reputation is larger than the positive urge to provide financial slack

[4]Figure 1 illustrates, using Papa John's and Dupont as examples, how reputational risk could be connected to trade credit usage.

to a (potentially) important customer. Since downstream firms are selling directly to the end-consumer — which are prone to start boycotts (Innes, 2006) — the reputation channel could dominate the equity stakes channel for these consumer-facing firms. Therefore, we expect that downstream firms are more susceptible to trade credit rationing following ESG violations. We posit our second hypothesis based on the discussion above:

H2: A firm's position in the supply chain modulates the effect of ESG risk on trade credit usage

However, the supply chain position may not be the only mechanism through which ESG issues can affect the use of inter-firm financing. Liang and Renneboog (2017) report that legal origins matter for firms' ESG activity: firms located in civil law countries significantly outscore firms in common law countries on ESG ratings. Similarly, Cai, Pan, and Statman (2016) find that ESG ratings are determined to a greater degree by country-level factors (such as cultural and institutional factors) than by firm-level factors. Given that there exists considerable variation in the emphasis put on stakeholder welfare across countries (Bénabou & Tirole, 2010), the effect of a negative ESG incident on trade credit could vary by a country's sensitivity to stakeholder issues (Dyck, Lins, Roth, & Wagner, 2019). Indeed, the negative relationship between CSR disclosure and cost of equity capital (Dhaliwal et al., 2014), and ESG disclosure as well as performance on cost of debt (Eliwa et al., 2021), is more pronounced in stakeholder-oriented countries. Hence, our third hypothesis relates to the inherent differences in stakeholder-orientation among countries, whereby we expect that firms located in countries with higher E and S norms are more likely to punish ESG-misbehavior of customer firms:

H3: Cross-country variation in environmental and social norms influences the degree to which a supplier limits trade-credit access of a customer firm with high ESG risk

3 Data

In this section, we describe our data for ESG risk and for various firm- and country-level characteristics, as well as present our empirical strategy.

3.1 RepRisk

Our primary data on ESG risk are from the RepRisk database.[5] The RepRisk database tracks daily risk incidents on ESG issues by screening more than 100,000 media and stakeholder (such as NGOs) sources each day in 23 different languages (as of October 2022) using machine learning techniques. When a risk incident is identified, RepRisk's analysts gather information on (1) the severity of the incident (how many people were affected), (2) the reach (i.e., the scope of the newspapers reporting on the incident), and (3) the novelty of the issue (has the issue been reported on before or is it a novel issue). Based on these criteria and the number of incidents in a month, RepRisk compiles a monthly index called the RepRisk Index (RRI), which is an integer variable ranging between 0 and 100. RRI values of 0-25 indicate low risk exposure, values of 26-49 medium, 50-59 indicate high, 60-74 very high, and 75-100 extremely high risk exposure.[6,7] Figure 2 depicts the origin of firm-year-quarter observations with high, very high, or extreme reputational risk. Figure 3 shows the worst ESG offenders (i.e., the firms with the most year-quarter observations of very high or extreme values of RRI) in our sample.[8]

In the standard RepRisk data package that we have access to, we have data on ESG risk exposures of more than 14,000 public companies worldwide on a monthly basis for year 2007 through 2019. Using this data, we calculate the maximum RRI value in the preceding

[5] See reprisk.com.

[6] Table IA.2 shows that only ten firms have RRI values $\geq$75 in our merged data.

[7] After a significant risk incident, the RRI value is constant for the first two weeks. If the RRI is above 25, and there is no significant ESG event highlighted, the RRI decays until it reaches 25 by a rate of 25 every two months. Upon reaching 25 (and for values already below 25), the RRI decays until it reaches zero by a rate of 25 every 18 months, provided that no significant exposure is captured. See RepRisk Methodology, 2022.

[8] Table IA.3 shows that the results are not driven by only the worst ESG-offenders; when excluding the worst offenders, the results are still significant.

quarter relative to a firm-year-quarter entering our panel data sample. As RepRisk notes, values between 0 and 49 are considered "normal levels" of risk exposure. Therefore, in our main analysis, we focus on the more severe levels of ESG risk by constructing an indicator for RRI values greater or equal to 60 (i.e., very high or extremely high ESG risk exposure). We then contrast this group to firm-year-quarters with lower levels of RRI. In untabulated tests, we also employ an indicator for high risk ($50 \geq RRI \geq 59$) and find that this level of risk exposure has a similar (yet not as strong) effect on a company's ability to access trade credit. Hence, the results are not insignificant for ESG events below an RRI value of 60; they are merely weaker in terms of economic magnitude and statistical significance.

3.2 Accounting Data

From Compustat North America and Compustat Global, we retrieve quarterly accounting information for non-financials.[9] We use data from January 2007 - December 2019. Since we end our sample in 2019, the COVID-19 pandemic that started in 2020 cannot distort our results with inter-country differences in trade credit (possibly) being driven by differences in countries' pandemic intensity, stringency of lockdown measures, or fiscal subsidies. We use fiscal dates that have been corrected for Compustat's fiscal year-end scheme.[10]

We exclude financials (SIC 6000-6999) (e.g., Adelino, Ferreira, Giannetti, & Pires, 2022; Garcia-Appendini & Montoriol-Garriga, 2013; Love et al., 2007). We drop observations with negative receivables (*rectrq*) and negative payables (*apq*) (Love et al., 2007), and negative sales (*saleq*). We translate values for different currencies (indicated by *curcdq*) into euros using data from Eurostat. We use the average exchange rate for the quarter (instead of the exchange rate at the end of the quarter) since sales and other accounting values are accumulated during the quarter.

We allocate firms in the supply chain into different "chains": upstream, intermedi-

[9] However, the control variables for Z-score, (real) GDP per capita growth (GDPpcg), and globalization index (KOFGI) relies on annual data.

[10] If the Compustat variable *fyr* — representing the month in which the fiscal year ends — is less than or equal to 5, we increase the year by one such that Compustat's *fyearq* no longer shows the preceding year.

ate, and downstream groups are created based on their distance to the end-consumer. To achieve this, we rely on data from Delgado and Mills (2020), calculated using U.S. benchmark Input-Output (IO) Accounts of the Bureau of Economic Analysis. Assuming that firms in the same industry outside of the U.S. has similar sales to households is reasonable since Antràs et al. (2012) provide evidence on how industry "upstreamness" is consistent between the U.S. and Europe, and also between countries in the latter. As in the baseline specification of Delgado and Mills, we consider firms to be downstream (i.e., B2C) if they belong to an industry (measured by the North American Industry Classification System (NAICS)) from where 35% (or more) of the output go to personal consumption.[11] Firms are considered upstream (i.e., B2B) if they sell only to other firms, and firms in-between downstream and upstream are allocated to the intermediate group.[12] This splits the supply chains into three roughly equal parts, in terms of available observations.

After merging our RepRisk data with data from Compustat (through ISIN), our baseline sample comprises roughly 181,000 firm-year-quarter observations for 5,709 firms in 70 countries for years 2007–2019. This (baseline) data is used in Subsection 1 (*Who is being Punished?*) and Subsection 2 (*What are the Consequences of being Punished?*) of our empirical approach.

3.3 Supply-Chain Relationship Data

In order to trace the impact of customer-firm ESG violations on trade credit extended by suppliers, we combine, in Section 3 (*Who is doing the Punishing?*), the baseline data from Compustat and RepRisk with data from FactSet Revere on supplier-customer pairs.[13] We first merge on company name (100% match on name in capital letters), as well as on CUSIP and (or) ISIN for the remaining firms. This creates a subsample of 3,394 suppliers,

[11] Output sold to personal consumption (i.e., end-consumers) comes from the measure *Personal Consumption Expenditure* (PCE). PCE captures the value of goods and services purchased by households, and it is derived from the 2002 U.S. Benchmark IO tables. See Delgado and Mills (2020) for details.

[12] Examples of downstream firms in our data are Seaworld and Kellogg, and upstream firms are, e.g., Lockheed Martin and Union Drilling.

[13] FactSet Revere data is also used in, e.g., Dai et al. (2021) and (Adelino et al., 2022).

and 3,598 customers, 33,476 supplier-customer pairs, for a total of almost 300,000 supplier-customer-year-quarters. In other words, not every firm in our Compustat-RepRisk-merged data can be found in the FactSet Revere data. While the firm-pair-year-quarter characteristic of the Compustat-RepRisk-Factset-merged data increases the total number of observations, the total number of firms in the data is, however, not increased.

Although we cannot see the relationship-specific trade-credit usage between the two firms in a firm-pair, we do, however, see the relationship-specific ranking in the data. For a supplier, this ranking is a measure of the importance of the customer, compared to all other relationships for the supplier. According to FactSet, it is an integer value between 1 and 999. In our Compustat-RepRisk-Factset-merged data the highest value of ranking is 19, implying that this particular customer (e.g., Air Canada) is the 19$^{\text{th}}$ most important to the supplier (Boeing).

3.4 Empirical Approach

3.4.1 Subsection 1: Who is being Punished?

To examine how ESG violations affect the use of trade credit in the supply chain, we use a panel fixed effects regression approach. Formally, we estimate the following model for our panel data:

$$TC_{i,t} = \beta_0 + \beta_1 High\ ESG\ Risk_{i,t} + \boldsymbol{\beta' X}_{i,t-1} + \boldsymbol{\theta' Firm}_i + \boldsymbol{\gamma' Time}_t * \boldsymbol{Industry}_i + \epsilon_{i,t}\ , \quad (1)$$

where the dependent variable TC is net trade credit received, calculcated as (payables (AP) - receivables (AR)) divided by sales (El Ghoul & Zheng, 2016; Love et al., 2007; McGuinness et al., 2018), credit received (AP divided by COGS), or credit extended (AR divided by sales) (Garcia-Appendini & Montoriol-Garriga, 2013; Gonçalves et al., 2018; Love et al., 2007) for firm i in year-quarter t. The main coefficient of interest is β_1, i.e., the estimated effect of $High\ ESG\ Risk_{i,t}$ $(= 1)$ on trade credit. $\boldsymbol{X}$ is a vector of controls variables, including size (and size^2), age (and age^2), asset tangibility (fixed assets scaled by total assets), net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP growth per capita (GDPpcg), the Globalization index (GI) by KOF Swiss Economic Institute, and lagged maximum RRI value. These variables are further defined in Table 1. (Summary statistics are shown in Table 2, and statistics by supply-chain group are shown in Table IA.1.) To reduce concerns about simultaneity (an endogeneity issue), we use lagged control variables in accordance with the literature (Casey & O'Toole, 2014; El Ghoul & Zheng, 2016; Garcia-Appendini & Montoriol-Garriga, 2013; Palacín-Sánchez, Canto-Cuevas, & Di-Pietro, 2019). ***Firm*** and ***Time********Industry*** represent vectors of firm and year-quarter*industry (by 2-digit SIC) fixed effects, respectively. Firm fixed effects control for unobserved, time-invariant effects that could affect trade credit usage. The year-quarter interacted with industry fixed effects capture unobserved trends in time, by industry. $\epsilon_{i,t}$ is the error term. By clustering standard errors by firm and year-quarter, we cluster on dimensions corresponding to our fixed effects (Petersen, 2009).

As we hypothesize that a firm's distance to would-be boycotting end-consumers is of a special importance in this setting, we divide firms into supply chain groups based on sales for personal consumption. To test whether a firm's distance to end-consumers matter for the ability to access trade credit following ESG violations (i.e., Hypothesis 2), we divide the ESG-risk dummy into three new indicators, one for each type of position a company can hold in the supply chain (downstream, intermediate, and upstream, respectively), and estimate the following model:

$$TC_{i,t} = \beta_0 + (\beta_1\ \beta_2\ \beta_3) \begin{pmatrix} High\ ESG\ Risk_{i,t} * Downstream_i \\ High\ ESG\ Risk_{i,t} * Intermediate_i \\ High\ ESG\ Risk_{i,t} * Upstream_i \end{pmatrix} + \boldsymbol{\beta' X}_{i,t-1} + \boldsymbol{\theta' Firm}_i + \boldsymbol{\gamma' Time}_t * \boldsymbol{Industry}_i + \epsilon_{i,t} \quad (2)$$

Focusing on net trade credit received (as TC; the dependent variable), we use the same controls, fixed effects, and clustering of standard errors as in Equation (1).

3.4.2 Subsection 2: What are the Consequences of being Punished?

To evaluate the real economic consequences of being trade-credit punished, we look at cash holdings subsequent to high ESG risk. If firms become liquidity-squeezed by their suppliers, they may use cash holdings to make up for the shortfall in liquidity (that is usually) being provided to them. Therefore, we estimate a cash-regression model:

$$Cash_{i,t} = \beta_0 + \beta_1 After\ High\ ESG\ Risk_{i,t} + \boldsymbol{\beta' C}_{i,t-1} + \boldsymbol{\theta' Firm}_i + \boldsymbol{\gamma' Time}_t + \epsilon_{i,t}\,, \tag{3}$$

where we use control variables, denoted by the vector $\boldsymbol{C}$, from Brisker, Çolak, and Peterson (2013); Harford, Mansi, and Maxwell (2008); McLean (2011).[14] First, we use cash holdings, calculated as cash and cash equivalents divided by assets (*cheq*/*atq*) as the dependent variable. Second, we use the three components of cash holdings: cash flow from financing (CFF), cash flow from investing (CFI), and cash flow from operations (CFO) as the dependent variable. CFF is derived from Compustat's *fincfy*, CFI from *ivncfy*, and CFO from *oancfy*, all scaled by assets (*atq*). Since the cash flow values for CFF, CFI, and CFO are on a (fiscal) year-to-date basis, we follow Duchin, Ozbas, and Sensoy (2010) and Sletten, Ertimur, Sunder, and Weber (2018) and convert the variables into quarterly data by subtracting the previous quarter's (*t-1*) value from the observation in quarter t for fiscal quarters 2, 3, and 4. (Fiscal quarter 1 is set equal to the year-to-date variable.) By using *niq* and *niy* (net income in quarterly and year-to-date formats, respectively), available in Compustat North America quarterly data, we verify that this methodology is correct; year-to-date values are converted to quarterly values. *After High ESG Risk*, the main variable is interest, represents how much time that has passed *after* a year-quarter with high ESG risk. Since cash flow volatility — one of the control variables — is calculated by a firm's industry and by year-quarter (following McLean (2011)), we include "only" firm

[14] Control variables for firms include the market to book value of equity, cash flow ratio, cash flow volatility, net working capital ratio, R&D expense, capex to net assets ratio, acquisitions, and distributions. These variables are further defined in Table 1.

and year-quarter fixed effects; not firm and year-quarter interacted with industry fixed effects.

