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How does mandated sustainability disclosure about conflict minerals affect supply chain finance?☆

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ABSTRACT

We use the 2010 Dodd-Frank Act, which mandated that firms disclose the use of conflict minerals in their supply chain, to investigate whether and how conflict minerals disclosure (CMD) impacts the trade credit that a firm receives from its suppliers. Using a large sample of U.S. firms from 2014 to 2016, we find that firms that provide more-specific, rather than less-specific, CMD receive 6.45% more trade credit. This finding is consistent with more-specific CMD enhancing firms' supply chain visibility, as well as reducing suppliers' adverse selection concerns about lending to socially irresponsible firms. Consistent with the enhanced supply chain visibility channel, we find that the positive association is more pronounced for firms with more product market competition or financial constraints. In keeping with the reduced adverse selection channel, we find a more pronounced positive association for firms with weaker monitoring by non-supplier stakeholders. Finally, we find that firms with more-specific CMD provide less downstream trade credit, suggesting that the reputational benefit gained from disclosing socially responsible sourcing enables these firms to rely less on trade credit to attract or capture customers. Overall, our paper offers novel insight into how mandated sustainability disclosures, specifically CMD, affect supply chain finance.

1. Introduction

Sustainability is a defining issue for our time. Yet, despite the significant attention paid to mandating sustainability disclosure, the literature on the issue is scarce. We fill this gap by studying firms' disclosure of socially responsible sourcing, which describes their procurement activities and their adherence to corporate social responsibility principles (Maignan et al., 2002). We focus on the mandatory disclosure of "conflict minerals," which refers to tantalum, tin, tungsten, gold, and their derivatives (3TGs), including their use and sources. Specifically, we study the conflict minerals disclosure (CMD) mandated by Section 1502 of the 2010 Dodd-Frank Wall

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Street Reform and Consumer Protection Act. We examine how CMD, as a type of sustainability disclosure related to the supply chain, affects supply chain finance. The results reveal wider implications of this mandated disclosure beyond that of promoting firms' sustainability behaviors.

The 2010 Dodd-Frank Act addresses the humanitarian crisis in the Democratic Republic of the Congo (DRC) and adjoining countries (i.e., Covered Countries) via a "naming and shaming" approach aimed at curbing funding to armed groups in the area. Because the 3TGs are intrinsically tied to the humanitarian crisis in this area, the act defines these minerals as conflict minerals (Woody, 2012). By requiring firms to provide CMD, Congress intends to "bring greater public awareness of the source of issuers' conflict minerals and promote the exercise of due diligence on conflict mineral supply chains … thereby inhibiting the ability of armed groups … to fund their activities by exploiting the trade in conflict minerals … and [pressuring] such groups to end the conflict" (SEC, 2012). To comply with this mandate, firms must investigate their production processes and upstream supply chains to determine whether their sourcing practices are socially responsible (Woody, 2012; KPMG, 2014).

We hypothesize two channels through which the specificity of a firm's CMD is positively associated with the trade credit it receives from its suppliers. First, for a firm to provide more-specific CMD, it must extensively investigate its production processes and supply chains. This process enhances the firm's supply chain visibility (e.g., Barratt and Oke, 2007; Francis, 2008; Yu and Goh, 2014). High supply chain visibility can enhance a firm's operational capabilities and creditworthiness (Swift et al., 2019).[1] Suppliers should then be more willing to provide the firm with trade credit. We label this first channel the enhanced supply chain visibility channel. Second, more-specific CMD signals that the firm cares enough about the social issue of conflict minerals to investigate its supply network. This signal matters to suppliers that take a firm's social responsibility into account when providing trade credit (Xu et al., 2020; Zhang et al., 2020; Wei et al., 2023). We label this second channel the reduced adverse selection channel.[2] Although we cannot disentangle the separate effects of these channels, we hypothesize that both serve as mechanisms through which suppliers are more likely to offer trade credit.

To test our hypothesis, we focus on a large sample of U.S. firms that file Conflict Minerals Reports with the SEC. For these filings, we follow Swift et al. (2019) and create an indicator variable to differentiate between firms with relatively more- or less-specific CMD.[3] We define more-specific CMD as CMD that includes a Conflict Minerals Reports that lists the smelters or refineries that produce the conflict minerals used in the firm's products. Conceptually, the measure captures the visibility of a firm's supply chain, the firm's knowledge about its supply chain partners, and its willingness to provide detailed reporting.[4] Using this measure, we find that firms with more-specific CMD obtain more trade credit from their suppliers. In terms of economic significance, we find that more-specific CMD generates 6.45 %, or about $43 million, more in trade credit for those firms. This finding is robust to a large array of tests that address measurement and endogeneity issues.

Next, we conduct several cross-sectional analyses to understand the channels through which CMD can affect trade credit. We first focus on the enhanced supply chain visibility channel. We expect a firm's CMD to have a stronger impact on its trade credit if the firm has more product market competition because the enhanced operational efficiencies that come with greater supply chain visibility are more important for firms in competitive product markets. To measure competition, we use Hoberg and Phillips' (2016) measure of a firm's product similarity with those of its peers, the Herfindahl-Hirschman Index, and operating cash flow volatility. We find that the positive effect of CMD on trade credit is more pronounced for firms in more competitive markets. We also conduct a cross-sectional analysis based on firms' financial constraints to corroborate the enhanced supply chain visibility channel. For financially constrained firms, operational efficiency due to supply chain visibility (and other factors) is important for generating the cash flows needed to pay creditors, including trade creditors. To measure financial constraints, we use Hadlock and Pierce's (2010) and Whited and Wu's (2006) indices of a firm's financial constraints and the availability of its credit rating. Consistent with our expectation, the evidence shows that the positive relation between more-specific CMD and trade credit is more salient for firms with more financial constraints.

We then present evidence in support of the reduced adverse selection channel, our second channel that links a firm's CMD to its trade credit. We expect adverse selection to be more of a concern for suppliers when external monitoring by non-supplier stakeholders is weak. Using institutional ownership, analyst coverage, and media coverage to measure external monitoring, we find that the association between CMD and trade credit is only pronounced for firms with weak external monitoring. The results are consistent with the reduced adverse selection channel.

We also explore the relation between a firm's CMD and the trade credit it gives to its customers. We document that firms with more-specific CMD obtain more trade credit from their suppliers, though it is unclear whether the firms pass this credit on to their customers. In addition, to the extent that more-specific CMD offers reputational benefits, such benefits also may reduce the firm's reliance on trade credit to attract customers. Consistent with this view, we find that firms with more-specific CMD provide less trade credit to their own

[1] Supply chain visibility refers to the collection and processing of data to track every tier of the supply chain. Increasing the data that is readily available to a firm for managing its supply chain improves and strengthens the chain and gives the firm an important competitive advantage.

[2] Section 2.2 details the hypothesis about the link between CMD and trade credit, as well as related hypotheses.

[3] Swift et al. (2019) use the variable to capture a firm's supply chain visibility; they argue that more-specific CMD indicates higher supply chain visibility. We use the same variable to capture the specificity of a firm's CMD. As we discuss later, CMD specificity can generate two effects: enhanced supply chain visibility for the firm and reduced adverse selection for the firm's suppliers.

[4] Consistent with the notion that firms can benefit from deeper knowledge about their supply chain, Swift et al. (2019) show that this measure is positively associated with product market performance and with stock market valuations. In Section 3.1, we offer more detail about how we construct the CMD measure.

customers.

Finally, we conduct supplementary analyses to directly validate the enhanced supply chain visibility channel, through which a firm's CMD improves its suppliers' perceptions of its operational capabilities and thus its creditworthiness. Specifically, we examine the effect of CMD on a firm's cost stickiness and operational efficiency. We find that firms with more-specific CMD have a lower cost stickiness and a higher operating efficiency. This finding suggests that CMD enhances a firm's supply chain visibility, which improves suppliers' perceptions of the firm's creditworthiness. Hence, CMD has real positive effects on the firm's operations. We also document evidence validating the reduced adverse selection channel by showing that more-specific CMD is linked to rating agencies' positive perceptions of the firm's socially responsible sourcing and corporate social responsibility.

Our study contributes to the literature in several ways. First, we extend the literature on the economic consequences of mandated supply-chain-related sustainability disclosure. Rely on mandated CMD, Swift et al. (2019) find that firms with greater supply chain visibility have a higher profitability and a better sales performance, compared to those with lower supply chain visibility. Baik et al. (2021) show that CMD mandates encourage responsible sourcing due to greater public attention, positive market reactions, and positive changes in socially responsible investor holdings, consistent with the reputational cost hypothesis. Exploiting a disclosure regulation in California, which mandates that firms disclose how they conduct due diligence to address their suppliers' human rights abuses, She (2022) finds that the treated firms increase their supply chain due diligence and that their suppliers' human rights performance improves in the wake of the regulation. Our paper complements and contrasts with this literature by studying how mandated CMD affects supply chain finance. Our paper thus responds to Christensen et al.'s (2021) call for more research into mandated sustainability reporting. In doing so, we introduce supply chain visibility as a novel channel linking CMD to trade credit from suppliers. Kim and Davis (2016) note that because the CMD mandate applies to all domestic and foreign corporations listed on U.S. stock markets, it offers a unique opportunity to examine supply chain visibility in a systematic way using a large population of firms. To the extent that more specific CMD proxies for greater supply chain visibility as argued by Swift et al. (2019), one inference from our study is that greater supply chain visibility helps improve the firm's liquidity by increasing the trade credit supply from suppliers (and reducing trade credit supply to customers).[5]

Second, we also extend the recent literature on the role of disclosure in trade credit (Chen et al., 2017; Li et al., 2021). For example, using a sample of U.S. firms and an accruals-based measure of accounting quality, Chen et al. (2017) find that firms' receipt of trade credit decreases with their accounting quality. They argue that this finding is consistent with low-accounting-quality firms' greater difficulty in obtaining traditional financing and suppliers' use of their information advantage to step and offer trade credit. We extend Chen et al. (2017) by studying another type of disclosure, that of socially responsible sourcing. After controlling for accounting quality, we find that firms with more-specific CMD receive more trade credit.[6] If higher accounting quality and more-specific CMD indicate better disclosure, the contrasting associations with trade credit are interesting. We posit two possible explanations for these contrasts. First, the disclosures differ in important ways. CMD reveals supply chain issues that are likely to be of interest to suppliers, whereas the firms' accounting numbers reveal their financial performance, which is likely to be of interest to traditional capital providers. Second, CMD has an additional real effect that is relevant to trade credit: improved supply chain visibility due to the investigative processes needed to produce the reports. Our evidence shows that more-specific CMD can improve a firm's supply chain finance by increasing its trade credit from suppliers and reducing the trade credit to its customers. This outcome is interesting because the trade credit literature commonly argues that when a firm receives more trade credit, it also provides more trade credit (e.g., Petersen and Rajan, 1997).

Finally, we further the extensive literature on corporate social responsibility (CSR). Specifically, our study relates to research on the link between CSR and trade credit financing from suppliers (e.g., Xu et al., 2020; Zhang et al., 2020; Wei et al., 2023). This research generally finds that higher CSR ratings, obtained from various CSR rating agencies, is associated with more trade credit. This finding aligns with arguments that suppliers provide more trade credit to firms with higher CSR ratings because the firms likely pay their suppliers, have a reputation that attracts more business, and face less risk in their supply chain. Our paper complements and contrasts with this research by focusing on the firm's internally created CMD, rather than an externally created CSR agency rating. Our study emphasizes that when firms are required to prepare CMD, their supply chain visibility can be enhanced. Our study also has practical implications. It highlights that as firms improve their supply-chain-related CSR disclosure, they benefit from enhanced supply chain finance, especially if the firm has more product market competition or financial constraints, or weak monitoring by non-supplier stakeholders.

2. Background and hypothesis development

2.1. Mandated CMD

To promote socially responsible sourcing, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 mandates the disclosure of 3TGs sourced from Covered Countries. Section 1502 of the Dodd-Frank Act adds Section 13(p) to the Securities Exchange Act of 1934, which directs the SEC to enforce the disclosure rules on registrants' use of 3TGs (e.g., Kim and Davis, 2016; Swift et al., 2019). Congress enacted Section 1502 out of concern that the exploitation and trade of these minerals could intensify conflict and

[5] Due to the supply chain visibility channel's novelty in the disclosure literature, a large part of our empirical analyses focuses on this channel. For example, we show that a firm's CMD affects its operations in terms of reducing cost stickiness and enhancing operational efficiency, consistent with such disclosure enhancing supply chain visibility.

[6] We find that within our sample, a firm's accounting quality is negatively associated with its trade credit.

contribute to humanitarian crises in the Covered Countries. The regulation encourages firms to source responsibly by not funding armed groups or human rights abusers. The SEC's rule on CMD was finalized in 2012, with the first filing due on May 31, 2014, for the reporting period of January 1 to December 31, 2013.[7]

The SEC's final rule specifies that companies must publicly report their use of conflict minerals via the annual filing of a "Specialized Disclosure Report" (Form SD). This rule applies to all listed companies that use any conflict minerals "necessary to the functionality or production" of a product the company produces or orders. To determine this necessity, companies must conduct extensive investigations of their production processes. If they identify conflict minerals in their production processes, they must conduct a reasonable country of origin inquiry, described on Form SD. If the mineral originates from a Covered Country, the company must undertake due diligence to identify the source and chain of custody. For minerals that cannot be verified for firms that do not originate from a Covered Country, companies must file a Conflict Minerals Report as an exhibit of Form SD. Companies also must post all of these disclosures on their website. See Appendix A for a flowchart of the SEC's rules for CMD.

Since 2014, between 1,100 and 1,400 firms have filed annual forms with the SEC that describe their due diligence in locating the sources of the minerals they use in their products (Woody, 2019). In April 2017, however, the SEC suspended enforcement of this due diligence requirement in response to a decision by the U. S. Court of Appeals for the District of Columbia. This decision found that the SEC's CMD requirements violated the First Amendment by creating unconstitutionally compelled commercial speech. According to the final rule, companies are no longer required to conduct due diligence on the source of and the chain of custody for conflict minerals. Nevertheless, they still need to file Form SD and conduct a reasonable country of origin inquiry.

2.2. Hypothesis development

2.2.1. The relation between CMD and trade credit

In this paper, we propose that a firm with more-specific CMD can obtain more trade credit from its suppliers. First, more-specific CMD indicates the firm conducts extensive investigations into its production processes, which in turn enhances its upstream supply chain visibility. Second, more-specific CMD reduces suppliers' adverse selection concerns about the potential negative consequences of lending to a socially irresponsible firm. We elaborate on these two channels below.

First, by encouraging a firm to extensively investigate its production processes, CMD can enhance the firm's supply chain visibility. The academic literature on supply chains has long recognized the importance of understanding the flow of supply chain materials, financing, and information (Lee and Billington, 1993; Chen, 1999; Patnayakuni et al., 2006). Firms that achieve higher supply chain visibility gain a better understanding of their sourcing operations. They are better equipped to evaluate and negotiate with existing suppliers, identify and switch to more cost-efficient suppliers, and streamline their sourcing practices. In addition, firms with improved knowledge of their upstream operations can better meet supply chain challenges (e.g., inventory management). From the perspective that corporate disclosure can have real effects of corporate actions (Kanodia and Sapra, 2016; Leuz and Wysocki, 2016), the mandate to report supply sourcing might have the "real effect" of inducing firms to enhance their upstream supply chain visibility. For example, Bayer (2014) documents that in response to the CMD mandate, many firms implement or modify information technology systems to support sourcing traceability. Enhanced supply chain visibility also enables a firm to obtain more trade credit from its suppliers. Recent research on the intersection between operations and finance suggests a growing interest in trade credit's role in enhancing supply chain efficiency (Birge, 2015; Lee et al., 2018; Wu et al., 2020). Through trade credit, customers leverage their business to capture growth opportunities and maximize profits. Trade credit also provides customers with a risk-sharing mechanism (Jacobson and Von Schedvin, 2015; Yang and Birge, 2018), ensuring that members in a supply network work towards a common goal.

