Economic Consequences of Financial Statement Comparability in Extractive Industries: Canadian Evidence

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Abstract

This study examines the economic effects of financial statement comparability (FSC) across extractive-industry (EI) firms on four important groups of market participants, i.e. analysts, investors, creditors, and auditors. Using data from 1599 EI firms in Canada from 2000 to 2019, we find that greater FSC enhances analyst forecast accuracy and stock liquidity, and reduces analyst forecast dispersion, cost of debt, and audit fees. These results are robust to alternative design and variable specifications. We further report the effects to vary across subindustry and extractive activity phase, suggesting heterogeneity in the use of comparable accounting information in the market participants' decision-making processes. In sum, our results suggest a beneficial role of financial statement comparability in a setting with high business uncertainty and less rigorous accounting standards. The study aims to contribute to the current literature on the diverse accounting practices of EI firms results. The results have implications for standard-setters aiming to improve accounting standards on extractive activities and related matters.

Keywords: Financial Statement Comparability; Extractive industry; Analyst forecasts; Market liquidity; Cost of debt; Audit Fees.
JEL classification: M41; G15.
Data Availability: The data used in this study are available from the indicated sources.

1. Introduction

Firms in the extractive industries (hereafter EI) represent enormous value on the stock exchange, yet a considerable variety in their accounting practices has prevailed for a long time. Luther (1996) investigates the development of accounting regulation and practices in EI firms in five countries (Australia, Canada, South Africa, the UK, and the US) and reports considerable accounting differences across (and within) these countries. Using the degree of conservatism as a yardstick, Stadler and Nobes (2020) identify nine accounting methods for exploration and evaluation (hereafter E&E) costs used by EI firms in ten IFRS countries. They document that the accounting practices for E&E costs differ by country, industry, and firm size and observe that different approaches are used under the same policy name. Stadler and Nobes further conclude that the current situation arises from "[…] the lack of definitions and guidance in IFRS6" (p. 17). IFRS 6 (*Exploration for and Evaluation of Mineral Resources*) explicitly addresses the recognition and measurement of E&E costs but offers substantial flexibility to EI firms. Specifically, EI firms under IFRS 6 may continue to apply the same E&E policies as before IFRS adoption, which implies that the IFRS accounting practices largely reflect the pre-IFRS national requirements (Stadler & Nobes, 2020). IFRS 6 also allows EI firms to change accounting method for E&E costs without meeting the requirements of IAS 8 (*Accounting Policies, Changes in Accounting Estimates and Errors*), thereby introducing an additional layer of flexibility (Gray, Hellman, & Ivanova, 2019). Finally, EI firms are exempted from conducting impairment tests as required by IAS 36 (*Impairment of Assets*). Overall, these exemptions imply a situation where almost any E&E treatment is IFRS compliant. Extractive activities give rise also to other EI-specific accounting issues, such as the depreciation of mineral and petroleum assets or the recognition of environment liabilities, but they are treated within the scope of general IFRS Standards. Gray et al. (2019) raise concerns that the flexibility given for E&E costs may spread to EI firms' application of other IFRS Standards.

Our study investigates the economic effects of financial statement comparability (hereafter FSC) on capital market participants, including analysts, stock investors, debt holders, and auditors. We follow De Franco, Kothari, and Verdi (2011) and Barth, Landsman, Lang, and Williams (2012) to define FSC as the similarity in the accounting outcomes of firms exposed to similar economic events. Comparability is one of the "enhancing qualitative characteristics" of financial reporting (IASB, 2018) and will be compromised by the use of diverse accounting practices. Prior literature suggests that comparability plays a vital role in enhancing reporting quality and reducing information asymmetry, which benefits many market participants (e.g., De Franco et al., 2011; Fang, Li, Xin, & Zhang, 2016; Neel, 2017). For example, Neel (2017) documents that the increases in FSC have first-order effects on the economic benefits associated with IFRS adoption. However, despite the potential benefits of FSC, prior studies find significant lobbying efforts dedicated to maintaining the flexibility in the financial reporting standards for EI firms (Asekomeh, Russell, & Tarbert, 2006). The argument is that flexibility enhances the decision making of managers and investors, in line with the findings of Power, Cleary, and Donnelly (2017).

Prior literature interprets the EI-accounting diversity from different perspectives. Some studies compare alternative methods used in practice, usually by measuring value relevance, and find mixed results (e.g., Harris & Ohlson, 1987; Bryant, 2003). In a recent study by Power et al. (2017), the value relevance of alternative E&E accounting policies is compared for a sample of firms listed on the London Stock Exchange. They report that the flexibility in E&E accounting choices enhances the value relevance of firms' financial disclosures. This result supports the view that managers use discretion to choose accounting methods that better reflect the firms' economic substance. In contrast, some studies find that EI firms' accounting choices are influenced by various opportunistic incentives (e.g., Chen & Lee, 1995). Given that essentially all treatments of E&E activities are IFRS compliant, auditing and other enforcement mechanisms are likely to be ineffective in restricting opportunistic behavior (e.g., Grenier, Pomeroy, & Stern, 2015).

Using a sample of Canadian EI firms between 2000 and 2019, we report significant benefits of FSC for auditors and three groups of financial statement users. Specifically, we find that FSC is positively associated with analyst forecast accuracy and market liquidity, and negatively associated with analyst forecast dispersion, cost of debt, and audit fee. We further report that the associations differ across subindustry and between different phases of the extractive activities cycle.

Our study makes two contributions. First, while prior studies compare the pros and cons of alternative accounting methods, and document considerable accounting diversity among EI firms, the economic effects of this diversity have not been much explored. A notable exception is Power et al. (2017) who document that the diversity with respect to E&E accounting improves the value relevance for a sample of EI firms in the UK. Our findings suggest that there are considerable economic benefits of higher FSC in EI firms for a broad range of capital market participants. Second, by assessing the effects of comparability, our study contributes to the literature on market participants in the extractive industries. Whereas prior studies report that market participants employ private information or geologic information in their decision-making process (e.g., Chen, Wright, & Wu, 2018; Ferguson, Kean, & Pündrich, 2020), our results suggest that market participants still benefit from more comparable financial information. These findings have potentially important implications for the IASB and other accounting standard setters. In particular, the laissez-faire solution for E&E costs, where compliance cannot be monitored as all treatments are compliant, represents an extreme case that we can learn from. As the “free market” for E&E accounting treatments seems to lead to significant accounting diversity with national clusters (Stadler & Nobes, 2020), IASB has an important role to play in order to safeguard high-quality information for primary users.

Moreover, even in a setting characterized by high accounting flexibility, our empirical results suggest that increased comparability contributes to financial reporting benefits for a broad range of financial market participants, and especially for capital-market investors subject to high information asymmetry. Given that the positive externalities of FSC can hardly be achieved by any single EI firm or market participant, we believe our findings provide relevant input to standard-setters and regulators considering the introduction of more rigorous accounting standards/regulation.

This paper proceeds as follows. Section 2 discusses the background. Section 3 reviews relevant literature and develops hypotheses. Section 4 describes the research design and sample. Section 5 reports descriptive statistics and the main analyses. In section 6, we discuss the results of the additional analysis. Finally, section 7 briefly summarizes the results and concludes.

2. Background

IASC (2000) defines EI as "those industries involved in finding and removing wasting natural resources located in or near the earth's crust" (IASC 2000, p. 14). EI firms generally follow a cycle with several phases, including acquiring legal rights, exploring and evaluating resources, developing and extracting deposits, processing, storing, and finally selling the products to arrive at the economic inflows. EI firms engage in these activities heterogeneously, depending on, for example, firm strategy, type of deposit (minerals, oil, gas), geological conditions, and production conditions (open pit, underground). Substantial uncertainty prevails in the early phases of the cycle, such as legal approval and the likelihood of finding deposits with enough economic value. Mineral and petroleum prices tend to be volatile, which creates uncertainty not only during the E&E phase but also during the development and production phases. There is also uncertainty about the value of the environmental liability incurred as the firm extracts the value of the deposits. The high level of uncertainty poses significant accounting challenges and contributes to accounting diversity among EI firms (e.g., Luther, 1996; Abdo, 2018; Gray et al., 2019).

Before IFRS, Canadian EI firms accounted for E&E costs in accordance with Canadian GAAP, which is close to U.S. GAAP, and permits both the full cost (FC) method and the successful efforts (SE) method.[1] In 2006, the Accounting Standard Board in Canada (AcSB) announced its decision to converge with IFRS. During 2007–2010, firms were given time to prepare and in January 2011 they had to adopt the complete body of IFRS Standards. IFRS 6 serves as a temporary standard, specifically guiding the accounting practices in the E&E phases. Once the E&E project reaches the development phase, it should be accounted for in accordance with IAS 16 (*Property, Plant, and Equipment*) and IAS 38 (*Intangible Assets*). Other EI-related accounting issues fall under the existing IFRS Standards applicable. For example, the environment liability referred to earlier shall be recognized and measured according to IAS 37 (*Provisions, Contingent Liabilities and Contingent Assets*).

IFRS 6 states that E&E assets shall be measured at cost at acquisition but let the entity determine an accounting policy that specifies which E&E expenditures are recognized as E&E assets (IFRS 6.8–6.9). By exempting preparers from paragraphs 11 and 12 of IAS 8, IFRS 6 also effectively allows all national accounting practices to continue. Without this exemption, firms would have had to follow the hierarchy of IAS 8 to determine an accounting policy for which E&E expenditures to capitalize. Finally, the impairment test requirements in IFRS 6 differ from IAS 36 in that IFRS 6 impairment tests are allowed to be postponed until sufficient data on technical feasibility and commercial viability of the resources are available (IFRS 6.17–

[1] Under the full cost method, all costs associated with the exploration of properties are capitalized for the appropriate geographic cost center (generally a country). Under the successful efforts method, the costs of drilling exploratory and exploratory-type stratigraphic test wells are capitalized, pending the determination of whether the well can produce proved reserves. If it is later determined that the well will not produce proved reserves, then the capitalized costs are expensed (KPMG, 2017, p. 406).

6.18, BC 39). In addition, IFRS 6 allows for using a unit of account for impairment test purposes that is greater than the cash-generating unit (CGU), thereby lowering the probability of impairment (IFRS 6.21). These exemptions grant management significant discretion to determine the firm's accounting policy for E&E costs and to postpone and avoid recognition of impairment losses. Both the firm-specific choice of capitalization policy, and professional judgment regarding the application of this policy and the soft impairment rules, compromise comparability across EI firms.

Disclosure of EI firms' reserves of mineral and petroleum deposits is another important aspect of EI reporting. The fair value of these reserves is highly uncertain but relevant to primary users of financial statements. As the fair value of the reserves is not used as input to accounting for the E&E assets during the E&E phase (data on technical feasibility and commercial viability of the resources are not yet available), fair values may deviate significantly from the reported E&E asset values (measured at cost). While the IASB acknowledges that commercial reserve quantities could be the most crucial disclosure for EI entities, it concludes that such disclosure goes beyond the stated scope of IFRS 6 (IFRS 6, BC 55). Thus, the disclosure of reserves is primarily subject to regulation at the country- or region level. In Canada, mining and O&G firms disclose reserves information according to National Instrument 43-101 (NI 43-101: *Standards of Disclosure for Mineral Projects*) and National Instrument 51-101 (NI 51-101: *Standards of Disclosure for Oil and Gas Activities*) respectively.[2]

Empirically, IFRS/IAS adoption does not seem to have introduced significant shifts for EI firms; researchers document that the diverse accounting practices of EI firms persist after the adoption of IFRS/IAS (e.g., Luther, 1996; Abdo, 2018). Gray et al. (2019) summarize the

[2] See https://mrmr.cim.org/en/standards/canadian-mineral-resource-and-mineral-reserve-definitions/ and https://www.bcsc.bc.ca/-/media/PWS/Resources/Securities_Law/Policies/Policy5/51101-NI-July-1-2015.pdf

literature investigating the reasons behind the diversity of practice and conclude that it is an outcome of the nexus of the economic significance of EI firms, the powerful role played by lobbying, and significant accounting challenges related both to technical aspects and high levels of uncertainty that persist over the mining cycle (e.g., Luther, 1996; Cortese, Irvine, & Kaidonis, 2009).

3. Related literature and hypothesis development

Related literature

Our study relates to the literature investigating accounting diversity across EI firms. In a wide-ranging literature review, Gray et al. (2019) document significant differences in national and international accounting regulation and practice. In the US, extensive studies compare and investigate the two accounting methods for E&E cost allowed under US GAAP (e.g., Horwitz & Koldony, 1982; Cortese et al., 2009). One observation is that while the conservative SE method is popular among large EI firms (with more projects in the production phase), junior EI firms prefer the FC method to reduce earnings volatility. Luther (1996) studies EI accounting regulations and practices in five countries (Australia, Canada, South Africa, the UK, and the US). He reports considerable accounting differences within and between the countries and concludes that "[…] comparing the actual and potential performance of individual companies within the same industry is problematical" (p. 68). Similarly, Abdo (2016) examines accounting practices under IFRS 6 for oil and gas (O&G) firms listed on six stock exchanges. Out of the 118 firms in his sample, Abdo finds that 47% report E&E assets using the SE method, 28% the FC method, 9% according to the area of interest, and 16% a non-specified method. In a recent study, Stadler and Nobes (2020) report diverse accounting practices among IFRS firms who refer to E&E cost methods by the same name. Specifically, they use hand-collected data and examine the accounting policies for E&E costs by IFRS firms in 10 countries. Even though most firms refer to their treatment of E&E costs as either FC or SE methods, Stadler and Nobes identify nine distinguishable methods with varying degrees of conservatism. Further, they find that the accounting policies differ by country, sub-sector (mining versus O&G), and firm size and conclude that the different practices result in a lack of comparability.

The significant variation in accounting practice among EI firms raises the question of what the implications for information users are. Several studies compare the value relevance of E&E costs under the two main alternative methods, SE and FC (e.g., Barth & Clinch, 1996; Spear 1996; Power et al., 2017; Ferguson et al., 2020). Using a sample of firms listed on the London Stock Exchanges (LSE), Power et al. (2017) find that the flexibility in E&E accounting methods enhances the value relevance of financial reporting. Their results justify accounting diversity with the view that EI firms need the flexibility to choose the accounting methods that best reflect the underlying economics. Alternatively, another stream of literature concerns the potential information asymmetry introduced by managerial discretion and finds evidence that different opportunistic incentives influence EI firms' accounting choices (e.g., Dharan & Mascarenhas, 1992; Chen & Lee, 1995). There is also evidence that market participants obtain information through other channels to facilitate the decision-making process (e.g., Chen et al., 2018; Ferguson et al., 2020). Based on a study of analyst forecasts of Australian EI firms, Chen et al. (2018) find that analysts develop private information to enhance forecast accuracy. Ferguson et al. (2020) report that investors use geological information to assess the value relevance of the capitalized E&E costs.

Taken together, with a focus on the accounting treatment of E&E costs, prior literature reports persisting and significant accounting differences across EI firms. While existing studies focus on the value relevance of different accounting methods, the evidence on the economic effects of comparability (or lack thereof) for EI firms is scarce. Indeed, Gray et al. (2019) call for more research on understanding how the diversity of accounting practices affect users of financial statement information provided by EI firms.