3.4.3 Subsection 3: Who is doing the Punishing?

Finally, to test for which supplier that is doing the punishing in terms of decreased access to trade credit financing for customer firms that are ESG-misbehaving, we estimate the following model in our Compustat-RepRisk-FactSet-merged data where firm-pair relationships (and their rankings in terms of importance) are visible in the data:

$$\begin{aligned} Punishment_{i,t} = \beta_0 + (\beta_1\ \beta_2) \begin{pmatrix} Customer\ High\ ESG\ Risk_{i,t} \\ Customer\ High\ ESG\ Risk_{i,t} * Customer Downstream_i \end{pmatrix} \\ + \boldsymbol{\beta' XS}_{i,t-1} + \boldsymbol{\delta' XC}_{i,t-1} + \boldsymbol{\theta' Firm{-}pair}_i + \boldsymbol{\gamma' Time}_t * \boldsymbol{Industry}_i + \epsilon_{i,t}\ , \end{aligned} \tag{4}$$

where *Punishment* is measured either as *Ranking* (Tables 8 and 9) or *Credit Extended* (the AR-to-sales ratio of the supplier, in Table 10) for firm-pair i in year-quarter t. We include the same set of controls as in Eq. (1), but we include them for both firms (i.e., for both the supplier ($\boldsymbol{XS}$) and the customer ($\boldsymbol{XC}$)). The variable of interest is *Customer High ESG Risk* which is an indicator for if the customer firm, in a supplier-customer firm-pair, has had a *High ESG Risk*. To allow for a (possibly) stronger punishment of consumer-adjacent compared to other (i.e., *non* consumer-adjacent) customers, we include *Customer Downstream* in an interaction effect. We use firm-pair fixed effects, combined with year-quarter interacted with industry (of the supplier) fixed effects.[15] Standard errors are clustered by firm-pair.

To test whether supplier-country matters, we divide the sample into foreign suppliers versus domestic suppliers (Table 8). Foreign (domestic) suppliers in a supplier-customer firm-pair are domiciled in another (the same) country as the customer. Furthermore, we directly test our third hypothesis by dividing the sample based on environmental

[15]The main effect for *Customer Downstream* is excluded since it would be collinear with the firm-pair fixed effects.

(E) and social (S) norms (Table 9). Following Dyck et al. (2019), we use the Environmental Performance Index (EPI) from Yale University (values updated biennially), and consider a supplier's country as *High E* if its EPI score is above the median for that year. In separate estimations, we substitute *High E* for *High S*. To measure a country's social norms we use the Employment Laws Index (static value) of Botero, Djankov, Porta, Lopez-de Silanes, and Shleifer (2004), same as Dyck et al. (2019).

4 Main Results

4.1 Subsection 1 - Who is being Punished?

In Table 3, we report our main results on the effects of ESG risk on trade credit. Columns (1)–(3) show results for our baseline regression Equation (1), where the main independent variable is an indicator for high reputational risk exposure ($60 \leq RRI \leq 100$). Columns (4)–(6) show results for the baseline regression where the main independent variable is an indicator for RRI values between 50–59 (rather than 60–100), and Columns (7)–(9) RRI values between 26–49. If high ESG risk has an adverse effect on trade credit, we predict a negative sign only for the high ESG risk indicator (Columns 1–3). We estimate our baseline regression using different lags for the period in which we track ESG risk. More specifically, we track ESG risk in the past 3 months (past year-quarter), the past 6 months (past two year-quarters), and the past 12 months (past year), respectively. We include firm fixed effects as well as industry interacted with year-quarter fixed effects.

As shown in Table 3, only the indicator for high ESG risk exposure ($60 \leq RRI \leq 100$) enters negatively with a statistical significance at a 5% level. The coefficient estimate in Column (1), where we track ESG risk in the past three months, is -0.039. Similarly, the coefficient estimate in Column (2), where ESG risk is tracked in the past two year-quarters, is also negative (-0.037) and significant at a 5% level. However, the coefficient estimate is lower and only borderline significant (10% level) in Column (3), where we track high ESG risk in the past year. This suggests that ESG violations have a significant adverse effect on a company's (net) ability to receive trade credit, but this effect diminishes over time (in a year or so). The economic effects of these coefficients are as follows: In Columns (1)–(3), the coefficient estimates indicate that firms receive roughly €3.5 - €3.9M less credit, in net terms (and for every 100M in sales), after ESG incidents. These amounts are economically non-trivial.

Finally, the coefficient estimates for the indicators for RRI values between 50–59 , and for RRI values between 26–49, are not significant at conventional levels. This suggests that high risk exposure, and not lower levels of risk exposure, has a negative impact on trade credit of firms. Overall, these findings lend support for our Hypothesis 1 that firms' access to trade credit is reduced following a shock to their ESG performance.

[Insert Table 3 around here]

The effect of size in Table 3 is convex on net trade credit usage. The indication that more liquid firms have a higher net trade credit received ratio is consistent with (El Ghoul & Zheng, 2016), where a higher liquidity is also connected to a lower AR-to-sales ratio (i.e., a decrease in AR would increase our (AP-AR)-to-sales ratio — the dependent variable). Moreover, a firm with high liquidity could be deemed as a less risky lender, implying that such a firm's AP could be higher. Furthermore, more profitable firms seem to have lower trade credit usage (El Ghoul & Zheng, 2016; Garcia-Appendini & Montoriol-Garriga, 2013; Giannetti et al., 2011; Mateut & Chevapatrakul, 2018). Garcia-Appendini and Montoriol-Garriga discuss how trade credit extension could be used to attract new clients for firms with smaller ratios of fixed to total assets and lower net profit margins. If firms with less fixed assets extend comparatively more credit (i.e., have higher levels of AR), that would be consistent with an increase in net trade credit received for tangible assets. Unsurprisingly, having a higher market share is favorable as these firms receive more credit from their suppliers (Mateut & Chevapatrakul, 2018). Additionally, Dass, Kale, and Nanda (2015) show that firms with a higher market power offer less financing on credit. Both of the effects — an increase in AP and a decrease in AR, from a higher market share — could help explain the large, positive, and significant coefficient for market share.

The negative (and significant) coefficient for Altman's (1968) Z-score (consistent with Y. Zhang et al. (2020)), could appear counter-intuitive at first. Firms with a higher Z-score (corresponding to a lower likelihood of financial distress) ought to have a better chance of receiving inter-firm financing, and vice versa. However, supplier financing could be more prevalent among firms with low Z-scores, since other (interest bearing) debt could be more difficult to come by — this line of reasoning is consistent with the substitution hypothesis of trade credit.

In Table 4, we use alternative measures of trade credit as dependent variables. More precisely, we separate net credit into two components: *Credit Received* (accounts payable divided by cost of goods sold) and *Credit Extended* (accounts receivable divided by sales). In Panel A, we find that high ESG risk leads to lower levels of credit received for exposed firms. Again, the effect diminishes over time and becomes insignificant when we track ESG risk in the past twelve months. In fact, the effects of ESG risk on credit received is quite sudden, and appears to hit the firm especially in the year-quarter following an ESG incident. In contrast, we find no significant effect of ESG incidents on credit extended (see Columns 5–8).

In Panels B and C of Table 4, we use alternative specifications of fixed effects. In Panel B, we include country fixed effects as well as industry interacted with year-quarter fixed effects and find that the results hold. In Panel C, we include firm fixed effects as well as industry interacted with country and year-quarter fixed effects and again find that the results hold (for the shorter, 3-month, window for credit received).

[Insert Table 4 around here]

We then proceed by testing our Hypothesis 2 about how a firm's position in the supply chain affects its ability to access trade credit following an ESG incident. More precisely, we test the hypothesis that companies that sell mostly to end-customers are more adversely affected by ESG incidents compared to companies that sell mostly to other corporate customers. Table 5 shows the results for estimating Equation (2), where net trade credit ((accounts payable - accounts receivables)/sales) is the dependent variable. The main independent variables are indicators for downstream firms with high ESG risk; intermediate firms with high ESG risk; and upstream firms with high ESG risk, respectively. We track ESG risk in the past three months (Column 3) through the past eighteen months (Column 6), and include the same controls and fixed effects as in Equation (1).

[**Insert Table 5 around here**]

As shown in Table 5, Panel A, a firm's position in the supply chain modulates the effect of ESG incidents on trade credit usage. On the one hand, the trade credit usage of upstream firms — which have other firms as their customers; not end-consumers — appear quite insulated from ESG-related risks. None of the coefficient estimates for the indicator for high ESG risk interacted with upstream firms are significantly different from zero. This is also the case for the interaction between high ESG risk and intermediate firms (apart for Column (1) where it enters significantly at a 10% level). On the other hand, the trade credit of downstream firms is negatively and significantly affected by ESG-misbehavior. The coefficient estimates for the indicator for high ESG risk and downstream firms is negative and significant at conventional levels when we track ESG risk in the past three and six months, respectively. For longer intervals, the effect diminishes both in size and significance. This suggests that it is mainly downstream firms that are driving the results in Table 3, and that the negative impact on trade credit occurs rather quickly after the incident. Furthermore, the economic significance of the results in Table 5's Panel A indicate that downstream firms, following negative media attention about ESG issues, suffer a decline in net trade credit received of roughly €5.3-€6.1M for every 100M in sales.

In Panel B, we match firms which have an ESG incident to firms with no incident using propensity score matching (PSM). Firms are matched so that they belong to the same supply chain group (downstream, intermediate, or upstream), the same industry (based on SIC2 codes), and these firms are matched exactly on the same year-quarter as the quarter in which the ESG incident takes place. For companies that meet these (exact) criteria, we match ESG-incident firms to the closest match using the (non-exact) covariates size, age, fixed assets, net profit margin, liquidity, market share, debt ratio, and PCE. Matching is done with replacement. We follow both the incident and non-incident firm from two years before the ESG incident and to the end of the sample (or until one of them no longer remains in the sample, in which case we stop following both firms).

As shown in Panel B (Table 5), when utilizing PSM, which creates a much smaller sample, only downstream firms are significantly punished for corporate ESG-misbehavior. The benefit of using PSM in this context is that it reduces endogeneity concerns, and shows that even when we match firms with high ESG risk to comparable firms with no incidents, access to trade credit decreases significantly for misbehaving firms. Taken together, the results in this section provide strong support for our Hypothesis 2. Panel C includes indicators for *Low ESG Risk*, interacted with the SC groups, alongside our previous indicators from Panel B. The non-significant results of the *Low-ESG-Risk* dummies confirm that it is indeed *High ESG Risk* that has the detrimental effect on trade credit usage.

4.2 Subsection 2: Consequences of being Punished

As Tables in previous sections have shown, especially downstream firms tend to be punished after ESG-related issues. And since these punished firms do not decrease the credit that they themselves extend to their own customers, they are thereby becoming liquidity providers. We posit that this liquidity is likely provided from a firm's cash holdings. Figure 4 (Panel A) illustrates how, during a year-quarter of *High ESG Risk*, and for the two subsequent years, a firm's level of cash holdings decrease, on average. Panel B of Figure 4, which show the components of cash holdings, namely cash flow from financing (CFF), cash flow from investing (CFI), and cash flow from operations (CFO), depict how CFF and CFO decrease while CFI increase after *High ESG Risk*. An increase in CFI is, however, not a good sign. In order to increase CFI, a firm would, for example, have to decrease (or even sell) investments. Although it could be a short-term solution to manage disrupted cash flows, this could have a long-term, adverse impact.

[Insert Figure 4 around here]

[Insert Table 6 around here]

Table 6 shows a two-sided t-test for the cross-sectional mean and median differences of cash holdings, and its three components CFF, CFI, and CFO, for two years before versus two years after high ESG risk. While the mean difference for overall cash shows a significant decrease on a 5% statistical level, the mean of the three cash components (CFF, CFI, and CFO) all show a significant difference on a 1% level.

[Insert Table 7 around here]

Table 7 reports the results of cash-regressions, which show how a firm's cash holdings (Panel A) indeed decrease in the year-quarters subsequent to *High ESG Risk*. While the overall cash holdings is being "cut" for firms for up to six year-quarters (i.e., a year and a half) after high ESG risk, they are not investing as much in the long-term, as shown by the increase in cash flow from investment activities (CFI) in Panel C. An increase in CFI, for example by selling off previous investments or by investing less in, e..g, property, plant, and equipment (PPE), may have detrimental long-run consequences for a firm. Such actions, due to short-term cash-management problems brought on by being liquidity squeezed by supplier(s), may sacrifice long-run firm-performance.

4.3 Subsection 3: Who is doing the Punishing?

In Table 8, we use a focal firm's ranking of its customer-firm's importance as the dependent variable. In Panel A, Columns (1)–(3) show that a supplier ranks a customer lower (i.e., the customer becomes less important to the supplier) when the customer has high ESG risk. Columns (4)–(6) reiterate the conclusions of previous tables: suppliers are lowering the ranking for ESG-misbehaving consumer-facing firms; not for all types of customer firms. Moreover, this effect in Panel A (full sample; all suppliers) appears to be driven by foreign suppliers (Panel B) since domestic suppliers (Panel C) shows no significance at conventional levels for the 3- and 6-month periods. In fact, Column (6) of Panel C show that domestic suppliers regard non-downstream customers with high ESG risk as more important (on a 10% level), while punishing downstream customers with high ESG risk (on a 5% level). However, this punishing effect (in Column 6) is not as harsh as it is for foreign suppliers. Hence, foreign suppliers (especially) are punishing consumer-adjacent customers.

[Insert Table 8 around here]

Table 9 directly tests our Hypothesis 3 about how the punishment, brought on by ESG-misbehavior, could vary by the stakeholder-orientation of a supplier's home country. We find that suppliers domiciled in countries with above the median environmental (E) and social (S) norms, rank consumer-facing customers lower upon ESG-misbehavior by the customer, compared to other customers that do not ESG-misbehave. This effect is significant on a 1% level for a 3-, 6-, and 12-month period (Columns 1–3) of both Panel A (sample split by median E-values for the supplier's home country) and Panel B (sample similarly split by median S-values).[16]

[Insert Table 9 around here]

Since Table 8 and 9 show that an ESG-misbehaving (downstream) customer is losing importance relative to a supplier's other (non-ESG-misbehaving) customers, we use, in Table 10, *Customer Unimportant* as an indicator for if the customer is unimportant for the supplier. However, if a relationship is reported by FactSet, that signals that the

[16] The prominence of U.S. suppliers in our Compustat-RepRisk-FactSet-merged data, causing the median E- and S-values to often become the U.S. values, results in the "low-norms" subsample becoming larger than the "high-norms" subsample since we assign low as ≤median and high as >median.

supplier-customer connection is already of a certain importance. Therefore, we use the 75$^{\text{th}}$ percentile of rankings, which is 7, as our threshold for unimportant (i.e., *Customer Unimportant*=1 if ranking$\geq$7; 0 otherwise). Following up on the results shown in Table 8 and 9 (with relationship-specific ranking as the dependent variable), Table 10 (with a focal firms overall level of credit extended as the dependent variable), we find that foreign (but not domestic) suppliers punish *unimportant* customers after ESG-misbehavior by extending less credit (see Panel A).

Moreover, suppliers in countries with high social norms (Columns 4–6, Panel B) appear more eager to trade-credit punish than suppliers in countries with high environmental norms (Columns 1–3, Panel B). This finding could be connected to how, out of the 16,222 instances when a customer has a high ESG risk in our Compustat-RepRisk-FactSet-merged data, 11,079 (3,061) of these instances have a social percentage$\geq$33% (50%).[17] Meanwhile, 3,283 (1,246) of the misbehavior-instances have an environmental percentage$\geq$33% (50%). Hence, S-related events (such as child labor) are more commonly part of the *High ESG Risk* than E-related events (such as chemical or oil spills). Therefore, it is (perhaps) not unsurprising that, when using a supplier's aggregate level of trade credit extended as the dependent variable (Table 10), the punishment of unimportant and ESG-misbehaving customers is seen more clearly for High-S suppliers.