Second, we consider the role of CMD in reducing trade creditors' adverse selection concerns about lending to a potentially socially irresponsible firm. Such lending can cause product market problems (e.g., a loss of customers) and regulatory sanctions, which in turn can adversely affect the firm's ability to pay its creditors. CMD helps to reduce information asymmetry between the firm and its trade creditors with regard to the firm's sourcing, which in turn reduces adverse selection concerns. Prior literature highlights that firms are likely to have less information asymmetry with their trade creditors relative to other types of creditors because of the knowledge gained through supply chain interactions (Petersen and Rajan, 1997). Despite suppliers' information advantage, we argue that more-specific CMD will nevertheless be useful to a supplier's decision to provide trade credit because the supplier is unlikely to be fully aware of the firm's purchases from other suppliers. Hence, more-specific CMD can reassure the supplier about the firm's procurement integrity, which ameliorates adverse selection concerns. We therefore posit that firms with more-specific CMD are likely to receive more trade credit from their suppliers.

In sum, the two channels through which the specificity of CMD can affect trade credit are enhanced supply chain visibility and reduced adverse selection concerns. Fig. 1 illustrates these two channels. Though we cannot disentangle the separate effects, we posit that both channels increase the likelihood that a supplier will lend trade credit. We state our primary hypothesis as follows:

H1: Firms with more-specific CMD receive more trade credit from their suppliers.

2.2.2. The moderating effect of product market competition

Our first cross-sectional analysis of the relation between CMD and trade credit focuses on the enhanced supply chain visibility channel. In our central hypothesis, we argue that CMD enhances firms' supply chain visibility. Product demand uncertainty can affect

[7] The reporting year for a conflict minerals report is always January 1 to December 31.

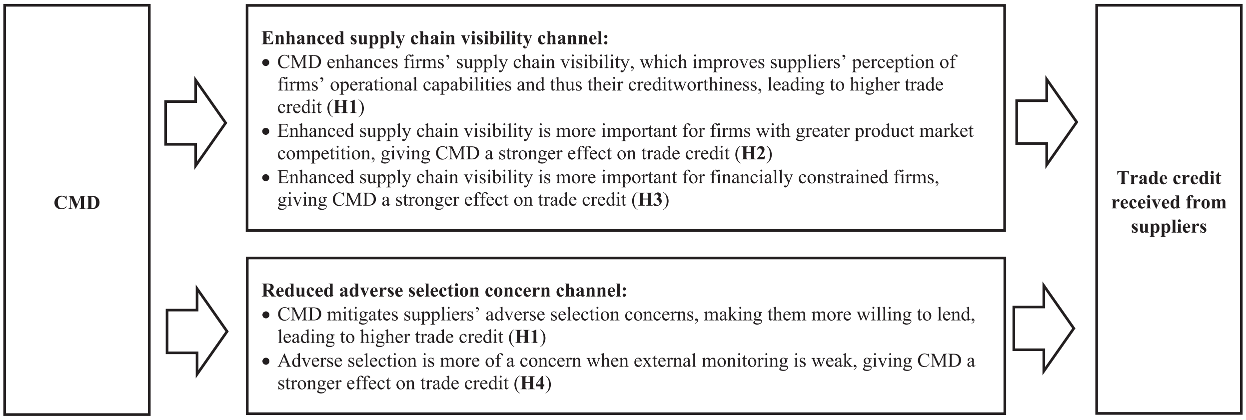


Fig. 1. Summary of channels linking a firm's CMD with the trade credit it receives from suppliers. This figure summarizes our hypotheses development in Section 2.2. In H1, we propose two channels, both of which lead to the same prediction: firm's CMD is positively associated with the trade credit received from suppliers. Under the supply chain visibility channel, we argue that CMD enhances firms' supply chain visibility, which can enhance their operational capabilities and thus their creditworthiness. Under the adverse selection concern channel, we argue that CMD can mitigate suppliers' adverse selection concerns, making them more willing to lend. To substantiate the supply chain visibility channel, we propose two cross-sectional hypotheses, H2 and H3. In H2, we predict that the positive relation between CMD and trade credit is more pronounced for firms with greater product market competition. In H3, we predict that the positive relation between CMD and trade credit is more pronounced for more financially constrained firms. To shed light on the adverse selection concern channel, we propose a cross-sectional hypothesis (H4) in which we predict that the positive relation between CMD and trade credit is more pronounced for firms with weaker external monitoring.

the need for supply chain visibility: as uncertainty increases, firms need more timely information from their upstream suppliers (Caridi et al., 2010). An important source of uncertainty is product market competition. When such competition is greater and particularly when competitors' products are more similar, firms need upstream supply chain information to compete effectively. Cost management also is more important as competition constrains firms' ability to raise prices to cover their higher costs. To the extent that information about the upstream supply chain is more important in more competitive markets and supply chain visibility helps to mitigate this concern, we expect the relation between a firm's CMD and its trade credit to be stronger if the firm has more competition. Hence, we state our next hypothesis as follows:

H2: The positive association between a firm's CMD and its trade credit is more pronounced for firms with greater product market competition.

2.2.3. The moderating effect of firms' financial constraints

We argue that the effect of CMD on trade credit is likely to be more significant for firms with greater financial constraints, such as liquidity needs, for which trade credit is a critical resource. Research suggests that a firm's reliance on trade credit is greater when it has difficulty obtaining other forms of credit. Specifically, prior literature highlights a substitution effect between trade credit and bank credit (e.g., Huang et al., 2011; Carbo-Valverde et al., 2016; Levine et al., 2018). For example, Petersen and Rajan (1997) document that small firms use more trade credit, in part because they have limited access to capital markets and financial institutions.

We posit that a firm's CMD affects how trade creditors evaluate its creditworthiness. For a financially constrained firm, operational efficiency helps to generate the cash flows it needs to pay off creditors, including trade creditors; it also reduces cost stickiness, which is the firm's ability to cut costs during product market difficulties (Anderson et al., 2003). Reduced cost stickiness helps the firm conserve cash outflows related to operating expenses, which enhances its creditworthiness. Assuming that greater supply chain visibility helps the firm achieve greater operational efficiency, it is likely to matter more in suppliers' decisions about providing trade credit to financially constrained firms, relative to non-financially constrained ones. Hence, to the extent that a firm's CMD enhances its supply chain visibility, such disclosure is likely to make trade creditors more comfortable about lending to financially constrained firms. Hence, our next hypothesis is as follows:

H3: The positive association between a firm's CMD and its trade credit is more pronounced if the firm has greater financial constraints.

2.2.4. The moderating effect of external monitoring

When external monitoring of a firm is weaker, trade creditors have adverse selection concerns related to the potential revelation that the firm engages in socially irresponsible sourcing. Prior literature documents that institutional investors, the media, and analysts play an important external monitoring role in promoting firms' socially responsible behavior (Jo and Harjoto, 2014; Dyck et al., 2019; El Ghoul et al., 2019). Hence, we posit that more monitoring by external entities diminishes the importance of CMD in reducing suppliers' adverse selection concerns, which leads us to our next hypothesis:

H4: The positive association between a firm's CMD and its trade credit is more pronounced for firms subject to weaker external monitoring.

2.2.5. The relation between CMD and downstream supply chain finance

Our analyses so far focus on the effect of CMD on upstream supply chain finance. Because we argue that a firm's CMD is positively related to the trade credit it receives from suppliers, a question arises about whether firms that obtain more supplier trade credit in turn offer more credit to their customers. This question leads us to explore the relation between CMD and downstream supply chain finance. Firms that are more able to obtain credit may have a higher capacity to offer trade credit to their own customers (e.g., Petersen and Rajan, 1997). However, prior literature also documents that suppliers use trade credit as an important strategic or competitive tool to promote sales (e.g., Wilson and Summers, 2002; Fabbri and Klapper, 2016; Lee et al., 2018). To the extent that a firm's more-specific CMD enhances its upstream supply chain visibility, which consequently increases its cost advantage, efficiency, and competitive power over the downstream supply chain, the firm may rely less on trade credit to attract or capture customers. Hence, our final hypothesis is as follows:

H5: Firms with more-specific CMD provide less trade credit to their customers.

3. Research design

3.1. Measures of CMD

We use the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 to construct our CMD measure. As described in Section 2.1, the SEC requires listed companies that use 3TGs in their products to file Form SD annually; the first reports were due May 31, 2014, for the January 1 to December 31, 2013 reporting period. The act requires companies to disclose how they exercise due diligence in sourcing conflict minerals. If companies cannot ensure that the minerals they use are not sourced from Covered Countries, they must submit a Conflict Minerals Report as an exhibit of Form SD. Although this disclosure is mandatory, managers have discretion over the details in the report.

To construct our CMD measure, we first download all the Forms SD filed with the SEC for the reporting years 2014–2016.[8] Given that we find substantial smelter and refinery information only for firms that file Form SD with a Conflict Minerals Report as an exhibit, we restrict our sample to those firms. In other words, our sample covers U.S. listed firms using conflict minerals that may be sourced from a Covered Country (see the flowchart in Appendix A). We then read each firm's Conflict Minerals Report and manually classify the firm as having less- or more-specific CMD.

Specifically, we follow Swift et al. (2019) and create an indicator variable, *CMD*, that equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, and 0 otherwise. For this measure, we rely on the firm's reporting of smelters or refineries' information about the origin of the materials used in their products. To determine a material's origin, firms need to trace it through several tiers of upstream suppliers. Because smelters and refineries are the initial suppliers of 3TGs, if a firm discloses these details, we regard it as providing more-specific CMD. In Appendix B, we illustrate how we construct *CMD* by providing examples of Conflict Minerals Reports.[9]

In addition, we follow Swift et al. (2019) in developing a composite measure. We categorize Conflict Minerals Report into four levels by decomposing the more-specific reports (i.e., $CMD = 1$) as follows[10]:

Level 1: Form SD does not include any substantial smelter or refinery information ($CMD = 0$).
Level 2: Form SD includes a number or list of known smelters or refineries.
Level 3: Form SD includes a detailed list and the conflict-free audit status of known smelters or refineries.
Level 4: Form SD includes a detailed list and the conflict-free audit status of known smelters or refineries, plus the minerals' countries of origin.

We respectively create three indicator variables (*CMD_LEVEL2*, *CMD_LEVEL3*, and *CMD_LEVEL4*) for levels 2, 3, and 4.[11]

3.2. Measure of trade credit

Trade credit is a type of financing provided by suppliers that enables firms to purchase goods from suppliers while deferring payment to a later scheduled date. We measure the trade credit that a firm receives from its suppliers using the balance of accounts payable in the firm's balance sheet. Trade credit from suppliers is closely tied to inventory purchases that are part of the cost of goods sold. Hence, when constructing our measure of trade credit, *TCR*, we follow the literature and scale accounts payable by the cost of goods sold to account for differences in the scale of purchases across different firms (e.g., Love et al., 2007; Shenoy and Williams, 2017;

[8] We end our sample period in 2016 for two reasons. First, as we discuss in Section 2, in 2017, the new guidance softened the SEC's enforcement of more detailed disclosure. In addition, as we discuss in subsequent paragraphs, the construction of our CMD measures involves manually collecting data from Conflict Minerals Reports, which take significant effort for firms to compile.

[9] In an earlier version of the paper, we constructed *CMD* using purchased data for reporting years 2014–2016 from Development International, a non-profit, non-political organization. The data enabled us to construct *CMD*, but not the other CMD measures we use. In the current version, we collect data directly from the Conflict Minerals Reports. Doing so allows us to show the robustness of our results to more composite CMD measures. We use the data from Development International to ensure data integrity in our data collection.

[10] Swift et al. (2019) use this composite measure in a robustness check of their main finding.

[11] When we add all three indicator variables to a regression model, firms with level 1 CMD serve as the benchmark group.

Levine et al., 2018; Chen et al., 2019; Shang, 2020; Li et al., 2021). *TCR* is essentially the commonly used accounts payable turnover ratio used in financial statement analysis; it captures both the extent to which a firm uses trade credit and the maturity of that trade credit.

3.3. Baseline sample and regression model

We combine our firm-year measure of CMD with firms' trade credit and other control variables from various sources. We extract firms' financial data from the Compustat annual file. We obtain management earnings forecasts from the I/B/E/S Guidance database. After dropping observations that are missing the necessary variables for the regression analyses in Eq. (1), we obtain a final sample of 2,639 firm-year observations for the conflict minerals reporting years 2014–2016.

Table 1 presents the sample distribution by industry. In our sample, three industries have the largest number of firms providing CMD; these account for more than 50 % of the total sample: Electronic & Other Electric Equipment, Instruments & Related Products, and Industrial Machinery & Equipment. These statistics align with Kim and Davis (2016) and Swift et al. (2019).[12] They also are consistent with the fact that 3TGs are widely used by firms in these industries (Kim and Davis, 2017).

We then use the following ordinary least squares (OLS) model to examine the association between CMD and the trade credit offered by suppliers.

$$\begin{aligned} TCR = {} & \beta_0 + \beta_1 CMD + \beta_2 SIZE + \beta_3 AGE + \beta_4 MKSH + \beta_5 SGRWPOS + \beta_6 SGRWNEG + \\ & \beta_7 ROA + \beta_8 MB + \beta_9 LEV + \beta_{10} CL + \beta_{11} CASH + \beta_{12} CA + \beta_{13} TANGI + \beta_{14} RATING + \\ & \beta_{15} BIG4 + \beta_{16} FRQ + \beta_{17} MEF + Industryfixedeffects + Yearfixedeffects + \varepsilon. \end{aligned} \tag{1}$$

The dependent variable is the trade credit that a firm receives from suppliers (*TCR*), measured as the balance of accounts payable divided by the annual cost of goods sold. The variable of interest is an indicator of more-specific CMD (*CMD*). Specifically, for firms required to file Form SD with a Conflict Minerals Report as an exhibit (i.e., firms that cannot rule out whether their conflict minerals are from the Covered Countries), *CMD* equals 1 if the firm's Conflict Minerals Report includes a list of smelters or refineries, and 0 otherwise. Eq. (1) is a lead-lag specification: trade credit, as the dependent variable, is measured at year $t + 1$, and all independent variables are taken at year t. We rely on Eq. (1) to test how current-year *CMD* is associated with the trade credit obtained in the subsequent year. A significantly positive coefficient on *CMD* (i.e., β_1) would support our prediction that a firm's more-specific CMD is positively related to its trade credit.

Following prior literature (e.g., Molina and Preve, 2012; Chen et al., 2017; Li et al., 2021), we control for a series of firm characteristics: firm size (*SIZE*), firm age (*AGE*), the market share of sales (*MKSH*), the positive and negative growth rates for sales (*SGRWPOS* and *SGRWNEG*, respectively), the return on assets (*ROA*), the market-to-book ratio (*MB*), financial leverage (*LEV*), current liabilities excluding accounts payable (*CL*), current assets (*CA*), cash and short-term investments (*CASH*), asset tangibility (*TANGI*), and an indicator of the S&P credit rating (*RATING*). To isolate the effect of CMD, we control for financial disclosures, including a Big 4 auditor (*BIG4*), financial reporting quality (*FRQ*), and management earnings forecasts (*MEF*). In addition, the model includes industry and year fixed effects. See Appendix C for the variable definitions. To evaluate the statistical significance of the coefficients on the independent variables, we use heteroskedasticity-robust standard errors.

Table 2 presents the descriptive statistics for the regression variables. Panel A shows the mean, standard deviation, 25th percentile, median, and 75th percentile of each regression variable. In our sample, the average trade credit received from suppliers is 15.5 % of the annual cost of goods sold, and 65.1 % of firm-year observations have more-specific CMD ($CMD = 1$). In Panel B, we split our sample into two subsamples, one with less-specific CMD ($CMD = 0$) and the other with more-specific CMD ($CMD = 1$). We compare regression variables' mean values for each subsample. This comparison lends initial support to our hypothesis because it shows that firms with more-specific CMD receive more trade credit from their suppliers. We also observe that firms with more-specific CMD tend to be larger, older, and more profitable. Panel C presents the Pearson correlations (below the diagonal) and the Spearman correlations (above the diagonal) for each pair of variables. The Pearson (Spearman) correlation coefficient between *TCR* and *CMD* is 0.083 (0.122), which is statistically significant at the 1 % level. These significantly positive correlations provide initial evidence of a positive relation between a firm's CMD and the trade credit it receives from suppliers.