Our study also relates to a stream of research directly examining the economic effects of financial statement comparability on multiple market participants (e.g., De Franco et al., 2011; Fang et al., 2016; Kim, Li, Lu, & Yu, 2016; Neel 2017; Choi, Choi, Myers, & Ziebart, 2019). De Franco et al. (2011) and Barth et al. (2012) construct intuitive output-based measures of comparability based on the correlation between reported earnings and market returns. Using a sample of US firms, De Franco et al. (2011) report that firm-level accounting comparability encourages analyst following and leads to more accurate and less dispersed forecasts. De Franco et al. (2011) interpret this result as evidence that comparability lowers the costs of acquiring and processing information and increases information quality, contributing to a better information environment that benefits information users. In a similar vein, Fang et al. (2016) posit that comparable financial information reduces the information asymmetry in the syndicated loan market and report that firms with high FSC benefit from more advantageous contract terms. Zhang (2018) documents that the benefits of FSC in terms of enhancing information quality and lowering information acquisition costs also accrue to external parties such as auditors. Specifically, Zhang (2018) reports negative associations between FSC and audit fees, audit delay, and the likelihood of audit-opinion errors. In an international study of comparability, Neel (2017) reports that an observed increase in FSC has first-order effects on the IFRS-adoption-associated economic benefits, including increases in Tobin's Q, stock liquidity, analyst forecast accuracy, and decreases in analyst forecast dispersion.

Other studies document the beneficial role of FSC in facilitating accounting-based performance evaluation (Lobo, Neel, & Rhodes, 2018), attracting foreign investment (Chauhan & Kumar, 2019), reducing investors' private information seeking (Kim & Lim, 2017), facilitating firm's M&A decisions (Chen, Collins, Kravet, & Mergenthaler, 2018) and improving firms' innovation efficiency (Chircop, Collins, Hass, & Nguyen, 2020). Most of these studies rely on US data and include industry only as a dummy variable and do not report on industry significance.

Overall, prior studies report positive effects of FSC for multiple market participants, including analysts, stock investors, creditors, and auditors. While these studies investigate the role of FSC in both US and international settings, to our knowledge, the effects of FSC for EI firms have not been directly explored. The EI-related literature suggests that flexibility offered by accounting regulation and the corresponding variety in accounting practices may be higher in EI firms compared to firms in other sectors. A few studies controlling for industry as a dummy variable point at this rather unique industry feature (Nobes, 2013; Stadler and Nobes, 2014; Hellman, Gray, Morris, & Haller, 2015). For example, Nobes (2013) argues that firms in extractive industries make different accounting choices than in other industries and should therefore be studied separately. Our study aims to fill the research gap outlined above by examining the economic effects of FSC for firms operating in the extractive industries.

Hypothesis Development

As discussed above, EI firms' accounting practices have, in the past, diverted (e.g., Luther, 1996; Abdo, 2018; Gray et al., 2019). Consequently, information users have developed different approaches to evaluate financial performance in these firms (e.g., Chen et al., 2018; Ferguson et al., 2020). Although firms involved in extractive activities have some unique business characteristics referred to in Section 2, and more flexible accounting regulation than other industries, we expect increased FSC to benefit EI-related market participants. There are several reasons: First, as specified by standard setters, comparability is identified as one of the qualitative characteristics of financial reporting that enhances the usefulness and faithfulness of financial information (IASB, 2018). Second, both in the US and international settings, prior research has reported positive correlations between FSC and economic consequences across industries, in terms of analyst forecast accuracy and dispersion (e.g., De Franco et al., 2011), stock liquidity (e.g., Neel, 2017; Kim, Kim, & Kim, 2020), financing costs (e.g., Kim, Kraft, & Ryan, 2013; Imhof, Seavey, & Smith, 2017), and auditor effort (e.g., Zhang, 2018). In general, these studies conclude that FSC reduces information asymmetry and improves the information environment by enhancing market participants' ability to interpret financial information. We expect this association to hold also in the EI setting. Third, as a complement to reporting quality (IASB, 2018), improved FSC can interact with other reporting qualities (e.g., Peterson, Schmardebeck, & Wilks, 2015; Kim et al., 2016; Neel, 2017). For example, Neel (2017) reports that the increase in FSC has a first-order effect on IFRS-related economic benefits related to firm valuation, stock market liquidity, and analyst forecasts. Hence, we propose the following hypothesis:

> *Hypothesis: Increased FSC for EI firms has positive effects on analysts' forecasts, market liquidity, cost of debt and audit efforts.*

4. Research Design and Sample

Measures of FSC

Our empirical analysis primarily aims to investigate the association between financial statement comparability and economic consequences in EI firms. To capture the level of FSC among Canadian EI firms, we employ the output-based firm-level measure of FSC developed by De Franco et al. (2011) and Barth et al. (2012). As discussed above, this output-based measure relies on the premise that financial reporting is, in essence, a mapping function between the economic events and the accounting data. Accordingly, FSC can be captured by the degree of similarity of comparable economic events reported under different systems.

Prior research has employed the output-based measures of FSC in various empirical settings and referred to them as superior to other approaches in assessing the effects of FSC on users of accounting information such as analysts (De Franco et al., 2011; Gross & Perotti, 2017). Appendix 2 summarizes the commonly used output-based measures. Although these measures differ in terms of the specific proxies used for economic and accounting outcomes, they all hinge on the notion that comparable financial reporting systems should produce similar accounting amounts for similar economic outcomes (and produce different accounting amounts for dissimilar economic outcomes). We utilize three measures commonly used in international settings (e.g., Barth et al., 2012; Cascino & Gassen, 2015; Neel, 2017).

FSC_Acct

Our first measure – FSC_Acct – follows De Franco et al. (2011) and Barth et al. (2012), who consider stock return as a proxy for a company's economic outcome and earnings as the relevant accounting outcome. Barth et al. (2012) argue that stock returns capture stockholders' investment decisions. Similarly, earnings are a primary summary measure of accounting performance commonly used in accounting research. A specific feature of EI firms is that they often report losses, reflecting the high business uncertainty of extractive activities. We therefore introduce a $LOSS_{it}$ dummy to permit the mapping function to differ for firms experiencing a loss.[3] $LOSS_{it}$ is set to 1 if a firm's earnings are less than 0 for two consecutive years, and 0 otherwise.

Following Barth et al. (2012), we use five steps to construct the FSC metrics based on time-series relations. First, we estimate the following equation separately for each firm in the mining and O&G industries:

[3] De Franco et al. (2011) include losses when calculating earnings comparability as the asymmetric timeliness of earnings can be a potential source of bias. Campbell and Yeung (2017) include an economic loss (negative return) dummy that serves the same purpose.

$$Earnings_{it} = a_i + b_i Return_{it} + c_i LOSS_{it} + d_i LOSS_{it} \times Return_{it} + \varepsilon_{it}$$

where $Earnings_{it}$ is net income before extraordinary items for firm i at time t, scaled by the market value of equity at the end of the prior fiscal year. $Return_{it}$ is the total investment return, including quarterly dividend per share. Earnings and return are winsorized at the top and bottom 5 percent level to mitigate the influence of outliers. For each firm-year, we then estimate a_i, b_i, c_i, and d_i using four consecutive years of data and winsorize each at the top and bottom 1 percent. The estimated coefficient vectors $(\hat{a}_i, \hat{b}_i, \hat{c}_i, \hat{d}_i)$ and $(\hat{a}_j, \hat{b}_j, \hat{c}_j, \hat{d}_j)$ capture how the accounting functions $f_i(\cdot)$ and $f_j(\cdot)$ transfer the economic outcomes (return) into accounting amounts (earnings) for firms i and j.

Second, for each firm i, we use the estimated coefficient vector (a_i, b_i, c_i, d_i) to calculate the fitted value of earnings $\widehat{Earnings}_{iit}$.

$$\widehat{Earnings}_{iit} = \hat{a}_i + \hat{b}_i Return_{it} + \hat{c}_i LOSS_{it} + \hat{d}_i LOSS_{it} \times Return_{it}$$

Third, for each firm i, we predict its fitted value of earnings using i's return and the estimated coefficients vector of firm j from the same industry in the same period.

$$\widehat{Earnings}_{ijt} = \hat{a}_j + \hat{b}_j Return_{it} + \hat{c}_j LOSS_{it} + \hat{d}_j LOSS_{it} \times Return_{it}$$

FSC lies in the similarity of accounting functions that produce similar accounting amounts for a specific economic outcome.

Fourth, we estimate FSC by calculating the negative value of the distance between the fitted value of earnings under different accounting functions.

$$FSC_{ijt} = -1/4 \times \sum_{t-3}^{t} |\widehat{Earnings}_{iit} - \widehat{Earnings}_{ijt}|$$

Greater (less negative) values for FSC_{ijt} indicate a smaller difference between the fitted values of earnings, thus a higher FSC level between firms i and j.

Fifth, we generate FSC_Acct_{it} as a firm-year level FSC measure for all EI firms by aggregating all of the firm i – firm j combinations for a given firm i during period t. Specifically, FSC_Acct_{it} is the median FSC_{ijt} for all firms j in the same subindustry (mining or O&G) as firm i during period t.

FSC_CF

The second measure of FSC considers the subsequent year's cash flow as a proxy for economic outcomes. Barth et al. (2012) argue that future cash flow is a crucial input to corporate valuation models. Besides, a firm's cash flow is relatively objective and insensitive to market factors such as the information environment or investors' investment behavior (Barth et al., 2012; Neel, 2017). Therefore, we replace returns with operating cash flow as the economic outcome and estimate the following equation:

$$Earnings_{it} = a_i + b_i CF_{it+1} + \varepsilon_{it}$$

where CF_{it+1} is the operating cash flow in year $t+1$, scaled by the market value of equity at the end of the prior fiscal year. $Earnings_{it}$ is net income before extraordinary items for firm i at time t, scaled by the market value of equity at the end of the prior fiscal year. We repeat the second to fifth step outlined above to construct FSC_CF_{it}.

FSC_Accrual

Our third FSC measure relies on the same notion of mapping and hinges on the relationship between contemporaneous operating cash flows and accruals. Specifically, we follow Cascino and Gassen (2015) and Neel (2017) to map operating cash flow into accruals. Neel (2017) argues that this cash-accrual measure represents a crucial aspect of financial statement quality as it captures "[…] both the noise reduction role of accruals (Dechow, 1994) and the gain and loss recognition role of accruals (Ball and Shivakumar, 2006)." (Neel, 2017, p. 666). Moreover, the matching between accounting numbers and cash flows loosens the strong assumption of a constant market-efficiency level across countries, industries, and time. Using four years of accounting data, we estimate the following equation:

$$Accrual_{it} = a_i + b_i CF_{it} + \varepsilon_{it}$$

where $Accrual_{it}$ is the difference between income from continued operations and net operating cash flow, scaled by the market value of equity at the end of the prior fiscal year. CF_{it} is the contemporaneous operating cash flow, scaled by the market value of equity at the end of the prior fiscal year. As before, each industry-peer firm's coefficients are used to compute the fitted values of accruals. The absolute difference of the fitted values is then aggregated to produce our third measure of FSC – $FSC\_Accrual_{it}$.

We utilize three different measures of FSC since they complement each other. For instance, the stock return used in FSC_Acct provides information about economic outcomes in the view of the stock market. However, this measure implicitly relies on the assumption that stock prices incorporate economic substance in a constant and timely manner. The other two measures, FSC_CF and $FSC\_Accrual$, follow the same mapping logic while using inputs independent of market efficiency, thus complementing the FSC_Acct measure. The second and the third measure also have certain limitations. Specifically, cash flow during a limited time horizon may fail to capture the full picture of economic substance. Besides, Neel (2017) warns about the complexity of accrual accounting as it "[…] is at the foundation of financial reporting and the association between accruals and cash flows is widely used as a summary measure to compare and contrast firms' financial reporting." (Neel 2017, p. 667). Thus, the third measure needs to be interpreted with caution as it might be oversimplified.

To better understand the applicability of the FSC measures in the EI setting, we conduct four validation tests and investigate whether FSC is higher for paired firms that (1) belong to the same sub-industry;[4] (2) report either losses or profits at the same time; (3) have the same direction of returns (negative or positive); (4) have a similar level of conservatism. The results indicate that all three FSC metrics are higher for firm-pairs that are in the same subindustries, report either losses or gains, have the same direction of returns, and have a similar conservatism level. Hence, we believe that our measures represent a valid proxy for FSC in the extractive industries. See Appendix 3 for details.

Dependent variables

We choose a number of different economic outcome variables to explore how EI firms' FSC affect different market participants, including analysts, stock investors, creditors, and auditors. We follow De Franco et al. (2011) and gauge the influence on analysts by applying three metrics: analysts coverage ($Coverage$), forecast accuracy ($Accuracy$), and forecast dispersion ($Dispersion$). $Coverage$ is the number of analysts making forecasts for each firm-year observation. $Coverage$ is zero if there are no analyst-forecast data. $Accuracy$ measures the distance between the analysts' forecast mean and the actual EPS, scaled by year-end price and multiplied by -100. $Dispersion$ is the standard deviation of the analysts' EPS forecasts for each firm-year, scaled by year-end price and multiplied by 100.

We use two stock-market indicators to capture the extent to which FSC affects stock investors' capital allocation decisions. Specifically, $Illiquidity$ is the yearly median of the price impact (Amihud, 2002). A low value of $Illiquidity$ indicates a better information environment where investors can trade in stocks without triggering significant price inflation. $BidAsk$ reflects the influence of transaction costs on daily stock returns variance (Roll, 1984).

[4] We identify 10 subindustries in the mining industry based on the TRBC classification, including Coal, Uranium, Precious Metals & Minerals, Gold, Iron & Coke Coal, Specialty Mining & Minerals, Integrated Mining, Bauxite Mining, and Lead, Copper, Nickel, Zinc and Nonferrous.

Since we are also interested in the effects of FSC on creditors and auditors, we apply two additional dependent variables – cost of debt (Cod) and audit fees ($AudFee$). Cod is defined as one-year forward-looking reported interest expense divided by the average of the opening and closing interest-bearing debt (Minnis, 2011). $AudFee$ is the natural logarithm of total audit fees during the fiscal year.

Considering the significant variance and potential noise contained in each economic-outcome variable, we winsorize all continuous variables at the yearly top and bottom 5 percent. Further, we follow Minnis's approach and truncate Cod more than 1,000 basis points over the yearly prime rate.

Sample selection

The empirical analysis focuses on a sample of Canadian EI firms over the period 2000–2019[5]. We obtain accounting data and yearly stock market data from Thompson Reuters Worldscope, daily stock data from COMPUSTAT North America, and analyst forecast data from I/B/E/S. We start with a sample of 25,468 firm-year observations for 2,381 EI firms, identified based on the TRBC classifications.[6] Following De Franco et al. (2011) and Neel (2017), we exclude three holding firms and limited partnerships (identified by the firm name) corresponding to 27 firm-year observations. We further eliminate 750 firms (10,031 observations) with missing returns and earnings data for at least four consecutive years. From this sample, we estimate the level of FSC in each firm-year observation in the sample by employing a 4-year time series regression. We then further exclude observations with missing key control variables. Our final

[5] Canadian firms are selected based on ISIN two-letter country code. This two-letter word code is allocated to the company's home country or, in most cases, where the company is domiciled or have a corporate headquarter base (https://www.isin.net/isin-explanation). We further confirm this by checking Worldscope item6026-Nation (country of domicile).