[Insert Table 10 around here]

4.4 Additional Results & Robustness Checks

4.5 Inverse Mills' Ratio

Our regression estimates could be impacted by reverse causality; an adverse change in the amount of trade credit received could have an effect on the likelihood of having ESG incidents. If a firm, for some reason (bad management, for instance) becomes trade credit

[17] With a further squaring of the data for Yale EPI values and S-values from Botero et al. (2004), the total number of observations is roughly 283,000.

rationed, it could also become less likely to care about ESG issues, resulting in events causing a higher RepRisk value.

We use an instrument for a firm's RepRisk value: the search interest for a firm on Google. For example, Google Search Volume Interest (SVI) has been used as an instrument for investor attention to stocks (Da, Engelberg, & Gao, 2011; Gao, Ren, & Zhang, 2020), as a measure of shifts in gambling attitudes (Chen, Kumar, & Zhang, 2021) or unemployment insurance's impact on job searches (Baker & Fradkin, 2017), and public attention to climate change (Choi, Gao, & Jiang, 2020; Ilhan, Sautner, & Vilkov, 2021).

Google SVI should fulfill both the relevance and the exclusion criteria of an instrument. If a firm has an extreme ESG incident (resulting in a correspondingly high RepRisk value), the search interest for that firm is likely to increase. Hence, the SVI should be correlated with the RepRisk value. This relevance criterion can also be tested in a first-stage regression. However, the exclusion criterion cannot be empirically tested. The exclusion criterion would be violated if SVI has an impact on trade credit (the dependent variable) other than through trade credit's association with the RepRisk value. We do not find this likely. We also find it unlikely that a firm's trade credit situation could be driving the (worldwide) search interest on Google — the search interest should only be impacted by peoples' interest in the company through bad (or good) news.[18]

In essence, by calculating the inverse Mills' Ratio (IMR), we control for if a firm self-selects to "be bad" (i.e., if the firm self-selects to have high RepRisk values). In the first stage, with a probit regression, we instrument *High ESG Risk* (i.e., the dummy for if RepRisk-Index values$\geq$60) with a similar dummy for if the maximum Google SVI (which

[18]We acknowledge that the Google SVI could increase due to bad as well as good news about a firm. The RepRisk value — representing a gauge of negative media attention to a company's ESG issues — should primarily be related to negative search interest about a company. On the other hand, good news (and therefore a positive search interest) could be correlated to a firm achieving a lower RepRisk value, and this could cause a problem. We had intended to use Google searches that include a combination of *company name* and, e.g., *scandal* (in English). However, for (too) many firms this results in no search data being available. Google topics (instead of search term interest), as used in Chen et al. (2021); Choi et al. (2020), would have been ideal as this includes misspellings, different languages, and related searches. Unfortunately, Google does not seem to have topics on ESG incidents for most companies in our sample — the *Deepwater Horizon Oil Spill*, for example, is a topic (disaster) while *BP oil spill* is a search term.

is on a scale of 0–100) has been ≥60 during the corresponding period. Hence, *High ESG Risk* over one year-quarter (3-months) is instrumented with the *Google SVI* dummy for one year-quarter, and so on for two, three, and four year-quarters in Table 11. In the second stage, the IMR calculated from the first stage is included as a control variable alongside all of the other control variables from Equation (1), which are used in both the first- and second-stage regressions. See, e.g., Colak et al. (2022) or Çolak and Whited (2007) for a more thorough description of the IMR methodology.

4.5.1 Inverse Mills' Ratio - Results

In short, the baseline results of Table 3 (for Net Trade Credit received) and Table 4 (for Credit Received and Credit Extended; the two components of Net Trade Credit), with IMR included — shown in Table 11 — hold.[19]. Panel A, of Table 11, show that firms which suffer *High ESG Risk*, experience a reduction of net trade credit received, and Panel B (Table 11) show that this effect seems to be primarily driven by how these ESG-misbehaving firms receive less trade credit financing from their suppliers while they do not alter their trade-credit extension to their customers. In other words, they still facilitate their customers' need for inter-firm financing, while being trade-credit limited by their suppliers; they become (net) liquidity providers (i.e., credit providers).

[Insert Table 11 around here]

4.6 Stale data in Compustat Global Quarterly

Unlike public firms in the U.S., firms in Compustat Global do not necessarily publish quarterly reports (Nallareddy, Pozen, Rajgopal, et al., 2021). EU regulations made quarterly reporting optional in 2013.[20] Exceptions (to optional quarterly reporting in Europe)

[19] The sample size is somewhat decreased when using Google SVI as an instrument, as some company names — which we use as the Google search term — is not available; the search interest is simply too low for certain company names. For company names, we use the first two words of a name (or longer if needed, i.e., if there are duplicates of a two-word company name).

[20] Directive 2013/50/EU of the European Parliament: link to Directive.

are Spanish firms, firms listed on Nasdaq Stockholm, and firms listed on the prime or STAR segments of the Frankfurt and Milan Stock Exchanges respectively (Hitz & Moritz, 2019). Hence, there could be some heterogeneity in reporting frequency; some firms have to disclose information quarterly, some choose to do so despite not having to, and a non-negligible part of firms could have chosen to forgo quarterly reporting.

When a firm does not report every quarter, Compustat Global imputes quarterly data from annual or semi-annual reports to fill in the gaps (Nallareddy et al., 2021). This creates a possible caveat in the data that we rely on. As a robustness check, we remove stale (i.e., imputed) observations (Finne, Haga, & Sundvik, 2023). In untabulated results, we confirm that our results are robust to these exclusions — both when including semi-annual reporters while removing their stale observations, but also when keeping only quarterly reporters in the sample.

5 Conclusion

Prior literature reports that socially responsible firms have an increased access to trade credit from suppliers (Y. Zhang et al., 2020). However, less is known about the relation between corporate social *irresponsibility* and trade credit. In our study, we examine whether negative news about a firm's Environmental, Social, and Governance (ESG) issues (ESG risk) has a negative impact on a firm's access trade credit. To examine the effects of ESG risk on trade credit, we focus on two main channels: (i) a firm's position in the supply chain, and (ii) supplier-country characteristics, such as foreign versus domestic suppliers, as well as the stakeholder-orientation of the country where a supplier is domiciled.

Our results show that a company's access to trade credit can decrease following high ESG risk. More specifically, downstream (i.e., business-to-consumer) firms with foreign suppliers or suppliers located in countries with high social norms receive less trade credit from suppliers following negative news about ESG issues.

References

Adelino, M., Ferreira, M. A., Giannetti, M., & Pires, P. (2022, 06). Trade Credit and the Transmission of Unconventional Monetary Policy. *The Review of Financial Studies*. Retrieved from https://doi.org/10.1093/rfs/hhac040 (hhac040) doi: 10.1093/rfs/hhac040

Aktas, N., De Bodt, E., Lobez, F., & Statnik, J.-C. (2012). The information content of trade credit. *Journal of Banking & Finance*, *36*(5), 1402–1413.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609.

Altman, E. I. (2000). Predicting financial distress of companies. *Revisiting Z-Score and ZETA Models, Stern School of Business, New York University*, 9–12.

Antràs, P., Chor, D., Fally, T., & Hillberry, R. (2012). Measuring the upstreamness of production and trade flows. *American Economic Review*, *102*(3), 412–16.

Baker, S. R., & Fradkin, A. (2017). The impact of unemployment insurance on job search: Evidence from google search data. *Review of Economics and Statistics*, *99*(5), 756–768.

Barrot, J.-N. (2016). Trade credit and industry dynamics: Evidence from trucking firms. *The Journal of Finance*, *71*(5), 1975–2016.

Bénabou, R., & Tirole, J. (2010). Individual and corporate social responsibility. *Economica*, *77*(305), 1–19.

Berg, F., Kölbel, J. F., & Rigobon, R. (2022, 05). Aggregate Confusion: The Divergence of ESG Ratings*. *Review of Finance*. Retrieved from https://doi.org/10.1093/rof/rfac033 (rfac033) doi: 10.1093/rof/rfac033

Biais, B., & Gollier, C. (1997). Trade credit and credit rationing. *The Review of Financial Studies*, *10*(4), 903–937.

Botero, J. C., Djankov, S., Porta, R. L., Lopez-de Silanes, F., & Shleifer, A. (2004). The regulation of labor. *The Quarterly Journal of Economics*, *119*(4), 1339–1382.

Box, T., Davis, R., Hill, M., & Lawrey, C. (2018). Operating performance and aggressive trade credit policies. *Journal of Banking & Finance*, *89*, 192–208.

Breuer, W., Müller, T., Rosenbach, D., & Salzmann, A. (2018). Corporate social responsibility, investor protection, and cost of equity: A cross-country comparison. *Journal of Banking & Finance*, *96*, 34–55.

Brisker, E. R., Çolak, G., & Peterson, D. R. (2013). Changes in cash holdings around the s&p 500 additions. *Journal of Banking & Finance*, *37*(5), 1787–1807.

Burkart, M., & Ellingsen, T. (2004). In-kind finance: A theory of trade credit. *American Economic Review*, *94*(3), 569–590.

Cai, Y., Pan, C. H., & Statman, M. (2016). Why do countries matter so much in corporate social performance? *Journal of Corporate Finance*, *41*, 591–609.

Casey, E., & O'Toole, C. M. (2014). Bank lending constraints, trade credit and alternative financing during the financial crisis: Evidence from european smes. *Journal of Corporate Finance*, *27*, 173–193.

Chatterji, A. K., Durand, R., Levine, D. I., & Touboul, S. (2016). Do ratings of firms converge? implications for managers, investors and strategy researchers. *Strategic Management Journal*, *37*(8), 1597–1614.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, *60*(9), 2223–2247. Retrieved from https://www.jstor.org/stable/24550583

Chen, Y., Kumar, A., & Zhang, C. (2021). Searching for gambles: gambling sentiment and stock market outcomes. *Journal of Financial and Quantitative Analysis*, *56*(6), 2010–2038.

Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic Management Journal*, *35*(1), 1–23.

Cheung, Y.-L., Tan, W., & Wang, W. (2018). National stakeholder orientation, corporate social responsibility, and bank loan cost. *Journal of Business Ethics*, *150*(2), 505–524.

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, *33*(3), 1112–1145.

Colak, G., Hickman, K., Korkeamäki, T., & Meyer, N. O. (2022). Esg issues and career prospects of directors: Evidence from the international director labor market. *Financial Markets, Institutions & Instruments*.

Çolak, G., & Whited, T. M. (2007). Spin-offs, divestitures, and conglomerate investment. *The Review of Financial Studies*, *20*(3), 557–595.

Cui, J., Jo, H., & Na, H. (2018). Does corporate social responsibility affect information asymmetry? *Journal of Business Ethics*, *148*(3), 549–572.

Cuñat, V., & Garcia-Appendini, E. (2012). Trade credit and its role in entrepreneurial finance. *Oxford handbook of entrepreneurial finance*, 526–557.

Cuñat, V. (2007). Trade credit: suppliers as debt collectors and insurance providers. *The Review of Financial Studies*, *20*(2), 491–527.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, *66*(5), 1461–1499.

Dai, R., Liang, H., & Ng, L. (2021). Socially responsible corporate customers. *Journal of Financial Economics*, *142*(2), 598–626.

Darendeli, A., Fiechter, P., Hitz, J.-M., & Lehmann, N. (2022). The role of corporate social responsibility (csr) information in supply-chain contracting: Evidence from the expansion of csr rating coverage. *Journal of Accounting and Economics*, *74*(2), 101525. Retrieved from https://www.sciencedirect.com/science/article/pii/S0165410122000489 doi: https://doi.org/10.1016/j.jacceco.2022.101525

Dass, N., Kale, J. R., & Nanda, V. (2015). Trade credit, relationship-specific investment, and product market power. *Review of Finance*, *19*(5), 1867–1923.

Delannay, A.-F., & Weill, L. (2004). The determinants of trade credit in transition countries. *Economics of Planning*, *37*(3), 173–193.

Delgado, M., & Mills, K. G. (2020). The supply chain economy: A new industry categorization for understanding innovation in services. *Research Policy*, *49*(8), 104039.

Dhaliwal, D., Li, O. Z., Tsang, A., & Yang, Y. G. (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review*, *86*(1), 59–100.

Dhaliwal, D., Li, O. Z., Tsang, A., & Yang, Y. G. (2014). Corporate social responsibility disclosure and the cost of equity capital: The roles of stakeholder orientation and financial transparency. *Journal of Accounting and Public Policy*, *33*(4), 328–355.

Dreher, A. (2006). Does globalization affect growth? evidence from a new index of globalization. *Applied economics*, *38*(10), 1091–1110.

Duchin, R., Ozbas, O., & Sensoy, B. A. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, *97*(3), 418–435.

Dyck, A., Lins, K. V., Roth, L., & Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? international evidence. *Journal of Financial Economics*, *131*(3), 693–714.

El Ghoul, S., & Zheng, X. (2016). Trade credit provision and national culture. *Journal of Corporate Finance*, *41*, 475–501.

Eliwa, Y., Aboud, A., & Saleh, A. (2021). Esg practices and the cost of debt: Evidence from eu countries. *Critical Perspectives on Accounting*, *79*, 102097.

Emery, G. W. (1984). A pure financial explanation for trade credit. *Journal of Financial and Quantitative Analysis*, *19*(3), 271–285.

Emery, G. W. (1987). An optimal financial response to variable demand. *Journal of Financial and Quantitative Analysis*, *22*(2), 209–225.

Finne, G., Haga, J., & Sundvik, D. (2023). Cost behaviour and reporting frequency during the COVID-19 outbreak. *Available at SSRN 4422731*.

Fisman, R., & Love, I. (2003). Trade credit, financial intermediary development, and industry growth. *The Journal of Finance*, *58*(1), 353–374.

Francis, J. R., Khurana, I. K., & Pereira, R. (2005). Disclosure incentives and effects on cost of capital around the world. *The Accounting Review*, *80*(4), 1125–1162.

Gantchev, N., Giannetti, M., & Li, R. (2022, 05). Does Money Talk? Divestitures and Corporate Environmental and Social Policies*. *Review of Finance*. Retrieved from https://doi.org/10.1093/rof/rfac029 (rfac029) doi: 10.1093/rof/rfac029

Gao, Z., Ren, H., & Zhang, B. (2020). Googling investor sentiment around the world. *Journal of Financial and Quantitative Analysis*, *55*(2), 549–580.

Garcia-Appendini, E., & Montoriol-Garriga, J. (2013). Firms as liquidity providers: Evidence from the 2007–2008 financial crisis. *Journal of Financial Economics*, *109*(1), 272–291.

Garvin, L. T. (1996). Credit, information, and trust in the law of sales: The credit seller's right of reclamation. *UCLA L. Rev.*, *44*, 247.

Giannetti, M., Burkart, M., & Ellingsen, T. (2011). What you sell is what you lend? explaining trade credit contracts. *The Review of Financial Studies*, *24*(4), 1261–1298.