4. Results

4.1. Baseline results for the association between a firm's CMD and its trade credit (H1)

Our central hypothesis argues that because CMD can enhance a firm's supply chain visibility and reduce suppliers' adverse selection concerns, such disclosure enhances suppliers' perceptions of the firm's creditworthiness. This creditworthiness should in turn lead to more trade credit from suppliers. We thus predict a positive association between a firm's CMD and the trade credit received from its suppliers.

Table 3 presents the results from testing H1. Column (1) presents the results for a model with no fixed effects; in columns (2) and (3), we respectively add industry and year fixed effects. In column (4), we run our baseline model with both year and industry fixed

[12] See Fig. 1 in Kim and Davis (2016) and Table 1 in Swift et al. (2019).

Table 1
Sample distribution by industry.

SIC code	Industry description	*N*	% of observations	% of firms with more-specific CMD (*CMD* = 1)
36	Electronic & Other Electric Equipment	593	22.47 %	70.83 %
38	Instruments & Related Products	418	15.84 %	60.53 %
35	Industrial Machinery & Equipment	387	14.66 %	68.73 %
37	Transportation Equipment	195	7.39 %	67.18 %
28	Chemical & Allied Products	159	6.03 %	66.67 %
73	Business Services	149	5.65 %	64.43 %
34	Fabricated Metal Products	68	2.58 %	48.53 %
50	Wholesale Trade – Durable Goods	65	2.46 %	60.00 %
56	Apparel & Accessory Stores	48	1.82 %	56.25 %
23	Apparel & Other Textile Products	44	1.67 %	75.00 %
48	Communications	42	1.59 %	50.00 %
13	Oil & Gas Extraction	40	1.52 %	60.00 %
25	Furniture & Fixtures	37	1.40 %	64.86 %
59	Miscellaneous Retail	33	1.25 %	81.82 %
39	Miscellaneous Manufacturing Industries	31	1.17 %	48.39 %
30	Rubber & Miscellaneous Plastics Products	30	1.14 %	60.00 %
33	Primary Metal Industries	29	1.10 %	51.72 %
53	General Merchandise Stores	24	0.91 %	75.00 %
26	Paper & Allied Products	23	0.87 %	65.22 %
87	Engineering & Management Services	18	0.68 %	44.44 %
49	Electric, Gas, & Sanitary Services	17	0.64 %	58.82 %
27	Printing & Publishing	16	0.61 %	56.25 %
24	Lumber & Wood Products	14	0.53 %	42.86 %
57	Furniture & Homefurnishings Stores	12	0.45 %	83.33 %
51	Wholesale Trade – Nondurable Goods	11	0.42 %	54.55 %
80	Health Services	10	0.38 %	40.00 %
NA	Other miscellaneous industries, each with $N < 10$	126	4.77 %	67.46 %

This table presents the sample distribution by industry, as defined by the 2-digit SIC code.

effects, as specified in Eq. (1). Across the four columns, the coefficients on *CMD* are positive and significant at the 1 % level, indicating that our inference is unaffected by year or industry fixed effects. Focusing on our baseline results in column (4), we find that the coefficient on *CMD* is 0.010, with a *t*-value of 2.75. Given that the sample mean of trade credit (*TCR*) is 0.155, as shown in Table 2, the magnitude of the coefficient on *CMD* is economically significant: compared to firms with less-specific CMD, firms with more-specific CMD receive 6.45 % (= 0.010/0.155) more trade credit. Note that we define trade credit (*TCR*) as a firm's accounts payable scaled by the cost of goods sold. Given that the mean value of the cost of goods sold in our sample is around \$4.3 billion, the positive coefficient on *CMD* (= 0.010) translates to an increase of \$43 million (=0.010×\$4.3 billion) in the average firm's accounts payable.[13]

The regression results for the control variables are largely consistent with prior literature. For example, our results show that larger firms and those with higher positive sales growth obtain more trade credit, which is consistent with Molina and Preve (2012) and Li et al. (2021). The return on assets is negatively associated with trade credit, and the level of current assets and that of current liabilities and the dummy for credit rating are positively associated with trade credit. These results are consistent with Chen et al. (2017).

In columns (5)–(8), we replicate columns (1)–(4) but replace *CMD* with *CMD_LEVEL2*, *CMD_LEVEL3*, and *CMD_LEVEL4*, respectively, using level 1 CMD as the benchmark group. We find that the coefficients on *CMD_LEVEL2*, *CMD_LEVEL3*, and *CMD_LEVEL4* are all positive and significant, indicating that firms with more-specific CMD (i.e., *CMD* = 1) at all three levels (i.e., levels 2, 3, and 4) exhibit significant differences in their performance relative to level 1 CMD (i.e., *CMD* = 0). In untabulated analyses of the differences between the coefficients on *CMD_LEVEL2*, *CMD_LEVEL3*, and *CMD_LEVEL4*, we find that the differences are not statistically different, that is, there is no difference in trade credit for firms with CMD at levels 2, 3, or 4. As a result, our subsequent analyses follow Swift et al. (2019), who also find no difference in their outcome variable for levels 2–4, by using *CMD* as our primary independent variable.[14]

4.2. Addressing endogeneity concerns

Although our baseline results suggest a strong positive relationship between CMD and trade credit, we are cautious about using them to draw causal inferences. We conduct a variety of robustness tests, including those addressing omitted variable bias. First, we test whether our main results are robust to alternative measures of CMD and trade credit. Specifically, we adopt two alternative measures of CMD. For the first, *CMD_LEVEL* equals 0 for level 1 disclosure and 1, 2, and 3, respectively, for disclosure at levels 2, 3, and

[13] In our final sample, the mean (median) of the annual cost of goods sold is \$4.3 (0.7) billion and the mean (median) of accounts payable is \$715 (88) million.

[14] We also check for multicollinearity in the regressions in Table 3. In Table 2, Panel B, some of the Pearson correlations for which *SIZE* is one of the variables exceed 0.5, which raises multicollinearity concerns. In untabulated analyses, we check the variation inflation factors (VIFs) of the independent variables in the eight regressions in Table 3. *SIZE* has the highest VIF, ranging from 3.55 to 4.36. Because no independent variable has a VIF above 5, we conclude that multicollinearity is not a significant concern.

Table 2
Descriptive statistics for the regression variables.

Panel A: Summary statistics ($N = 2,639$)

	Mean	SD	P25	Median	P75
TCR	0.155	0.087	0.100	0.138	0.186
CMD	0.651	0.477	0.000	1.000	1.000
SIZE	7.168	2.149	5.758	7.316	8.615
AGE	3.240	0.624	2.890	3.219	3.761
MKSH	0.016	0.041	0.000	0.002	0.011
SGRWPOS	0.091	0.174	0.000	0.024	0.106
SGRWNEG	−0.045	0.094	−0.050	0.000	0.000
ROA	0.056	0.143	0.023	0.077	0.125
MB	3.252	5.493	1.420	2.369	3.902
LEV	0.221	0.190	0.049	0.201	0.334
CL	0.144	0.088	0.083	0.124	0.180
CASH	0.188	0.165	0.061	0.142	0.265
CA	0.327	0.155	0.213	0.307	0.421
TANGI	0.184	0.151	0.075	0.135	0.242
RATING	0.403	0.491	0.000	0.000	1.000
BIG4	0.801	0.399	1.000	1.000	1.000
FRQ	−0.062	0.063	−0.082	−0.043	−0.020
MEF	0.820	0.958	0.000	0.000	1.792

Panel B: Comparing the means between two subsamples

	Mean value in the subsample of *CMD* = 0	Mean value in the subsample of *CMD* = 1	Comparison between the two subsamples	
	($N = 920$)	($N = 1,719$)	Diff. in means	(t-values)
TCR	0.145	0.160	−0.015***	(−4.25)
SIZE	6.479	7.537	−1.059***	(−12.40)
AGE	3.207	3.257	−0.050**	(−1.98)
MKSH	0.012	0.019	−0.007***	(−4.16)
SGRWPOS	0.106	0.083	0.023***	(3.29)
SGRWNEG	−0.047	−0.044	−0.003	(−0.76)
ROA	0.026	0.071	−0.045***	(−7.81)
MB	2.932	3.423	−0.491**	(−2.19)
LEV	0.206	0.229	−0.023***	(−2.99)
CL	0.144	0.145	−0.001	(−0.34)
CASH	0.187	0.188	−0.002	(−0.28)
CA	0.350	0.314	0.036***	(5.72)
TANGI	0.183	0.185	−0.002	(−0.39)

(*continued on next page*)

Table 2 (*continued*)

Panel B: Comparing the means between two subsamples				
	Mean value in the subsample of *CMD* = 0	Mean value in the subsample of *CMD* = 1	Comparison between the two subsamples	
	(*N* = 920)	(*N* = 1,719)	Diff. in means	(t-values)
RATING	0.316	0.449	−0.133***	(−6.68)
BIG4	0.703	0.854	−0.151***	(−9.40)
FRQ	−0.068	−0.059	−0.009***	(−3.45)
MEF	0.672	0.900	−0.228***	(−5.85)

Panel C: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.*TCR*		**0.122**	**0.174**	−0.050	0.049	−0.009	**−0.061**	**−0.135**	**0.083**	**0.083**	**0.079**	**0.079**	**−0.081**	**−0.114**	**0.157**	**0.091**	−0.043	0.019
2.*CMD*	**0.083**		**0.230**	0.032	**0.176**	−0.043	−0.013	**0.136**	**0.106**	**0.080**	0.041	0.024	**−0.108**	0.013	**0.129**	**0.180**	**0.063**	**0.112**
3.*SIZE*	**0.110**	**0.235**		**0.278**	**0.847**	**−0.078**	0.029	**0.404**	**0.262**	**0.436**	0.030	**−0.301**	**−0.340**	**0.177**	**0.698**	**0.541**	**0.185**	**0.345**
4.*AGE*	**−0.097**	**0.038**	**0.274**		**0.287**	**−0.183**	**−0.071**	**0.201**	0.022	0.036	−0.003	**−0.197**	**0.097**	**0.111**	**0.297**	0.049	**0.111**	**0.125**
5.*MKSH*	0.010	**0.081**	**0.414**	**0.180**		**−0.094**	0.040	**0.455**	**0.245**	**0.355**	**0.071**	**−0.349**	**−0.141**	**0.236**	**0.600**	**0.507**	**0.203**	**0.332**
6.*SGRWPOS*	**0.088**	**−0.064**	**−0.130**	**−0.237**	−0.042		**0.843**	**0.169**	**0.225**	**−0.067**	**−0.057**	**0.102**	**−0.085**	**−0.151**	**−0.136**	−0.044	**−0.099**	0.042
7.*SGRWNEG*	**−0.059**	0.015	**0.080**	−0.015	**0.060**	**0.254**		**0.306**	**0.254**	−0.034	**−0.054**	0.026	−0.046	**−0.095**	−0.047	0.020	0.026	**0.115**
8.*ROA*	**−0.242**	**0.150**	**0.453**	**0.249**	**0.192**	**−0.140**	**0.296**		**0.452**	**0.096**	**−0.077**	**−0.123**	−0.031	**0.100**	**0.233**	**0.246**	**0.152**	**0.256**
9.*MB*	**0.057**	0.043	**0.128**	−0.031	**0.096**	**0.053**	**0.094**	**0.113**		**0.126**	**0.113**	**0.061**	**−0.169**	−0.048	**0.144**	**0.205**	**0.068**	**0.276**
10.*LEV*	0.046	**0.058**	**0.325**	−0.037	**0.109**	−0.020	−0.017	0.017	**0.062**		0.046	**−0.462**	**−0.206**	**0.193**	**0.472**	**0.243**	**0.096**	**0.113**
11.*CL*	**0.128**	0.007	**−0.059**	−0.046	0.036	0.017	**−0.063**	**−0.214**	**0.066**	**0.078**		**0.078**	**0.208**	−0.049	0.044	**0.056**	−0.040	**0.054**
12.*CASH*	**0.113**	0.005	**−0.326**	**−0.224**	**−0.142**	**0.144**	−0.040	**−0.288**	0.030	**−0.353**	0.049		**−0.153**	**−0.282**	**−0.260**	**−0.103**	**−0.075**	**−0.113**
13.*CA*	**−0.100**	**−0.111**	**−0.355**	**0.083**	−0.045	**−0.070**	−0.007	−0.010	**−0.051**	**−0.191**	**0.217**	**−0.237**		0.029	**−0.215**	**−0.189**	**−0.073**	**−0.119**
14.*TANGI*	**−0.079**	0.008	**0.183**	0.047	**0.123**	**−0.128**	**−0.108**	**0.066**	−0.012	**0.191**	**−0.103**	**−0.306**	**−0.139**		**0.131**	**0.110**	**0.053**	**−0.072**
15.*RATING*	**0.094**	**0.129**	**0.665**	**0.293**	**0.342**	**−0.130**	0.001	**0.248**	**0.090**	**0.418**	−0.025	**−0.274**	**−0.221**	**0.136**		**0.357**	**0.159**	**0.248**
16.*BIG4*	**0.065**	**0.180**	**0.557**	**0.057**	**0.181**	**−0.069**	**0.059**	**0.215**	**0.097**	**0.209**	0.005	**−0.118**	**−0.201**	**0.088**	**0.356**		**0.118**	**0.257**
17.*FRQ*	**−0.080**	**0.067**	**0.197**	**0.133**	**0.090**	**−0.289**	**0.103**	**0.191**	0.022	**0.069**	**−0.092**	**−0.080**	**−0.071**	−0.009	**0.145**	**0.129**		**0.108**
18.*MEF*	−0.041	**0.113**	**0.328**	**0.132**	**0.102**	−0.043	**0.137**	**0.236**	**0.165**	**0.052**	0.010	**−0.117**	**−0.123**	**−0.110**	**0.242**	**0.258**	**0.114**	

This table presents the descriptive statistics for the regression variables. Our sample period is from 2014 to 2016, and our final sample includes 2,639 firm-year observations. Panel A presents the mean, standard deviation (SD), 25th percentile (P25), median, and 75th percentile (P75) of the regression variables in our final sample. Panel B compares the regression variables' mean values for two subsamples that have, respectively, more- (*CMD* = 1) and less-specific CMD (*CMD* = 0). Panel C presents the Pearson correlations (below the diagonal) and Spearman correlations (above the diagonal) for each pair of variables. Correlation coefficients with significance at the 1 % level are in boldface. We summarize the variable definitions in Appendix C. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

4. For the second measure, *CMD_WORDS* equals the decile ranking (ranging from 1 to 10) of the word count of the list of smelters or refineries, divided by 10, for firms that disclose a Conflict Minerals Report; *CMD_WORDS* equals 0 for firms that do not disclose such information. This variable assumes that firms engage in more-specific CMD when their Form SD includes more words. We also adopt three alternative measures of trade credit. The first, *TCR1*, is measured as accounts payable at the end of year $t + 2$ scaled by the cost of goods sold in year $t + 2$.[15] The second, *TCR2*, is accounts payable at the end of year $t + 1$ scaled by the total purchases in year $t + 1$, where total purchases is the sum of the cost of goods sold and the change in inventory. Finally, *TCR3* is accounts payable at the end of year $t + 1$ scaled by the total assets in year $t + 1$.[16] Table 4, Panel A report the results. As shown, our finding of a positive association between CMD and trade credit remains robust to these alternative measures.

Second, to assess the extent of the bias from correlated, omitted variables, we employ the Oster (2019) test, which the recent literature increasingly uses. Table 4, Panel B presents the results. We start by estimating the model without controls and fixed effects. The coefficient on *CMD* is 0.015, and the *R*-square is 0.007. We then add controls and fixed effects and obtain our baseline results: the coefficient decreases to 0.010, and the *R*-square increases to 0.246.[17] Assuming that the maximum *R*-square is 0.320 ($= 1.3 \times 0.246$), we find a δ of 3.451, suggesting our results are unlikely to be driven by omitted variable bias.[18] In addition, we follow Argyle et al. (2021) and use the Oster (2019) technique to estimate the bias-adjusted coefficient on *CMD*. We find that the bias-adjusted coefficient is 0.008, which is close to 0.010 (the estimated coefficient in our baseline model) and within the confidence interval of our baseline results.[19] Overall, the results from the Oster (2019) test suggest that our main findings are unlikely to be affected by correlated omitted variables.