[6] Specifically, we identify EI firms with the following TRBC codes: 5010101010, 5010201010, 50102020, 5010202010, 5010202011, 5010202012, 5010202013, 5010202015, 5030101010, 5030101011, 5120101010, 5120101011, 5120101012, 5120101013, 5120101014, 5120101016, 5120106010, 5120106011, 5120102011, 5120102012, 5120105010, 5120105011, 5120105012, 5120105013, 5120105014, 5120105015, 5120105017, 5120108010, 5120103016

sample contains 1,597 EI firms (9,771 firm-year observations). Table 1 summarizes the sample selection process.

[Please insert Table 1 about here]

5. Sample description and results

Estimation of FSC

Table 2 presents the descriptive statistics for the inputs to the FSC estimations. Panel A reports the economic and accounting outcome variables, winsorized at the yearly top- and bottom 5-percent level. Panels B to D show the estimated coefficients used to compute FSC_Acct, FSC_CF and FSC_Accrual and their explanatory power. Compared with the descriptive statistics of international firms in 2004–2008 reported by Neel (2017), EI firms in our sample have more volatile earnings, returns, and accruals, consistent with the heterogeneous accounting practices of EI firms documented in prior literature (e.g., Luther, 1996). [7]

[Please insert Table 2 about here]

Table 3 summarizes the descriptive statistics for the FSC measures, economic-consequence variables, and firm-level control variables, separately for mining and O&G firms. For our main FSC_Acct measure, 7,626 observations belong to the mining industry and 2,145 belong to the O&G industry. The mean (median) difference indicates that compared to the O&G firms, the mining firms in our sample have higher FSC according to all three metrics. Although the average analyst's coverage is higher for O&G firms, analysts following mining firms have better forecast accuracy and smaller dispersion. Interestingly, O&G firms have

[7] For example, Neel (2017) reports the standard errors of earnings and returns as 0.23 and 0.56, while the standard deviations of the EI firms in our setting are 0.47 and 0.88, respectively, even after being winsorized at top and bottom 5 percent on an annual basis. Correspondingly, the standard errors of estimated coefficients are larger in the EI setting.

higher liquidity than mining firms, along with lower cost of debt (Cod) and higher audit fees ($Audfee$).[8]

[Please insert Table 3 about here]

In Table 3, we further present the firm-level control variables for mining and O&G firms. The first set of variables controls for the general attributes of firms that, according to prior literature, may influence the studied economic outcomes (e.g., De Franco et al., 2011; Neel , 2017; Lobo et al., 2018). $SIZE$ is the natural logarithm of the market value of equity at the fiscal year-end. $Lever$ is the debt leverage ratio. BTM is the ratio of the book value of equity to the market value. Vol is the logarithm of trading volume in dollars during the year. $ISSUE$ is an indicator variable that equals one if the firm issues new shares or debt of more than five percent of the total assets during the year. $LOSS$ is an indicator variable equal to one if the firm has reported earnings of less than zero for two consecutive years. Additionally, we create an indicator variable – $Production$ – to indicate whether the firm is in a production stage or not. Specifically, $Production$ equals one if the firm reports accounting numbers for depreciation at the fiscal year end.[9] Following prior literature (e.g., Dechow & Dichev 2002; ; De Franco et al., 2011; Francis, Lafond, Olsson, & Schipper, 2005), we control for predictability ($Predicty$) and return volatility ($Ln\_returnvar$) in the analysis with analysts coverage as the dependent variable. We also add unexpected earnings (SUE), logarithm of the number of days from the forecast date to the earnings announcement date ($Days$), an indicator of decreasing earnings

[8] We further compare the main variables with prior literature. FSC in both mining and O&G industries is lower than those reported by Neel (2017), in line with the expectation that EI firms have lower FSC in general. Moreover, we observe larger $Illiquidity$ and $Bidask$ mean numbers than in Neel (2017), indicating lower liquidity for Canadian EI firms than for the cross-country, cross-industry sample used by Neel (2017). Comparing the analyst attributes with those observed in the study by De Franco et al. (2011), referring to a US setting, although the number of analyst's coverage is similar, the forecast accuracy is lower, and dispersion is larger for the Canadian EI firms.

[9] IAS 16 specifies that "Depreciation of an asset begins when it is available for use, i.e., when it is in the location and condition necessary for it to be capable of operating in the manner intended by management" (IAS 16, p. 55). Accordingly, only EI firms in production stage are expected to recognize depreciation on their E&E assets. Thus, we use a $Production$ indicator that equals one if the firm reports depreciation data and zero otherwise to capture its extractive-activity stage.

compared to last year (Neg_UE), and the number of analysts following ($Coverage$) into the analysis on analysts' forecasts.

For the illiquidity analysis, we follow Neel (2017) and control for $Asset$, $Lever$, MTB, Vol, market value of equity at the end of the prior year (L_Size), lagged value of return volatility and lagged value of stock turnover ($L\_ln\_turnover$).

For the models with cost of debt as the dependent variable, besides $Asset$, $Lever$, $Loss$ and Neg_UE, we control for a firm's bankruptcy risk captured by Altman z-score ($Zscore$), the volatility of operating cash flows (OCF), and for debt-paying ability using variables related to profitability (RoA), investments in production (New_PPE), tangible assets ($TANG$), and cash holding ($Cashhold$) (Jung, Herbohn, & Clarkson, 2018).

For the audit fee model, we follow Zhang (2018) and control for other determinants of audit fees such as size ($Asset$), an indicator for Big four auditor firms (BIG), and an indicator for specialist auditors ($specialist$). Additionally we control for factors that might increase accounting complexity such as issuing debt or equity of more than five percent of the total assets ($ISSUE$), foreign sales ($ForgSales$), geographical segments (Seg), Pension ($Pension$) and an indicator for fiscal year-end in December ($Season$), and factors that might further increase audit risk including RoA, $LOSS$, OCF, $Lever$, quick ratio ($QUICK$), the annual change in Zmijewski's probability-of-bankruptcy score (D_PB), and issuing a modified auditor opinion (Mod_OP). See Appendix 3 for definitions of the variables.

The mean and median t-tests in Table 3 reveal significant differences between Canadian mining and O&G firms across many attributes. While the mining firms have smaller average capitalization ($SIZE$), assets($Asset$) and lower trading volume (Vol), they have higher return volatility ($Ln\_returnvar$), higher market-to-book ratio (MTB) and lower predictability ($Predicty$) compared to the O&G firms, suggesting heterogeneous economic and accounting attributes between these two sub-industries. Accordingly, we find that mining firms have lower profitability (RoA), lower operating cash flows (OCF), and are more likely to report a loss ($LOSS$) and to make a new issue ($ISSUE$). On the other hand, O&G firms are more likely to be audited by big-4 audit firms (BIG) and less likely to receive a modified audit opinion ($ModOP$). Taken together, Table 3 indicates that although mining and O&G firms are generally subject to the same accounting standards for EI (e.g., IFRS 6), there are important differences between these two subindustries across many firm-level characteristics in our sample. Thus, we control for sub-industry fixed effects and investigate the differences between the sub-industries in supplementary analyses.

Univariate results

In the final sample of 597 EI firms (9,771 firm-year observations) with available FSC_Acct data, 590 firms (3,001 firm-year observations) are followed by at least one analyst and 367 firms (1,461 firm-year observations) report non-zero outstanding interest-bearing debt. Considering that more than half of the observations in our sample are without analysts following and are not financed through debt, we split the sample by whether the firm has analyst data from I/B/E/S ($following$) and whether the firm reports debt on the balance sheet ($borrower$) to conduct univariate tests of the FSC differences. We further investigate whether the FSC level differs significantly for firms in the production stage ($Production$).

Table 4 consistently shows that analysts tend to follow firms with higher FSC across the three measures in both mining and O&G industries. Similarly, firms with at least some debt funding have higher FSC compared to those entirely financed by equity. The results for the extractive-activities stage are mixed. While for the pooled sample and the sample of firms in the mining industry, firms in the production stage show a lower level of FSC, the result is the opposite for O&G firms.

[Please insert Table 4 about here]

Multivariate results: Economic consequences of FSC in EI.

In this section, we investigate how firm-level FSC is associated with economic consequences. Specifically, we test whether analysts coverage ($Coverage$) and forecast performance ($Accuracy$ and $Dispersion$), market liquidity ($Illiquidity$ and $Bidask$), cost of debt (Cod), and audit fees ($AudFee$) are connected to firm-level FSC captured by the three FSC measures in the following model:

$$Economic\ Benefits = \alpha + \beta_1 FSC + \gamma Control + \varepsilon$$

For each dependent variable, we control for other determinants of the economic benefits following prior literature as discussed above. We also control for sub-industry and year fixed effects. To control for the impact of outliers, we either take the logarithm form or winsorize continuous variables at the top and bottom 5 percent level on an annual basis. Considering the potential cross-sectional dependence, we cluster the standard errors at the firm level.

Analysis of analysts' coverage and forecast effects

Table 5 presents the results for estimating the effects of FSC on analysts' coverage, forecast accuracy and forecast dispersion. The coefficient of interest is the first row, FSC. Columns (1), (2), and (3) report the association between FSC and analysts' coverage. The first FSC_Acct measure is positively associated with analysts' coverage at the 10 percent significant level, indicating that FSC_Acct at least to some extent motivates analysts to follow a firm. Specifically, a one-standard-deviation change in FSC_Acct increases the logarithm of analyst following by around 0.02 (0.216*0.08). Given that the average analysts coverage is relatively low in our sample (0.787), the above result can be translated into a modest economic effect of about 4.7 % increase in analysts following (=exp [0.581+0.02] –1). However, the results for the FSC_CF and $FSC\_Accrual$ measures do not capture a significant association.

Columns (4)–(6) of Table 5 report the regression results for analysts' forecast accuracy. Consistent with our expectations, all three FSC measures are positively associated with forecast accuracy. The association is both statistically and economically significant. A one-standard-deviation increase in FSC_Acct is associated with an average increase in accuracy of about 1.40% of the stock price (= 0.216* 6.47) in EI firms, consistent with the results reported by De Franco et al. (2011). The results are qualitatively and quantitatively similar for FSC_CF (1.93%) and $FSC\_Accrual$ (2.30%).

Columns (7)–(9) present the results for the models with analysts' forecast dispersion as the dependent variable. We find a significantly negative association between FSC and analysts' forecast dispersion. In terms of the economic significance, a one-standard-deviation increase in the three FSC measure is associated with an average decrease in forecast dispersion of between 0.78% and 1.03%. These findings show that while FSC does not appear to be significantly associated with coverage, it improves forecast accuracy and reduces forecast dispersion. This is in line with the expectations that FSC reduces information asymmetry and enhances the information environment. The coefficients of the control variables are generally in line with the expectations and are consistent with prior literature. One exception is the effect of monthly return volatility ($Ln\_returnvar$). Although De Franco et al. (2011) expect and report that high return volatility decreases analysts' forecast accuracy and increases forecast dispersion, we observe the opposite effects for EI firms.[10]

[Please insert Table 5 about here]

[10] One possible explanation is that given the diverse and complex accounting practices in EI firms, return volatility might reflect how market participants process information through different channels. In such circumstances, analysts' expertise might have greater value, which could lead to increased analyst effort and better forecasts.

Analysis of stock liquidity

Table 6 reports the estimation results using $Illiquidity$ and $Bidask$ as inverse measures of stock liquidity. Following prior research (e.g., Neel, 2017; Li, Siciliano, & Venkatachalam, 2020), we control for $Asset$, $Lever$, MTB, Vol, and lagged value of $SIZE$, $Ln\_returnvar$ and lagged stock turnover ($L\_ln\_turnover$). Considering the potential difference between EI firms in the exploration vs. production stages, we control for the stage by adding the $Production$ dummy to the estimation model. Columns (1), (2), and (3) in Table 6 present consistent negative coefficients of FSC on the $Illiquidity$ measure of Amihud (2002), indicating that FSC is positively (negatively) associated with liquidity (illiquidity). Similarly, the negative coefficients reported in Columns (4), (5), and (6) show that higher FSC is associated with smaller bid-ask spreads. Hence, for a large sample of Canadian EI firms, the results consistently indicate that FSC improves the information environment for capital market investors.

[Please insert Table 6 about here]

Analysis of cost of debt

Table 7 reports the estimation of the effects of FSC on the cost of debt. Fang et al. (2016) find that FSC facilitates lenders' information processing and reduces private loan-interest spreads. Based on their findings, we expect FSC to be negatively associated with cost of debt. To capture the cost of debt (*Cod*), we use a direct measure of one-year-forward-looking average interest cost on interest-bearing debt. Following prior research (e.g., Jung, Herbohm, & Clarkson, 2018), we control for other Cod determinants, including $Asset$, $Lever$, $Zscore$, RoA, New_PPE, $TANG$, OCF, $Cashhold$, $LOSS$, Neg_UE and $Production$. In all three columns of Table 7, the estimated coefficients for FSC are negative and significant at less than 1% significance levels, indicating a negative association between FSC and cost of debt in line with the expectations. In terms of economic significance, our results indicate that a one-standard-deviation increase in FSC is associated with between 0.37% and 0.43% lower average cost of debt. Given that the average cost of debt in our sample is 6.8%, this translates into a 5% decrease in the cost of debt.

[Please insert Table 7 about here]

Analysis of audit fee

Next, we investigate the economic benefits of FSC to auditors in EI firms. Zhang (2018) suggests that FSC facilitates audit work by lowering information costs and allowing a better understanding of inherent risks. Compared to the sample used by Zhang (2018), EI firms have both lower FSC levels and lower audit fees. We adopt an empirical model similar to Zhang (2018) to test whether the negative association holds in the EI setting. Table 8 shows that all three FSC measures are negatively associated with audit fees, although the coefficient for FSC_Acct is not statistically significant. As regards economic significance, the coefficient in column (2) suggests that a one-standard-deviation increase in FSC_CF reduces audit fees by 5.3% (0.43*0.214). The effect is even more economically significant for $FSC\_Accrual$ (16.1%).

[Please insert Table 8 about here]

Taken together, our main analyses pertaining to auditors and various users of financial information indicate that the positive association between FSC and economic outcomes found in prior literature is valid also for EI firms, despite the persisting accounting challenges in this industry and the considerable lobbying efforts to preserve the financial reporting flexibility. Using three measures to capture FSC, we provide evidence that an increase in FSC is associated with economic benefits for multiple capital market participants, including analysts, investors, creditors, and auditors.

Robustness tests

We conduct several additional tests to gauge the sensitivity of our results to (1) a different measure of FSC – FSC_Acct_4 – as in De Franco et al. (2011), which supplements the FSC_Acct with an additional measure based on the average of the four highest FSC values for firm i; (2) using the mean (instead of the median) FSC of a firm with its industry peers; and (3) winsorizing variables at top and bottom two percent on an annual basis instead of at the top and bottom five percent level. All coefficients remain qualitatively and quantitatively similar to our main findings.

Additionally, Lobo et al. (2018) suggest that each individual FSC measure may contain uncorrelated noise and therefore conduct principal-component analysis to estimate the FSC in addition to the main measures. Accordingly, we generate another FSC measure based on the component analysis of the three individual FSC measures. Our results remain unchanged. Finally, following prior studies, we use the Fama and MacBeth (1973) model to address concerns about cross-sectional dependencies and serial correlation and find unchanged results (e.g., Choi & Suh, 2019). The results of the robustness checks are untabulated for brevity and available from the authors upon request.