Gonçalves, A. B., Schiozer, R. F., & Sheng, H. H. (2018). Trade credit and product market power during a financial crisis. *Journal of Corporate Finance*, *49*, 308–323.

Guiso, L., Sapienza, P., & Zingales, L. (2004). The role of social capital in financial development. *American Economic Review*, *94*(3), 526–556.

Gygli, S., Haelg, F., Potrafke, N., & Sturm, J.-E. (2019). The kof globalisation index–revisited. *The Review of International Organizations*, *14*(3), 543–574.

Harford, J., Mansi, S. A., & Maxwell, W. F. (2008). Corporate governance and firm cash holdings in the us. *Journal of Financial Economics*, *87*(3), 535–555.

Hitz, J.-M., & Moritz, F. (2019). Turning back the clock on disclosure regulation?–

evidence from the termination of the quarterly reporting mandate in europe. *Evidence from the Termination of the Quarterly Reporting Mandate in Europe (September 11, 2019)*.

Huang, H., Shi, X., & Zhang, S. (2011). Counter-cyclical substitution between trade credit and bank credit. *Journal of Banking & Finance*, *35*(8), 1859–1878.

Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, *34*(3), 1540–1571.

Innes, R. (2006). A theory of consumer boycotts under symmetric information and imperfect competition. *The Economic Journal*, *116*(511), 355–381.

Innes, R., & Sam, A. G. (2008). Voluntary pollution reductions and the enforcement of environmental law: An empirical study of the 33/50 program. *The Journal of Law and Economics*, *51*(2), 271–296.

Jacobson, T., & Von Schedvin, E. (2015). Trade credit and the propagation of corporate failure: An empirical analysis. *Econometrica*, *83*(4), 1315–1371.

Jain, N. (2001). Monitoring costs and trade credit. *The Quarterly Review of Economics and Finance*, *41*(1), 89–110.

Krüger, P. (2015). Corporate goodness and shareholder wealth. *Journal of Financial Economics*, *115*(2), 304-329. Retrieved from https://EconPapers.repec.org/RePEc:eee:jfinec:v:115:y:2015:i:2:p:304-329

Krüger, P., Sautner, Z., & Starks, L. T. (2020, 02). The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067-1111. Retrieved from https://doi.org/10.1093/rfs/hhz137 doi: 10.1093/rfs/hhz137

Liang, H., & Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance*, *72*(2), 853–910.

Lopes, A. B., & de Alencar, R. C. (2010). Disclosure and cost of equity capital in emerging markets: the brazilian case. *The International Journal of Accounting*, *45*(4), 443–464.

Love, I., Preve, L. A., & Sarria-Allende, V. (2007). Trade credit and bank credit: Evidence from recent financial crises. *Journal of Financial Economics*, *83*(2), 453–469.

Mateut, S., & Chevapatrakul, T. (2018). Customer financing, bargaining power and trade credit uptake. *International Review of Financial Analysis*, *59*, 147–162.

McGuinness, G., Hogan, T., & Powell, R. (2018). European trade credit use and sme survival. *Journal of Corporate Finance*, *49*, 81–103.

McLean, R. D. (2011). Share issuance and cash savings. *Journal of Financial Economics*, *99*(3), 693–715.

Nallareddy, S., Pozen, R., Rajgopal, S., et al. (2021). Consequences of more frequent reporting: The uk experience. *Journal of Law, Finance, and Accounting*, *6*(1), 51–88.

Ng, C. K., Smith, J. K., & Smith, R. L. (1999). Evidence on the determinants of credit terms used in interfirm trade. *The Journal of Finance*, *54*(3), 1109–1129.

Palacín-Sánchez, M.-J., Canto-Cuevas, F.-J., & Di-Pietro, F. (2019). Trade credit versus bank credit: a simultaneous analysis in european smes. *Small Business Economics*, *53*(4), 1079–1096.

Pattnaik, D., Hassan, M. K., Kumar, S., & Paul, J. (2020). Trade credit research before and after the global financial crisis of 2008–a bibliometric overview. *Research in International Business and Finance*, 101287.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), 435–480.

Petersen, M. A., & Rajan, R. G. (1997). Trade credit: theories and evidence. *The Review of Financial Studies*, *10*(3), 661–691.

Rajan, R. G., & Zingales, L. (1995). What do we know about capital structure? some evidence from international data. *The Journal of Finance*, *50*(5), 1421–1460.

Sletten, E., Ertimur, Y., Sunder, J., & Weber, J. (2018). When and why do ipo firms manage earnings? *Review of Accounting Studies*, *23*, 872–906.

Wilner, B. S. (2000). The exploitation of relationships in financial distress: The case of trade credit. *The Journal of Finance*, *55*(1), 153–178.

Wu, W., Firth, M., & Rui, O. M. (2014). Trust and the provision of trade credit. *Journal of Banking & Finance*, *39*, 146–159.

Xu, H., Wu, J., & Dao, M. (2020). Corporate social responsibility and trade credit. *Review of Quantitative Finance and Accounting*, *54*(4), 1389–1416.

Zhang, M., Lijun, M., Su, J., & Zhang, M. (2014). Do suppliers applaud corporate social performance? *Journal of Business Ethics*, *121*, 543–557. Retrieved from https://doi.org/10.1007/s10551-013-1735-x

Zhang, Y., Lara, J. M. G., & Tribó, J. A. (2020). Unpacking the black box of trade credit to socially responsible customers. *Journal of Banking & Finance*, *119*, 105908.

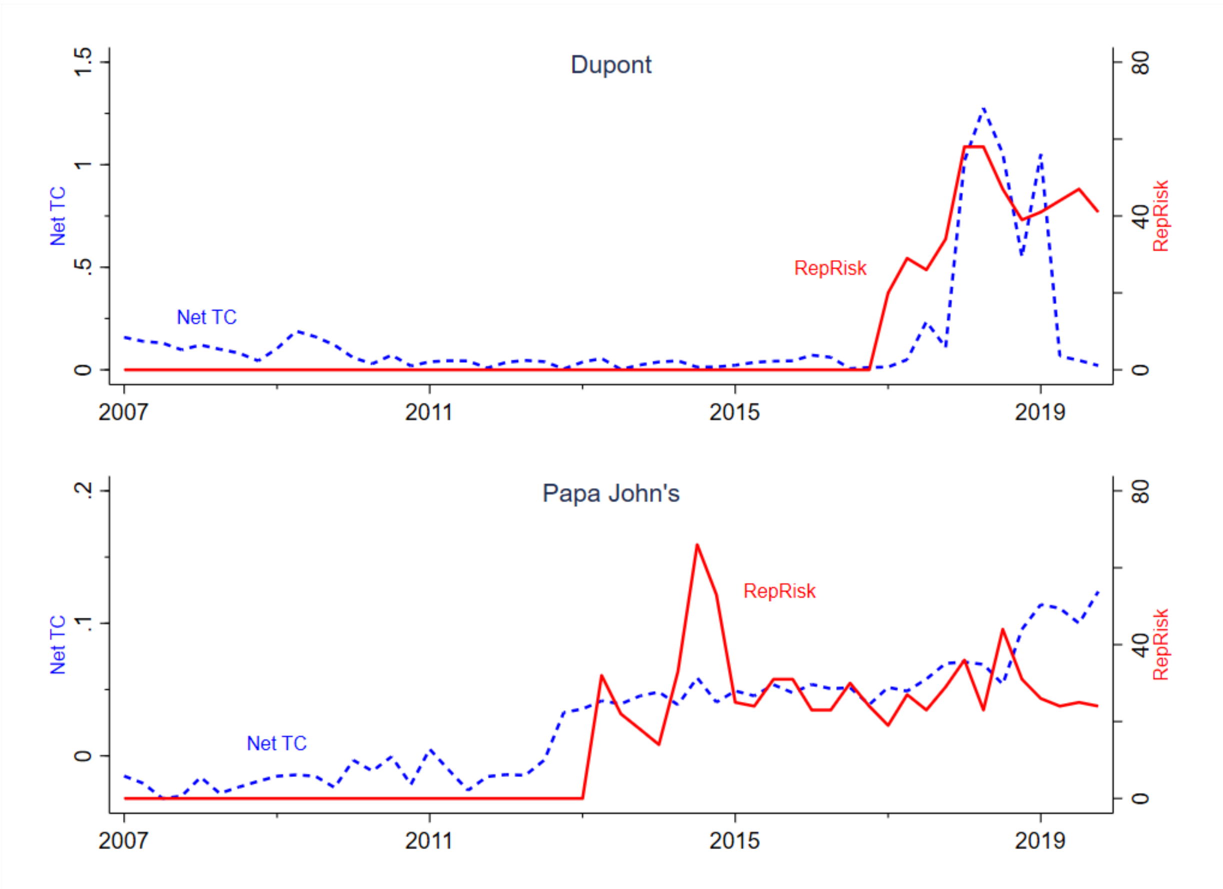

Figure 1: **Net Trade Credit extended & Negative Media Attention**
The figure shows net trade credit extended, calculated as (AR-AP) divided by sales, on the left y-axis, while the right y-axis shows the negative media attention as measured by the RepRisk Index (RRI). A higher RRI value implies more negative exposure in media.

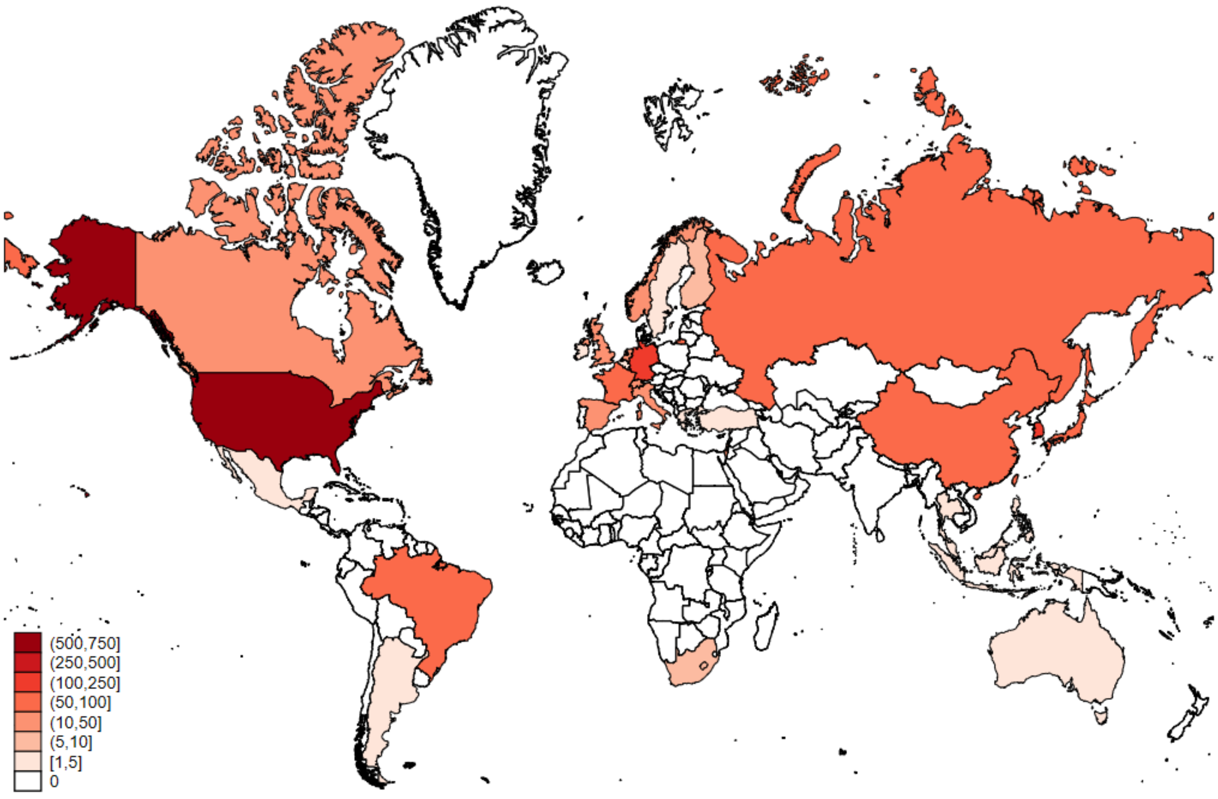

Figure 2: **Origin of observations with high reputational risk**
The figure shows the country of incorporation for firm-year-quarter observations with a high, very high, or extreme reputational risk (as defined by RepRisk). The RepRisk Index (RRI) is classified accordingly: 0-25 is a low (reputational) risk exposure, 26-49 is medium, 50-59 is high, 60-74 is very high, and 75-100 is extremely high risk exposure. The figure shows observations with RRI$\geq$50. For the purposes of this world map, Taiwan (TWN) and Hong Kong (HKG) are depicted as part of China (CHN).

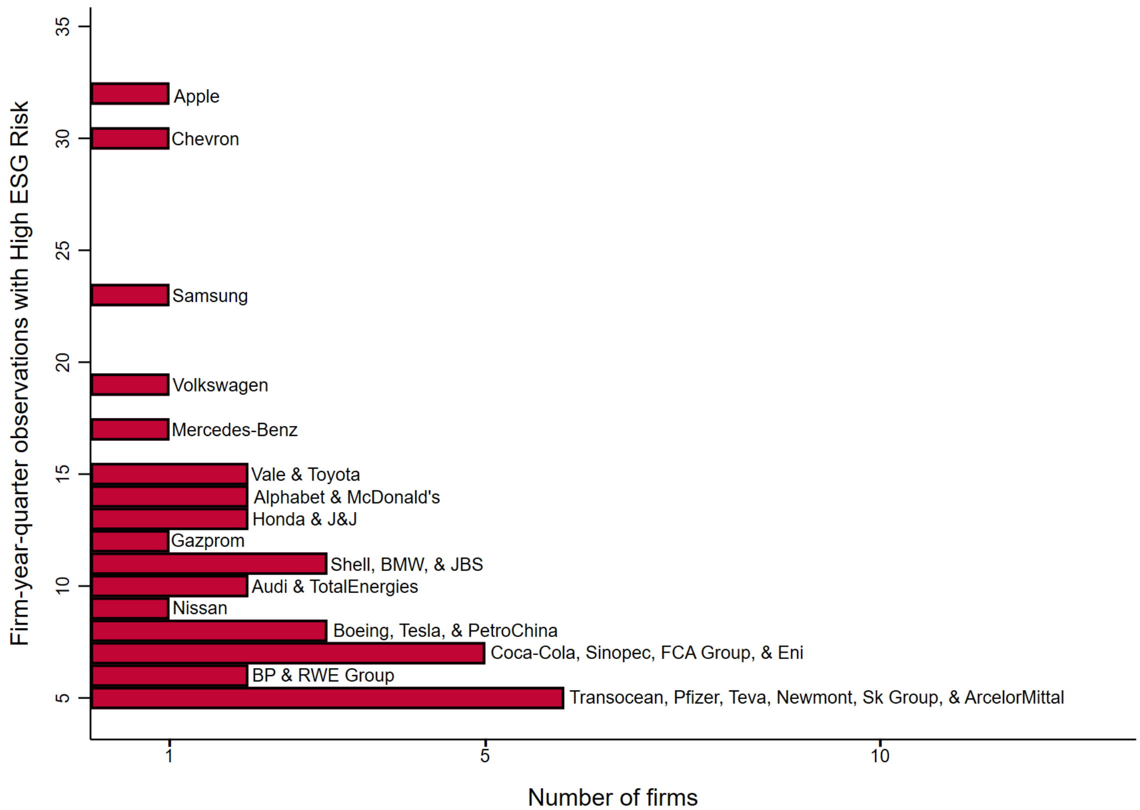

Figure 3: **Worst ESG offenders in sample**
The figure shows the firms that most frequently have a high ESG risk (measured as RepRisk Index (RRI)$\geq$60). The y-axis shows a firm's number of year-quarter observations with high ESG risk. For the y-axis, we implement a cutoff at $\geq$5 firm-year-quarter observations (i.e., we show the "worst ESG offenders"). Hence, the roughly 80 firms with $\leq$4 year-quarter observations with high ESG risk are not shown here for brevity. Apple, which takes the number one spot as the worst ESG offender from Shell after squaring available observations for dependent and independent variables in our sample, has many severe RepRisk violations related to *violations of national legislation*. However, especially predominant are the issues related to *human rights abuses and corporate complicity* (e.g., child labor).