Third, we address endogeneity using alternative model specifications. We control for year and industry fixed effects in our baseline regression. In Table 4, Panel C, we add more granular fixed effects to account for unobserved heterogeneity. Specifically, we include industry $\times$ year fixed effects in column (1). We continue to find a significantly positive coefficient on *CMD*. In column (2), we replace industry fixed effects with firm fixed effects, although our sample period covers only three years. Again, we find a significantly positive coefficient on *CMD*, suggesting that our main finding is not driven by the omission of time-invariant firm characteristics. The numbers of observations in columns (1) and (2) are smaller because the inclusion of industry-year (firm) fixed effects requires at least two observations for each industry-year (firm) and the statistical software drops singletons automatically. For an alternative and powerful way of dealing with omitted variable problems, we further determine whether our results are robust to a change specification. In column (3), we regress the first difference of the dependent variable on the first differences of all the independent variables.[20] We continue to find a significantly positive result, suggesting that improvement in CMD results in increased trade credit. It is likely that firm-year observations within the same firm or industry might have correlated errors in our trade credit regressions. Although the use of firm and year fixed effects can help mitigate the problem of biased standard errors due to correlated errors, a more general approach that is commonly used in the literature is clustered standard errors (Petersen, 2008). The appropriateness of clustered standard errors depends on cluster-related factors such as the number of observations within each cluster and the number of clusters (Cameron et al., 2008; Cameron and Miller, 2015; Abadie et al., 2023). Given that we have at most three observations per firm and few industry clusters (see Table 1), we do not implement clustered standard errors in our baseline regression specification. Instead, we check to see if our results are robust to clustering the error terms in the regressions. Table 4, Panel C, columns (4) and (5) present the results using standard errors with clustering by firm and industry, respectively. The results indicate a significantly positive association between CMD and trade credit.

Fourth, we conduct three falsification tests based on various pre-disclosure periods. We argue that a firm's more-specific CMD enhances its supply chain visibility because it must investigate its production process and supply chain. Given that enhanced supply chain visibility is a benefit, one might suspect that firms would improve supply chain visibility well before the CMD mandate. In this case, our measure of CMD may capture variation in visibility in the pre-disclosure period, and our results should hold for that period. Using 2009–2011, 2010–2012, and 2011–2013 as the respective sample periods, we falsely measure CMD in 2014 (the earliest year for which the CMD measure is available). We find insignificant results in all columns of Table 4, Panel D, which suggests that our results are unlikely to be driven by firms' actions in the pre-disclosure period. This falsification test increases confidence that our results are driven by the disclosure regulation.

Finally, we employ propensity score matching to alleviate concerns about functional form misspecification. To obtain unbiased estimates, our baseline regression model requires proper specification of the relation between CMD and trade credit and the other

[15] We adopt this measure to determine whether our results hold for a model with a longer lead-lag horizon.

[16] One concern about using total assets as a scalar is that total assets are affected by other sources of financing, such as equity and debt (total assets = total liabilities + equity). CMD can also affect these other sources of financing as it affects trade credit, and these sources of financing might have complementary or substitution effects with trade credit (Biais and Gollier, 1997; Burkart and Ellingsen, 2004; Chen et al., 2017), which makes it difficult to use the ratio of accounts payable to total assets to isolate these effects.

[17] In Table 3, column (4), where we present our baseline results, we report the adjusted *R*-square, which is slightly smaller than the raw *R*-square reported here.

[18] The Oster (2019) test generates the coefficient of proportionality, δ, based on the coefficient and *R*-square movements. Oster (2019) recommends that researchers estimate the maximum *R*-square as $1.3 \times$ the *R*-square from the regression model with a full set of observable controls. A higher value of δ indicates a smaller likelihood that omitted variables have a significant effect. For example, a δ of 1.00 indicates that omitted variables need to be as important as observables to overturn the results. Thus, values of δ that exceed 1.00 suggest a robust result.

[19] In our baseline results, the 95% confidence interval of the coefficient on *CMD* is [0.003, 0.017].

[20] To simplify the presentation, we omit the first-difference operator for control variables in Table 4, Panel C, column (3). Because we lose one year of data by taking the first difference of each regression variable, the number of observations in this change analysis decreases by around one third.

control variables. The potential bias from functional form misspecification decreases as the treatment and control groups become more similar (Shipman et al., 2017). Given that our final sample is unbalanced between firms with less-specific ($CMD = 0$) and more-specific ($CMD = 1$) CMD, we use one-to-one matching to create a balanced sample. Importantly, the characteristics of the two groups of firms are more similar in our matched sample. To implement propensity score matching, we first use a probit model to predict *CMD*. The model specification is similar to Eq. (1), except that we use *CMD* as the dependent variable. Based on this probit estimation, we can derive a propensity score for each observation in our final sample. Because we have fewer observations for the less-specific group ($CMD = 0$) relative to the more-specific group ($CMD = 1$), we match each observation in the former group with the observation that has the closest propensity score in the latter group. To ensure similarity between the matched pairs, we drop pairs for which the difference in propensity scores exceeds three specific cutoffs (i.e., 0.10, 0.05, and 0.01). The choice of a smaller cutoff in the propensity score difference results in a smaller sample size. We then compare the sample means of the control variables between the matched treatment and control groups. Table 4, Panel E shows that for each cutoff, the differences in the sample means are statistically insignificant, suggesting that our matching procedure performs well.

Table 4, Panel F presents the regression results based on the matched samples. In column (1), we present the results of the Probit model that we use to derive the propensity scores. In columns (2)–(4), we again use the three cutoffs; we continue to find that more-specific CMD is associated with higher trade credit, and that the magnitudes of the coefficients on *CMD* are very close to those in our baseline results. In short, the results from propensity score matching indicate that our findings in general are unlikely to be affected by an unbalanced sample or by model misspecification. In column (5), we employ an entropy-balanced sample to mitigate the concern that the treatment (i.e., more-specific CMD) firms differ from the control (less-specific CMD) firms. Specifically, by assigning a weight to each observation in the control group, we construct a counterfactual control group with essentially the same observable characteristics as our treatment group. When we estimate our baseline model using this entropy-balanced sample, we continue to find a significantly positive coefficient on *CMD*, suggesting our results are not affected by any distributional difference between the covariates of the treatment and control groups.

Taken together, our findings in Table 4 show that our results are unlikely to be affected by omitted variables and sample selection bias and that they are robust to alternative model specifications and matched samples.

Several of the robustness checks in the previous table deal with one form of endogeneity, omitted variable bias. We now address endogeneity in another form, reverse causality. Trade credit could have a causal effect on more transparent CMD in several ways. For example, trade credit could provide a financial cushion and enhance supplier relationships, enabling firms to invest in socially responsible sourcing practices and thus be more transparent in their CMD. As another example, the provision of trade credit often signals trust between suppliers and buyers, which can then translate into more transparent CMD.

Two common methods that the literature uses to deal with reverse causality are the instrumental variable (IV) and difference-in-differences (DID) approaches. We first conduct an IV analysis using political ideology as an IV. As Kim et al. (2020) document, firms with democratic-oriented institutional shareholders are more likely to issue environmental reports, to achieve a better environmental performance, and to engage in green innovations. Chin et al. (2013) hypothesize and find that democratic CEOs exhibit better CSR. Di Giuli and Kostovetsky (2014) find that firms with founders, CEOs, or directors who are Democrats achieve a better CSR performance and that the external political environment matters: firms headquartered in Democratic-leaning states have a better CSR performance than those headquartered in Republican-leaning states.

Specifically, our IV is an indicator variable for state government trifectas (*DEMOTRIFECTA*).[21] It equals 1 for firms headquartered in states where the Democratic Party holds the governorship and controls both branches of the state legislature, and 0 otherwise. If $DEMOTRIFECTA = 1$, we expect the firm to care more about socially responsible sourcing and to provide more-specific CMD. As stakeholders (e.g., employees, investors, suppliers and customers) are more likely to live in the firm's headquarters state, their political views can influence the firm's attitudes about socially responsible sourcing. In addition, Democrat-leaning stakeholders can promote regulation that favors socially responsible business practices, which could affect local firms' CMD. At the same time, it is unlikely that the state government trifectas directly affect the trade credit that firms receive from suppliers.

Table 5, Panel A reports the results of the IV analysis.[22] In column (1), we find that the IV (*DEMOTRIFECTA*) is strongly associated with more-specific CMD (*CMD*). The F-statistics from the first-stage regression passes the weak identification test at the 1 % level (p-value < 0.01). The Kleibergen-Paap rk LM statistics also pass the associated under-identification test (p-value < 0.01). Column (2) presents the second-stage results.[23] We find a significantly positive coefficient on the instrumented *CMD*, consistent with the main results reported in Table 3. This finding affirms a causal link between CMD and trade credit financing.

[21] The state government trifecta data are publicly available at https://ballotpedia.org/State_government_trifectas.

[22] The sample size in Table 5, Panel A is smaller than that for our main analyses primarily because the Compustat database is missing data on firms' headquarters states.

[23] The R^2 statistic in column (2) of Table 5, Panel A is not reported because it has no statistical meaning (Wooldridge, 2012, 523).

Table 3
Relation between CMD and the trade credit received from suppliers (H1).

Dep. Var. = *TCR*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CMD	0.013***	0.012***	0.010***	0.010***				
	(3.72)	(3.60)	(2.76)	(2.75)				
CMD_LEVEL2					0.011**	0.012**	0.010**	0.011**
					(2.33)	(2.54)	(2.10)	(2.34)
CMD_LEVEL3					0.014***	0.010**	0.013***	0.009**
					(2.97)	(2.17)	(2.74)	(1.98)
CMD_LEVEL4					0.015***	0.012***	0.013***	0.011***
					(3.76)	(3.18)	(3.28)	(2.74)
SIZE	0.014***	0.013***	0.014***	0.013***	0.014***	0.013***	0.014***	0.013***
	(9.13)	(7.88)	(9.20)	(7.93)	(9.12)	(7.91)	(9.19)	(7.96)
AGE	−0.011***	−0.014***	−0.011***	−0.014***	−0.010***	−0.014***	−0.011***	−0.014***
	(−3.92)	(−5.34)	(−4.05)	(−5.45)	(−3.85)	(−5.27)	(−3.98)	(−5.40)
MKSH	−0.101***	0.075	−0.103***	0.073	−0.100***	0.074	−0.102***	0.071
	(−3.02)	(1.52)	(−3.07)	(1.47)	(−3.02)	(1.50)	(−3.07)	(1.44)
SGRWPOS	0.016	0.028**	0.015	0.027**	0.016	0.028**	0.015	0.027**
	(1.32)	(2.29)	(1.22)	(2.21)	(1.32)	(2.31)	(1.23)	(2.22)
SGRWNEG	0.012	−0.013	0.017	−0.008	0.009	−0.016	0.015	−0.010
	(0.55)	(−0.58)	(0.78)	(−0.37)	(0.40)	(−0.72)	(0.70)	(−0.43)
ROA	−0.202***	−0.187***	−0.201***	−0.186***	−0.202***	−0.186***	−0.202***	−0.186***
	(−9.99)	(−9.14)	(−9.95)	(−9.11)	(−9.95)	(−9.10)	(−9.94)	(−9.09)
MB	0.001**	0.000	0.001**	0.000	0.001**	0.001	0.001**	0.001
	(2.41)	(1.40)	(2.41)	(1.41)	(2.46)	(1.44)	(2.46)	(1.44)
LEV	−0.019*	−0.021*	−0.021*	−0.023**	−0.020*	−0.021*	−0.022*	−0.023**
	(−1.69)	(−1.90)	(−1.85)	(−2.05)	(−1.72)	(−1.87)	(−1.92)	(−2.06)
CL	0.057**	0.073***	0.057**	0.073***	0.057**	0.072***	0.057**	0.072***
	(2.31)	(2.81)	(2.33)	(2.81)	(2.32)	(2.77)	(2.33)	(2.76)
CASH	0.031**	0.014	0.033**	0.015	0.030**	0.014	0.031**	0.015
	(2.27)	(1.01)	(2.36)	(1.09)	(2.16)	(1.01)	(2.24)	(1.09)
CA	0.008	0.024	0.010	0.026*	0.006	0.023	0.009	0.026*
	(0.60)	(1.62)	(0.79)	(1.77)	(0.46)	(1.55)	(0.69)	(1.75)
TANGI	−0.050***	−0.035**	−0.049***	−0.034**	−0.050***	−0.034**	−0.049***	−0.034**
	(−4.05)	(−2.19)	(−3.98)	(−2.18)	(−4.07)	(−2.14)	(−3.99)	(−2.15)
RATING	0.011**	0.010**	0.011**	0.010**	0.010**	0.010**	0.011**	0.010**
	(2.44)	(2.23)	(2.55)	(2.32)	(2.28)	(2.11)	(2.42)	(2.23)
BIG4	−0.007	−0.003	−0.006	−0.002	−0.007	−0.002	−0.006	−0.002
	(−1.31)	(−0.52)	(−1.21)	(−0.42)	(−1.27)	(−0.48)	(−1.18)	(−0.38)
FRQ	−0.071**	−0.036	−0.082**	−0.045	−0.067**	−0.034	−0.080**	−0.046
	(−2.20)	(−1.09)	(−2.48)	(−1.35)	(−2.06)	(−1.02)	(−2.42)	(−1.37)
MEF	−0.007***	−0.006***	−0.007***	−0.005***	−0.007***	−0.006***	−0.007***	−0.006***
	(−4.18)	(−3.25)	(−4.10)	(−3.15)	(−4.25)	(−3.29)	(−4.16)	(−3.18)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
N	2,639	2,639	2,639	2,639	2,639	2,639	2,639	2,639
Adj. R^2	0.161	0.225	0.163	0.226	0.161	0.224	0.164	0.226

This table presents the main results from testing the relation between CMD and the trade credit received from suppliers. The dependent variable is the trade credit received from suppliers (*TCR*), defined as accounts payable scaled by the cost of goods sold in year $t + 1$. All independent variables are calculated at year *t*. In columns (1)–(4), the variable of interest, *CMD*, is an indicator of more-specific CMD. Specifically, for firms required to file Form SD with a Conflict Minerals Report as an exhibit (i.e., firms that cannot rule out the possibility that their conflict minerals are from Covered

Countries), *CMD* equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, 0 otherwise. In columns (5)–(8), we follow Swift et al.'s (2019) approach and classify CMD based on four levels. Level 1 disclosure has no substantial information about smelters or refineries. Level 2 includes a number or list of known smelters or refineries. Level 3 includes a list and the conflict-free audit status of known smelters or refineries. Level 4 includes a list and the conflict-free audit status of known smelters or refineries, plus the minerals' countries of origin. *CMD_LEVEL2*, *CMD_LEVEL3*, and *CMD_LEVEL4* are indicator variables for firms with levels 2, 3, and 4 disclosure, respectively. We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

Next, we conduct a DID analysis that includes all U.S. firms between 2010 and 2012 (pre-CMD period, *POST* = 0) and 2014 and 2016 (post-CMD period, *POST* = 1). We drop 2013, the first year of the CMD mandate. The treatment group (*TREAT* = 1) includes firms that are subject to the CMD mandate; the remaining firms comprise the control group (*TREAT* = 0). After dropping observations with missing values for the regression variables, the final sample has 18,782 firm-year observations, 50.55 % (49.45 %) of which are in the pre- (post-) period. The treatment (control) group makes up 29.76 % (70.24 %) of the sample.[24]

Table 5, Panel B reports the results of the DID analysis.[25] In column (1), we find a significantly positive coefficient on the interaction term, *POST* × *TREAT*, suggesting that on average, the CMD mandate has a positive effect on affected firms' trade credit financing. In column (2), we divide the treatment group into three subgroups: firms that file Form SD only (*TREAT_SDONLY* = 1); firms that file Form SD with a Conflict Minerals Report as an exhibit listing known smelters or refineries (*TREAT_CMRHIGH* = 1); and firms that file Form SD with a Conflict Minerals Report but no accompanying list (*TREAT_CMRLOW* = 1). We then interact these three indicator variables with *POST*. We find a significantly positive coefficient on *POST* × *TREAT_CMRHIGH*, but the coefficients on *POST* × *TREAT_CMRLOW* and *POST* × *TREAT_SDONLY* are statistically insignificant. Overall, our DID analyses suggest that the CMD mandate has a causal effect on trade credit financing that is concentrated among those treatment firms that provide more specific CMD.