6. Additional analysis

Subindustry analysis

Our analyses so far indicate that FSC is associated with positive economic outcomes for multiple information users in the pooled sample of EI firms in Canada. To investigate these associations further, we conduct several additional analyses. In particular, the descriptive statistics in Table 3 show that mining and O&G firms differ significantly in terms of accounting and economic attributes. Although IFRS 6 treats mining and O&G firms indifferently, there are significant geophysical differences. Indeed, CPA Canada issues viewpoints for these two sub-industries separately.[11] Prior literature documents different accounting practices across these two sub-industries (e.g., Power et al., 2017; Stadler & Nobes, 2020). Power et al. (2017) report that O&G firms listed on the LSE employ E&E-cost accounting policies ranging from the relatively conservative SE method to the most aggressive FC method, while mining firms, in general, adopt more conservative approaches, ranging from the SE method to the most prudent Expense-all method. In line with this, Stadler and Nobes (2020) find that accounting practices vary by sub-industries by the degree of conservatism. In addition, differences may be directly observed in the few firms operating in both industries. For example, BHP, a listed multinational mining and petroleum company, has reported different accounting policies for the capitalization of the E&E costs.[12] To conclude, both research and anecdotal evidence suggests that there are notable differences between the accounting policies of mining and O&G firms. Therefore, we investigate whether the relationship between FSC and the different economic outcomes varies depending on subindustry belonging.

Table 9 shows that the associations between FSC and economic outcomes are heterogeneous across mining and O&G industries. The $O\&G$ indicator equals one if the firm is in the O&G industry and 0 for firms in the mining industry. All coefficients on the FSC measures remain significant except those in the audit fee analysis. The interaction variables in columns (1)–(3) in Panel A of Table 9 are significantly positive, indicating that O&G firms with higher FSC are more likely to attract analysts compared to firms in the mining industry. However, there is no significant difference in terms of forecast performance. Panel B reports coefficients on the interaction items in different directions. Therefore, the effects of FSC on enhancing market liquidity may differ between industries. The positive coefficients in the first

[11] See https://www.cpacanada.ca/en/business-and-accounting-resources/financial-and-non-financial-reporting/viewpoints
[12] For minerals, BHP capitalizes E&E costs related to acquisition or after sufficient data is available to assess its commercial viability while for E&E costs for petroleum, they apply the area of interest method and capitalization begins before viability is assessed (BHP Annual Report 2018, p. 177).

three columns of Panel B reveal that for O&G firms, the influence of FSC on market liquidity measured inversely by the price influences on trade is mitigated, although the main effects remain positive. Conversely, the effect of FSC on reducing bid-ask spreads is more substantial for O&G firms. We find no significant difference in the impact of FSC on Cod or $AudFee$ between mining and O&G industries, as presented in Panel C.

[Please insert Table 9 about here]

The effect of uncertainty and alternative information sources for different users

In this section, we consider the relation between FSC and the economic consequences conditional on the complexity of EI firm's extractive activities. Prior studies document that the equity investors benefit more from FSC in a poor information environment as the opaqueness increases the adverse-selection risks faced by less-informed investors (e.g., Imhof et al., 2017; Kim et al., 2020). Alternatively, market participants in EI firms may turn to other channels of information to evaluate firms when the level of uncertainty or complexity is high (e.g., Chen et al., 2018; Ferguson et al., 2020). For example, Chen et al. (2018) report positive associations between the intensity of E&E activities and analysts' development of private information. Notably, it is likely that the four groups of market participants in our study possess different levels of information advantages through different channels. Specifically, compared to analysts, creditors, and auditors, we expect capital market investors to have less opportunities to access information through other channels other than the public financial reporting. Therefore, we expect the associations between FSC and the economic benefits to differ among market participants when the level of uncertainty varies.

We investigate the potential differences by adding the Production indicator and its interactions with the FSC measures. The Production indicator equals one if the firm is in the production stage. Compared to firms in the production stage, EI firms in the exploration phase bear more uncertainty about the success of the discovery of commercial deposits and provide less information about future economic inflows, suggesting higher information asymmetry. Table 10 reports the results of this analysis. Panel A and C indicate that, in general, analysts, creditors, and auditors benefit more from the FSC of EI firms in the production stage. On the contrary, the positive coefficients on the interaction items in Columns (1)–(3) of Panel B reveal that capital market investors benefit from the FSC of EI firms in the exploration stage. These results are consistent with the theoretical and empirical insights from prior literature that FSC is more crucial for investors' understanding of information when information asymmetry is high (e.g., Kim et al., 2016; Imhof et al., 2017; Kim et al., 2020). For the observed enhanced benefits of FSC in the production stage for analysts, creditors, and auditors, one possible explanation is that they develop other information about firms' extractive activities and reduce the reliance on financial statement information when the uncertainty is high.

We believe the results regarding investors to be of particular relevance to the IASB and regulators. It is only the equity investors who benefit significantly from increased FSC during the E&E phase – analysts, creditors and auditors seem able to use other information sources during this phase. Such indications of large information asymmetries affecting equity investors negatively would suggest some urgency in developing a new IFRS Standard on extractive activities.

[Please insert Table 10 about here]

We conduct further tests to investigate the information use of different participants. First, we conduct a subsample analysis by splitting the main sample by the median of FSC. Consistent with above arguments, we observe statistically significant differences in coefficients on FSC across the different subgroups. The results consistently indicate that analysts benefit more from FSC in the high-FSC group, while investors benefit more from FSC improvement when the FSC level is relatively low. This result suggests that for firms in the low FSC quantile, the efforts to improve FSC can significantly enhance liquidity.[13]

Additionally, previous studies investigating analysts and investors suggest that investors rely on analysts' industry expertise. Gray et al. (2019) state that "[…] this is of particular importance in EI, where analysts appear to […] add significant value beyond the financial statements" (p. 81). A few FSC studies employ analyst coverage or forecast in their investigations of the relationship between FSC and capital market factors, including short-window earnings response, delayed trading volume, and informativeness of stock prices (e.g., Kim et al., 2016; Choi et al., 2019; Kim et al., 2020). They use analyst information as an indicator to proxy for a better information environment and report consistent results showing that the associations between FSC and capital market benefits are higher when the information asymmetry is high (when the analyst coverage is low). Accordingly, we add analyst following and its interaction item with FSC to the analysis of market liquidity. We observe more substantial effects of FSC on lowering the price impact on trading ($Illiquidity$) when there is no analyst following. Alternatively, the moderating effects of analyst following can be due to analysts' ability to provide more information, reducing investors' reliance on financial statements. Gray et al. (2019) note that from the accounting standard setters' perspective, investors' reliance on analysts to reduce information asymmetry in EI firms "[…] may be interpreted as an urgent need for the development of a comprehensive IFRS standard" (p. 81). To benchmark, we add analyst following and its interaction with FSC measures in the analyses of the FSC effects on creditors and auditors. The coefficients on the interaction items are not significant, suggesting that creditors and auditors rely less on analyst information.[14] We

[13] These results are not tabulated for brevity and are available by the authors upon request.

[14] Alternatively, a stream of studies uses bid-ask spread as the proxy for information transparency for capital market investors (e.g., Imhof et al., 2017; Choi & Suh, 2019). We follow the same approach and create a variable indicating whether the bid-ask spread is higher or lower than the industry median. We include this variable and its interaction with FSC measures in the analysts', creditors', and auditors' analyses. The interaction items do not

substitute analyst following with the natural logarithm of analyst coverage and find similar results. The results of these tests are untabulated for brevity and available from the authors on request.

The effect of IFRS adoption

Previous literature indicates that the implementation of IFRS enhances cross-country comparability (e.g., Yip & Young, 2012) and the comparability between IFRS-based and US GAAP-based accounting (Barth et al., 2012). However, it is not clear how the IFRS adoption could influence FSC for Canadian EI firms. First, IFRS is more principle-based relative to Canadian GAAP and US GAAP and IFRS 6 permits considerable managerial discretion. Indeed, prior studies report that the substantial variation in accounting practices among EI firms remains after IFRS (e.g., Abdo, 2018). Second, prior studies suggest that the extent to which IFRS adoption improves FSC depends on its implementation and practice, which, in turn, depends on local institutional and economic factors (e.g., Nobes, 2006; Nobes, 2011; Cascino & Gassen, 2015). In a study on the effects of IFRS adoption in Germany and Italy, Cascino and Gassen (2015) find that the improvement in comparability is contingent on firm-level compliance. This relates to the concern that auditing and other enforcement mechanisms are likely to be ineffective in restricting opportunistic behavior of EI firms, given that essentially all treatments of E&E activities are IFRS compliant. In this section, we examine whether there are notable changes in FSC for Canadian EI firms following IFRS adoption.

Figure 1 shows a decreasing trend of all FSC measures in mining and O&G industries over time, especially after 2009 and 2014.

[Please insert Figure 1 about here]

statistically differ from zero, suggesting the interpretation and incorporation of comparable financial information of analysts, creditors, and auditors does not vary with the information transparency, probably due to their informational advantages.

To investigate whether the pre-FSC level influences this trend, we categorize firm-year observations by the FSC quartile. Figure 2 shows that the decreases are mainly driven by firms falling into the first quartile (the lowest FSC group), indicating that accounting information becomes less comparable for a particular group of firms around IFRS adoption.

[Please insert Figure 2 about here]

Table 11 presents descriptive statistics for firms categorized by their level of FSC_Acct. We observe that all three FSC measures for firms in the first quartile are significantly lower than firms in other quartiles. Additionally, firms in the lowest comparability group have lower analyst coverage, lower liquidity, higher cost of debt, and are less likely to be audited by a big-four auditor. Specifically, only 13 percent of the observations in Q1 have analysts following, while analysts follow more than 30 percent of firms in Q2 – Q4. Moreover, firms in Q1 have higher return volatility, lower operating cash flows, and are more likely to issue new equity or debt.

[Please insert Table 11 about here]

To better understand the impact of IFRS adoption, we follow prior research on IFRS adoption and re-estimate the FSC measures with balanced data from 2007–2014 (e.g., Neel, 2017).[15] We require firms to have data for the entire period and who adopt IFRS in 2011. We use four years of annual data to estimate the three FSC measures for both the pre-IFRS (2007–2010) and post-IFRS (2011–2014) periods. Panel A of Table 12 presents how FSC measures change between the pre- and post-IFRS periods for IFRS adopters, both in the full sample and in $High\ \Delta FSC$ and $Low\ \Delta FSC$ subsamples. $High\ \Delta FSC$($Low\ \Delta FSC$) indicates a comparability change above (below) the industry median. Panel B and C report the results in the two subindustries. While the average comparability decreases for each measure, we observe that

[15] We require a balanced sample for this analysis, because the number of observations increases over time in our full sample, which mechanically decreases the industry-median FSC measures.

the changes differ in high and low subsamples. Specifically, $Low\ \Delta FSC$ ($High\ \Delta FSC$) firms exhibit a large decrease (small increase) in FSC, consistent with the conjecture that the effect of IFRS adoption varies across different EI firms. Further, in the subindustry analyses, we observe that the decrease in FSC is more significant in the mining industry.

[Please insert Table 12 about here]

To illustrate the economic effects of IFRS adoption through FSC, we rerun our main analyses with an $HFSC$ indicator and its interaction with an IFRS adoption indicator $Post$. $HFSC$ equals one if firm i is in the $High\ \Delta FSC$ group (change of FSC for i is higher than the industry median). We include all firm-level controls discussed above and subindustry fixed effects. Table 13 reports the coefficient estimates clustered at the firm level. Consistent with prior studies (e.g., Neel, 2017), our results suggest that the economic benefits are at least to some extent associated with improved accounting comparability following IFRS adoption. Specifically, we observe lower dispersion and illiquidity and higher forecast accuracy for firms in the $High\ \Delta FSC$ group after the IFRS adoption.

[Please insert Table 13 about here]

7. Conclusion

This study examines firm-level financial statement comparability and its economic consequences in Canadian extractive-industry firms. Financial statement comparability enables information users to identify similarities and differences in firms' economic outcomes through accounting information. Despite the significant lobbying power dedicated to maintaining the flexibility of reporting in the extractive industries, we find that increased financial statement comparability benefits a broad range of market participants. Using data for EI firms in Canada from 2000 to 2019, our study investigates how auditors and various information users – analysts, capital market investors, and creditors – are affected by FSC. After controlling for various firm-level, subindustry-, and year fixed effects, we find significant positive FSC effects for all four groups of market participants. Consistent with prior literature, our results support the prediction that comparability reduces information asymmetry between firms and market participants and contributes to a better information environment for EI firms. We further report that the association differs by subindustry and extractive-activities phase, suggesting that comparable accounting information benefits market participants heterogeneously across these dimensions. In general, analysts benefit more from the FSC of firms with a lower level of uncertainty, while capital market investors benefit more from FSC when the information asymmetry level is high. This is consistent with prior research suggesting that market participants develop different information channels to evaluate EI firms' performance in response to the varying levels of uncertainty.

Our results contribute to the literature by providing a better understanding of the economic effects of increasing FSC in the extractive industries, in particular the relationship between FSC, specific business conditions (subindustry, phase) and the behavior of various market participants. Our paper responds to the call of Gray et al. (2019) about the need to understand how information users are affected by the diverse accounting practices in EI firms. Our results support the importance of comparability as one of the qualitative characteristics in the general IFRS conceptual framework (e.g., IFRS, 2018). The findings in our study also have implications for standard-setters, such as the IASB. IFRS 6 does not define or place any significant limitation on the accounting practices allowed for E&E costs. The positive economic effects of FSC observed in the current study point at the potential benefits of introducing more rigorous accounting standards for EI firms. Especially, capital market investors can benefit more from comparable information when information asymmetry is high.

Notwithstanding the above findings, our study has some limitations. First, the data used pertain only to one country – Canada. Second, the data required to estimate the FSC measures and each of the economic outcome variables reduces the sample size significantly, where small EI firms in the preliminary stage are likely to be excluded.[16] Third, we rely on association tests, whereas causality would require more evidence of the mechanism through which FSC affects market participants. Theoretically, FSC contributes to a better information environment by lowering information asymmetry, reducing information acquisition costs, and enhancing the understanding of the financial statement information (e.g., De Franco et al., 2011; Barth et al., 2012). However, access to information to examine each channel is limited. Last, we investigate the effect on auditors from an information user perspective. It would be interesting to further investigate auditors' behavior as, for example, IFRS 6 would not seem to be enforceable, which presumably makes it difficult for auditors to determine what accounting treatments are compliant with regulation.

[16] The significant shrinking of sample size is common for all the studies employing the output-based comparability measures, mainly due to the requirement of at least four years of consecutive earnings and return data.