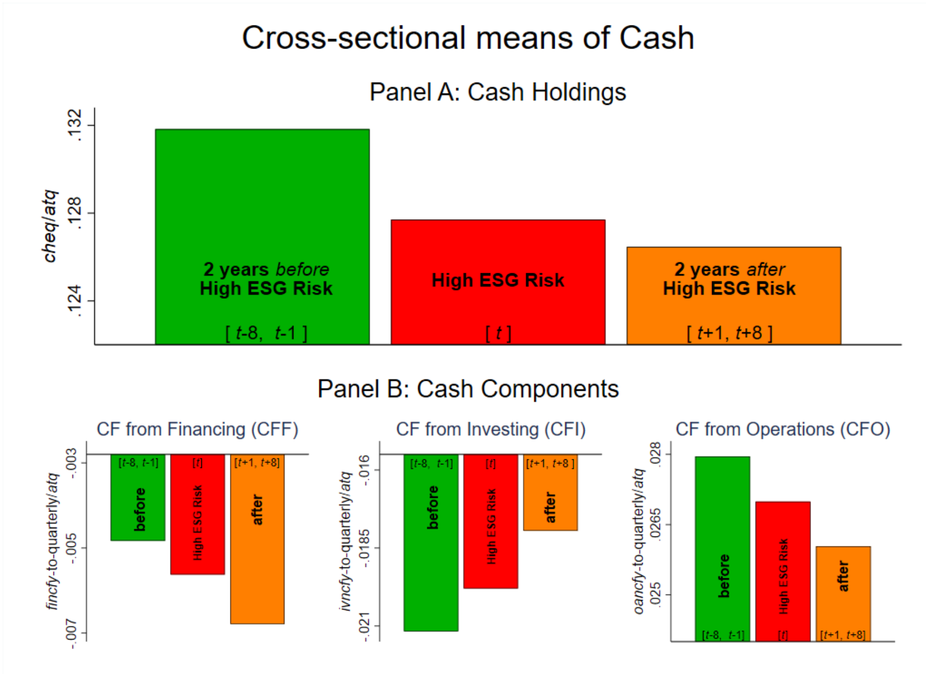

Figure 4: The figure shows cash holdings ($cheq/atq$), in Panel A, and the three components of cash holdings: cash flow from financing (CFF), cash flow from investing (CFI), and cash flow from operations (CFO) in Panel B. For each firm-year-quarter with high ESG risk (i.e., RepRisk Index≥60), we calculate the mean values of cash holdings, CFF, CFI, and CFO. In the figure, *before* shows the pre-high-ESG-risk values, calculated for a period of 2 years before ([t-8,t-1]) the year-quarter with high ESG risk ([t]) , and *after* shows the post-high-ESG-risk values, calculated for a period of 2 years after ([$t+1$,$t+8$]).

Table 1 - Variable descriptions

Variable	Definition
PCE	Personal Consumption Expenditure. Captures the value of goods and services purchased by households (see Delgado & Mills, 2020). Based on U.S. benchmark Input-Output accounts. Scale of 0-1
AP	Accounts Payable, trade (quarterly). Compustat item *apq*. Also used by, for example, Gonçalves et al. (2018)
AR	Accounts Receivable, trade (quarterly). Compustat item *rectrq*. Also used by, for example, Gonçalves et al. (2018)
Dependent variables	
Net TC received	(AP - AR) divided by sales (e.g., El Ghoul & Zheng, 2016; Love et al., 2007; McGuinness et al., 2018)
Received	AP divided by COGS (e.g., Garcia-Appendini & Montoriol-Garriga, 2013; Gonçalves et al., 2018; Love et al., 2007)
Extended	AR divided by sales (e.g., Garcia-Appendini & Montoriol-Garriga, 2013; Gonçalves et al., 2018; Love et al., 2007)
Main variable of interest	
High ESG Risk	Takes the value of 1 if a firm has had a negative RepRisk event (RRI$\geq$60) during the year-quarter ; 0 otherwise.
Covariates	
Size	ln(total assets)=ln(*atq*). See, e.g., Garcia-Appendini and Montoriol-Garriga (2013); Giannetti et al. (2011); Jacobson and Von Schedvin (2015); McGuinness et al. (2018); Petersen and Rajan (1997).
Size^2	$(\text{Size})^2$, see Jacobson and Von Schedvin (2015).
Age	ln(1+firm age). See, e.g., Garcia-Appendini and Montoriol-Garriga (2013); Giannetti et al. (2011); Mateut and Chevapatrakul (2018); McGuinness et al. (2018); Petersen and Rajan (1997). It is based on the first available observation in Compustat's data. Age is in (log of) years; not year-quarters.
Age^2	$(\text{Age})^2$, see Petersen and Rajan (1997) and McGuinness et al. (2018).
Fixed Assets	Measures the ability to pledge collateral, for example. Calculated as fixed assets (PPE gross total minus depreciation) divided by total assets, i.e. *ppent/atq*. See, e.g., El Ghoul and Zheng (2016); Garcia-Appendini and Montoriol-Garriga (2013); Giannetti et al. (2011); Jacobson and Von Schedvin (2015).
net Profit Margin	Measure of profitability. Calculated as (pretax income - taxes)/revenues = (*piq-txtq*)/*revtq*. See, e.g., Delannay and Weill (2004); El Ghoul and Zheng (2016); Garcia-Appendini and Montoriol-Garriga (2013); Giannetti et al. (2011); Mateut and Chevapatrakul (2018); Petersen and Rajan (1997).
Sales Growth	$=(saleq_{q} - saleq_{q-1})/saleq_{q-1}$. Suppliers should be more willing to provide credit to firms with positive sales growth. See, e.g., El Ghoul and Zheng (2016); Garcia-Appendini and Montoriol-Garriga (2013); McGuinness et al. (2018); Petersen and Rajan (1997).

Table 1 - Variable descriptions (Continued)

Debt Ratio	Calculated as debt in current liabilities (total) plus long-term debt (total) divided by assets (total), i.e., *(dlcq+dlttq)/atq*. More debt, scaled by assets, could indicate that 1) a supplier with more leverage might have better access to public debt markets and is therefore in a good position to provide credit to its customers (Garcia-Appendini & Montoriol-Garriga, 2013), and 2) it may be more problematic for a firm with more leverage to receive credit from a supplier. See also Aktas, De Bodt, Lobez, and Statnik (2012) and McGuinness et al. (2018) for the use of leverage as a control variable.
LIQ	Liquidity, calculated as the (natural) logarithm of cash and short-term investments divided by total assets = $\ln(cheq/atq)$. See, e.g., Aktas et al. (2012), El Ghoul and Zheng (2016), Garcia-Appendini and Montoriol-Garriga (2013), Mateut and Chevapatrakul (2018), and McGuinness et al. (2018).
Market Share	A firm's share of its 2-digit SIC industry's sales, i.e. $saleq_{\text{firm i}}/\text{sum}(saleq_{\text{industry}})$. See, e.g., Dass et al. (2015), Garcia-Appendini and Montoriol-Garriga (2013), and Mateut and Chevapatrakul (2018).
Z-score	Altman's (1968) Z-score. Calculated as in the clarification of Altman (2000). We use Compustat's annual data, given the high amount of missing observations in quarterly data. Z-score = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5, where X1 = *(act-lct)/at*, X2 = *re/at*, X3 = *(oibdp-dp)/at*, X4 = *(Market value of E)/(Book value of D)*, and X5 = *sale/at*. For market value of equity, we use *csho*prcc_f* from Compustat NA, and *cshoc*prccd* from Compustat Global Securities Daily for firms in Compustat Global. Book value of debt = *at-ceq*. Z-score is also used in, e.g., Y. Zhang et al. (2020), Aktas et al. (2012), and McGuinness et al. (2018).
GPDpcg	(Real) GDP per capita growth is used as in McGuinness et al. (2018) to control for the level of economic activity in countries. We use (annual) data from the World Bank. Data is in constant 2017 USD, i.e., adjusted against inflation.
KOFGI	Globalization Index (annual) from the KOF Swiss Economic Institute, is used as in Liang and Renneboog (2017) to control for the level of globalization of different countries. A higher score implies a higher a degree of globalization. See also Dreher (2006) and Gygli, Haelg, Potrafke, and Sturm (2019).
Lagged Max RRI	The maximum RRI value for each firm in the preceding period. For ESG incidents in the last 3-, 6-, and 12-month windows, we use the maximum RRI in the corresponding window (i.e., highest RRI in the last 3, 6, or 12 months). Along with the Z-score, it is used to control for endogeneity issues arising from if a firm is not well governed. In such a scenario, trade credit could be a affected and the RRI value could go up. The previous period's RRI value, together with the Z-score, are used as controls to limit the influence of latent variables related to whether the firm is not governed well.

Table 1 - Variable descriptions (Continued)

Cash-variables used for Figure 4, Table 6, and Table 7:

Cash holdings	Calculated as cash and cash equivalents divided by total assets, i.e., *cheq/atq*.
CFF	Cash Flow from Financing (CFF), calculated from Compustat's *fincfy* and scaled by total assets (*atq*). Since *fincfy* are (fiscal) year-to-date values, we follow Duchin et al. (2010) and Sletten et al. (2018) and convert the variables into quarterly data by subtracting the previous quarter's (t-1) value from the observation in quarter t for fiscal quarters 2, 3, and 4. (Fiscal quarter 1 is set equal to the year-to-date variable.)
CFI	Cash Flow from Investing (CFI), calculated as *ivncfy* (converted to quarterly values) divided by assets (*atq*). In the same way as for CFI, we convert the year-to-date values of *ivncfy* into quarterly values.
CFO	Cash Flow from Operations (CFO), calculated as *oancfy* (converted to quarterly values) divided by assets (*atq*). We convert *oancfy* (i.e., the year-to-date values) into quarterly values following the same methodology as for CFF and CFI.
MtoB	Market-to-book value of equity, calculated as (share price*shares outstanding)/*ceq*.
CF-ratio	Cash flow ratio, calculated as operating income before depreciation (*oibdpq*) divided by net assets (*atq* - *cheq*).
CF Volatility	Calculated as McLean (2011). First, the variance of a firm's CF-ratio is calculated for a rolling window of 5 years (20 year-quarters). Second, the average of this variance, within 2-digit SIC codes, is calculated. The CF volatility is finally the natural logarithm of the industry average for a year-quarter. Following McLean, we require firms to have a minimum of 6 observations within the 20-year-quarter rolling windows.
NWC-ratio	Net working capital ratio, calculated as current assets minus cash and cash equivalents and minus current liabilities, divided by net assets (*(actq-cheq-lctq)/(atq-cheq)*).
R&D	R&D expenditure, calculated using *xrdq* from Compustat NA and *xrd* from Compustat Global (*xrdq* is not avaiable in Compustat Global data). We divide *xrd* (annual values) by 4 for Compustat Global firms (R&D expenditure is assumed to be accumulated evenly across year-quarters). We replace missing values with zero, and divide by total assets (*atq*).
Capex_NetA	Capex-to-net-assets ratio, calculated as capex (from *capxy* converted to quarterly values) divided by net assets *atq-cheq*. We convert *capxy* (i.e., the year-to-date values) into quarterly values following the same methodology as for CFF, CFI, and CFO.
Acquisitions	Acquisitions-to-sales ratio, calculated as acquisitions (from *aqcy* converted to quarterly values) divided by sales (*saleq*). We convert *aqcy* (i.e., the year-to-date values) into quarterly values following the same methodology as for CFF, CFI, CFO, Capex_NetA.
Distributions	A dummy variable, equal to 1 if dividends, in a year-quarter, are above zero; 0 otherwise. We use *dvy* (i.e., the year-to-date values) which we convert into quarterly values following the same methodology as for CFF, CFI, CFO, Capex_NetA, and Acquisitions.