4.3. Cross-sectional analyses

Thus far, we establish a robust and positive relation between a firm's CMD and the trade credit it receives from suppliers. To identify the channels through which CMD can affect trade credit, we conduct several cross-sectional analyses of the association between the disclosure and trade credit. We rely on proxies of product market competition, financial constraints, and external monitoring by non-supplier stakeholders to partition our sample into subsamples. The number of observations in each set of analyses is smaller than that in our main sample (2,639 observations) because we are missing some values for the partitioning proxies or we drop singletons generated by the partitioning.

4.3.1. The moderating effect of product market competition (H2)

Our central hypothesis proposes that one channel through which a firm's CMD affects its trade credit is enhanced supply chain visibility. Information sharing and collaboration, which help to manage costs and improve efficiency for supply chain partners, are especially important for firms in competitive product markets. Therefore, we expect enhanced supply chain visibility to have a more pronounced effect on such firms.

To test this prediction, we use three measures to capture firms' product market competition. First, we rely on Hoberg and Phillips' (2016) measure of product similarity (*SIMILARITY*) to capture product market competition. This text-based measure compares a firm's product description, as disclosed in a 10-K, with those of its peer firms in the market. Based on their textual analysis, Hoberg and Phillips (2016) also create text-based network industry classifications and a corresponding Herfindahl-Hirschman Index (HHI). We use this HHI, multiplied by −1, as our second competition measure (*NEGHHI*). As an alternative proxy for product market competition, we calculate operating cash flow volatility (*CFOVOL*) as the standard deviation of operating cash flow scaled by the lagged total assets over the 5-year period from years *t*-4 to *t*. Firms in more competitive markets are likely to have more volatile operating cash flows for two reasons: i) revenues are more volatile because the price and quantity of sales are affected by competitors and ii) operating costs are more volatile because competition can affect resource pricing and availability.

Table 6 presents the results from testing the moderating effect of product market competition. In columns (1)–(2), we partition our sample based on the median value of the product similarity measure (*SIMILARITY*). We find that the coefficient on *CMD* is significantly positive only for the subsample of firms with higher product similarity, suggesting that the positive relation between a firm's CMD and its trade credit is concentrated among firms in more competitive product markets. The coefficient on *CMD* in column (2) is larger than that in column (1), and the difference is significant at the 1 % level. In columns (3)–(4), we divide the sample based on the median value of *NEGHHI*. The coefficient on *CMD* is still significantly larger for firms with stronger competition. In columns (5)–(6), we split

[24] Our DID analysis has two important limitations. First, a DID analysis makes the important assumption that the treatment and control firms are similar in all aspects except for the treatment (i.e., in our study, the CMD mandate). Firms required to file CMD reports are likely to be in different sectors than firms that face no such requirement, and those in the same sector might rely on different mineral production methods. Another important assumption underlying a DID research design is that confounding events do not affect the treatment and control firms in different ways. The requirement that certain firms file Form SD is likely a small part of the various regulations introduced under the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. Many parts of this act and the financial crisis and government measures leading up to it are also likely to affect firms' financing.

[25] The main effect of *POST* is absorbed by year fixed effects; for this reason, we omit it.

Table 4
Robustness checks.

Panel A: Alternative measures of CMD and trade credit

	(1)	(2)	(3)	(4)	(5)
Dep. Var. =	*TCR*	*TCR*	*TCR1*	*TCR2*	*TCR3*
CMD_LEVEL	0.004***				
	(2.81)				
CMD_WORDS		0.011***			
		(2.63)			
CMD			0.007**	0.009***	0.004**
			(2.03)	(2.66)	(1.96)
Controls	Yes	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes
N	2,639	2,639	2,479	2,625	2,639
Adj. R^2	0.226	0.226	0.222	0.226	0.496

Panel B: Evaluating the omitted variable concern

	Coefficient on *CMD*	R^2
Model without controls and fixed effects	0.015	0.007
Model with controls and fixed effects (our baseline model)	0.010	0.246
Outputs from the Oster (2019) test:		
The maximum R^2 (1.3 × the R^2 from the baseline model)	0.320	
δ	3.451	
Is the bias-adjusted coefficient within the original confidence interval?	Yes	
Bias-adjusted coefficient on *CMD*	0.008	

Panel C: Alternative model specifications

	Industry × year FE	Firm FE	Change analysis	Firm-level clustering	Industry-level clustering
	(1)	(2)	(3)	(4)	(5)
Dep. Var. =	*TCR*	*TCR*	Δ*TCR*	*TCR*	*TCR*
CMD	0.010***	0.010***		0.010**	0.010*
	(2.69)	(2.91)		(2.23)	(1.74)
Δ*CMD*			0.008*		
			(1.73)		
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Industry × year FE	Yes	No	No	No	No
Firm FE	No	Yes	No	No	No
N	2,610	2,459	1,580	2,639	2,639
Adj. R^2	0.205	0.798	0.039	0.226	0.226

Panel D: Falsification tests

Sample period:	2009–2011	2010–2012	2011–2013
Dep. Var. = *TCR*	(1)	(2)	(3)
CMD	−0.000	−0.000	−0.000
	(−0.94)	(−0.86)	(−0.57)
Controls	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes
N	2,459	2,528	2,589
Adj. R^2	0.200	0.201	0.222

Panel E: Check for covariate balance after propensity scores matching

	(1)Matched pairs with a propensity score difference of <0.10 (*N* = 679 pairs)		(2)Matched pairs with a propensity score difference of <0.05 (*N* = 639 pairs)		(3)Matched pairs with a propensity score difference of <0.01 (*N* = 512 pairs)	
	Diff. in means	(t-values)	Diff. in means	(t-values)	Diff. in means	(t-values)
SIZE	−0.026	(−0.23)	−0.027	(−0.23)	−0.055	(−0.42)
AGE	0.025	(0.74)	0.017	(0.49)	0.014	(0.36)
MKSH	0.002	(0.92)	0.002	(0.87)	0.002	(1.14)

(*continued on next page*)

Table 4 (*continued*)

Panel E: Check for covariate balance after propensity scores matching

	(1)Matched pairs with a propensity score difference of <0.10 (*N* = 679 pairs)		(2)Matched pairs with a propensity score difference of <0.05 (*N* = 639 pairs)		(3)Matched pairs with a propensity score difference of <0.01 (*N* = 512 pairs)	
	Diff. in means	(t-values)	Diff. in means	(t-values)	Diff. in means	(t-values)
SGRWPOS	−0.005	(−0.59)	−0.004	(−0.51)	−0.014	(−1.58)
SGRWNEG	0.001	(0.27)	0.001	(0.19)	0.004	(0.63)
ROA	0.000	(0.03)	0.003	(0.40)	0.005	(0.64)
MB	0.007	(0.02)	0.036	(0.12)	−0.024	(−0.07)
LEV	0.002	(0.17)	0.003	(0.29)	0.002	(0.17)
CL	0.001	(0.17)	0.001	(0.28)	−0.000	(−0.02)
CASH	−0.007	(−0.76)	−0.010	(−1.04)	−0.004	(−0.38)
CA	0.004	(0.51)	0.004	(0.41)	0.006	(0.62)
TANGI	−0.004	(−0.50)	0.000	(0.02)	−0.003	(−0.32)
RATING	−0.003	(−0.11)	−0.003	(−0.12)	−0.027	(−0.89)
BIG4	0.006	(0.26)	0.000	(0.00)	−0.020	(−0.78)
FRQ	0.000	(0.02)	−0.000	(−0.05)	0.001	(0.14)
MEF	0.044	(0.87)	0.025	(0.48)	−0.001	(−0.02)
Propensity scores	0.010	(1.13)	0.006	(0.72)	0.001	(0.16)

Panel F: Regression results based on matched samples

	(1) Probit model used to derive propensity scores	(2) Matched pairs with a propensity score difference of <0.10	(3) Matched pairs with a propensity score difference of <0.05	(4) Matched pairs with a propensity score difference of <0.01	(5) Entropy balanced sample
Dep. Var. =	*CMD*	*TCR*	*TCR*	*TCR*	*TCR*
CMD		0.010**	0.011**	0.013***	0.009**
		(2.35)	(2.48)	(2.67)	(2.47)
Controls	Yes	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes
N	2,607	1,358	1,278	1,024	2,639
Adj. [Pseudo] R^2	[0.164]	0.232	0.228	0.220	0.234

In this table, we conduct a series of tests to assess the robustness of our main results. In Panel A, we determine whether our results are robust to alternative measures of CMD and trade credit. In Panel B, we conduct the Oster (2019) test to evaluate omitted variable concerns. In Panel C, we address endogeneity using alternative model specifications. The regression models in columns (1) and (2) respectively include industry × year fixed effects and firm fixed effects. In column (3), we conduct a change analysis by taking the first differences of the dependent and independent variables. In columns (4) and (5), we respectively cluster standard errors by firm and industry. In Panel D, we conduct falsification tests based on various pre-disclosure periods (2009–2011, 2010–2012, and 2011–2013). In this test, the variable of interest, *CMD*, is falsely defined in 2014 (the earliest year with an available CMD measure). In Panel E, we check for covariate balance after propensity score matching. In Panel F column (1), we present the probit model estimation used to derive propensity scores. In columns (2)–(4), we use propensity score matching to construct matched samples. To implement propensity score matching, we first use a probit model to predict *CMD* and to obtain the propensity scores. *CMD* is an indicator variable that is equal to 1 for firms with more-specific CMD, and 0 otherwise. Specifically, for firms required to file Form SD with a Conflict Minerals Report as an exhibit (i.e., they cannot rule out the possibility that their conflict minerals are from Covered Countries), *CMD* equals 1 if the firm's Conflict Minerals Report includes a list of smelters or refineries that produce the conflict minerals used in the firm's products, and 0 otherwise. Because we have fewer observations for the less-specific reporting group (*CMD* = 0) relative to the more-specific reporting group (*CMD* = 1), we match each observation in the former group with the observation in the latter group that has the closest propensity score. To ensure similarity between the matched pairs, we drop pairs for which the difference between the propensity scores exceeds some cutoffs. We choose three different cutoffs (i.e., 0.10, 0.05, and 0.01) and we rerun our baseline model on the propensity-score-matched samples. In column (5), we rerun our baseline model using an entropy-balanced sample. We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

the sample based on operating cash flow volatility (*CFOVOL*); the results show that the positive relation between CMD and trade credit is pronounced only for firms with more volatile cash flows. Taken together, these results support our hypothesis that the relation between CMD and trade credit is more pronounced for firms with stronger product market competition. These results corroborate the enhanced supply chain visibility channel through which a firm's CMD can affect the trade credit it receives from suppliers.

4.3.2. The moderating effects of financial constraints (H3)

To further explore the enhanced supply chain visibility channel, we conduct another cross-sectional analysis. To the extent that greater supply chain visibility helps firms achieve greater operational efficiency, the enhanced visibility induced by CMD is likely to

Table 5
Identification tests.

Panel A: Instrumental variable analysis		
	(1) First stage	(2) Second stage
Dep. Var. =	*CMD*	*TCR*
CMD (instrumented)		0.150**
		(2.28)
DEMOTRIFECTA	0.077***	
	(3.39)	
Controls	Yes	Yes
Industry and year FE	Yes	Yes
N	2,281	2,281
Adj. R^2	0.198	NA
First-stage F statistic	16.74	
p-value	< 0.01	
Kleibergen-Paap rk LM statistic	11.82	
p-value	< 0.01	

Panel B: Difference-in-differences analysis		
Dep. Var. = *TCR*	(1)	(2)
POST×*TREAT*	0.026**	
	(2.24)	
POST×*TREAT_CMRHIGH*		0.037***
		(3.13)
POST×*TREAT_CMRLOW*		−0.007
		(−0.54)
POST×*TREAT_SDONLY*		0.024
		(1.52)
TREAT	−0.044***	−0.043***
	(−4.25)	(−4.14)
Controls	Yes	Yes
Industry and year FE	Yes	Yes
N	18,782	18,782
adj. R^2	0.210	0.210

This table presents the results of our identification tests. In Panel A, we use an instrumental variable (IV) approach to establish causality. Our IV for firms' CMD is the state government's political ideology. Specifically, it is an indicator variable for state government trifectas; the variable is equal to 1 for firms headquartered in states where the Democratic Party holds the governorship and controls both branches of the state legislature, and 0 otherwise. Column (1) presents the first-stage results of the IV-2SLS estimation. Column (2) reports the results from the second-stage. The R^2 statistic is not reported because it has no statistical meaning (Wooldridge 2012, 523). In Panel B, we perform difference-in-differences (DID) analyses that include all US firms between 2010 and 2012 (pre-CMD period, *POST* = 0) and 2014–2016 (post-CMD period, *POST* = 1). We drop 2013, the first year that firms are required to prepare a conflict minerals report. In column (1), the treatment group (*TREAT* = 1) includes firms subject to CMD regulation (i.e., they need to file Form SD), and the remaining firms serve as the control (*TREAT* = 0). In column (2), we further divide the treatment group into three subgroups: firms that file Form SD only (*TREAT_SDONLY* = 1); firms that file Form SD with a Conflict Minerals Report as an exhibit and the Conflict Minerals Report includes a number or list of smelters or refineries (*TREAT_CMRHIGH* = 1); and firms that file Form SD with a Conflict Minerals Report as an exhibit but the Conflict Minerals Report does not include a number or list of known smelters or refineries (*TREAT_CMRLOW* = 1). Our analyses focus on the two-way interaction terms. Note that the main effect of *POST* is absorbed by year fixed effects. We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

matter more in terms of trade credit to financially constrained firms, relative to unconstrained firms. Therefore, we predict that the positive association between a firm's CMD and its trade credit is more pronounced for more financially constrained firms.

To test the moderating effect of financial constraints, we construct three measures that capture the extent to which a firm is financially constrained. First, we construct two widely used indexes of financial constraints. The first is Hadlock and Pierce's (2010)

Table 6
The moderating effects of product market competition (H2).

Subsamples are partitioned by:	Product similarity (*SIMILARITY*)		HHI multiplied by − 1 (*NEGHHI*)		Operating cash flow volatility (*CFOVOL*)	
	Low	High	Low	High	Low	High
Dep. Var. = *TCR*	(1)	(2)	(3)	(4)	(5)	(6)
CMD	0.006	0.021***	0.009*	0.018***	0.003	0.016***
	(1.28)	(4.03)	(1.89)	(3.45)	(0.80)	(2.70)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,172	1,168	1,168	1,171	1,316	1,314
Adj. R^2	0.225	0.212	0.207	0.220	0.279	0.214
Test of the difference between the coefficients (*p*-value)	0.000***		0.003***		0.001***	

This table presents the results from testing the moderating effect of product market competition on the relation between CMD and trade credit. The dependent variable is the trade credit received from suppliers (*TCR*), defined as accounts payable scaled by the cost of goods sold in year $t+1$. All independent variables are calculated at year *t*. The variable of interest, *CMD*, is an indicator of more-specific CMD. Specifically, for our sample firms (i. e., firms required to file Form SD with a Conflict Minerals Report as an exhibit), *CMD* equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, and 0 otherwise. To test the moderating effect, we divide our sample into two subsamples based on various measures of product market competition, and we use Fisher's permutation test with bootstrapping to test the difference between the coefficients on *CMD* for each subsample. In columns (1)–(2), we use Hoberg and Phillips' (2016) measure of product similarity (*SIMILARITY*) as our partitioning variable. In columns (3)–(4), we use the Herfindahl-Hirschman index (*NEGHHI*) based on firms' text-based network industry classifications multiplied by − 1). In columns (5)–(6), we use operating cash flow volatility (*CFOVOL*) to partition our sample. We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

size-age index of financial constraints (*SAINDEX*), which is based on firms' size and age. The second is Whited and Wu's (2006) index of financial constraints (*WWINDEX*), which is based on various financial statement items. Higher index values indicate more financial constraints. We also create an indicator variable (*RATING*) that equals 1 for firms with an S&P credit rating in the Compustat database, and 0 otherwise. Firms without a credit rating are likely to be more financially constrained.