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Figure 1

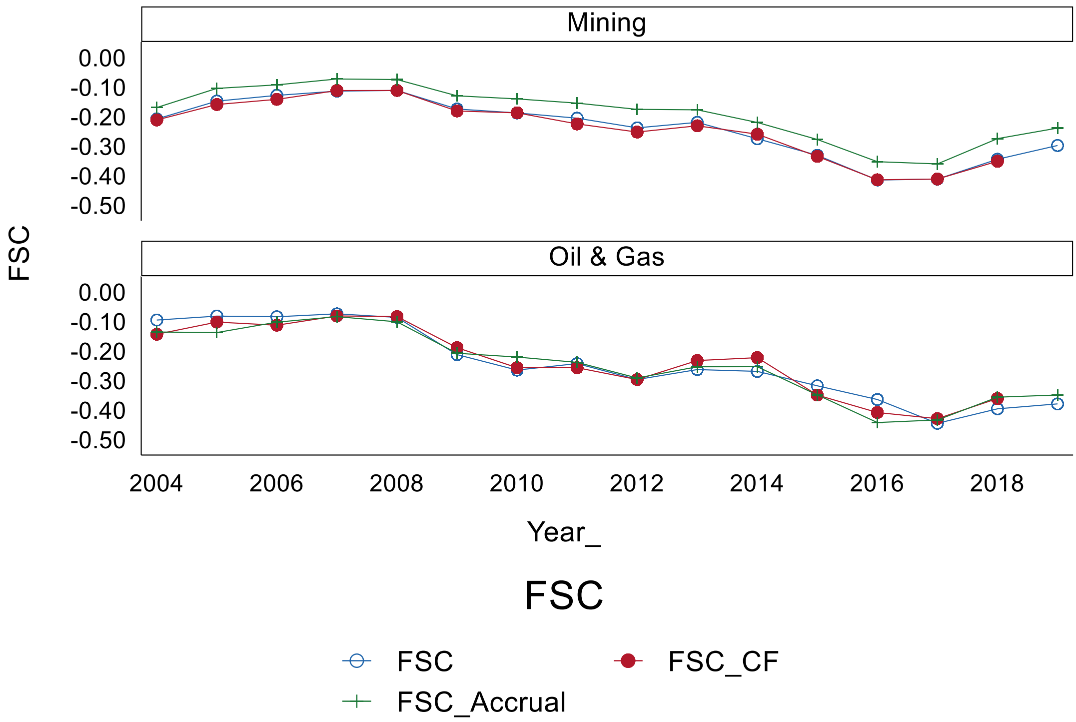
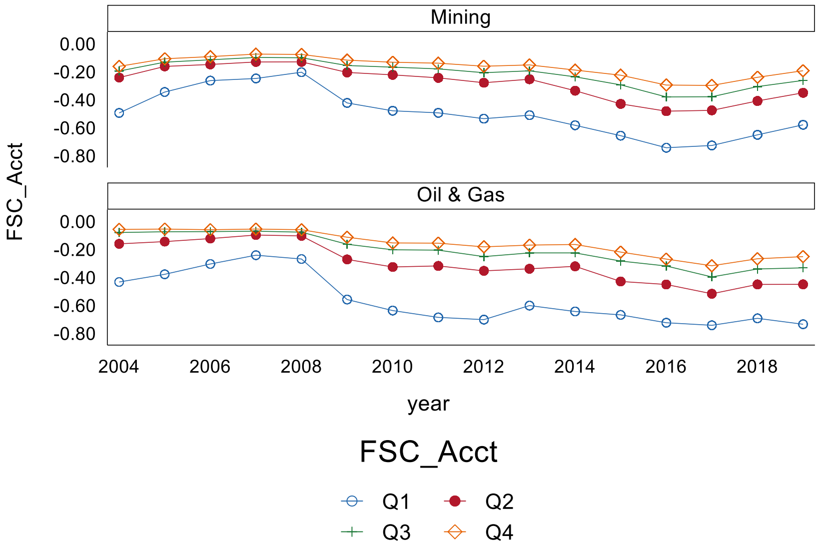
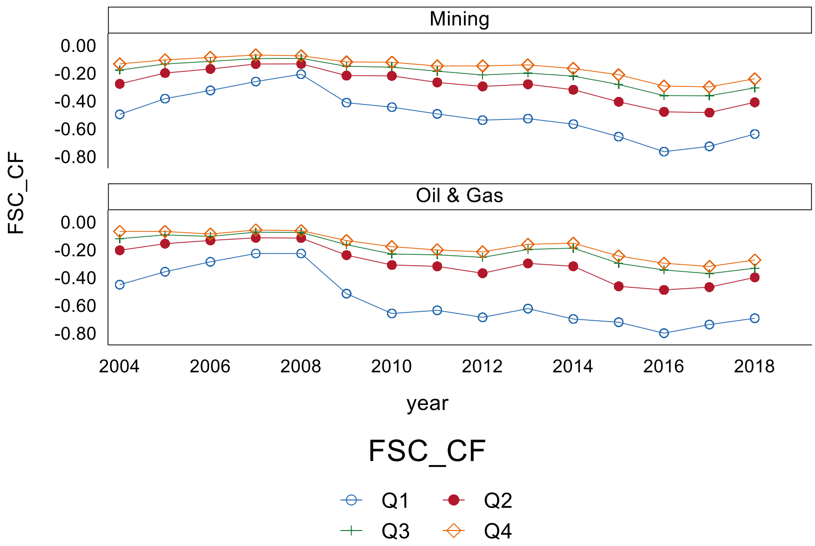

Mining
0.00
-0.10
-0.20
-0.30
-0.40
-0.50
FSC
Oil & Gas
0.00
-0.10
-0.20
-0.30
-0.40
-0.50
2004
2006
2008
2010
2012
2014
2016
2018
Year_
FSC
FSC
FSC_CF
FSC_Accrual

Figure 2



Mining
Oil & Gas
FSC_Acct
0.00
-0.20
-0.40
-0.60
-0.80
2004
2006
2008
2010
2012
2014
2016
2018
year
FSC_Acct
Q1
Q2
Q3
Q4



Mining
Oil & Gas
FSC_CF
0.00
-0.20
-0.40
-0.60
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2004
2006
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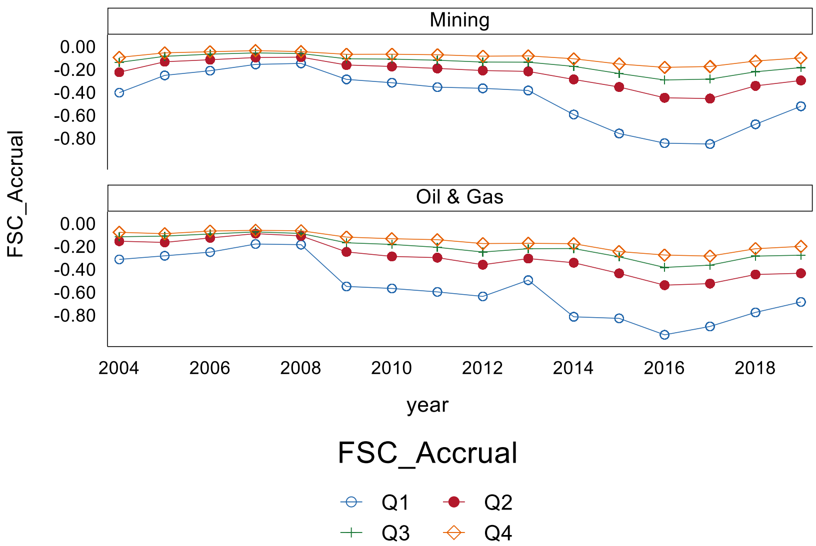
year
FSC_CF
Q1
Q2
Q3
Q4



Mining
Oil & Gas
FSC_Accrual
0.00
-0.20
-0.40
-0.60
-0.80
2004
2006
2008
2010
2012
2014
2016
2018
year
FSC_Accrual
Q1
Q2
Q3
Q4

Table 1: Sample selection

Sample selection procedure	Obs	Firms
EI firms from Worldscope	25468	2381
Delete: Holding Companies	(27)	(3)
Delete: Firms with missing earnings or returns	(9194)	(329)
Delete: Firms missing 4 consecutive years' data	(837)	(421)
Sample used for FSC calculation	15410	1628
Delete: Firms missing the main FSC_Acct data	(5302)	(0)
EI firms with FSC score	10108	1628
Delete: Missing Main Control Variables	(337)	(31)
Final Sample	9771	1597
Final sample with different economic consequence variables		
- FSC – Analysts Forecast	2464	590
- FSC – Liquidity	8352	1355
- FSC – Cost of Debts	1898	367
- FSC – Auditing Fee	1982	488

Notes: This table presents the sample selection procedures used to obtain our final sample.

Table 2: FSC measures - inputs

	Mining				Oil & Gas				All			
Panel A: Descriptive statistics for variables used in regressions to estimate FSC												
VarName	Obs	Mean	Median	SD	Obs	Mean	Median	SD	Obs	Mean	Median	SD
$Earnings_t$	12084	-0.315	-0.136	0.467	3326	-0.268	-0.082	0.477	15410	-0.305	-0.127	0.470
$Return_t$	12084	0.132	-0.145	0.897	3326	0.076	-0.132	0.806	15410	0.120	-0.143	0.879
CF_t	10841	-0.127	-0.070	0.226	2983	0.014	0.029	0.228	15398	-0.096	-0.056	0.228
CF_{t-1}	12075	-0.126	-0.070	0.220	3323	0.016	0.023	0.221	13824	-0.097	-0.055	0.233
$Accrual_t$	12075	-0.200	-0.047	0.458	3323	-0.296	-0.147	0.462	15398	-0.221	-0.063	0.461
$LOSS$	12084	0.745	1.000	0.436	3326	0.525	1.000	0.499	15410	0.698	1.000	0.459
Panel B: FSC_Acct estimations ($Earnings_{it} = a_i + b_i Ret_{it} + c_i Neg_{it} + d_i Neg_{it} \times Ret_{it} + \varepsilon_{it}$)												
VarName	Obs	Mean	Median	SD	Obs	Mean	Median	SD	Obs	Mean	Median	SD
$Intercept$	7910	-0.256	-0.139	1.082	2198	-0.223	-0.066	1.280	10108	-0.249	-0.124	1.128
b_Return	7910	-0.069	-0.032	2.032	2198	0.041	-0.005	2.535	10108	-0.045	-0.027	2.152
b_LOSS	7910	-0.067	0.000	3.428	2198	-0.047	0.000	2.631	10108	-0.063	0.000	3.271
b_LOSS	7910	-0.013	0.000	5.554	2198	-0.011	0.000	4.638	10108	-0.013	0.000	5.368
reg_R2	7910	0.600	0.688	0.363	2198	0.595	0.657	0.364	10108	59.9	68.1	36.3
Panel C: FSC_CF estimations ($Earnings_{it} = a_i + b_i CF_{it+1} + \varepsilon_{it}$)												
VarName	Obs	Mean	Median	SD	Obs	Mean	Median	SD	Obs	Mean	Median	SD
$Intercept$	6679	-0.280	-0.151	0.447	1862	-0.247	-0.113	0.480	8541	-0.273	-0.143	0.455
b_CF_{t-1}	6679	0.260	-0.033	3.330	1862	0.328	0.082	3.193	8541	0.274	-0.004	3.301
reg_R2	6679	0.319	0.214	0.304	1862	0.342	0.266	0.301	8541	32.4	22.5	30.3
Panel D: $FSC\_Accrual$ estimations ($Accrual_{it} = a_i + b_i CF_{it} + \varepsilon_{it}$)												
VarName	Obs	Mean	Median	SD	Obs	Mean	Median	SD	Obs	Mean	Median	SD
$Intercept$	7891	-0.133	-0.048	0.385	2195	-0.162	-0.073	0.450	10086	-0.139	-0.052	0.400
b_CF_t	7891	0.089	-0.038	3.050	2195	-0.306	-0.456	3.366	10086	0.003	-0.117	3.125
reg_R2	7891	0.439	0.402	0.338	2195	0.476	0.487	0.338	10086	44.7	41.7	33.8

Notes: This table presents descriptive statistics for the variables used in our FSC estimations. Panel A presents the statistics for economic and accounting outcome variables. A minimum requirement for the firms included here is to have at least 4 consecutive years of earnings and returns data. $Earnings$ refer to earnings before extraordinary items. $Return$ is the total investment return, including quarterly dividends per share. CF is the operating cash flow. $Accrual$ denotes accruals. $Loss$ is an indicator that equals one if the firm's earnings are less than zero for two consecutive years. We scale $Earnings$, CF, $Accrual$ by market value of equity at prior fiscal-year end. All variables are winsorized at the 5th and 95th percentiles on annual basis. Panel B–D presets descriptive statistics of the estimated coefficients. All estimated coefficients are winsorized at the 1st and 99th percentile.

Table 3: Summary statistics by sub-industries

	Pooled sample				Mining(a)				Oil & Gas(b)				(a)-(b)	
VarName	Obs	Mean	Median	SD	Obs	Mean	Median	SD	Obs	Mean	Median	SD	Mean_diff	Median_diff
FSC and Dependent Variables														
FSC_Acct	9771	-0.349	-0.292	0.216	7626	-0.346	-0.291	0.208	2145	-0.356	-0.293	0.243	0.010*	0.002
FSC_CF	8260	-0.345	-0.291	0.214	6438	-0.343	-0.292	0.206	1822	-0.352	-0.289	0.239	0.009*	0.003
$FSC\_Accrual$	9754	-0.307	-0.227	0.255	7611	-0.294	-0.211	0.253	2143	-0.354	-0.274	0.258	0.060***	0.063***
$Coverage$	8120	0.581	0.000	0.959	6327	0.462	0.000	0.882	1793	1.001	0.693	1.091	-0.539***	-0.693***
$Accuracy$	2464	-5.738	-2.067	9.500	1577	-4.991	-1.887	8.159	887	-7.066	-2.525	11.390	2.076***	0.638***
$Dispersion$	2128	3.939	2.287	4.791	1296	3.700	2.134	4.424	832	4.311	2.457	5.293	-0.611***	-0.323**
$Illiquidity$	8352	1.549	0.779	2.135	6479	1.571	0.835	2.099	1873	1.475	0.469	2.254	0.096*	0.366***
$Bidask$	8114	4.523	3.752	2.813	6304	4.686	3.949	2.728	1810	3.953	2.867	3.023	0.733***	1.082***
Cod	1898	0.068	0.064	0.029	1062	0.070	0.069	0.031	836	0.065	0.060	0.026	0.005***	0.009***
$AudFee$	1982	12.840	12.785	1.357	1291	12.767	12.748	1.378	691	12.977	12.819	1.308	-0.209***	-0.071
Control Variables														
$SIZE$	9771	17.017	16.691	2.501	7626	16.798	16.495	2.368	2145	17.794	17.750	2.792	-0.996***	-0.952***
$Asset$	9771	16.690	16.731	3.025	7626	16.335	16.354	2.889	2145	17.952	18.395	3.159	-1.617***	-2.041***
$Lever$	9771	0.071	0.000	0.142	7626	0.058	0.000	0.133	2145	0.120	0.000	0.160	-0.062***	0***
BTM	9771	0.843	0.538	1.254	7626	0.814	0.500	1.252	2145	0.946	0.698	1.253	-0.131***	-0.198***
Vol	9771	16.250	15.651	2.738	7626	16.004	15.493	2.526	2145	17.125	16.713	3.239	-1.121***	-1.22***
$ISSUE$	9771	0.617	1.000	0.486	7626	0.634	1.000	0.482	2145	0.556	1.000	0.497	0.078***	.
$Predicty$	9771	0.272	0.172	0.276	7626	0.268	0.164	0.275	2145	0.289	0.205	0.281	-0.021***	-0.041***
$Ln\_returnvar$	9771	0.254	0.223	0.176	7626	0.261	0.231	0.165	2145	0.229	0.192	0.210	0.032***	0.039***
$LOSS$	9771	0.743	1.000	0.437	7626	0.788	1.000	0.409	2145	0.582	1.000	0.493	0.206***	.
SUE	9771	4.929	0.223	17.325	7626	5.217	0.267	18.069	2145	3.903	0.102	14.327	1.314***	0.165***
Neg_UE	9771	0.515	1.000	0.500	7626	0.517	1.000	0.500	2145	0.508	1.000	0.500	0.009	.
MTB	9771	1.848	1.204	3.777	7626	1.984	1.305	4.024	2145	1.362	0.988	2.670	0.622***	0.317***
RoA	9771	-0.739	-0.151	2.044	7626	-0.827	-0.181	2.167	2145	-0.424	-0.073	1.484	-0.403***	-0.108***
OCF	9771	-0.352	-0.059	0.864	7626	-0.407	-0.079	0.891	2145	-0.156	0.030	0.729	-0.251***	-0.109***
$Production$	9771	0.523	1.000	0.499	7626	0.496	0.000	0.500	2145	0.619	1.000	0.486	-0.123***	.
L_Size	8352	17.216	16.945	2.482	6479	16.990	16.749	2.345	1873	18.001	18.125	2.768	-1.011***	-1.376***
$L\_ln\_turnover$	8352	0.511	0.399	0.430	6479	0.498	0.384	0.418	1873	0.554	0.447	0.467	-0.055***	-0.063***
Fcs_days	2592	5.260	5.316	0.365	1908	5.215	5.303	0.447	1095	5.309	5.332	0.264	-0.094***	-0.029***