Table 2 - Summary statistics

Panel A: Overall statistics

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
PCE	181,439	0.277	0.090	0.321	0.000	1.000	0.792	2.187
Net TC/sales	181,439	-0.162	-0.169	0.688	-2.597	3.335	1.082	11.489
Extended	181,439	0.722	0.592	0.664	0.000	4.348	2.865	14.118
Received	181,439	0.942	0.594	1.262	0.025	9.068	4.182	23.995
High ESG Risk	181,439	0.003	0.000	0.053	0.000	1.000	18.635	348.271
Assets	181,439	4614.558	921.336	16961.780	0.000	494717.506	11.602	189.438
L.Size	181,439	6.782	6.801	1.782	2.356	11.115	-0.020	2.781
L.Age	181,439	2.608	2.639	0.652	0.693	3.989	-0.303	3.296
L.Fixed assets	181,439	0.300	0.252	0.224	0.006	0.877	0.728	2.632
L.net PM	181,439	-0.075	0.046	0.806	-6.742	0.571	-6.942	54.543
L.Sales Growth	181,439	0.053	0.014	0.295	-0.616	1.710	2.548	14.878
L.Debt Ratio	181,439	0.256	0.236	0.197	0.000	0.953	0.886	3.925
L.LIQ	181,439	0.152	0.104	0.153	0.001	0.763	1.831	6.552
L.Market share	181,439	0.014	0.002	0.049	0.000	1.000	10.241	151.619
L.Z-score	181,439	3.497	2.606	4.069	-6.436	24.810	2.483	12.881
L.GDPpcg	181,439	2.378	1.701	3.264	-5.455	12.509	0.564	3.796
L.KOFGI	181,439	76.717	80.671	10.180	42.842	90.906	-1.033	3.559
Lagged Max RRI (3mon)	178,843	7.145	0.000	11.815	0.000	87.000	1.683	5.611

Panel B: Pairwise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Net TC/sales	1														
(2) Extended	-0.502	1													
(3) Received	0.294	0.352	1												
(4) L.Size	-0.026	-0.092	-0.060	1											
(5) L.Age	-0.000	-0.072	-0.055	0.317	1										
(6) L.Fixed Assets	0.183	-0.212	-0.027	0.067	-0.062	1									
(7) L.net PM	-0.333	-0.063	-0.153	0.234	0.077	0.028	1								
(8) L.Sales Growth	0.019	0.025	0.029	-0.053	-0.045	-0.023	0.010	1							
(9) L.Debt Ratio	0.073	-0.040	0.033	0.181	0.011	0.239	-0.077	-0.013	1						
(10) L.LIQ	0.042	0.009	0.031	-0.221	-0.110	-0.335	-0.215	0.052	-0.310	1					
(11) L.Market Share	0.028	-0.081	-0.054	0.270	0.135	-0.011	0.045	0.002	0.028	-0.077	1				
(12) L.Z-score	-0.150	-0.013	-0.093	-0.097	-0.024	-0.174	0.120	0.024	-0.446	0.294	-0.012	1			
(13) L.GDPpcg	0.000	0.141	0.074	-0.104	-0.080	0.059	0.059	0.061	-0.038	0.060	-0.071	0.073	1		
(14) L.KOFGI	0.004	-0.099	-0.035	0.100	0.089	-0.134	-0.049	-0.043	-0.003	-0.034	0.078	-0.041	-0.515	1	
(15) Lagged Max RRI (3mon)	0.022	-0.065	-0.028	0.457	0.186	0.044	0.050	-0.034	0.059	-0.076	0.195	-0.053	-0.073	0.106	1

Table 3: High ESG Risk turn firms into Liquidity Providers

This table is created using data from 2007–2019. *ESG Risk* signals if a firm's Reputational Risk Index (RepRisk Index; RRI)≥60 (i.e., high risk exposure; extremely high at 75 or above) in Columns (1)–(3), 50≤RRI≤59 (elevated risk exposure) in Columns (4)–(6), or 26≤RRI≤49 (medium risk exposure) in Columns (7)–(9), within a certain time-frame (3-, 6-, or 12-month window). These RRI-intervals are defined by RepRisk. Hence, the non-ESG Risk firm-year-quarters have RRI values below 60 in Columns (1)–(3), other than 50-59 in Columns (4)–(6), and other than 26-49 in Columns (7)–(9). The dependent variable is net trade credit received, defined as (payables (AP) - receivables (AR)) divided by sales (El Ghoul & Zheng, 2016; Love et al., 2007; McGuinness et al., 2018). Control variables for firms, lagged one quarter, include size (natural logarithm of total assets), firm age, asset tangibility, net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP per capita growth rate, globalization index, and lagged maximum RRI-score. Size and age are also squared to allowed for non-linear relationships with the dependent variable (Jacobson & Von Schedvin, 2015). All continuous variables are winsorized with replacement (1,99 cuts). Fixed effects are by firm and year-quarter*industry (where industry is represented by 2-digit SIC codes). Standard errors are clustered at the firm and year-quarter (YQ) levels. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The fixed effects' coefficients are omitted.

Dependent variable is **Net Trade Credit Received** = (AP-AR)/sales

⟹ **ESG Risk declines** in direction ⟹

	High Reputational Risk Exposure *RRI≥60 as ESG Risk*			**Elevated** Reputational Risk Exposure *50≤RRI≤59 as ESG Risk*			**Medium** Reputational Risk Exposure *26≤RRI≤49 as ESG Risk*		
	Firm had ESG Risk in last			Firm had ESG Risk in last			Firm had ESG Risk in last		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	3-month	6-month	12-month	3-month	6-month	12-month	3-month	6-month	12-month
ESG Risk	-0.039**	-0.037**	-0.035*	-0.027*	-0.027*	-0.016	0.006	0.004	0.004
	(-2.44)	(-2.40)	(-1.72)	(-1.84)	(-1.93)	(-1.16)	(1.26)	(1.00)	(0.92)
<u>*Controls*</u>									
L.Size	-0.103**	-0.103**	-0.107**	-0.103**	-0.103**	-0.107**	-0.102**	-0.102**	-0.107**
	(-2.31)	(-2.27)	(-2.29)	(-2.31)	(-2.27)	(-2.29)	(-2.30)	(-2.26)	(-2.28)
L.Size^2	0.007**	0.006**	0.007**	0.007**	0.006**	0.007**	0.006**	0.006**	0.007**
	(2.20)	(2.14)	(2.13)	(2.20)	(2.14)	(2.13)	(2.18)	(2.13)	(2.12)
L.Age	0.019	0.018	0.026	0.019	0.019	0.026	0.019	0.018	0.026
	(0.41)	(0.39)	(0.56)	(0.42)	(0.40)	(0.57)	(0.41)	(0.39)	(0.56)
L.Age^2	-0.003	-0.003	-0.006	-0.004	-0.003	-0.006	-0.003	-0.003	-0.006
	(-0.21)	(-0.19)	(-0.34)	(-0.23)	(-0.21)	(-0.35)	(-0.21)	(-0.19)	(-0.34)
L.Fixed Assets	0.446***	0.443***	0.447***	0.446***	0.443***	0.447***	0.446***	0.443***	0.447***
	(7.01)	(6.93)	(6.86)	(7.01)	(6.93)	(6.86)	(7.01)	(6.93)	(6.86)
L.net PM	-0.122***	-0.119***	-0.116***	-0.122***	-0.119***	-0.116***	-0.122***	-0.119***	-0.116***
	(-10.49)	(-10.48)	(-10.28)	(-10.48)	(-10.48)	(-10.28)	(-10.48)	(-10.48)	(-10.28)
L.Sales Growth	-0.000	-0.003	-0.004	-0.000	-0.003	-0.004	-0.000	-0.003	-0.004
	(-0.03)	(-0.32)	(-0.43)	(-0.03)	(-0.32)	(-0.43)	(-0.03)	(-0.32)	(-0.42)
L.Debt Ratio	-0.104***	-0.108***	-0.111***	-0.104***	-0.108***	-0.111***	-0.104***	-0.108***	-0.111***
	(-2.71)	(-2.81)	(-2.82)	(-2.70)	(-2.81)	(-2.82)	(-2.71)	(-2.81)	(-2.82)
L.LIQ	0.384***	0.378***	0.370***	0.384***	0.378***	0.370***	0.384***	0.378***	0.370***
	(7.83)	(7.70)	(7.45)	(7.83)	(7.70)	(7.45)	(7.83)	(7.71)	(7.45)
L.Market Share	0.573**	0.590***	0.618***	0.571**	0.589***	0.619***	0.572**	0.590***	0.619***
	(2.66)	(2.73)	(2.76)	(2.66)	(2.72)	(2.77)	(2.66)	(2.73)	(2.77)
L.Z-score	-0.009***	-0.010***	-0.010***	-0.009***	-0.010***	-0.010***	-0.009***	-0.010***	-0.010***
	(-6.42)	(-6.52)	(-6.40)	(-6.41)	(-6.52)	(-6.40)	(-6.41)	(-6.52)	(-6.39)
L.GDPpcg	0.001	0.001	0.002	0.001	0.001	0.002	0.001	0.001	0.002
	(0.27)	(0.47)	(0.85)	(0.28)	(0.48)	(0.86)	(0.27)	(0.47)	(0.85)
L.KOFGI	-0.003	-0.002	-0.002	-0.003	-0.003	-0.002	-0.003	-0.002	-0.002
	(-0.60)	(-0.56)	(-0.43)	(-0.60)	(-0.56)	(-0.44)	(-0.60)	(-0.56)	(-0.44)
Lagged Max RRI	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.72)	(1.09)	(1.45)	(0.70)	(1.07)	(1.41)	(0.55)	(0.99)	(1.41)
Constant	0.241	0.233	0.213	0.242	0.237	0.217	0.239	0.232	0.213
	(0.63)	(0.60)	(0.53)	(0.63)	(0.61)	(0.54)	(0.62)	(0.60)	(0.53)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (YQ)*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & YQ Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.675	0.678	0.683	0.675	0.678	0.683	0.675	0.678	0.683
N	178,410	175,709	170,026	178,410	175,709	170,026	178,410	175,709	170,026

Table 4: Firms are Punished after High ESG Risk

This table is created using data from 2007–2019. *High ESG Risk* signals if a firm's RepRisk Index (RRI)$\geq$60 within a certain time-frame (3-, 6-, 9-, or 12-month window). The non-High-ESG Risk firm-year-quarters have RRI values below 60, i.e., less than a very high Reputational Risk. *Credit Received* is Accounts Payable normalized by COGS and *Credit Extended* is Accounts Receivable normalized by sales (Garcia-Appendini & Montoriol-Garriga, 2013; Gonçalves et al., 2018; Love et al., 2007). Control variables for firms, lagged one quarter, include size (natural logarithm of total assets), firm age, asset tangibility, net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP per capita growth rate (GDPpcg), globalization index (KOFGI; excluded together with GDPpcg from Panel C due to collinearity with the fixed effects), and lagged maximum RRI-score. Size and age are also squared to allowed for non-linear relationships with the dependent variable (Jacobson & Von Schedvin, 2015). All continuous variables are winsorized with replacement (1,99 cuts). Fixed effects, in Panel A, are by firm and year-quarter*industry (where industry is represented by 2-digit SIC codes), Panel B substitute the firm-level dummies for country dummies, and Panel C combine both firm and year-quarter*industry*country fixed effects. Standard errors are clustered at the firm and year-quarter (YQ) levels. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The constant's, controls', and fixed effects' coefficients are omitted.

	Components of **Net Trade Credit** ↙ ↘							
	Credit Received as dependent variable				**Credit Extended** as dependent variable			
	Firm had High ESG Risk in last				Firm had High ESG Risk in last			
	(1) 3-month	(2) 6-month	(3) 9-month	(4) 12-month	(5) 3-month	(6) 6-month	(7) 9-month	(8) 12-month
Panel A								
High ESG Risk	-0.056**	-0.048*	-0.044*	-0.037	0.013	0.014	0.023	0.021
	(-2.07)	(-1.93)	(-1.76)	(-1.42)	(0.97)	(0.92)	(1.15)	1.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YQ*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & YQ Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.581	0.582	0.584	0.587	0.714	0.717	0.719	0.722
N	178,410	175,709	172,950	170,026	178,410	175,709	172,950	170,026
Panel B								
High ESG Risk	-0.173**	-0.165***	-0.158**	-0.148**	0.072	0.080	0.091*	0.088*
	(-2.66)	(-2.69)	(-2.60)	(-2.48)	(1.33)	(1.56)	(1.72)	(1.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YQ*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & YQ Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.146	0.146	0.146	0.147	0.259	0.259	0.259	0.260
N	178,523	175,816	173,050	170,124	178,523	175,816	173,050	170,124
Panel C								
High ESG Risk	-0.068**	-0.042	-0.042	-0.036	0.019	0.027	0.035	0.026
	(-2.05)	(-1.33)	(-1.24)	(-0.99)	(1.13)	(1.41)	(1.45)	(1.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YQ*Industry*Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & YQ Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.605	0.606	0.608	0.611	0.726	0.729	0.731	0.734
N	158,388	156,011	153,608	151,051	158,388	156,011	153,608	151,051

Table 5: High ESG Risk hurts Consumer-Adjacent Firms more

This table is created using data from 2007–2019. *High ESG Risk* signals if a firm's RepRisk Index (RRI)≥60 within a certain time-frame (3-, 6-, 9-, 12-, 15-, or 18-month window). The non-scandal sample has RRI values below 60, i.e., less than a very high Reputational Risk. *Downstream*, *Intermediate*, and *Upstream* are indicators for a firm's Supply Chain (SC) position. *Downstream* indicates (=1) if a firm's sales to personal consumption expenditure (PCE)≥0.35, while *Intermediate* shows if a firm's PCE is 0<PCE<0.35. Upstream firms have a PCE=0. The dependent variable is net trade credit received, defined as (payables (AP) - receivables (AR)) divided by sales (El Ghoul & Zheng, 2016; Love et al., 2007; McGuinness et al., 2018). Panel A shows the results from a sample consisting of all firms, while Panels B and C show a propensity score matched (PSM) sample. We match firms with high ESG risk (i.e., firms with RRI≥60) to non-scandal firms that do not have "ESG incidents" in the sample. We match exactly on SC group and industry-year-quarter (date of the ESG incident), where industry is measured by 2-digit SIC codes. Other (non-exact) matching covariates used are size, age, fixed assets, net profit margin, liquidity, market share, debt ratio, and PCE. Matching is done with replacement. We follow both the scandal and non-scandal firm from 2-years (8 year-quarters) before the ESG incident, and to the end of the sample provided that both firms have observations within this time-window; if not, we use observations only from the window within which both firms "exist" in the sample. *Low ESG Risk*, in Panel C, shows if a firm's RRI≤25 within the time-window (=1 if yes; 0 otherwise). Control variables for firms (used in all panels), lagged one quarter, include size (natural logarithm of total assets), firm age, asset tangibility, net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP per capita growth rate, globalization index, and lagged maximum RRI-score. Size and age are also squared to allowed for non-linear relationships with the dependent variable (Jacobson & Von Schedvin, 2015). All continuous variables are winsorized with replacement (1,99 cuts). Fixed effects are by firm and year-quarter*industry (where industry is represented by 2-digit SIC codes). Standard errors are clustered at the firm and year-quarter (YQ) levels. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The constant's, controls', and fixed effects' coefficients are omitted.