Table 7 presents the results from testing the moderating effect of financial constraints. First, we use Hadlock and Pierce's (2010) size-age index of financial constraints to divide our sample in two. As shown in columns (1)–(2), the positive association between CMD and trade credit is pronounced only for more financially constrained firms. We also formally test the difference between the coefficients on *CMD* in the two columns; the coefficient estimated from the more constrained subsample is significantly larger. In columns (3)–(4), we repeat our analysis using Whited and Wu's (2006) index of financial constraints and find similar results. In columns (5)–(6), we rely on the S&P credit rating to identify financially constrained firms. Again, we find that the positive relation between CMD and trade credit is pronounced only for more constrained firms (i.e., those without a credit rating). Taken together, these results support our hypothesis and corroborate evidence of the enhanced supply chain visibility channel.

4.3.3. The moderating effects of external monitoring by non-supplier stakeholders (H4)

In our central hypothesis, we propose another channel that could link a firm's CMD to its trade credit: reduced adverse selection concerns for suppliers. Prior literature documents that institutional investors, the media, and analysts encourage corporate social responsibility by acting as external monitors (e.g., Jo and Harjoto, 2014; Dyck et al., 2019; El Ghoul et al., 2019). When external monitoring is weak, suppliers worry that firms will engage in socially irresponsible sourcing. Accordingly, we predict that the relation between a firm's CMD and its trade credit is more pronounced for firms with weaker external monitoring.

To test this prediction, we divide our sample into two subsamples based on three distinct measures of external monitoring. We then test the difference between the coefficients on *CMD* for the two subsamples.[26] In line with prior literature on external firm monitors (e.g., Dyck et al., 2008; Fang et al., 2015; Bradley et al., 2017), we construct three measures of external monitoring: institutional ownership (*INSTOWN*), analyst coverage (*ANACOV*), and media coverage (*MEDCOV*). Specifically, we obtain institutional holdings (13f) data from Thomson/Refinitiv, and we define *INSTOWN* as the proportion of a firm's shares held by institutional investors. Using data from I/B/E/S, we define *ANACOV* as the log of 1 plus the number of analysts following the firm. We define media coverage (*MEDCOV*) as the log of 1 plus the number of news articles about the firm in the RavenPack database.

Table 8 presents the results from testing the moderating effect of external monitoring. First, we partition our sample based on the median value of institutional ownership (*INSTOWN*). Columns (1) and (2) respectively present the results for each subsample. We find that the coefficient on *CMD* is significantly positive only for the subsample of firms with lower institutional ownership, suggesting that the positive relation between CMD and trade credit is concentrated among firms with weaker external monitoring. We also test

[26] Throughout our cross-sectional analyses, we use Fisher's permutation test with bootstrapping to test the difference between the coefficients for the two subsamples. This approach is widely used in the literature (e.g., Gong et al., 2019; Hsu et al., 2022).

Table 7
The moderating effects of financial constraints (H3).

Subsamples are partitioned by:	SA index (*SAINDEX*)		WW index (*WWINDEX*)		Availability of the S&P credit rating (*RATING*)	
	Low	High	Low	High	Yes	No
Dep. Var. = *TCR*	(1)	(2)	(3)	(4)	(5)	(6)
CMD	0.003	0.019***	0.001	0.020***	−0.000	0.016***
	(0.76)	(3.27)	(0.24)	(3.82)	(−0.05)	(3.34)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,318	1,320	1,314	1,314	1,056	1,573
Adj. R^2	0.288	0.205	0.261	0.224	0.285	0.215
Test of the difference between the coefficients (*p*-value)						
	0.000***		0.000***		0.000***	

This table presents the results from testing the moderating effect of financing constraints on the relation between CMD and trade credit. The dependent variable is the trade credit received from suppliers (*TCR*), defined as accounts payable scaled by the cost of goods sold in year $t+1$. All independent variables are calculated at year *t*. The variable of interest, *CMD*, is an indicator of more-specific CMD. Specifically, for our sample firms (i.e., those required to file Form SD with a Conflict Minerals Report as an exhibit), *CMD* equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, and 0 otherwise. To test the moderating effect, we divide our sample into two subsamples based on various measures of financial constraints, and we use Fisher's permutation test with bootstrapping to test the difference between the coefficients on *CMD* for each subsample. In columns (1)–(2), we use Hadlock and Pierce's (2010) size-age index of financial constraints (*SAINDEX*) as our partitioning variable. In columns (3)–(4), we use Whited and Wu's (2006) index of financial constraints (*WWINDEX*). In columns (5)–(6), we rely on the availability of the S&P credit rating (*RATING*) to partition our sample. We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

whether the coefficients on *CMD* in columns (1) and (2) are statistically different; we find that both are significant at the 1 % level. In columns (3)–(4), we use analyst coverage (*ANACOV*) as our partitioning variable, and in columns (5)–(6) we use media coverage (*MEDCOV*). Across these four columns, we continue to find that the relation between CMD and trade credit is pronounced only for subsamples with weaker external monitoring. Taken together, our results support our hypothesis that the relation between CMD and trade credit is more pronounced for firms with weaker external monitoring. These results provide corroborative evidence of a reduced adverse selection channel through which a firm's CMD affects the trade credit it receives from suppliers.

4.4. The relation between CMD and the trade credit given to customers (H5)

To test whether and how a firm's CMD is associated with the trade credit the firm gives to its customers, we run a regression model

Table 8
The moderating effects of external monitoring (H4).

Subsamples are partitioned by:	Institutional ownership (*INSTOWN*)		Analyst coverage (*ANACOV*)		Media coverage (*MEDCOV*)	
	Low	High	Low	High	Low	High
Dep. Var. = *TCR*	(1)	(2)	(3)	(4)	(5)	(6)
CMD	0.019***	−0.004	0.014***	−0.001	0.015***	0.008
	(3.45)	(−0.93)	(2.60)	(−0.13)	(2.88)	(1.54)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,130	1,132	1,048	1,050	1,122	1,124
Adj. R^2	0.271	0.188	0.242	0.234	0.217	0.199
Test of the difference between the coefficients (*p*-value)						
	0.000***		0.000***		0.023**	

This table presents the results from testing the moderating effect of external monitoring on the relation between CMD and trade credit. The dependent variable is the trade credit received from suppliers (*TCR*), defined as accounts payable scaled by the cost of goods sold in year $t+1$. All independent variables are calculated at year *t*. The variable of interest, *CMD*, is an indicator of more-specific CMD. Specifically, for our sample firms (i.e., firms required to file Form SD with a Conflict Minerals Report as an exhibit), *CMD* equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, and 0 otherwise. To test the moderating effect, we divide our sample into two subsamples based on various measures of external monitoring, and we use Fisher's permutation test with bootstrapping to test the difference between the coefficients on *CMD* for each subsample. In columns (1)–(2), we use firms' institutional ownership (*INSTOWN*) to partition our sample into two. In columns (3)–(4), we use analyst coverage (*ANACOV*) as our partitioning variable. In columns (5)–(6), we use media coverage (*MEDCOV*). We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

Table 9
Relation between CMD and the trade credit given to customers (H5).

Dep. Var. = *TCG*	(1)	(2)
CMD	−0.006**	−0.007**
	(−1.97)	(−2.46)
SIZE	0.011***	0.009***
	(8.68)	(7.34)
AGE	−0.003	−0.001
	(−1.41)	(−0.56)
MKSH	−0.080**	−0.090**
	(−2.06)	(−2.29)
SGRWPOS	0.006	0.002
	(0.54)	(0.18)
SGRWNEG	−0.051**	−0.050**
	(−2.44)	(−2.45)
ROA	−0.071***	−0.045***
	(−5.22)	(−3.30)
MB	−0.001***	−0.001***
	(−2.95)	(−3.31)
LEV	−0.013	−0.009
	(−1.33)	(−0.99)
CL	0.007	−0.003
	(0.32)	(−0.16)
CASH	−0.007	−0.010
	(−0.68)	(−0.89)
CA	0.132***	0.128***
	(9.07)	(8.95)
TANGI	−0.072***	−0.067***
	(−5.89)	(−5.54)
RATING	−0.005	−0.006*
	(−1.27)	(−1.71)
BIG4	−0.003	−0.003
	(−0.77)	(−0.72)
FRQ	0.040	0.046*
	(1.45)	(1.72)
MEF	−0.003**	−0.002
	(−1.96)	(−1.43)
TCR		0.142***
		(6.65)
Industry and year FE	Yes	Yes
N	2,639	2,639
Adj. R^2	0.328	0.346

This table presents the results from testing the relation between CMD and downstream trade credit. The dependent variable, trade credit given to customers (*TCG*), is defined as a firm's accounts receivable scaled by its sales revenue in year $t + 1$. In column (1), all independent variables are calculated at year *t*. The variable of interest, *CMD*, is an indicator of more-specific CMD. Specifically, for our sample firms (i.e., those required to file Form SD with a Conflict Minerals Report as an exhibit), *CMD* equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, and 0 otherwise. In column (2), we further control for the trade credit received from suppliers in year $t + 1$ (*TCR*). We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

Table 10
Further examination of the enhanced supply chain visibility channel.

Panel A: Cost stickiness		
	(1)	(2)
Dep. Var. =	ΔSGA	$\Delta COGS$
$\Delta SALE \times DEC \times CMD$	0.162*	0.184**
	(1.88)	(2.48)
$\Delta SALE \times CMD$	−0.069	−0.055*
	(−1.06)	(−1.80)
CMD	0.001	0.004
	(0.15)	(0.97)
$\Delta SALE \times DEC$	−0.262***	−0.158**
	(−2.76)	(−2.35)
$\Delta SALE$	0.707***	1.020***
	(13.05)	(40.82)
$\Delta SALE \times DEC \times ATINT$	−0.043	−0.116*
	(−0.49)	(−1.91)
$\Delta SALE \times DEC \times EMPINT$	−0.180**	0.002
	(−2.13)	(0.07)
$\Delta SALE \times DEC \times LAGDEC$	0.448***	−0.010
	(5.09)	(−0.17)
$\Delta SALE \times DEC \times LAGFCF$	−0.956	0.412
	(−1.15)	(0.77)
$\Delta SALE \times DEC \times LAGROA$	−0.240	−0.569
	(−0.54)	(−0.94)
$\Delta SALE \times DEC \times LAGRD$	−0.010	−0.202
	(−0.02)	(−0.60)
$\Delta SALE \times DEC \times MBZ$	0.816**	0.523
	(2.06)	(0.94)
$\Delta SALE \times ATINT$	0.019	0.037
	(0.43)	(1.63)
$\Delta SALE \times EMPINT$	0.104***	−0.020
	(2.99)	(−1.25)
$\Delta SALE \times LAGDEC$	−0.308***	0.021
	(−5.80)	(0.81)
$\Delta SALE \times LAGFCF$	0.699***	−0.276*
	(2.93)	(−1.91)
$\Delta SALE \times LAGROA$	0.106	0.289
	(0.42)	(1.11)
$\Delta SALE \times LAGRD$	−0.360	0.192
	(−1.39)	(0.82)
$\Delta SALE \times MBZ$	0.207	−0.062
	(0.66)	(−0.19)
$ATINT$	0.006	−0.004
	(0.73)	(−0.82)
$EMPINT$	0.003	0.008**
	(0.73)	(2.31)

(continued on next page)

Table 10 (*continued*)

Panel A: Cost stickiness		
	(1)	(2)
Dep. Var. =	ΔSGA	$\Delta COGS$
LAGDEC	−0.004	0.001
	(−0.78)	(0.43)
LAGFCF	0.113**	−0.006
	(2.01)	(−0.29)
LAGROA	0.036	0.050
	(0.75)	(1.44)
LAGRD	0.105***	0.016
	(4.27)	(0.51)
MBZ	0.021**	0.001
	(2.46)	(0.08)
Industry and year FE	Yes	Yes
N	2,566	2,566
Adj. R^2	0.587	0.876

Panel B: Operational efficiency		
	(1)	(2)
Dep. Var. =	*EFFICIENCY*	*STCRATIO*
CMD	0.013**	0.006**
	(2.46)	(1.97)
SIZE	0.025***	0.007***
	(10.73)	(5.76)
AGE	−0.024	−0.017*
	(−1.43)	(−1.74)
MKSH	0.126**	−0.138***
	(2.12)	(−4.09)
FCF	0.031***	0.046***
	(4.05)	(8.27)
SEGCON	0.023***	0.010**
	(2.81)	(2.12)
FOREIGN	−0.005	−0.001
	(−1.16)	(−0.20)
LAGEFFICIENCY	0.725***	
	(42.90)	
LAGSTCRATIO		0.864***
		(59.03)
Industry and year FE	Yes	Yes
N	2,558	2,558
Adj. R^2	0.817	0.889

In this table, we validate the supply chain visibility channel by examining the effect of CMD on firm operations. Panel A presents the results from testing the effect of CMD on cost stickiness. In column (1), the dependent variable is the log change in SG&A expenses; in column (2), it is the log change in the cost of goods sold. $\Delta SALE$ is the log change in sales revenue from years $t-1$ to t. *DEC* is an indicator variable that equals 1 if sales revenue decreases from years $t-1$ to t, and 0 otherwise. *CMD* is an indicator of more-specific CMD. Specifically, for our sample firms (i.e., those required to file Form SD with a Conflict Minerals Report as an exhibit), *CMD* equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, and 0 otherwise. We focus on the three-way interaction term $\Delta SALE \times DEC \times CMD$, which captures the effect of CMD on cost stickiness. Panel B presents the results from testing the effect of CMD on operational efficiency. In column (1), the dependent variable (*EFFICIENCY*) is Demerjian et al.'s (2012) measure of operational efficiency estimated using a data envelopment analysis. In column (2), the dependent variable is the sales-to-costs ratio (*STCRATIO*), calculated as sales revenue divided by the sum of the cost of goods sold and SG&A expenses. We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively.

Table 11
Further examination of the reduced adverse selection channel.

Panel A: Correlation between *CMD* and CSR performance						
	Summary statistics			Correlation matrix		
	N	Mean	SD	1	2	3
1.*CMD*	1,534	0.709	0.454		0.139***	0.196***
2.*CSR_SC*	1,534	0.124	0.352	0.139***		0.291***
3.*CSR*	1,534	1.295	2.218	0.186***	0.340***	

Panel B: Controlling for CSR performance			
Dep. Var. = *TCR*	(1)	(2)	(3)
CMD	0.006**	0.006**	0.005**
	(2.16)	(2.22)	(2.10)
CSR_SC	0.015**		0.012***
	(2.46)		(2.62)
CSR		0.002	0.002
		(1.34)	(0.87)
Controls	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes
N	1,534	1,534	1,534
Adj. R^2	0.262	0.261	0.262

This table validates the CMD measure (*CMD*), an indicator of more-specific CMD. Specifically, for our sample firms (i.e., those required to file Form SD with a Conflict Minerals Report as an exhibit), *CMD* equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, and 0 otherwise. Panel A presents the correlations between *CMD* and CSR measures relevant to socially responsible sourcing practices. Panel B examines the effect of CMD on trade credit after controlling for CSR performance. We summarize the variable definitions in Appendix C. We winsorize the continuous variables at the 1st and 99th percentiles. We present the *t*-values based on heteroscedasticity-robust standard errors in parentheses. Constant terms are estimated but omitted for brevity. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

similar to Eq. (1), replacing the dependent variable with *TCG*, defined as accounts receivable scaled by annual sales. In Table 9, we present the results of this analysis. In column (1), the significantly negative coefficient on *CMD* indicates that firms with more-specific CMD tend to provide less trade credit to their own customers. This finding supports Fabbri and Klapper's (2016) view that firms with stronger (weaker) bargaining power are less (more) likely to offer their customers trade credit.