$Zscore$	1898	-1.306	-2.609	5.856	1062	-1.408	-2.824	6.089	836	-1.176	-2.459	5.547	-0.232	-0.365***
$TANG$	1898	0.736	0.804	0.227	1062	0.672	0.725	0.232	836	0.818	0.888	0.191	-0.146***	-0.163***
New_PPE	1898	0.722	0.749	0.216	1062	0.774	0.843	0.221	836	0.655	0.669	0.190	0.120***	0.174***
$Cashhold$	1898	0.103	0.054	0.142	1062	0.141	0.090	0.157	836	0.056	0.016	0.103	0.085***	0.074***
$QUICK$	1982	4.671	1.629	7.409	1291	6.032	2.486	8.333	691	2.130	0.854	4.225	3.902***	1.632***
$ForgSales$	1982	0.257	0.000	0.411	1291	0.266	0.000	0.418	691	0.240	0.000	0.397	0.026	0.000
D_PB	1982	0.127	0.030	1.402	1291	0.114	0.013	1.495	691	0.151	0.052	1.211	-0.037	-0.039
Seg	1982	1.362	1.000	0.542	1291	1.400	1.000	0.565	691	1.291	1.000	0.490	0.108***	0.000***
$Season$	1982	0.855	1.000	0.352	1291	0.807	1.000	0.395	691	0.944	1.000	0.231	-0.136***	.
$Pension$	1982	0.110	0.000	0.314	1291	0.127	0.000	0.333	691	0.080	0.000	0.271	0.047***	0.000***
$ModOp$	1982	0.017	0.000	0.128	1291	0.020	0.000	0.141	691	0.010	0.000	0.100	0.010*	0.000*
BIG	1982	0.856	1.000	0.351	1291	0.823	1.000	0.382	691	0.919	1.000	0.273	-0.096***	.
$specialist$	1982	0.336	0.000	0.472	1291	0.375	0.000	0.484	691	0.263	0.000	0.441	0.112***	0.000***

Notes: This table presents the descriptive statistics for the variables used in our main analyses. The maximum number of observations for each variable is 9,771. The number of observations varies depending on the data availability for the control variables. $Coverage$, $SIZE$, $Asset$, Vol, $Ln\_returnvar$, and $L\_ln\_turnover$ are computed in the natural log form. Other continuous variables are winsorized at the 5th and 95th percentiles on annual basis. See Appendix 1 for definitions of all the variables.

Table 4: Univariate tests of analysts following, debt issuing and extractive activities stage

Panel A: Univariate tests of FSC differences in EI firms (pooled industry data)

Variables	Obs	Mean	Med	Obs	Mean	Med	Mean-diff	Med-diff
Analysts following	No follower(a)			Analysts following(b)			(a)–(b)	
FSC_Acct	6768	-0.386	-0,328	3003	-0.264	-0.231	-0.122***	-0.097***
FSC_CF	5681	-0.382	-0.329	2579	-0.262	-0.229	-0.121***	-0.100***
$FSC\_Accrual$	6758	-0.337	-0.253	2996	-0.239	-0.185	-0.099***	-0.068***
Debt financing	No debt(a)			Debt financing(b)			(a)–(b)	
FSC_Acct	7873	-0.368	-0.310	1898	-0.268	-0.221	-0.100***	-0.089***
FSC_CF	6365	-0.364	-0.311	1895	-0.280	-0.236	-0.084***	-0.075***
$FSC\_Accrual$	7859	-0.321	-0.237	1895	-0.249	-0.199	-0.072***	-0.038***
EI stage	Pre-preproduction(a)			Production(b)			(a)–(b)	
FSC_Acct	4661	-0.344	-0.281	5110	-0.353	-0.298	0.008***	0.017 ***
FSC_CF	4128	-0.342	-0.280	4132	-0.348	-0.298	0.005	0.018***
$FSC\_Accrual$	4654	-0.293	-0.214	5100	-0.320	-0.238	0.026***	0.024***

Panel B: Univariate tests of FSC differences in Mining-industry firms

Variables	Obs	Mean	Med	Obs	Mean	Med	Mean-diff	Med-diff
Analysts following	No follower(a)			Analysts following(b)			(a)–(b)	
FSC_Acct	5718	-0.373	-0.319	1908	-0.266	-0.232	-0.108***	-0.087***
FSC_CF	4796	-0.369	-0.318	1642	-0.266	-0.233	-0.103***	-0.085***
$FSC\_Accrual$	5709	-0.319	-0.237	1902	-0.219	-0.164	-0.100***	0.073***
Debt financing	No debt(a)			Debt financing(b)			(a)–(b)	
FSC_Acct	6564	-0.360	-0.305	1062	-0.263	-0.220	-0.097***	-0.085***
FSC_CF	5378	-0.355	-0.304	1060	-0.281	-0.239	-0.074***	-0.065***
$FSC\_Accrual$	6552	-0.305	-0.219	1059	-0.223	-0.176	-0.082***	-0.043***
EI stage	Pre-preproduction(a)			Production(b)			(a)–(b)	
FSC_Acct	3844	-0.338	-0.275	3782	-0.355	-0.305	0.017***	0.030***
FSC_CF	3397	-0.334	-0.272	3041	-0.353	-0.306	0.019***	0.034***
$FSC\_Accrual$	3838	-0.279	-0.199	3773	-0.309	-0.224	0.031***	0.025***

Panel C: Univariate tests of FSC differences in Oil & Gas industry firms

Variables	Obs	Mean	Med	Obs	Mean	Med	Mean-diff	Med-diff
Analysts following	No follower(a)			Analysts following(b)			(a)–(b)	
FSC_Acct	1050	-0.454	-0.385	1095	-0.262	-0.227	-0.193***	-0.158***
FSC_CF	885	-0.456	-0.399	937	-0.255	-0.222	-0.201***	-0.177***
$FSC\_Accrual$	1049	-0.438	-0.364	1094	-0.274	-0.225	-0.164***	-0.139***
Debt financing	No debt(a)			Debt financing(b)			(a)–(b)	
FSC_Acct	1309	-0.409	-0.340	836	-0.274	-0.221	-0.134***	-0.119***
FSC_CF	987	-0.415	-0.354	835	-0.278	-0.233	-0.137***	-0.121***
$FSC\_Accrual$	1307	-0.400	-0.318	836	-0.281	-0.227	-0.119***	-0.091***
EI stage	Pre-preproduction(a)			Production(b)			(a)–(b)	
FSC_Acct	817	-0.374	-0.317	1328	-0.345	-0.286	-0.029***	-0.088***
FSC_CF	731	-0.381	-0.321	1091	-0.333	-0.273	-0.047***	-0.048***
$FSC\_Accrual$	816	-0.362	-0.296	1327	-0.349	-0.263	-0.013	-0.033***

Notes: This table summarizes the mean and median differences in the FSC level for the pooled sample and across subgroups. The median difference is tested using Wilcoxon signed-rank tests.

Table 5: FSC and Analysts Coverage, Forecast Accuracy and Forecast Dispersion

$$Analysts\ Metric_{it+1} = \alpha + \beta_1 FSC_{it} + \gamma Controls_{it} + \varepsilon_{it+1}$$

	Coverage			*Accuracy*			*Dispersion*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FSC_Acct	*FSC_CF*	*FSC_Accrual*	*FSC_Acct*	*FSC_CF*	*FSC_Accrual*	*FSC_Acct*	*FSC_CF*	*FSC_Accrual*
FSC	**0.08***	**-0.04**	**-0.05**	**6.47*****	**9.00*****	**9.00*****	**-3.59****	**-4.82*****	**-3.73*****
	(0.05)	**(0.05)**	**(0.04)**	**(2.24)**	**(2.20)**	**(2.21)**	**(1.48)**	**(1.45)**	**(1.02)**
SIZE	0.10***	0.10***	0.10***	1.96***	1.91***	1.96***	-1.20***	-1.19***	-1.18***
	(0.01)	(0.01)	(0.01)	(0.35)	(0.35)	(0.35)	(0.20)	(0.20)	(0.20)
Lever	0.33***	0.32***	0.31***	-11.24***	-10.97***	-10.69***	8.21***	8.08***	7.87***
	(0.09)	(0.09)	(0.09)	(1.83)	(1.81)	(1.83)	(1.31)	(1.29)	(1.26)
BTM	-0.01**	-0.01*	-0.01*	-2.66***	-2.58***	-2.55***	1.34***	1.28***	1.28***
	(0.01)	(0.01)	(0.01)	(0.42)	(0.42)	(0.41)	(0.23)	(0.24)	(0.23)
Vol	0.19***	0.19***	0.19***	-0.25	-0.27	-0.30	0.16	0.17	0.18
	(0.01)	(0.01)	(0.01)	(0.26)	(0.26)	(0.26)	(0.12)	(0.12)	(0.12)
ISSUE	-0.10***	-0.10***	-0.10***	0.09	0.04	0.08	-0.24	-0.22	-0.25
	(0.02)	(0.02)	(0.02)	(0.40)	(0.40)	(0.40)	(0.20)	(0.20)	(0.21)
Predicty	0.01	0.01	0.01	-0.07	-0.04	-0.14	-0.02	-0.04	0.01
	(0.02)	(0.02)	(0.02)	(0.59)	(0.59)	(0.59)	(0.29)	(0.29)	(0.30)
Ln_returnvar	-0.05	-0.09	-0.08	4.93**	4.91**	4.26**	-2.52**	-2.48**	-2.42**
	(0.06)	(0.07)	(0.07)	(2.02)	(1.94)	(1.90)	(1.03)	(0.98)	(0.98)
LOSS	-0.20***	-0.20***	-0.20***	0.13	-0.05	0.05	0.43*	0.52**	0.48*
	(0.03)	(0.03)	(0.03)	(0.48)	(0.49)	(0.47)	(0.25)	(0.25)	(0.24)
SUE	0.00***	0.00***	0.00***	-0.04	-0.02	-0.02	0.03	0.02	0.01
	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Neg_UE	-0.05***	-0.05***	-0.05***	-0.31	-0.29	-0.34	0.06	0.05	0.09
	(0.01)	(0.01)	(0.01)	(0.32)	(0.32)	(0.32)	(0.15)	(0.15)	(0.15)
Production	-0.02	-0.02	-0.02	-0.05	-0.11	-0.02	-0.13	-0.10	-0.14
	(0.02)	(0.02)	(0.02)	(0.39)	(0.39)	(0.40)	(0.23)	(0.23)	(0.23)
Days				-1.59***	-1.66***	-1.62***	1.50***	1.58***	1.52***
				(0.47)	(0.47)	(0.47)	(0.39)	(0.39)	(0.38)
Coverage				0.51	0.67*	0.63	0.36	0.26	0.25
				(0.38)	(0.38)	(0.39)	(0.25)	(0.25)	(0.25)

_cons	-4.07***	-4.12***	-4.13***	-30.33***	-28.28***	-29.49***	14.22***	13.13***	13.39***
	(0.16)	(0.17)	(0.16)	(5.43)	(5.37)	(5.38)	(3.32)	(3.24)	(3.20)
Subindustry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.702	0.702	0.702	0.282	0.287	0.284	0.361	0.365	0.367
r2_a	0.70	0.70	0.70	0.27	0.28	0.27	0.35	0.35	0.36
N	8120	8106	8106	2464	2458	2458	2128	2124	2125

Notes: This table presents the relation between FSC and analysts' coverage, forecast accuracy and forecast dispersion. The sample is restricted to observations at the firm level with available data to calculate all the variables used. The standard errors reported in parentheses are clustered at the firm level. *, **, *** present significance at the ten, five, and one percent level, respectively.

Table 6: FSC and Illiquidity

$$Illiquidity\ Metric_{it} = \alpha + \beta_1 FSC_{it} + \gamma Controls_{it} + \varepsilon_{it}$$

	Illiquidity			*Bidask*		
	(1)	(2)	(3)	(4)	(5)	(6)
	FSC_Acct	FSC_CF	FSC_Accrual	FSC_Acct	FSC_CF	FSC_Accrual
FSC	**-0.68*** **	**-1.11*** **	**-0.75*** **	**-0.81*** **	**-1.12*** **	**-0.71*** **
	(0.21)	**(0.22)**	**(0.19)**	**(0.23)**	**(0.24)**	**(0.18)**
Asset	-0.11***	-0.12***	-0.12***	-0.21***	-0.23***	-0.21***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Lever	0.76***	0.80***	0.69***	0.72***	0.73***	0.67***
	(0.26)	(0.29)	(0.27)	(0.25)	(0.27)	(0.25)
MTB	-0.03***	-0.02***	-0.03***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Vol	-0.48***	-0.46***	-0.48***	-0.10***	-0.09**	-0.10***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
L_Size	0.13***	0.14***	0.14***	-0.38***	-0.35***	-0.37***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)
L_ln_returnvar	0.04	-0.21	0.05	0.90***	0.90**	0.97***
	(0.32)	(0.28)	(0.31)	(0.31)	(0.38)	(0.32)
L_ln_turnover	0.21***	0.19***	0.21***	0.27***	0.22**	0.27***
	(0.06)	(0.06)	(0.06)	(0.08)	(0.09)	(0.08)
Production	-0.23***	-0.22***	-0.24***	-0.23***	-0.26***	-0.23***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
_cons	9.31***	8.80***	9.23***	15.39***	15.23***	15.41***
	(0.52)	(0.53)	(0.52)	(0.56)	(0.57)	(0.55)
Subindustry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.456	0.461	0.458	0.492	0.502	0.492
r2_a	0.45	0.46	0.46	0.49	0.50	0.49
N	8352	7090	8341	8114	6908	8103

Notes: This table presents the relation between FSC and the two liquidity measures. The sample is restricted to observations at the firm level with available data to calculate all the variables used. The standard errors reported in parentheses are clustered at the firm level. *, **, *** present significance at the ten, five, and one percent level, respectively.