	Dependent variable is **Net Trade Credit Received** = (AP-AR)/sales					
	Firm had High ESG Risk in last					
	(1)	(2)	(3)	(4)	(5)	(6)
	3-month	6-month	9-month	12-month	15-month	18-month
Panel A: Full sample						
High ESG Risk & Downstream	-0.053**	-0.056**	-0.061*	-0.061*	-0.058*	-0.050
	(-2.24)	(-2.14)	(-1.91)	(-1.78)	(-1.78)	(-1.56)
High ESG Risk & Intermediate	-0.042*	-0.021	-0.016	0.002	-0.010	0.008
	(-1.80)	(-1.20)	(-0.71)	(0.07)	(-0.40)	(0.25)
High ESG Risk & Upstream	0.004	-0.014	-0.024	-0.030	-0.023	-0.022
	(0.11)	(-0.38)	(-0.63)	(-0.72)	(-0.56)	(-0.52)
Adj. R^2	0.675	0.678	0.681	0.683	0.685	0.688
N	178,410	175,709	172,950	170,026	167,224	164,252
Panel B: PSM sample						
High ESG Risk & Downstream	-0.033**	-0.042**	-0.054***	-0.060**	-0.062**	-0.057**
	(-2.01)	(-2.62)	(-2.67)	(-2.64)	(-2.64)	(-2.18)
High ESG Risk & Intermediate	-0.045	-0.045*	-0.040	-0.036	-0.041	-0.041
	(-1.63)	(-1.90)	(-1.41)	(-1.13)	(-1.27)	(-1.23)
High ESG Risk & Upstream	0.060**	0.025	-0.002	0.002	0.012	0.017
	(2.22)	(0.94)	(-0.06)	(0.06)	(0.42)	(0.59)
Adj. R^2	0.810	0.810	0.810	0.810	0.810	0.811
N	5,779	5,763	5,746	5,723	5,700	5,673

Continuing on next page

Table 5: Cont'd

	Dependent variable is Net Trade Credit Received = (AP-AR)/sales					
	Firm had High ESG Risk in last					
	(1)	(2)	(3)	(4)	(5)	(6)
	3-month	6-month	9-month	12-month	15-month	18-month
Panel C: PSM sample						
Low-Risk indicator included						
High ESG Risk & Downstream	-0.034**	-0.042**	-0.053**	-0.059**	-0.061**	-0.056**
	(-2.04)	(-2.61)	(-2.61)	(-2.60)	(-2.59)	(-2.13)
High ESG Risk & Intermediate	-0.046	-0.047*	-0.042	-0.036	-0.040	-0.040
	(-1.63)	(-1.94)	(-1.44)	(-1.09)	(-1.22)	(-1.17)
High ESG Risk & Upstream	0.063**	0.028	0.002	0.006	0.015	0.020
	(2.37)	(1.11)	(0.06)	(0.19)	(0.49)	(0.65)
Low ESG Risk & Downstream	-0.009	0.009	0.013	0.007	0.009	0.011
	(-0.43)	(0.52)	(0.74)	(0.38)	(0.37)	(0.40)
Low ESG Risk & Intermediate	-0.001	-0.006	-0.010	0.004	0.006	0.009
	(-0.07)	(-0.38)	(-0.47)	(0.18)	(0.26)	(0.35)
Low ESG Risk & Upstream	0.022	0.043	0.048*	0.050	0.036	0.038
	(0.92)	(1.50)	(1.70)	(1.29)	(0.70)	(0.64)
Adj. R^2	0.810	0.810	0.810	0.810	0.810	0.811
N	5,779	5,763	5,746	5,723	5,700	5,673
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time (YQ)*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm & YQ Clustering	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: T-test for changes in Cash and Cash Holdings' components

This table shows the p-values of a two-sided t-test, comparing mean and median of Cash Holdings (Cash and Cash Equivalents (*cheq*)), Cash Flow from Financing (CFF), Cash Flow from Investing (CFI), and Cash Flow from Opertions (CFO), for 2 years before and after firm-year-quarters with High ESG Risk (measured as RepRisk Index$\geq$60). All cash flows are scaled by assets. The mean (median) are calculated for each firm by taking the arithmetic average (median) from year-quarter -8 through -1 and +1 through +8 for before and after, respectively. N shows the number of firms with available before and after observations of the cash and cash holdings' components, for which the (two-sided) t-tests are computed cross-sectionally, examining whether the difference is zero. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively.

	N	Statistic	Before	After	Difference	Difference test (p-values)
Cash Holdings	503	Mean	0.1316	0.1267	-0.0049	0.0413**
	503	Median	0.1303	0.1260	-0.0043	0.0777*
Cash Holdings' components:						
CF from Financing (CFF)	503	Mean	-0.0045	-0.0068	-0.0023	0.0010***
	503	Median	-0.0055	-0.0071	-0.0016	0.0119**
CF from Investing (CFI)	503	Mean	-0.0215	-0.0178	0.0037	0.0000***
	503	Median	-0.0213	-0.0181	0.0032	0.0000***
CF from Operations (CFO)	503	Mean	0.0280	0.0259	-0.0021	0.0001***
	503	Median	0.0276	0.0256	-0.0020	0.0014***

Table 7: High ESG Risk hurts Cash Flow from Investing Activities

This table is created using data from 2007 - 2019. *High ESG Risk* signals if a firm's RepRisk Index (RRI)≥60 (very high risk exposure). Hence, the control sample has RRI values below 60. In Panel A, the dependent variable is Cash Holdings, scaled by assets (*cheq/atq*). In Panels B–D, the dependent variable is CFF, CFI, and CFO, respectively, calculated from *fincfy*, *ivncfy*, and *oancfy*, respectively, where year-to-date values are converted to quarterly values, all scaled by assets. ***AFTER***, the variable of main interest, is an indicator (=1) for firm-year-quarters after *High ESG Risk* (0 otherwise). Columns (1)–(9) show a varying window-length for when ***AFTER*** is 1. *t* is the year-quarter where the *High ESG Risk* occurs. Control variables for firms include Market to Book value of Equity, Cash Flow Ratio, Cash Flow Volatility, Net Working Capital ratio, R&D Expense, Capex to net Assets ratio, Acquisitions, and Distributions. All continuous variables are winsorized with replacement (1,99 cuts). Standard errors are clustered at the firm and year-quarter (YQ) levels. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The constant's, controls', and fixed effects' coefficients are omitted.

	Dependent variable is Cash (Panel A) or Cash Holdings' components (Panels B–D)								
	⟹ increasing time since High ESG Risk in year-quarter *t* ⟹								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t	*t* to *t+1*	*t* to *t+2*	*t* to *t+3*	*t* to *t+4*	*t* to *t+5*	*t* to *t+7*	*t* to *t+9*	*t* to *t+11*
Panel A: Cash as dependent									
AFTER High ESG Risk	-0.016*	-0.015**	-0.014**	-0.012*	-0.011*	-0.010*	-0.009	-0.009	-0.008
	(-1.97)	(-2.04)	(-2.03)	(-1.90)	(-1.71)	(-1.70)	(-1.55)	(-1.56)	(-1.45)
Adj. R^2	0.762	0.762	0.762	0.762	0.762	0.762	0.762	0.762	0.762
N	175,038	175,038	175,038	175,038	175,038	175,038	175,038	175,038	175,038
Panel B: CFF as dependent									
AFTER High ESG Risk	-0.000	-0.000	-0.001	-0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(-0.30)	(-0.16)	(-0.63)	(-0.12)	(0.15)	(-0.39)	(-0.06)	(-0.32)	(-0.37)
Adj. R^2	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226
N	175,038	175,038	175,038	175,038	175,038	175,038	175,038	175,038	175,038
Panel C: CFI as dependent									
AFTER High ESG Risk	0.001	0.001	0.001	0.001	0.001*	0.002**	0.001**	0.001**	0.002***
	(0.56)	(1.25)	(1.51)	(1.56)	(1.88)	(2.59)	(2.33)	(2.31)	(3.10)
Adj. R^2	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
N	175,038	175,038	175,038	175,038	175,038	175,038	175,038	175,038	175,038
Panel D: CFO as dependent									
AFTER High ESG Risk	-0.001	-0.000	-0.000	-0.000	-0.001	-0.001	-0.002*	-0.002	-0.001
	(-0.57)	(-0.38)	(-0.35)	(-0.48	(-1.27)	(-1.39)	(-1.76)	(-1.54)	(-1.38)
Adj. R^2	0.361	0.361	0.361	0.361	0.361	0.361	0.361	0.361	0.361
N	175,038	175,038	175,038	175,038	175,038	175,038	175,038	175,038	175,038
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter (YQ) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & YQ clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8 - Foreign suppliers Punish Consumer-Adjacent customers

This table is created by combining our baseline data (Compustat and RepRisk) with FactSet data from 2007–2019, where we can trace suppliers-customer relationship, and the importance of this relationship (by *Ranking*) for the supplier, relative to all other relationships of the supplier. A higher *Ranking* signals that the customer is more important for the supplier. We use this *Ranking* as the dependent variable. *Customer High ESG Risk* is an indicator for whether the customer, in the supplier-customer pair, has a High ESG Risk (=1 if true; 0 otherwise). Similarly, *Customer Downstream* is an indicator for whether the customer, in the supplier-customer pair, is a downstream (i.e., consumer-adjacent) firm (=1 if true; 0 otherwise). In Panel A, we use the full sample of supplier-customer pairs. In Panel B, we include only foreign suppliers (i.e., the supplier and the customer are domiciled in different countries). In Panel C, only domestic suppliers are included — the supplier and the customer are domiciled in the same country. Control variables for *both* supplier and customers firms, lagged one quarter, include size (natural logarithm of total assets), firm age, asset tangibility, net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP per capita growth rate, globalization index, and lagged maximum RRI-score. Size and age are also squared to allowed for non-linear relationships with the dependent variable (Jacobson & Von Schedvin, 2015). All continuous variables are winsorized with replacement (1,99 cuts). Firm-pair fixed effects (FEs) are included in all columns along with year-quarter interacted with supplier-industry (by 2-digit SIC codes) FEs. The main effect for *Customer Downstream* is omitted due to collinearity with the firm-pair FEs. Standard errors are clustered at the firm-pair level. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The constant's, controls', and fixed effects' coefficients are omitted.

	Dependent variable is **Ranking** of Customer Importance					
	Customer firm had High ESG Risk in last					
	(1) 3-month	(2) 6-month	(3) 12-month	(4) 3-month	(5) 6-month	(6) 12-month
Panel A: All suppliers						
Customer High ESG Risk	-0.117***	-0.131***	-0.124***	-0.005	-0.008	0.023
	(-4.48)	(-4.61)	(-3.88)	(-0.13)	(-0.20)	(0.55)
Customer High ESG Risk*Customer Downstream				-0.195***	-0.212***	-0.263***
				(-3.63)	(-3.73)	(-4.13)
Adj. R^2	0.843	0.844	0.845	0.843	0.844	0.845
N	290,753	288,235	282,328	290,753	288,235	282,328
Panel B: Foreign suppliers						
Customer High ESG Risk	-0.153***	-0.177***	-0.210***	-0.035	-0.041	-0.036
	(-4.71)	(-4.99)	(-5.14)	(-0.73)	(-0.87)	(-0.71)
Customer High ESG Risk*Customer Downstream				-0.192***	-0.226***	-0.310***
				(-2.93)	(-3.25)	(-3.86)
Adj. R^2	0.836	0.837	0.838	0.836	0.837	0.838
N	162,624	161,701	159,385	162,624	161,701	159,385
Panel C: Domestic suppliers						
Customer High ESG Risk	-0.014	-0.018	0.013	0.031	0.049	0.128*
	(-0.33)	(-0.43)	(0.28)	(0.50)	(0.73)	(1.81)
Customer High ESG Risk*Customer Downstream				-0.097	-0.132	-0.217**
				(-1.20)	(-1.54)	(-2.37)
Adj. R^2	0.820	0.821	0.822	0.820	0.821	0.822
N	127,752	126,165	122,587	127,752	126,165	122,587
Supplier Controls	Yes	Yes	Yes	Yes	Yes	Yes
Customer Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
YQ*Supplier-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Pair clustering	Yes	Yes	Yes	Yes	Yes	Yes

Table 9 - Suppliers in Countries with High E- and S-norms Punish Consumer-Adjacent customers

This table is created by combining our baseline data (Compustat and RepRisk) with FactSet data from 2007–2019, where we can trace suppliers-customer relationship, and the importance of this relationship (by *Ranking*) for the supplier, relative to all other relationships of the supplier. A higher *Ranking* signals that the customer is more important for the supplier. We use this *Ranking* as the dependent variable. *Customer High ESG Risk* is an indicator for whether the customer, in the supplier-customer pair, has a High ESG Risk (=1 if true; 0 otherwise). Similarly, *Customer Downstream* is an indicator for whether the customer, in the supplier-customer pair, is a downstream (i.e., consumer-adjacent) firm (=1 if true; 0 otherwise). In Panel A (Panel B), we divide the sample into High (>median; Columns 1–3) and Low (≤median; Columns 4–6) subsamples based on a supplier-country's E-scores (S-scores for Panel B). A country's E-scores are based on the Environmental Performance Index by Yale University (values updated biennially), and a country's S-scores are based on the Employment Laws Index (static value) of Botero et al. (2004). Control variables for *both* supplier and customers firms, lagged one quarter, include size (natural logarithm of total assets), firm age, asset tangibility, net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP per capita growth rate, globalization index, and lagged maximum RRI-score. Size and age are also squared to allowed for non-linear relationships with the dependent variable (Jacobson & Von Schedvin, 2015). All continuous variables are winsorized with replacement (1,99 cuts). Firm-pair fixed effects (FEs) are included in all columns along with year-quarter interacted with supplier-industry (by 2-digit SIC codes) FEs. The main effect for *Customer Downstream* is omitted due to collinearity with the firm-pair FEs. Standard errors are clustered at the firm-pair level. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The constant's, controls', and fixed effects' coefficients are omitted.

	Dependent variable is **Ranking** of Customer Importance					
	Suppliers in **High-norm** countries			Suppliers in **Low-norm** countries		
	Customer firm had High ESG Risk in last			Customer firm had High ESG Risk in last		
	(1)	(2)	(3)	(4)	(5)	(6)
	3-month	6-month	12-month	3-month	6-month	12-month
Panel A: High E vs. Low E suppliers						
Customer High ESG Risk	0.022	-0.002	0.006	-0.054	-0.047	-0.037
	(0.35)	(-0.03)	(0.09)	(-1.13)	(-0.96)	(-0.79)
Customer High ESG Risk*Customer Downstream	-0.345***	-0.363***	-0.333***	-0.055	-0.078	-0.069
	(-3.85)	(-3.98)	(-3.83)	(-0.84)	(-1.11)	(-1.08)
Adj. R^2	0.842	0.843	0.844	0.854	0.855	0.856
N	73,825	73,536	72,781	202,273	200,123	195,148
Panel B: High S vs. Low S suppliers						
Customer High ESG Risk	0.058	0.058	0.086	-0.104*	-0.106*	-0.058
	(1.16)	(1.18)	(1.58)	(-1.76)	(-1.70)	(-0.86)
Customer High ESG Risk*Customer Downstream	-0.261***	-0.293***	-0.409***	-0.080	-0.095	-0.121
	(-3.94)	(-4.26)	(-5.12)	(-0.93)	(-1.03)	(-1.21)
Adj. R^2	0.845	0.846	0.847	0.848	0.848	0.850
N	114,646	114,236	113,192	161,861	159,830	155,128
Supplier Controls	Yes	Yes	Yes	Yes	Yes	Yes
Customer Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
YQ*Supplier-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Pair clustering	Yes	Yes	Yes	Yes	Yes	Yes

Table 10 - Foreign and High-S suppliers Punish Unimportant customers

This table is created by combining our baseline data (Compustat and RepRisk) with FactSet data from 2007–2019, where we can trace suppliers-customer relationship, and the importance of this relationship (by *Ranking*) for the supplier, relative to all other relationships of the supplier. A higher ranking signals that the customer is more important for the supplier. *Customer Unimportant* is an indicator for if the supplier-customer relationship is unimportant to the supplier: the supplier ranking is $\geq$7 (which is the 75$^{\text{th}}$ percentile of rankings in our sample). If a relationship is reported by FactSet, that signals that the supplier-customer connection is already of a certain importance. Hence, we use the 75$^{\text{th}}$ percentile as our threshold for unimportant. *Customer High ESG Risk* is an indicator for whether the customer, in the supplier-customer pair, has a High ESG Risk (=1 if true; 0 otherwise). In Panel A, we compare foreign suppliers (Columns 1–3) with domestic suppliers (Columns 4–6). In Panel B, we compare High E (Columns 1–3) with High S (Columns 4–6) suppliers. Suppliers are considered as High E (High S) if the are domiciled in a country with above median E-scores (S-scores). A country's E-scores are based on the Environmental Performance Index by Yale University (values updated biennially), and a country's S-scores are based on the Employment Laws Index (static value) of Botero et al. (2004). The dependent variable is a supplier's (i.e., the focal firm's) Credit Extended, calculated as Accounts Receivable normalized by sales (Garcia-Appendini & Montoriol-Garriga, 2013; Gonçalves et al., 2018; Love et al., 2007). Control variables for *both* supplier and customers firms, lagged one quarter, include size (natural logarithm of total assets), firm age, asset tangibility, net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP per capita growth rate, globalization index, and lagged maximum RRI-score. Size and age are also squared to allowed for non-linear relationships with the dependent variable (Jacobson & Von Schedvin, 2015). All continuous variables are winsorized with replacement (1,99 cuts). Firm-pair fixed effects (FEs) are included in all columns along with year-quarter interacted with supplier-industry (by 2-digit SIC codes) FEs. Standard errors are clustered at the firm-pair level. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The constant's, controls', and fixed effects' coefficients are omitted.