Prior literature finds that when a firm receives more trade credit from its suppliers, it is able to give its customers' more trade credit. In column (2), we control for the trade credit received from suppliers (*TCR*). Consistent with prior literature, we find a significantly positive association between *TCR* and *TCG*. We also find that the coefficient on *CMD* remains significantly negative, which highlights CMD's unique role in attracting sales. Although giving trade credit to customers can be viewed as a way of attracting sales, our results suggest that CMD reduces firms' need to do so through the provision of trade credit.

5. Supplementary analyses

5.1. Further examination of the enhanced supply chain visibility channel

In this subsection, we conduct supplementary analyses to validate the enhanced supply chain visibility channel, which we view as the primary channel that links CMD to supply chain finance. Under this channel, a firm's CMD enhances its supply chain visibility, which in turn can improve its operational capabilities and creditworthiness. To validate the channel, we study two potential benefits: the effect of a firm's CMD on both its cost stickiness and its operational efficiency. First, we follow Liu et al. (2019) and use the following regression specification to examine the effect of CMD on cost stickiness:

$$\begin{aligned}\Delta SGA = {} & \beta_0 + \beta_1 \Delta SALE \times DEC \times CMD + \beta_2 \Delta SALE \times CMD + \beta_3 CMD + \beta_4 \Delta SALE \times DEC + \\ & \beta_5 \Delta SALE + (\beta_6 ATINT + \beta_7 EMPINT + \beta_8 LAGDEC + \beta_9 LAGFCF + \beta_{10} LAGROA + \\ & \beta_{11} LAGRD + \beta_{12} MBZ) \times \Delta SALE \times DEC + (\beta_{13} ATINT + \beta_{14} EMPINT + \beta_{15} LAGDEC + \\ & \beta_{16} LAGFCF + \beta_{17} LAGROA + \beta_{18} LAGRD + \beta_{19} MBZ) \times \Delta SALE + \beta_{20} ATINT + \\ & \beta_{21} EMPINT + \beta_{22} LAGDEC + \beta_{23} LAGFCF + \beta_{24} LAGROA + \beta_{25} LAGRD + \beta_{26} MBZ + \\ & Industry fixed effects + Year fixed effects + \varepsilon.\end{aligned} \tag{2}$$

The dependent variable, ΔSGA, is the log change in selling, general, and administrative (SG&A) expenses from years $t-1$ to t. $\Delta SALE$ is the log change in sales revenue from years $t-1$ to t. *DEC* is an indicator variable that equals 1 if sales revenue decreases from years $t-1$ to t, and 0 otherwise. If costs are sticky, we should see a significantly negative coefficient on the two-way interaction term $\Delta SALE \times DEC$. We are interested in the three-way interaction term $\Delta SALE \times DEC \times CMD$: its regression coefficient, β_1, captures the moderating effect of CMD on a firm's cost stickiness. To the extent that improved visibility in the supply chain can facilitate managers' resource adjustment decisions, we expect firms with more-specific CMD to have a less sticky cost structure and a significantly positive β_1.

Following prior literature (e.g., Liu et al., 2019), we control for asset intensity (*ATINT*), employment intensity (*EMPINT*), a lagged sales decrease dummy (*LAGDEC*), lagged free cash flow (*LAGFCF*), lagged return on assets (*LAGROA*), and lagged research and development expenses (*LAGRD*). In addition, we include a dummy for the meet-or-beat zero benchmark (*MBZ*) to control for earnings management incentives (Dierynck et al., 2012). To control for the effects of these variables on cost stickiness, we include in the model their main effects, the two-way interaction terms with $\Delta SALE$, and the three-way interaction terms with $\Delta SALE \times DEC$. Finally, we include year and industry fixed effects.

Table 10, Panel A presents the results based on the above regression specification. As shown in column (1), the significantly negative coefficient on $\Delta SALE \times DEC$ confirms that firms' SG&A expenses are sticky. More importantly, the coefficient on the three-way interaction term, $\Delta SALE \times DEC \times CMD$, is significantly positive, with a *t*-value of 1.88. This finding shows that firms with more-specific CMD have a lower stickiness, which is consistent with the notion that enhanced supply chain visibility can facilitate cost management. In column (2), we replace the dependent variable with the log change in the cost of goods sold ($\Delta COGS$). We find that the cost of goods sold is also sticky and that firms with more-specific CMD experience this stickiness to a lesser extent, as evidenced by the significantly negative (positive) coefficients on $\Delta SALE \times DEC$ ($\Delta SALE \times DEC \times CMD$). Taken together, our results show that firms with more-specific CMD have a lower stickiness both in their SG&A expenses and in the cost of goods sold. These results are consistent with our argument that CMD enhances firms' supply chain visibility, which facilitates managers' cost-cutting decisions when demand decreases, resulting in a lower cost stickiness.

Next, we examine the association between CMD and firms' operational efficiencies in terms of the use of inputs to generate outputs. If CMD enhances firms' supply chain visibility, we expect firms with more-specific CMD to achieve higher operational efficiency. Generally speaking, better supply chain management (e.g., enhanced supply chain visibility) would lead to more output being produced per unit of input (Caridi et al., 2014; Swift et al., 2019). To examine the association between CMD and input–output efficiency, we estimate the following regression model:

$$EFFICIENCY = \beta_0 + \beta_1 CMD + \beta_2 SIZE + \beta_3 AGE + \beta_4 MKSH + \beta_5 FCF + \beta_6 SEGCON + \beta_7 FOREIGN + \beta_8 LAGEFFICIENCY + Industryfixedeffects + Yearfixedeffects + \varepsilon. \tag{3}$$

The dependent variable *EFFICIENCY* is Demerjian et al.'s (2012) measure of operational efficiency estimated using a data envelopment analysis. By construction, this measure captures the extent to which a firm can minimize the input resources used for a given level of output. As an alternative measure of operational efficiency, we use the sales-to-costs ratio (*STCRATIO*), calculated as sales revenue divided by the sum of the cost of goods sold and SG&A expenses. This ratio measures the revenue generated by each dollar of operating costs, and a higher value indicates higher operational efficiency. If firms with more-specific CMD achieve higher operational efficiency, we expect the coefficient on *CMD* (i.e., β_1) to be significantly positive. Following Cheng et al. (2018), we use control variables for firm size, firm age, market share, free cash flow, segment concentration, foreign operations, and lagged operational efficiency. We also include industry and year fixed effects.

Table 10, Panel B presents the results based on the above regression specification. In column (1), we use Demerjian et al.'s (2012) efficiency measure as the dependent variable; we find a significantly positive coefficient on *CMD*. Specifically, the regression coefficient is 0.013 (t-value = 2.46), which is significant at the 5 % level. In column (2), we use the sales-to-costs ratio (*STCRATIO*) as the dependent variable. Consistent with our expectation, we continue to find a positive relation between *CMD* and *STCRATIO*, indicating a positive association between CMD and operational efficiency (by increasing revenue per dollar of operating costs). Overall, using two distinct measures of operational efficiency, we consistently find that firms with more-specific CMD have higher operational efficiency in terms of the input–output relationship. These results are consistent with our argument that CMD enhances firms' supply chain visibility, which can help them achieve higher operational efficiency.

5.2. Further examination of the reduced adverse selection channel

To validate that more-specific CMD reduces suppliers' adverse selection concerns about firms' CSR, we examine whether more-specific CMD is associated with a better CSR rating. The underlying logic is that if CSR rating agencies view firms with more-specific CMD as more socially responsible, suppliers are likely to share that view. We obtain CSR ratings from the KLD database for 1,534 of the 2,639 observations in our main sample (used in Table 3). Specifically, we obtain KLD's rating for controversial supply chain sourcing (*CSR_SC*) and firms' overall CSR rating (*CSR*). We then run a simple analysis of the correlations between *CMD*, *CSR_SC*, and *CSR*. Table 11, Panel A shows a Pearson correlations of 0.139 between *CMD* and *CSR_SC*, 0.186 between *CMD* and *CSR*, and 0.340 between *CSR_SC* and *CSR*. As expected, *CMD* is positively correlated with *CSR_SC* and *CSR*, but the correlations are not very strong. One inference from the correlations is that more-specific CMD relates to the perception (or rather, KLD's perception) of more socially responsible sourcing and higher CSR in general.

Next, we determine whether our earlier finding of a positive association between CMD and trade credit is robust to controlling for *CSR_SC* and *CSR*. In Table 11, Panel B, columns (1)–(3), we continue to find a significantly positive association after adding *CSR_SC*, *CSR*, and both as controls. The results offer at least two inferences. First, to the extent that one views KLD ratings (or ratings from CSR rating agencies in general) as sufficient information for suppliers' trade credit decisions, CMD has an incremental effect beyond simply providing socially responsible sourcing information due to other channels such as supply chain visibility. Second, when KLD ratings are not sufficient, more-specific CMD can provide incremental information to fill in trade creditors' information gap.

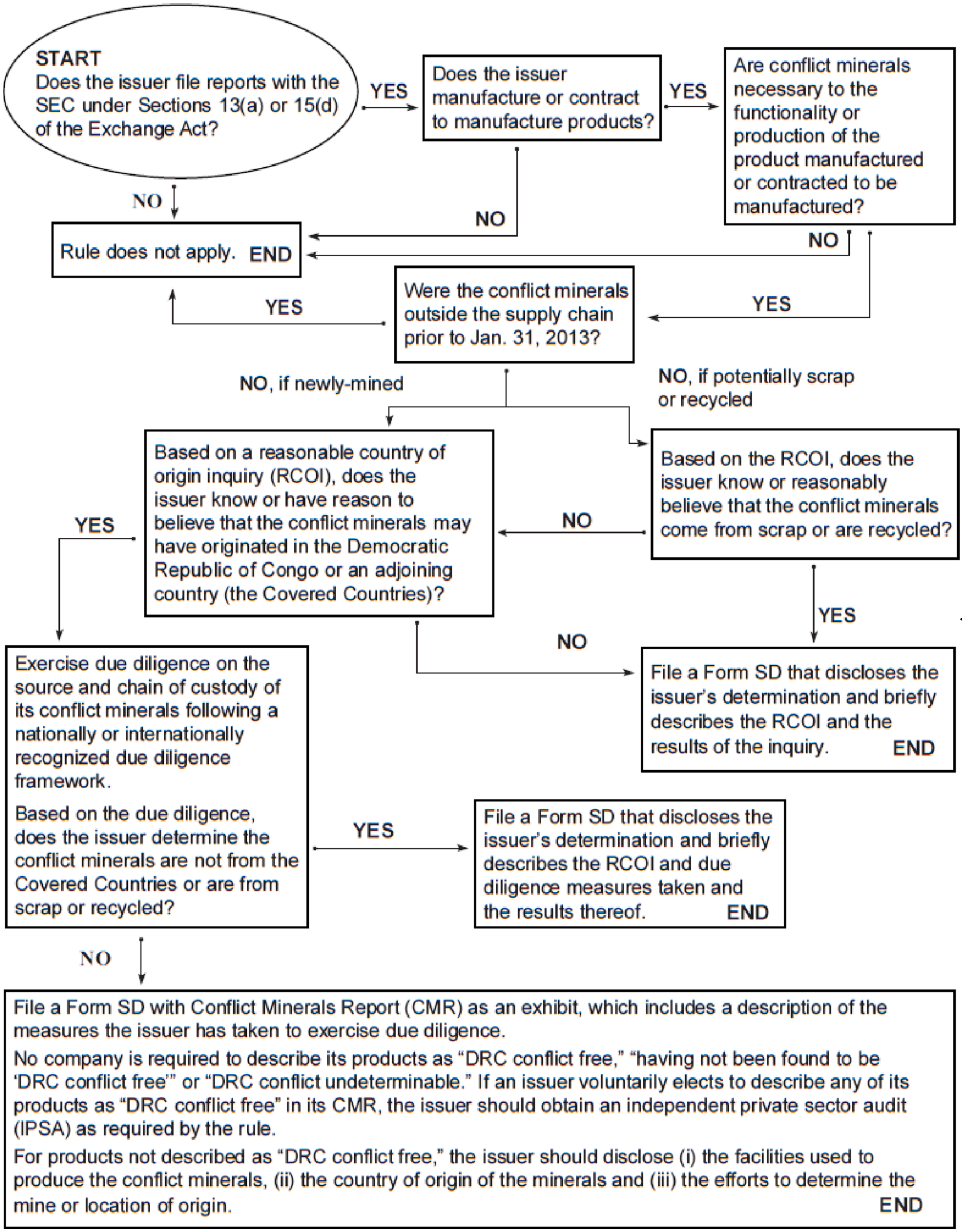
6. Conclusion

In this paper, we investigate the relation between a firm's CMD and its trade credit. Using the CMD mandate in the 2010 Dodd-Frank Act, we construct a measure of the specificity of CMD that is applicable to a large sample of U.S. listed firms. Our measure captures firms' supply chain visibility and their willingness to provide detailed public information about their sourcing of conflict minerals. We find that firms with more-specific CMD receive more trade credit. Our results are robust to alternative measures of CMD and trade credit, alternative model specifications, sample selection bias correction, and propensity score matching. Our channel tests offer supporting evidence that the positive association between a firm's CMD and its trade credit can be explained by the disclosure's role in enhancing the firm's supply chain visibility and in reducing its suppliers' adverse selection concerns. Consistent with the enhanced supply chain visibility channel, we find that this positive association is more pronounced for firms with stronger product market competition and more financial constraints. Consistent with the reduced adverse selection channel, we find that the positive association between CMD and trade credit is more pronounced for firms with weaker external monitoring by non-supplier stakeholders. We also find that more-specific CMD is associated with less downstream trade credit, suggesting that the reputational benefit of CMD enables firms to rely less on trade credit as a means of attracting or capturing customers. Overall, our study provides new insights into how firms' disclosure of their socially responsible sourcing practices can strengthen supply chain finance, an important resource for business growth and profitability.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Jeffrey Ng reports financial support was provided by Research Grants Council of Hong Kong. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper].

Appendix A. Flowchart of SEC rules for conflict minerals reporting



Note: This flowchart is based on information from three documents: (1) The SEC's final rule adopted on August 22, 2012, Release No. 34–67716 (https://www.sec.gov/rules/final/2012/34–67716.pdf); (2) the compliance guide, last modified on November 13, 2012, available on the SEC's website (https://www.sec.gov/info/smallbus/secg/conflict-minerals-disclosure-small-entity-compliance-guide.htm); and (3) the SEC's public statement on the effect of the recent court of appeals decision on the conflict minerals rule, released on April 29, 2014 (https://www.sec.gov/news/public-statement/2014-spch042914kfh).

Appendix B. How we define the indicator variable *CMD* based on conflict Minerals reports

Example 1 Excerpts from Philips' 2015 Conflict Minerals Report indicating more-specific CMD ($CMD = 1$).

6. Determination

We have not been able to confirm the identification of a conflict-free status under the CFSP standards for all smelters used in our supply chain. The number of smelters in our supply chain validated through CFSP or equivalent audit scheme increased substantially compared to the previous years. None of the smelters identified in our supply chain is known to us as sourcing 3TG that directly or indirectly finances or benefits armed groups in the DRC or adjoining countries.

As a result of the due diligence measures performed, Philips provides below the known smelter facilities that may have been used to process 3TG metals contained in Philips products, and their conflict-free status. The conflict-free status is based on the CFSI RCOI report which the CFSI provides to its members. We include the category "CFSI Active" as it shows smelters who committed to or are currently in the process of undertaking an audit. Our list of smelter facilities provided in Section 8 of this Conflict Minerals Report includes all 317 entities that were confirmed to be smelters.