Table 7: FSC and Cost of Debt

$$Cost\ of\ Debt_{it+1} = \alpha + \beta_1 FSC_{it} + \gamma Controls_{it} + \varepsilon_{it+1}$$

	(1) FSC_Acct	(2) FSC_CF	(3) $FSC\_Accrual$
FSC	**-0.017***** **(0.007)**	**-0.020***** **(0.007)**	**-0.016***** **(0.006)**
Asset	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Lever	0.031*** (0.008)	0.030*** (0.008)	0.030*** (0.008)
Zscore	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
RoA	0.001 (0.002)	0.001 (0.002)	0.000 (0.002)
New_PPE	0.001 (0.005)	0.002 (0.005)	0.003 (0.005)
TANG	-0.008 (0.006)	-0.008 (0.006)	-0.008 (0.006)
OCF	-0.002 (0.007)	-0.002 (0.007)	-0.003 (0.007)
Cashhold	-0.002 (0.009)	-0.002 (0.009)	-0.002 (0.009)
LOSS	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)
Neg_UE	0.003* (0.001)	0.002* (0.001)	0.002* (0.001)
Production	0.005** (0.002)	0.005** (0.002)	0.005** (0.002)
_cons	0.110*** (0.014)	0.110*** (0.013)	0.110*** (0.013)
Subindustry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
r2	0.086	0.087	0.085
r2_a	0.072	0.074	0.072
N	1898	1895	1895

Note: This table presents the relation between FSC and firms' cost of debt. The sample is restricted to observations at the firm level with available data to calculate all the variables used. The standard errors reported in parentheses are clustered at the firm level. *, **, *** present significance at the ten, five, and one percent level, respectively.

Table 8: FSC and Audit Fee

$$Audit\ Fee_{it} = \alpha + \ \beta_1 FSC_{it} + \gamma Controls_{it} + \varepsilon_{it}$$

	(1) FSC_Acct	(2) FSC_CF	(3) $FSC\_Accrual$
$\boldsymbol{FSC}$	**-0.18**	**-0.43****	**-0.63*****
	(0.18)	**(0.21)**	**(0.16)**
$Asset$	0.44***	0.45***	0.45***
	(0.03)	(0.03)	(0.03)
$ISSUE$	0.01	0.01	0.01
	(0.04)	(0.04)	(0.04)
$LOSS$	-0.04	-0.05	-0.04
	(0.06)	(0.06)	(0.06)
$Lever$	0.08	0.06	-0.05
	(0.21)	(0.23)	(0.21)
$QUICK$	-0.01*	-0.01	-0.01
	(0.00)	(0.00)	(0.00)
RoA	-0.11	-0.10	-0.06
	(0.08)	(0.09)	(0.08)
$ForgSales$	0.41***	0.38***	0.39***
	(0.10)	(0.11)	(0.10)
Seg	0.21**	0.21**	0.21**
	(0.08)	(0.08)	(0.08)
$Season$	0.08	0.08	0.07
	(0.08)	(0.08)	(0.08)
OCF	-0.76***	-0.77***	-0.82***
	(0.13)	(0.13)	(0.13)
$Pension$	0.28***	0.27***	0.27***
	(0.09)	(0.09)	(0.10)
D_PB	-0.00	-0.01	-0.00
	(0.01)	(0.01)	(0.01)
$ModOp$	-0.19	-0.20	-0.19
	(0.13)	(0.14)	(0.12)
BIG	0.45***	0.44***	0.43***
	(0.12)	(0.12)	(0.12)
$Specialist$	-0.13	-0.11	-0.12
	(0.08)	(0.08)	(0.08)
$Borrower$	0.09*	0.10*	0.09*
	(0.05)	(0.06)	(0.05)
$Production$	-0.13*	-0.12	-0.12
	(0.08)	(0.08)	(0.08)
$\_cons$	2.99***	2.80***	2.70***
	(0.50)	(0.52)	(0.50)
$Subindustry\ FE$	Yes	Yes	Yes
$Year\ FE$	Yes	Yes	Yes
$r2$	0.627	0.637	0.631
$r2\_a$	0.62	0.63	0.62
N	1982	1812	1978

Note: This table presents the relation between FSC and firms' audit fees. The sample is restricted to observations at the firm level with available data to calculate all the variables used. The standard errors reported in parentheses are clustered at the firm level. *, **, *** present significance at the ten, five, and one percent level, respectively.

Table 9: FSC and Economic Outcomes in Mining VS O&G Industries

$$Economic\ Benefits = \alpha + \ \beta_1 FSC + \beta_2 Industry + \beta_3 FSC \times O\&G + \gamma Control + \varepsilon$$

Panel A: FSC and analysts' coverage, forecast accuracy and dispersion in the Mining vs. O&G subindustries

	Coverage			*Accuracy*			*Dispersion*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FSC_Acct	*FSC_CF*	*FSC_Accrual*	*FSC_Acct*	*FSC_CF*	*FSC_Accrual*	*FSC_Acct*	*FSC_CF*	*FSC_Accrual*
FSC_Acct	-0.02	-0.17***	-0.16***	4.82**	8.04***	4.98***	-4.23**	-6.04***	-4.31***
	(0.05)	(0.05)	(0.04)	(2.45)	(2.43)	(1.89)	(1.71)	(1.72)	(1.13)
1. *O&G*	0.21***	0.24***	0.22***	-0.37	-0.77	-0.42	0.13	0.52	0.07
	(0.07)	(0.07)	(0.06)	(0.77)	(0.83)	(0.66)	(0.48)	(0.50)	(0.43)
1. *O&G# FSC*	0.14	0.23**	0.22**	3.19	1.91	1.98	0.95	2.31	1.48
	(0.11)	(0.11)	(0.10)	(2.87)	(3.05)	(2.50)	(1.91)	(2.02)	(1.81)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.70	0.70	0.70	0.27	0.27	0.27	0.35	0.35	0.35
N	8120	8106	8106	2464	2458	2458	2128	2124	2125

Panel B: FSC and Illiquidity in the Mining vs. O&G subindustries

	Illiquidity			*Bidask*		
	(1)	(2)	(3)	(4)	(5)	(6)
	FSC_Acct	*FSC_CF*	*FSC_Accrual*	*FSC_Acct*	*FSC_CF*	*FSC_Accrual*
FSC	-0.96***	-1.41***	-0.96***	-0.52**	-0.89***	-0.59***
	(0.25)	(0.25)	(0.20)	(0.25)	(0.26)	(0.19)
1. *O&G*	0.69***	0.70***	0.65***	-0.33*	-0.30	-0.22
	(0.15)	(0.16)	(0.15)	(0.17)	(0.19)	(0.17)
1. *O&G#c. FSC*	0.92**	0.95**	0.94**	-1.03**	-0.84*	-0.62
	(0.38)	(0.42)	(0.38)	(0.44)	(0.47)	(0.40)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.45	0.46	0.46	0.49	0.50	0.49
N	8352	7090	8341	8114	6908	8103

Panel C: FSC and Cost of debt / Audit Fee in the Mining vs. O&G subindustries

	Cod			$AuditFee$		
	(1)	(2)	(3)	(4)	(5)	(6)
	FSC_Acct	FSC_CF	$FSC\_Accrual$	FSC_Acct	FSC_CF	$FSC\_Accrual$
FSC	-0.02**	-0.02**	-0.01*	-0.14	-0.41	-0.81***
	(0.01)	(0.01)	(0.01)	(0.23)	(0.27)	(0.17)
$1.O\&G$	-0.00	-0.00	-0.01*	-0.24**	-0.21*	-0.17
	(0.00)	(0.00)	(0.00)	(0.11)	(0.12)	(0.11)
$1.O\&G\#c.FSC$	-0.00	-0.00	-0.01	-0.14	-0.06	0.29
	(0.01)	(0.01)	(0.01)	(0.31)	(0.30)	(0.27)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ FE$	Yes	Yes	Yes	Yes	Yes	Yes
$r2\_a$	0.07	0.07	0.07	0.62	0.63	0.63
N	1898	1895	1895	1982	1812	1978

Notes: This table reports the estimation after adding the industry indicator and its interaction with the variable of concern, FSC. $Industry$ equals one if the firm is in the Oil and Gas subindustry and zero for firms in the Mining subindustry. Same control variables are used as in the prior section and unpresented for brevity purpose. We control for yearly fixed effects and cluster the standard error at firm level.

Table 10: FSC and Economic Outcomes for Exploring vs. Producing firms

$$Economic\ Benefits = \alpha + \beta_1 FSC + \beta_2 Production + \beta_3 FSC \times Production + \gamma Control + \varepsilon$$

Panel A: FSC and analysts' coverage and forecast for Exploring vs. Producing firms

	$Coverage$			$Accuracy$			$Dispersion$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FSC_Acct	FSC_CF	$FSC\_Accrual$	FSC_Acct	FSC_CF	$FSC\_Accrual$	FSC_Acct	FSC_CF	$FSC\_Accrual$
FSC_Acct	-0.09*	-0.22***	-0.22***	2.59	5.05**	1.39	-2.25	-2.99*	-2.03
	(0.05)	(0.06)	(0.05)	(2.29)	(2.39)	(1.96)	(1.70)	(1.66)	(1.72)
$1.Production$	0.08*	0.09**	0.05	1.52**	1.55**	1.13**	-0.62	-0.79*	-0.56
	(0.04)	(0.04)	(0.04)	(0.70)	(0.75)	(0.55)	(0.41)	(0.42)	(0.35)
$1.Prod\#FSC$	0.30***	0.32***	0.23***	6.87**	7.12**	5.74***	-2.24	-3.08*	-2.17
	(0.08)	(0.08)	(0.06)	(2.67)	(2.98)	(2.18)	(1.79)	(1.83)	(1.79)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Subindustry\ FE$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ FE$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$r2\_a$	0.70	0.70	0.70	0.27	0.28	0.28	0.35	0.36	0.36
N	8120	8106	8106	2464	2458	2458	2128	2124	2125

Panel B: FSC and Illiquidity in for Exploring vs. Producing firms

	$Illiquidity$			$Bidask$		
	(1)	(2)	(3)	(4)	(5)	(6)
	FSC_Acct	FSC_CF	$FSC\_Accrual$	FSC_Acct	FSC_CF	$FSC\_Accrual$
FSC_Acct	-1.07***	-1.51***	-1.25***	-0.91***	-1.13***	-0.91***
	(0.26)	(0.28)	(0.26)	(0.28)	(0.29)	(0.24)
$1.Production$	0.02	0.05	0.02	-0.16	-0.25**	-0.13
	(0.10)	(0.11)	(0.09)	(0.11)	(0.12)	(0.09)
$1.Prod\#FSC$	0.77***	0.81**	0.87***	0.20	0.02	0.33
	(0.28)	(0.33)	(0.28)	(0.32)	(0.36)	(0.28)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
$Subindustry\ FE$	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ FE$	Yes	Yes	Yes	Yes	Yes	Yes
$r2\_a$	0.45	0.46	0.46	0.49	0.50	0.49
N	8352	7090	8341	8114	6908	8103

Panel C: FSC and Cost of debt / Audit Fee for Exploring vs. Producing firms

	Cod			$AuditFee$		
	(1)	(2)	(3)	(4)	(5)	(6)
	FSC_Acct	FSC_CF	$FSC\_Accrual$	FSC_Acct	FSC_CF	$FSC\_Accrual$
FSC_Acct	-0.01	-0.01	-0.01	0.43	0.18	-0.19
	(0.01)	(0.01)	(0.01)	(0.41)	(0.45)	(0.38)
$1.Production$	0.00	-0.00	0.00	-0.32**	-0.32**	-0.24**
	(0.00)	(0.00)	(0.00)	(0.13)	(0.14)	(0.10)
$1.Prod\#FSC$	-0.02	-0.02**	-0.01	-0.87**	-0.88**	-0.65*
	(0.01)	(0.01)	(0.01)	(0.41)	(0.43)	(0.35)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
$Subindustry\ FE$	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ FE$	Yes	Yes	Yes	Yes	Yes	Yes
$r2\_a$	0.08	0.08	0.08	0.63	0.64	0.64
N	1898	1895	1895	1982	1812	1978

Notes: This table reports the estimation after adding the production indicator and its interaction with the variable of concern FSC. $Production$ equals one if the firm reports depreciation and zero otherwise. Same control variables are used as in the prior section and unpresented for brevity purpose. We control for subindustry and yearly fixed effects and cluster the standard error at firm level.

Table 11: Firm characteristics by FSC_Acct quartiles

$Variables$	Q1	Q2	Q3	Q4	T-test: Q4-Q1
FSC_Acct	-0.620	-0.340	-0.248	-0.188	0.433***
FSC_CF	-0.599	-0.322	-0.244	-0.221	0.378***
$FSC\_Accrual$	-0.574	-0.296	-0.195	-0.165	0.409***
$Follow$	0.131	0.314	0.408	0.375	0.244***
$Coverage$	0.198	0.566	0.795	0.753	0.555***
$Accuracy$	-9.103	-6.261	-4.739	-5.349	3.754***
$Dispersion$	5.688	4.489	3.356	3.649	-2.039***
$Illiquidity$	2.241	1.512	1.177	1.340	-0.901***
$Bidask$	5.882	4.561	3.913	3.906	-1.976***
$Borrow$	0.115	0.186	0.235	0.240	0.126***
Cod	0.074	0.073	0.065	0.065	-0.009***
$AudFee$	12.428	12.696	12.933	12.993	0.565***
$SIZE$	15.763	16.977	17.736	17.584	1.822***
$Asset$	15.355	16.550	17.429	17.419	2.064***
$Lever$	0.072	0.062	0.070	0.081	0.009**
BTM	0.588	0.813	0.933	1.037	0.448***
Vol	15.172	16.239	16.883	16.698	1.526***
$ISSUE$	0.672	0.625	0.593	0.578	-0.095***
$Predicty$	0.264	0.264	0.283	0.279	0.015**
$Ln\_returnvar$	0.336	0.264	0.219	0.197	-0.139***
$LOSS$	0.850	0.700	0.684	0.737	-0.114***
SUE	11.914	5.543	1.360	0.938	-10.976***
Neg_UE	0.535	0.514	0.520	0.491	-0.044***
MTB	1.667	2.056	2.072	1.593	-0.074
RoA	-1.370	-0.778	-0.404	-0.407	0.963***
OCF	-0.574	-0.360	-0.227	-0.249	0.325***
$Production$	0.378	0.493	0.569	0.567	0.188***
BIG	0.747	0.877	0.880	0.853	0.106***
$Specialist$	0.258	0.343	0.343	0.350	0.092**

Notes: This table reports the mean of measures of FSC, economic variables, and firm characteristics in our sample. Quartiles of FSC_Acct are determined each year. The t-statistic is for a difference of means test between the fourth (Highest FSC_Acct) and the first (Lowest FSC_Acct) quartile.