	Dependent variable is **Credit Extended**					
Panel A: Foreign suppliers vs. Domestic Suppliers	**Foreign** suppliers			**Domestic** suppliers		
	Customer firm had High ESG Risk in last			Customer firm had High ESG Risk in last		
	(1)	(2)	(3)	(4)	(5)	(6)
	3-month	6-month	12-month	3-month	6-month	12-month
Customer High ESG Risk	0.003	0.005	0.005	-0.004	0.003	0.010*
	(0.75)	(1.18)	(0.99)	(-0.72)	(0.55)	(1.78)
Customer Unimportant	-0.004	-0.003	-0.002	-0.002	-0.002	-0.002
	(-1.18)	(-0.84)	(-0.76)	(-0.64)	(-0.64)	(-0.64)
Customer High ESG Risk*Customer Unimportant	**-0.013****	**-0.019*****	**-0.018*****	**0.003**	**0.000**	**-0.011**
	(-2.01)	**(-2.86)**	**(-2.73)**	**(0.28)**	**(0.02)**	**(-1.08)**
Adj. R^2	0.850	0.851	0.853	0.836	0.837	0.840
N	162,624	161,701	159,385	127,752	126,165	122,587
Panel B: High E vs. High S suppliers	**High E** suppliers			**High S** suppliers		
	Customer firm had High ESG Risk in last			Customer firm had High ESG Risk in last		
	(1)	(2)	(3)	(4)	(5)	(6)
	3-month	6-month	12-month	3-month	6-month	12-month
Customer High ESG Risk	0.002	0.008*	0.008*	-0.003	0.005	0.004
	(0.48)	(1.67)	(1.77)	(-0.59)	(1.00)	(0.91)
Customer Unimportant	0.001	0.002	0.003	-0.010***	-0.009**	-0.009***
	(0.41)	(0.64)	(0.79)	(-2.93)	(-2.54)	(-2.62)
Customer High ESG Risk*Customer Unimportant	**-0.011**	**-0.014***	**-0.015***	**-0.013***	**-0.022*****	**-0.021*****
	(-1.36)	**(-1.65)**	**(-1.69)**	**(-1.65)**	**(-2.78)**	**(-2.65)**
Adj. R^2	0.895	0.895	0.895	0.876	0.877	0.877
N	73,825	73,536	72,781	114,646	114,236	113,192
Supplier Controls	Yes	Yes	Yes	Yes	Yes	Yes
Customer Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
YQ*Supplier-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Pair clustering	Yes	Yes	Yes	Yes	Yes	Yes

Table 11 - Inverse Mills' Ratio as robustness check

This table is created using data from 2007–2019. *High ESG Risk* signals if a firm's RepRisk Index (RRI)≥60 within a certain time-frame (3-, 6-, 9-, or 12-month window). The non-High-ESG Risk firm-year-quarters have RRI values below 60, i.e., less than a very high Reputational Risk. Net Trade Credit Received, the dependent variable in Panel A, is defined as (payables (AP) - receivables (AR)) divided by sales (El Ghoul & Zheng, 2016; Love et al., 2007; McGuinness et al., 2018). In Panel B, the dependent variables are Credit Received, defined as Accounts Payable normalized by COGS, and Credit Extended, defined as Accounts Receivable normalized by sales (Garcia-Appendini & Montoriol-Garriga, 2013; Gonçalves et al., 2018; Love et al., 2007). The inverse Mills' Ratio (IMR) has been computed using Google Search Volume Interest for a company's name as an instrument for RRI. Control variables for firms, lagged one quarter, include size (natural logarithm of total assets), firm age, asset tangibility, net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP per capita growth rate, globalization index, and lagged maximum RRI-score. Size and age are also squared to allowed for non-linear relationships with the dependent variable (Jacobson & Von Schedvin, 2015). All continuous variables are winsorized with replacement (1,99 cuts). Fixed effects are by firm and year-quarter*industry (where industry is represented by 2-digit SIC codes). Standard errors are clustered at the firm and year-quarter (YQ) levels. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The constant's, controls', and fixed effects' coefficients are omitted.

Panel A: *Net Trade Credit Received* as dependent variable

	Net Trade Credit Received			
	Firm had High ESG Risk in last			
	(1)	(2)	(3)	(4)
	3-month	6-month	9-month	12-month
High ESG Risk	-0.037**	-0.037**	-0.040**	-0.036*
	(-2.37)	(-2.41)	(-2.18)	(-1.76)
IMR	-0.012	-0.009	-0.013	-0.006
	(-0.71)	(-0.58)	(-0.80)	(-0.36)
Adj. R^2	0.689	0.691	0.693	0.695
N	160,815	158,340	155,808	153,104

Panel B: *Credit Received* & *Credit Extended* as dependent variables

	Credit Received				Credit Extended			
	Firm had High ESG Risk in last				Firm had High ESG Risk in last			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	3-month	6-month	9-month	12-month	3-month	6-month	9-month	12-month
High ESG Risk	-0.067**	-0.055**	-0.054**	-0.045*	0.012	0.015	0.026	0.024
	(-2.58)	(-2.40)	(-2.27)	(-1.81)	(0.96)	(0.98)	(1.27)	(1.17)
IMR	0.030	0.012	-0.006	0.005	0.026*	0.019	0.014	0.013
	(0.84)	(0.38)	(-0.18)	(0.14)	(1.94)	(1.50)	(1.01)	(0.88)
Adj. R^2	0.596	0.597	0.599	0.602	0.711	0.713	0.715	0.718
N	160,815	158,340	155,808	153,104	160,815	158,340	155,808	153,104
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (YQ)*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & YQ Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Internet Appendix

to

Trade Credit Flow along the Supply Chain and Disruptions from ESG Risk

by

Gonul Colak, Jonas Gustafsson, and Niclas Meyer

Internet Appendix (IA) content:

IA, Table 1 - Descriptive statistics by Supply-Chain Group

IA, Table 2 - Statistics by Firms on RRI values

IA, Table 3 - Without the Worst ESG Offenders

Table IA.1 - Descriptive statistics by Supply Chain group

Panel A: Downstream firms

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
PCE	62,276	0.675	0.660	0.188	0.351	1.000	-0.058	1.801
Net TC/sales	62,276	-0.106	-0.070	0.637	-2.597	3.335	0.596	11.504
Extended	62,276	0.588	0.454	0.606	0.000	4.348	2.949	15.877
Received	62,276	0.926	0.584	1.253	0.025	9.068	4.209	24.538
High ESG Risk	62,276	0.004	0.000	0.062	0.000	1.000	16.117	260.772
Assets	62,276	5173.669	920.397	19718.331	0.021	494717.506	11.115	175.660
L.Size	62,276	6.797	6.796	1.786	2.356	11.115	0.055	2.826
L.Age	62,276	2.597	2.639	0.645	0.693	3.989	-0.329	3.282
L.Fixed assets	62,276	0.303	0.263	0.212	0.006	0.877	0.711	2.754
L.net PM	62,276	-0.032	0.050	0.678	-6.742	0.571	-8.148	76.185
L.Sales Growth	62,276	0.054	0.013	0.289	-0.616	1.710	2.593	15.330
L.Debt Ratio	62,276	0.270	0.250	0.210	0.000	0.953	0.821	3.579
L.LIQ	62,276	0.155	0.105	0.157	0.001	0.763	1.748	6.098
L.Market share	62,276	0.019	0.003	0.055	0.000	1.000	7.289	79.419
L.Z-score	62,276	3.772	2.724	4.266	-6.436	24.810	2.427	11.870
L.GDPpcg	62,276	2.239	1.597	3.224	-5.455	12.509	0.593	4.011
L.KOFGI	62,276	76.761	80.671	10.197	43.835	90.906	-1.085	3.739
Lagged Max RRI (3mon)	61,365	7.742	0.000	12.532	0.000	78.000	1.642	5.411

Panel B: Intermediate firms

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
PCE	66,695	0.125	0.065	0.127	0.000	0.349	0.690	1.865
Net TC/sales	66,695	-0.191	-0.195	0.615	-2.597	3.335	1.153	13.156
Extended	66,695	0.738	0.615	0.615	0.000	4.348	3.153	16.443
Received	66,695	0.880	0.568	1.168	0.025	9.068	4.465	27.356
High ESG Risk	66,695	0.003	0.000	0.053	0.000	1.000	18.908	358.516
Assets	66,695	4769.387	984.243	17945.013	0.001	381182.445	10.965	153.250
L.Size	66,695	6.817	6.870	1.788	2.356	11.115	-0.070	2.751
L.Age	66,695	2.650	2.708	0.649	0.693	3.989	-0.258	3.331
L.Fixed assets	66,695	0.288	0.233	0.226	0.006	0.877	0.788	2.678
L.net PM	66,695	-0.034	0.042	0.631	-6.742	0.571	-8.583	85.241
L.Sales Growth	66,695	0.047	0.013	0.277	-0.616	1.710	2.619	16.254
L.Debt Ratio	66,695	0.252	0.235	0.187	0.000	0.953	0.849	3.979
L.LIQ	66,695	0.143	0.097	0.143	0.001	0.763	1.870	6.865
L.Market share	66,695	0.010	0.002	0.035	0.000	1.000	9.477	132.101
L.Z-score	66,695	3.370	2.644	3.721	-6.436	24.810	2.670	14.982
L.GDPpcg	66,695	2.497	1.795	3.319	-5.455	12.509	0.532	3.640
L.KOFGI	66,695	76.252	80.671	10.434	42.842	90.906	-1.000	3.482
Lagged Max RRI (3mon)	65,719	6.855	0.000	11.509	0.000	80.000	1.721	5.803

Panel C: Upstream firms

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
PCE	52,468	0.000	0.000	0.000	0.000	0.000	.	.
Net TC/sales	52,468	-0.191	-0.250	0.819	-2.597	3.335	1.304	9.667
Extended	52,468	0.860	0.689	0.753	0.000	4.348	2.589	11.162
Received	52,468	1.039	0.638	1.377	0.025	9.068	3.853	20.254
High ESG Risk	52,468	0.002	0.000	0.043	0.000	1.000	23.314	544.543
Assets	52,468	3754.119	851.406	11087.428	0.000	270754.930	9.878	150.402
L.Size	52,468	6.719	6.721	1.767	2.356	11.115	-0.048	2.762
L.Age	52,468	2.568	2.639	0.661	0.693	3.989	-0.327	3.247
L.Fixed assets	52,468	0.312	0.261	0.235	0.006	0.877	0.668	2.445
L.net PM	52,468	-0.180	0.046	1.085	-6.742	0.571	-5.136	29.809
L.Sales Growth	52,468	0.060	0.015	0.322	-0.616	1.710	2.395	12.931
L.Debt Ratio	52,468	0.245	0.223	0.193	0.000	0.953	0.977	4.246
L.LIQ	52,468	0.161	0.110	0.159	0.001	0.763	1.849	6.545
L.Market share	52,468	0.012	0.002	0.057	0.000	1.000	12.357	188.752
L.Z-score	52,468	3.331	2.413	4.230	-6.436	24.810	2.345	11.961
L.GDPpcg	52,468	2.391	1.750	3.233	-5.455	12.509	0.569	3.763
L.KOFGI	52,468	77.256	80.828	9.796	43.835	90.906	-0.995	3.356
Lagged Max RRI (3mon)	51,759	6.804	0.000	11.282	0.000	87.000	1.649	5.409

Table IA.2 - Statistics by Firms on RRI values

Number of firms and firm-year-quarter observations in RepRisk Index (RRI) intervals

RRI interval	*N* firms with **highest** observed RRI in interval	*N* of firm-year-quarter observations in interval
0–25	2,234	166,292
≥26	3,475	15,147
≥50	261	1,491
≥60	113	518
≥75	10	14

Table IA.3 - Without the Worst ESG Offenders

This table is created using data from 2007 - 2019. *High ESG Risk* signals if a firm's RepRisk Index (RRI)≥60 within a certain time-frame (3-, 6-, 9, or 12-month window). The non-High-ESG Risk firm-year-quarters have RRI values below 60, i.e., less than a very high Reputational Risk. In Panel A, we drop firms with ≥15 year-quarter observations of High ESG Risk, i.e., we remove the most "ESG-misbehaving" firms. In Panel B, we drop firms with ≥10 year-quarter observations of High ESG Risk. In Panel C, we drop firms with ≥5 year-quarter observations of High ESG Risk. The dependent variable is net trade credit received, defined as as (payables (AP) - receivables (AR)) divided by sales (El Ghoul & Zheng, 2016; Love et al., 2007; McGuinness et al., 2018). Control variables for firms, lagged one quarter, include size (natural logarithm of total assets), firm age, asset tangibility, net profit margin, sales growth, debt ratio, liquidity, market share, Z-score, real GDP per capita growth rate (GDPpcg), globalization index, and lagged maximum RRI-score. Size and age are also squared to allowed for non-linear relationships with the dependent variable (Jacobson & Von Schedvin, 2015). All continuous variables are winsorized with replacement (1,99 cuts). Fixed effects are by firm and year-quarter*industry (where industry is represented by 2-digit SIC codes. Standard errors are clustered at the firm and year-quarter (YQ) levels. The t-statistics are included in parenthesis. Superscripts ***, **, and * correspond to statistical significance at the one-, five-, and ten-percent levels, respectively. The constant's, controls', and fixed effects' coefficients are omitted.

	Net Trade Credit Received			
	Firm had High ESG Risk in last			
	(1)	(2)	(3)	(4)
	3-month	6-month	9-month	12-month
Panel A: ≤15 Year-Quarters of High ESG Risk in sample				
High ESG Risk	-0.059***	-0.053***	-0.054**	-0.047**
	(-3.52)	(-3.18)	(-2.66)	(-2.16)
Adj. R^2	0.675	0.678	0.681	0.683
N	178,068	175,372	172,619	169,700
Panel B: ≤10 Year-Quarters of High ESG Risk in sample				
High ESG Risk	-0.080***	-0.068***	-0.069***	-0.058**
	(-3.64)	(-3.26)	(-2.82)	(-2.29)
Adj. R^2	0.675	0.678	0.680	0.682
N	177,619	174,930	172,184	169,274
Panel C: ≤5 Year-Quarters of High ESG Risk in sample				
High ESG Risk	-0.047**	-0.042**	-0.038**	-0.028
	(-2.36)	(-2.44)	(-2.14)	(-1.49)
Adj. R^2	0.675	0.677	0.680	0.682
N	176,973	174,291	171,552	168,651
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
YQ*Industry FE	Yes	Yes	Yes	Yes
Firm & YQ Clustering	Yes	Yes	Yes	Yes