This conflict minerals report covers Philips' entire product portfolio. Given Philips' large product portfolio and extensive supplier base, Philips does not have component level information from all of our 10,000 first tier suppliers, and therefore our approach is to conduct supply chain due diligence and report at the company level for our entire product portfolio, rather than for specific Philips products, which allows us to focus our efforts on building, maintaining, and improving a robust due diligence program that makes a difference for the communities in the DRC or adjoining countries.

7. Steps to improve future due diligence

For the next reporting year, Philips plans to.

- Leverage its new position as strategic partner in the European Partnership for Responsible Minerals (ERPM), a public–private cooperation that supports and complements the forthcoming EU conflict minerals legislation. As a strategic partner we will engage in responsible sourcing projects (with a scope broadened to conflict and high-risk areas world-wide as well as wider array of human rights related as well as environmental issues addressed) in order to increase the supply of and the demand for responsibly sourced minerals.
- Continue our engagement with existing industry programs and groups to encourage further adoption, improvement and reliability in relevant programs, tools and standards.
- Continue to reach out to smelters to encourage their participation in relevant responsible sourcing initiatives.
- Continue our work with priority suppliers to help them understand and satisfy Philips responsible sourcing expectations; to investigate their supply chain and identify smelters; and to confirm the conflict-free status of identified smelters.
- Communicate to priority suppliers our expectation that they steer their supply chain towards CFSP (or equivalent) compliant smelters only.

8. List of smelter facilities

The table below represents a consolidated list of smelters (317 in total) identified by Philips' priority suppliers. The results are based on:

- Information provided by our priority suppliers in their CMRTs
- Smelter database information available to the CFSI members
- CFSI smelter reference list, as included in the CMRT version 4.10 (released April 29, 2016)
- RCOI report provided by the CFSI – version May 3rd 2016

Metal	Smelter Name	Smelter ID	CFSP Complaint	CFSI Active
Gold	Advanced Chemical Company	CID000015	No	Yes
Gold	Aida Chemical Industries Co., Ltd.	CID000019	Yes	No
Gold	Al Etihad Gold Refinery DMCC	CID002560	No	No
Gold	Allgemeine Gold-und Silberscheideanstalt A.G.	CID000035	Yes	No
Gold	Almalyk Mining and Metallurgical Complex (AMMC)	CID000041	No	Yes
Gold	AngloGold Ashanti Córrego do Sítio Mineração	CID000058	Yes	No

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Metal	Smelter Name	Smelter ID	CFSP Complaint	CFSI Active
Gold	Argor-Heraeus S.A.	CID000077	Yes	No
Gold	Asahi Pretec Corp.	CID000082	Yes	No
Gold	Asahi Refining Canada Ltd.	CID000924	Yes	No
Gold	Asahi Refining USA Inc.…….	CID000920	Yes	No

Source: https://www.sec.gov/Archives/edgar/data/313216/000119312516607860/d189292dex101.htm.

Example 2 Excerpts from FuelCell Energy's 2015 Conflict Minerals Report indicating less-specific CMD (*CMD* = 0).

4. Conflict Minerals Due Diligence.

Our due diligence measures include the following:

- We made further inquiries to our direct suppliers with the goal of improving our understanding of each supplier's 3TG Metals supply chain. We are still awaiting responses and adequate information from some suppliers. If we become aware of a supplier whose due diligence process needs improvement, we intend to continue the trade relationship and we will work with that supplier to improve its processes and performance, including through additional training, subject to possible termination of the relationship if requested improvements are not forthcoming.
- Report to senior management on direct suppliers' responses to the CMRT and follow up inquiries. We continue to monitor, track and report on progress of direct suppliers to senior management.
- We are assembling an internal team to support the appropriate supply chain due diligence and implement internal measures to strengthen our engagement with suppliers on their due diligence efforts and are in the process of refining the FuelCell Energy Conflicts Mineral Policy, which details the standards by which our supply chain due diligence will be conducted.
- Continue to drive our suppliers to obtain current, accurate, and complete information about the smelters and refineries of Covered Minerals in their supply chains so that they in turn can report accurate and complete information to FuelCell Energy.
- Consider the availability of alternative sources of products if we determine that a supplier has supplied us with any Covered Minerals that directly or indirectly finance or benefit an armed group in a Covered Country.

5. Conflict Minerals status analysis and conflict status conclusion

Despite having conducted a good faith reasonable country of origin inquiry and further due diligence, we have concluded that a very small portion of our supply chain remains "DRC conflict undeterminable." We have reached this conclusion because we have been unable to determine the origin of all the 3TG Metals used in our products. Tracing minerals back to their mine of origin is a complex aspect of responsible sourcing in our supply chain. We have determined that the information regarding smelters and refiners that we gathered from our supply chain was inconclusive.

Source: https://www.sec.gov/Archives/edgar/data/886128/000088612815000012/exhibit101.htm.

Appendix C. Variable definitions

Variable	Definition
Variables used in the main regression	
TCR	Trade credit received from suppliers, measured as accounts payable at the end of year $t + 1$ scaled by the cost of goods sold in year $t + 1$.
CMD	Indicator variable that is equal to 1 for firms with more-specific CMD, and 0 otherwise. For firms required to file Form SD with a Conflict Minerals Report as an exhibit (i.e., firms with conflict minerals that may be sourced from Covered Countries), *CMD* equals 1 if the firm's Conflict Minerals Report includes at least a number or list of known smelters or refineries, and 0 otherwise.
CMD_LEVEL2	Indicator variable that is equal to 1 for firms with level 2 CMD, and 0 otherwise. Level 2 disclosure includes a number or list of known smelters or refineries.
CMD_LEVEL3	Indicator variable that is equal to 1 for firms with level 3 CMD, and 0 otherwise. Level 3 disclosure includes a list and the conflict-free audit status of known smelters or refineries.
CMD_LEVEL4	Indicator variable that is equal to 1 for firms with level 4 CMD, and 0 otherwise. Level 4 disclosure includes a list and the conflict-free audit status of known smelters or refineries, plus the minerals' countries of origin.
SIZE	Firm size defined as the natural logarithm of its total assets in year *t*.
AGE	Natural logarithm of 1 plus the number of years since the first year that the firm appeared in Compustat to year *t*.
MKSH	Market share, defined as the ratio of the firm's annual sales to aggregated sales in its own industry in year *t*.
SGRWPOS	Sales growth rate from years $t - 1$ to *t* if the sales growth rate is positive, and 0 otherwise.
SGRWNEG	Sales growth rate from years $t - 1$ to *t* if the sales growth rate is negative, and 0 otherwise.
ROA	Return on assets, calculated as the operating income in year *t* divided by the lagged total assets.
MB	Market-to-book ratio at the end of year *t*, calculated as the market value of equity divided by the book value of equity.
LEV	Leverage ratio in year *t*, defined as the sum of long-term and short-term debt divided by total assets.
CL	Current liabilities, excluding accounts payable, divided by the total assets in year *t*.
CASH	Cash and short-term investment scaled by the total assets in year *t*.
CA	Current assets divided by the total assets in year *t*.
TANGI	Tangible assets divided by the total assets in year *t*.

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Variable	Definition
RATING	Equals 1 if the firm has an S&P credit rating available in Compustat, and 0 otherwise.
BIG4	Equals 1 for firms audited by a Big 4 auditor, and 0 otherwise.
FRQ	Financial reporting quality in year *t*, measured as the absolute value of discretionary accruals multiplied by −1. To derive the discretionary accruals, we follow Kothari et al. (2005) and estimate the following model separately for each industry-year with at least 10 observations: $TA_{i,t} = \beta_0 + \beta_1(1/AT_{i,t\text{-}1}) + \beta_2\Delta REV_{i,t} + \beta_3 PPE_{i,t} + \beta_4 ROA_{i,t} + \varepsilon_{i,t}$.The dependent variable is total accruals (*TA*), calculated as the change in non-cash current assets minus the change in non-interest-bearing current liabilities and minus depreciation and amortization expenses. Independent variables include the ratio of 1 to the lagged total assets, Δ*REV* (change in sales scaled by the lagged total assets), and *PPE* (net property, plant, and equipment scaled by the lagged total assets). The model also controls for firm performance, as captured by *ROA*, calculated as income before extraordinary items divided by the lagged total assets. Discretionary accruals are the residuals estimated from the model.
MEF	Natural logarithm of 1 plus the number of management earnings forecasts for annual earnings per share in year *t*.
Other variables: (in alphabetical order)	
Δ*COGS*	The log change in the cost of goods sold from years $t-1$ to *t*.
Δ*SALE*	The log change in sales revenue from years $t-1$ to *t*.
Δ*SGA*	The log change in SG&A expenses from years $t-1$ to *t*.
Δ*TCR*	The change in the trade credit received from suppliers from years *t* to $t+1$.
ANACOV	Analyst coverage in year *t*, calculated as the logarithm of 1 plus the number of financial analysts following the firm.
ATINT	Asset intensity in year *t*, defined as the logarithm of the ratio of total assets to sales revenue.
CFOVOL	Cash flow volatility, calculated as the standard deviation of operating cash flow scaled by the lagged total assets over the 5-year period from years $t-4$ to *t*.
CMD_LEVEL	CMD measure following Swift et al.'s (2019) approach, which classifies CMD based on four levels. Level 1 disclosure contains no substantial information about smelters or refineries. Level 2 disclosure includes a list of the smelters or refineries producing the conflict minerals used in the firm's products. Level 3 disclosure includes a list and the conflict-free audit status of known smelters or refineries. Level 4 disclosure includes a list and the conflict-free audit status of known smelters or refineries, plus the minerals' countries of origin. *CMD_LEVEL* equals 0 for level 1 disclosure and 1, 2, and 3, respectively, for levels 2, 3, and 4 disclosure.
CMD_WORDS	CMD measure based on decile-ranked word counts. For firms that disclose a list of smelters or refineries in their Conflict Minerals Reports (*CMD* = 1), we count the number of words in the report. *CMDW_WORDS* equals the decile ranking (ranging from 1 to 10) of the word count divided by 10. For firms that do not disclose a list of smelters or refineries in their Conflict Minerals Reports (*CMD* = 0), the variable equals 0.
CSR	A firm's overall CSR rating in year *t*, calculated as the sum of the net CSR counts across five dimensions in the KLD database (community, diversity, employee relations, environment, and product), where the net CSR count for each dimension equals the total number of strengths minus the total number of concerns.
CSR_SC	A firm's CSR rating in supply chain practices, calculated as the sum of the following two indicators in the employee relations dimension of the KLD database. The first indicator is about supply chain labor standards; it assesses how well companies manage production disruptions and brand value damage due to the substandard treatment of workers in the supply chain. Companies score higher if they establish labor management policies that meet stringent international norms, implement programs to verify compliance with the policies, and introduce incentives for suppliers' compliance. The second indicator covers controversial sourcing and is designed to assess how companies manage the risks of incurring regulatory compliance costs, reputational damage, or supply chain disruptions that result from a reliance on raw materials originating in areas associated with severe human rights and labor rights abuses (e.g., slave labor). The score depends on the material and industry. In general, companies able to trace the origin of raw materials and certify that their sourcing processes minimize social harm score higher.
DEC	Equals 1 for firms that experience a decrease in sales revenue from years $t-1$ to *t*, and 0 otherwise.
DEMOTRIFECTA	Indicator variable for state government trifectas. It equals 1 for firms headquartered in states where the Democratic Party holds the governorship and controls both branches of the state legislature, 0 otherwise.
EFFICIENCY	Demerjian, Lev, and McVay's (2012) measure of operational efficiency estimated using a data envelopment analysis.
EMPINT	Employee intensity, defined as the logarithm of the ratio of the number of employees to the sales revenue in year *t*.
FCF	Free cash flow divided by total assets, where free cash flow is calculated as earnings before depreciation and amortization minus the change in working capital and capital expenditure.
FOREIGN	Equals 1 for firms with foreign operations, as evidenced by reporting a non-zero value for the foreign currency adjustment in year *t*, and 0 otherwise.
INSTOWN	Institutional ownership in year *t*, calculated as the proportion of a firm's shares held by institutional investors.
LAGDEC	Equals 1 for firms that experience a decrease in sales revenue from years $t-2$ to $t-1$, and 0 otherwise.
LAGEFFICIENCY	Lagged value of Demerjian et al.'s (2012) operational efficiency measure estimated using a data envelopment analysis.
LAGFCF	Lagged value of free cash flows scaled by total assets.
LAGRD	Lagged research and development expenses scaled by total assets.
LAGROA	Lagged returns on assets, calculated as the operating income in year $t-1$ divided by the total assets in year $t-2$.
LAGSTCRATIO	Lagged value of the sales-to-costs ratio, calculated as sales revenue divided by the sum of the cost of goods sold and SG&A expenses.
MBZ	Equals 1 for firms that meet or beat the zero earnings benchmark, which means their operating income scaled by their lagged total assets is larger than 0 but smaller than 1 % in year *t*, and 0 otherwise.
MEDCOV	Media coverage in year *t*, calculated as the logarithm of 1 plus the number of news articles covering the firm.
NEGHHI	Hoberg and Phillips' (2016) Herfindahl-Hirschman Index based on their text-based network industry classifications, multiplied by − 1.
POST	Indicator variable that equals 1 for years 2014 − 2016, and 0 for years 2010 − 2012.
RETVOL	Return volatility, calculated as the standard deviation of the monthly abnormal stock returns in year *t*.
SAINDEX	Hadlock and Pierce's (2010) size-age index of financial constraints, calculated as $(-0.737 \times Size) + (0.043 \times Size^2) - (0.040 \times Age)$, where *Size* is the natural logarithm of the firm's total assets, and *Age* is the number of years that it appears in the Compustat database.
STCRATIO	Sales-to-costs ratio, calculated as sales revenue divided by the sum of the cost of goods sold and SG&A expenses.
SEGCON	Segment concentration ratio, calculated as the square of the ratio of sales in each individual business segment to total sales, summed across all business segments in year *t*.

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Variable	Definition
SIMILARITY	Hoberg and Phillips' (2016) measure of product similarity, which compares a firm's product descriptions, as disclosed in the firm's 10-K filing, with those of its competitors.
TCR1	Trade credit received from suppliers in year $t + 2$, measured as accounts payable at the end of the year scaled by the cost of goods sold during that year.
TCR2	Trade credit received from suppliers, measured as accounts payable at the end of year $t + 1$ scaled by the total purchases in year $t + 1$. The total purchase is the sum of the cost of goods sold and the change in inventory.
TCR3	Trade credit received from suppliers, measured as accounts payable at the end of year $t + 1$ scaled by the total assets in year $t + 1$.
TCG	The trade credit given to customers, measured as accounts receivable scaled by the sales revenue in year $t + 1$.
TREAT	Indicator variable that equals 1 for the treatment firms, and 0 otherwise. Treatment firms are those subject to CMD regulation that need to file Form SD.
TREAT_CMRHIGH	Indicator variable that equals 1 for treatment firms that file Form SD with a Conflict Minerals Report as an exhibit and the Conflict Minerals Report includes a list of smelters or refineries that produce the conflict minerals used in the firm's products, and 0 otherwise.
TREAT_CMRLOW	Indicator variable that equals 1 for treatment firms that file Form SD with a Conflict Minerals Report as an exhibit but the Conflict Minerals Report does not include a list of smelters or refineries, and 0 otherwise.
TREAT_SDONLY	Indicator variable that equals 1 for treatment firms that file Form SD only (i.e., a Conflict Minerals Report is not included as an exhibit), and 0 otherwise.
WWINDEX	Whited and Wu's (2006) index of financial constraints, calculated as ($-0.091 \times Cf - 0.062 \times Divpos + 0.021 \times Tltd - 0.044 \times Size + 0.102 \times Isg - 0.035 \times Sg$), where *Cf* equals operating cash flows scaled by total assets, *Divpos* is an indicator that equals 1 for firms paying cash dividends, *Tltd* equals long-term debt scaled by total assets, *Size* equals the natural logarithm of the firm's total assets, *Isg* is the industry average sales growth rate, and *Sg* is the firm's sales growth rate.

This table summarizes the definitions and data sources for the variables used in our analyses.

Data availability

Data will be made available on request.

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