Table 12: FSC changes pre- and post-IFRS

Panel A: FSC in pre- and post-IFRS periods

Variables	Firms	Pre-period (a)	Post-period (b)	(b) - (a)	T
FSC_Acct	437	-0.279	-0.342	-0.063***	-4.743
$High\ \Delta FSC$	219	-0.335	-0.251	0.084***	5.123
$Low\ \Delta FSC$	218	-0.222	-0.433	-0.211***	-11.513
FSC_CF	400	-0.271	-0.334	-0.063***	-4.563
$High\ \Delta FSC$	201	-0.314	-0.233	0.081***	5.036
$Low\ \Delta FSC$	199	-0.228	-0.436	-0.208***	-10.624
$FSC\_Accrual$	435	-0.204	-0.321	-0.116***	-8.277
$High\ \Delta FSC$	218	-0.236	-0.195	0.041***	2.947
$Low\ \Delta FSC$	217	-0.173	-0.447	-0.274***	-13.048

Panel B: FSC in pre- and post-IFRS periods in the Mining subindustry

Variables	Firms	(a)	(b)	(b) - (a)	T
FSC_Acct	322	-0.253	-0.341	-0.087***	-6.289
$High\ \Delta FSC$	161	-0.301	-0.244	0.056***	3.354
$Low\ \Delta FSC$	161	-0.206	-0.437	-0.231***	-12.449
FSC_CF	297	-0.246	-0.330	-0.084***	-5.938
$High\ \Delta FSC$	149	-0.292	-0.238	0.054***	3.028
$Low\ \Delta FSC$	148	-0.199	-0.422	-0.223***	-12.082
$FSC\_Accrual$	320	-0.174	-0.303	-0.128***	-8.593
$High\ \Delta FSC$	160	-0.201	-0.174	0.027**	2.023
$Low\ \Delta FSC$	160	-0.148	-0.432	-0.284***	-12.769

Panel C: FSC in pre- and post-IFRS periods in the O&G subindustry

Variables	Firms	(a)	(b)	(b) - (a)	T
FSC_Acct	115	-0.350	-0.346	0.004	0.130
$High\ \Delta FSC$	58	-0.431	-0.270	0.161***	4.217
$Low\ \Delta FSC$	57	-0.268	-0.423	-0.155***	-3.346
FSC_CF	103	-0.345	-0.347	-0.002	-0.052
$High\ \Delta FSC$	52	-0.379	-0.221	0.157***	4.665
$Low\ \Delta FSC$	51	-0.312	-0.475	-0.164***	-3.110
$FSC\_Accrual$	115	-0.288	-0.371	-0.082***	-2.620
$High\ \Delta FSC$	58	-0.333	-0.254	0.079**	2.417
$Low\ \Delta FSC$	57	-0.242	-0.489	-0.247***	-5.053

Notes: This table reports comparison of the three FSC measures between the pre-IFRS (2007–2010) and post-IFRS (2011–2014) periods. The $High\ \Delta FSC$ and $low\ \Delta FSC$ groups are classified based on the industry-median FSC change.

Table 13: FSC and Economic Outcomes – Pre- and Post-IFRS

$$Economic\ Benefits = \alpha + \ \beta_1 HFSC + \beta_2 Post + \beta_3 FSC \times Post + \gamma Control + \varepsilon$$

Panel A: FSC and analysts' coverage and forecast accuracy and dispersion – Pre- and Post-IFRS

	Coverage			*Accuracy*			*Dispersion*		
	(1) FSC_Acct	(2) FSC_CF	(3) FSC_Accrual	(4) FSC_Acct	(5) FSC_CF	(6) FSC_Accrual	(7) FSC_Acct	(8) FSC_CF	(9) FSC_Accrual
$1.HFSC$	0.05	0.05	0.05	-0.46	0.49	0.58	0.41	-0.39	-0.57*
	(0.05)	(0.06)	(0.06)	(0.59)	(0.68)	(0.57)	(0.33)	(0.36)	(0.30)
$1.Post$	0.16***	0.12***	0.15***	-1.72***	-2.03***	-2.19***	0.63*	0.68	0.89**
	(0.03)	(0.03)	(0.03)	(0.61)	(0.75)	(0.63)	(0.37)	(0.46)	(0.40)
$\mathbf{1.HFSC\#1.Post}$	**-0.06**	**0.00**	**-0.04**	**1.53****	**1.78****	**2.11*****	**-0.64**	**-0.68**	**-0.92***
	(0.04)	**(0.04)**	**(0.04)**	**(0.76)**	**(0.88)**	**(0.76)**	**(0.46)**	**(0.53)**	**(0.47)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subindustry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.70	0.71	0.70	0.37	0.36	0.38	0.34	0.36	0.36
N	2472	2264	2462	893	819	887	790	722	783

Panel B: FSC and Illiquidity - Pre and Post IFRS

	Illiquidity			*Bidask*		
	(1) FSC_Acct	(2) FSC_CF	(3) FSC_Accrual	(4) FSC_Acct	(5) FSC_CF	(6) FSC_Accrual
$1.HFSC$	0.15*	0.21**	0.13	-0.07	0.06	-0.05
	(0.08)	(0.08)	(0.08)	(0.11)	(0.12)	(0.11)
$1.Post$	0.39***	0.42***	0.33***	0.03	0.04	0.08
	(0.08)	(0.08)	(0.08)	(0.11)	(0.12)	(0.11)
$\mathbf{1.HFSC\#1.post}$	**-0.27****	**-0.29*****	**-0.14**	**-0.11**	**-0.17**	**-0.22**
	(0.11)	**(0.11)**	**(0.10)**	**(0.14)**	**(0.14)**	**(0.14)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Subindustry FE	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.47	0.48	0.46	0.49	0.50	0.49
N	3000	2752	2992	2937	2692	2929

Panel C: FSC and Cod / Audit Fee – Pre- and Post-IFRS

	Cod			*AudFee*		
	(1)	(2)	(3)	(4)	(5)	(6)
	FSC_Acct	FSC_CF	FSC_Accrual	FSC_Acct	FSC_CF	FSC_Accrual
$1.HFSC$	0.00	-0.00	0.00	0.03	0.20	0.21*
	(0.00)	(0.00)	(0.00)	(0.12)	(0.13)	(0.12)
$1.Post$	0.00	-0.00	0.00	0.03	0.15*	0.18**
	(0.00)	(0.00)	(0.00)	(0.08)	(0.09)	(0.08)
$\mathbf{1.}\boldsymbol{HFSC}\#\mathbf{1.}\boldsymbol{Post}$	**-0.01**	**-0.00**	**-0.01****	**-0.02**	**-0.24****	**-0.28*****
	(0.00)	**(0.00)**	**(0.00)**	**(0.10)**	**(0.10)**	**(0.10)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Subindustry FE	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.07	0.07	0.08	0.70	0.71	0.71
N	977	887	976	893	824	890

Notes: This table reports the estimation with IFRS adoption and the change in FSC. $HFSC$ equals one if the firm experiences an FSC change higher than the industry median after IFRS adoption. $Post$ equals one for observations in the post-IFRS period (2011–2014). The same control variables are used as in the prior section and are not reported for brevity. The standard errors are clustered at the firm level.

Appendix 1

Variable Definitions:

Dependent variables:

$Coverage$	Logarithm of the number of analysts following a firm for each firm-year observation plus one
$Accuracy$	Absolute value of the forecast error multiplied by -100 and scaled by the stock price at the end of the prior fiscal year. Forecast error is the first IBES analysts' annual EPS forecast less the accrual earnings
$Dispersion$	Cross-sectional standard deviation of individual analysts' annual forecasts, scaled by the stock price at the end of the prior fiscal year
$Illiquidity$	Annual median of the Amihud (2002) price impact measure
$Bidask$	Annual average bid-ask spread (Roll, 1984)
Cod	Interest rate calculated as interest expense divided by the average amount of interest-bearing debt at the year beginning and year end. We take one-year forward looking interest rate and truncate observations with more than 1,000 basis points over the prime rate for the year
$AudFee$	Logarithm of the reported annual audit fees

FSC variables:

FSC_Acct	Measure of FSC using returns and earnings, see section 3
FSC_CF	Measure of FSC using forward-looking operating cash flows and earnings, see section 3
$FSC\_Accrual$	Measure of FSC using operating cash flows and accruals, see section 3

Control Variables:

$Asset$	Logarithm of a firm's year-end total assets
BIG	Indicator that equals 1 if the firm is audited by a big 4 audit firm
BTM	Book to market ratio of equity value
$Cashhold$	The ratio of cash and cash equivalent divided by total assets at the year end
D_PB	Annual change in Zmijewski's probability of bankruptcy score
Fcs_days	Logarithm of the number of days between the first forecast date to the actual earnings announcement date
$ForgSales$	Ratio of revenue from foreign sales to total sales
$ISSUE$	Indicator that equals 1 if the firm issues debt or equity with a value larger than 5% of total asset, 0 otherwise
$Lever$	Ratio of year-end total debt to total assets
$Ln\_returnvar$	Logarithm of the standard deviation of 48 months of stock returns

$LOSS$	Indicator that equals 1 if the firm reports negative earnings for the current year and the year before, 0 otherwise
$L\_ln\_turnover$	Lagged logarithm of annual $US trading volume divided by market value of common equity
L_Size	Lagged market value of equity
$ModOP$	Modified auditor opinion at year end
MTB	Ratio of market value of equity to book value of equity
Neg_UE	Indicator variable that equals 1 if the firm's current earnings are below the reported earnings during the previous year, 0 otherwise
New_PPE	Ratio of net PPE to the gross PPE at the year end
OCF	Operating cash flow for one year divided by total assets at the year end
$Pension$	Ratio of pension assets (liability) to total assets at the year end
$Predicty$	R^2 of a regression of annual earnings on prior-year annual earnings for the same firm
$Production$	Indicator that equals 1 if the firm reports depreciation expense, and 0 otherwise
$QUICK$	Ratio of the sum of cash and cash equivalents, marketable securities, and accounting receivables to current liabilities at the year end
RoA	Ratio of NIBE to total assets at prior year's end
$Season$	Indicator that equals 1 if the firm's fiscal year-end month is December, and 0 otherwise
Seg	Square root of the number of geographic segments
$Size$	Logarithm of the market value of equity measured at the end of the year
$Specialist$	Indicator that equals 1 if the auditor's market share is greater than 10% of the market share of the closest competitor
SUE	Absolute value of unexpected earnings scaled by the share price at prior year end. Unexpected earnings are calculated as the difference between current earnings and earnings in previous year.
Vol	Logarithm of trading volume in USD
$TANG$	Tangible assets, measured as net property, plant and equipment divided by total assets at year end
$Zscore$	The Aldamen and Duncan (2012) Z-score to measure default risk

Appendix 2

Main outcome based FSC measures in prior literature

$$Financial\ Statement\ Amount_{it} = f(Economic\ Outcomes_{it})$$

Literature	Economic Outcomes	Accounting Outcomes	References
De Franco et al. (2011)	$Return_t$	NI_t/MVE_{t-1}	Cascino and Gassen (2015) Choi and Suh (2019) Lin et al. (2019) Neel (2017) Yip and Young (2012, with ROA)
	$Return_t$; Neg_Ret_t and interaction	NI_t/MVE_{t-1}	Champell and Yeung (2017)
Barth et al. (2012);	$Return_t$	$\frac{NI(PS)_t}{P_{t-1}}, \frac{\Delta NI(PS)_t}{P_{t-1}}, Loss_t$ (& interactions)	Choi and Suh (2019) Lin et al. (2019) Lobo et al. (2018);
	P_t	$NI(PS)_t, BVE(PS)_t$	Lobo et al. (2018) Yip and Young (2012, with country/industry indicator)
	CFO_{t+1}/TA_t	$NI(PS)_t/TA(PS)_{t-1}$	Choi and Suh (2019) Kim et al. (2020) Lobo et al. (2018) Neel (2017, scaled by MVE)
	$Return_t$	$Accrual_t, CFO_t, \Delta Accrual_t,, \Delta CFO_t,, Loss_t$	Caban-Garcia et al. (2020, with disaggregate earnings)
Cascino and Gassen (2015); Neel (2017)	CFO_t	$Accrual_t$	Lin et al. (2019)

Notes: Barth et al. (2012) and Labo et al. (2018) use a reverse version. $Return$ is the fiscal year-end buy-and-hold return (De Franco et al., 2011; Cascino & Gassen, 2015). BVE is book value of equity. NI is net income before extraordinary item. CFO is operating cash flow. TA denotes total assets. P is stock price. $Accrual$ is either computed using the balance sheet, scaled by MVE 9 months prior to the fiscal year-end (Neel, 2017) or as net income less CFO, adjusted for industry average (Champell & Yeung, 2017; Caban-Garcia et al., 2020).

Appendix 3

Validation tests

	Lower FSC pairs(a)		Higher FSC pairs(b)		(b)–(a)	
Variables	obs(0)	mean(0)	obs(1)	mean(1)	mean-diff	T
Panel A: Same subindustry						
FSC_Acct_samind	2401616	0.267	2401615	0.273	0.006***	44.963
FSC_CF_samind	1832807	0.267	1832805	0.272	0.005***	33.428
$FSC\_Accrual\_samind$	2391699	0.268	2391699	0.272	0.004***	34.581
Panel B: Experiencing earnings or losses						
$FSC\_Acct\_samearn$	2564006	0.628	2564007	0.717	0.090***	407.646
$FSC\_CF\_samearn$	1959015	0.624	1959013	0.697	0.073***	297.924
$FSC\_Accrual\_samearn$	2553518	0.643	2553518	0.702	0.059***	273.863
Panel C: Negative or positive returns						
FSC_Acct_samret	2567604	0.596	2567605	0.600	0.004***	22.558
FSC_CF_samret	1959015	0.607	1959013	0.612	0.005***	22.308
$FSC\_Accrual\_samret$	2553518	0.595	2553518	0.601	0.006***	32.574
Panel D: Conservatism level						
FSC_Acct_samCSV	2561074	0.137	2561075	0.118	-0.019***	-241.988
FSC_CF_samCSV	1957314	0.150	1957312	0.129	-0.021***	-237.820
$FSC\_Accrual\_samCSV$	2550598	0.134	2550598	0.121	-0.013***	-164.890

Notes: This table reports the results of a t-test between the means for different subsamples to verify the applicability of the FSC measures to the EI setting. For each firm i, we rank its peer firm j by its FSC score. We divide firms j into high and low groups based on the FSC between i and j. Then for each paired-firm observation we compare whether the j from group of high FSC are more likely to be (1) in the same subindustry with firm i (Panel A); (2) reports profits / losses at the same time with firm i (Panel B); (3) has positive / negative returns at the same time with firm i (Panel C); have similar level of conservatism as firm i (Panel D).

We conduct the first test concerning the potential variance of accounting standards in subindustries, even though most GAAPs and IFRS suggest that accounting practices for EI firms should, in general, be similar. We consider the second and third tests as relevant since, due to the particularities of extractive activities, a vast portion of the sample is reporting losses, likely because those firms are still in the exploration and evaluation stage. It is reasonable to assume that firms in the same stage of extractive activities have more comparable accounting information. Last, CSV is the conservatism level (from Khan & Watts, 2009). The choice between the full cost method and the successful efforts method for evaluation and exploration cost has for long been considered a source of reporting differences in EI firms. While the successful efforts method allows capitalization of costs proven to lead to a successful discovery, the full cost method recommends a less conservative approach and the capitalization of all costs. The choice between alternative methods reveals different levels of conservatism, which in turn is a potential source of the observed diversity in EI firms. We use the CSV measure to reflect EI firms' various accounting choices and expect firm-pairs with higher FSC scores to have similar CSV. Specifically, we first calculate the CSV for firm i and its matched firm j, and then compute the absolute value of the difference between the levels of CSV for each firm-pair. We then test whether the CSV distance is lower for peer firms with higher FSC.