Operational Performance and Disclosure Tone

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Abstract

This paper examines whether operational performance, as measured by technical efficiency, is reflected in corporate disclosure tone. In addition, we analyze which dimensions of operational performance most concern managers and whether they are reflected in the tone of corporate reports. In particular, we investigate whether balances/imbalances in levels of efficiency are reflected in the tone of corporate reports. Using disclosure narratives of the annual reports of 4,348 US companies for the period 1993–2021, we find that better operational performance is generally related to larger levels of positive tone (generated by including less negativity), less uncertainty, and less hesitancy in disclosure tone. We also find that balances in efficiency reflect operational performance, while imbalances are not related to narrative tone in the way one would expect, which seems to indicate a more strategic managerial disclosure approach.

Keywords: Disclosure Tone; Content Analysis; Operational Performance; Technical Efficiency

1. Introduction

Prior literature establishes the link between disclosure tone in corporate reports and a firm's current and future performance, as well as market reaction. However, the focus has been on financial rather than operational performance. This study expands the business and disclosure literature by investigating whether corporate disclosure tone reflects operational performance analogously to the evidence shown for financial performance, along with how informative corporate reports are in relation to the operational aspects of performance. Operational performance is assessed through technical efficiency indices (Fried et al., 2008). Moreover, we seek to determine the dimensions of operational performance that most concern managers and whether these are reflected in the tone of corporate report narratives. In particular, we assess whether the tone in corporate narratives reflects balances and imbalances in technical efficiency. If corporate reports reflect the technical efficiency balance and imbalance of operating performance differently, this implies that such reports are informative for external users.

Corporate performance assessment and evaluation are crucial to identifying shortcomings in managerial activity and to set objectives for improvement. Managers who have a better understanding of technology and the industry in which their companies operate are likely to better predict product demand or invest in better projects. To assess corporate performance, managers need to understand not only financial but also operational performance (Bendickson & Chandler, 2019; Sherman & Zhu, 2006). Operational performance is relevant to determining corporate efficiency and the ability to compete in a market that has become extremely competitive. The competitiveness of firms is ultimately concerned with efficiency results (Orala et al., 1999), and efficiency is the most reliable indicator of competitiveness over the long term (European Commission, 2009). Only the most efficient companies will have a competitive advantage to face challenging global markets.

Operational performance focuses on efficient use of corporate resources. More specifically, it is based on the transformation of inputs and outputs, which managers control. Managers who understand technology and industry trends are able to reliably predict product demand, invest in better projects and manage employees more efficiently. Operational performance, along with its efficiency measurement, identifies the resource inefficiencies preventing a firm from reaching its full potential, whereas financial performance, and its measurement through profitability, may indicate that the firm is a high performer (Avkiran, 2011). This means that operational performance may detect issues and inefficiencies not captured by financial performance, thereby adding new and valuable information for users. According to, Sherman and Zhu (2006: 302) "studies of benchmarking practices have identified numerous sources of inefficiency in some of the most profitable firms." Indeed, prior studies find that the relationship between financial and operational performance is not clear or is even negative (Avkiran, 2011; Campisi et al., 2019; Chen & McGinnis, 2007; Curtis et al., 2020; Thanassoulis et al., 1996). Therefore, operational performance is useful, especially for managers who make decisions on the use of resources, but also for policymakers or investors who decide whether the company is entitled to a "license to operate." However, operational performance is usually reserved for insiders, as they use it to make decisions internally and to increase efficiency. Thus, analysis of operational performance, and whether it is embedded in the tone of corporate reports, is of utmost importance and is the focus of the present paper.

In assessing operational performance, corporate activities can be expressed as a transformation of inputs into outputs, where the desired goal is to produce more output (e.g., sales) with less input (e.g., employees and assets). Technical efficiency is about comparing the observed and the optimal values of the inputs consumed and outputs produced by firms, that is, comparison of the units under analysis with best practice units (Førsund, 2018; Fried et al., 2008). Better companies generate higher output using the resources they have (i.e., output-oriented dimension of technical efficiency), or they minimize the resources used for a given level of output (i.e., input-oriented dimension of technical efficiency). Companies can also simultaneously increase output and decrease input in pursuing better operational performance outcomes (i.e., hyperbolic, non-oriented, or input-output dimension of technical efficiency) (Färe et al., 1985). We refer to the latter measure as input-output technical efficiency. Thus, operational performance provides important signals about a company's trustworthiness, its ability to conduct business responsibly, and its effectiveness in managing resources. This, in turn, can positively impact stakeholder perceptions and confidence in the company's performance and potential for future success. To compute the measures of operational performance, we use data envelopment analysis (DEA)[1], a mathematical programming method (non-parametric) for evaluating the relative efficiency of decision making units (DMUs), such as firms with multiple inputs and multiple outputs (Banker et al., 1984; Charnes et al., 1978). DEA derives the measures of operational performance and, although related, they differ from financial performance measures (which are the main focus of business research) in general, and accounting and finance research, in particular. In general, operational performance measures add information and complement evaluation of firm performance via such financial performance measures as ratio analysis (Halkos & Salamouris, 2004; Thanassoulis et al., 1996). DEA measures offer an advantage over ratios: they capture the multidimensionality of firm performance in a single measure (Avkiran, 2011). DEA measures also allow for an objective weighting in the aggregation of several input and output variables, since weightings are not chosen a priori, but are derived directly from the data (Chen et al., 2015). Also, we would need several ratios to capture all dimensions of firm performance, and it is possible that each of these ratios provides different views of a firm's current performance (Curtis et al., 2020; Feroz et al., 2003), while using only one ratio may lead to an unfair and incomplete image of firm performance, which is multidimensional in nature (Avkiran, 2011).We test whether operational performance is embedded in the corporate report narratives (10-K) of US companies, and whether disclosure tone reflects this performance in the same way as shown in the literature on financial performance. Technical efficiency measures several aspects of firm performance related to analysis of internal efficiency in transforming resources as a basis of competitive advantage (Chen et al., 2015). Technical efficiency as a measure of operational performance is

[1] It is important to consider that previous research has applied DEA, for example, to create managerial ability proxies (e.g., Demerjian et al., 2012). However, we concentrate on technical efficiency and not managerial ability. Demerjian et al. (2012) compute technical efficiency using DEA relative to industry peers and then modify it by removing key firm-specific characteristics, industry and time to arrive at managerial ability measure. In this paper, we estimate technical efficiency using DEA for all industrial sectors simultaneously which differs from Demerjian et al. (2012). In our study, we aim for a broader meaning of efficiency in which we analyze the general technology as possibilities to make sales out of investments into major inputs regardless of specific industry features. More information about our DEA calculation and its application can be found on the Appendix C.

relevant mostly to internal parties but should also be of interest to external ones (Bendickson & Chandler, 2019). Given its relevance and its difference from financial performance, whether technical efficiency is reflected in corporate narrative tone is an empirical question. Prior studies use linguistic analysis tools to examine various aspects of the language used by managers in corporate reports (Hasan & Habib, 2020; Cho et al., 2024; Li, 2008; Li, 2010a; Lim et al., 2018; Loughran et al., 2009; Twedt & Rees, 2012). The literature also examines the tone and other aspects of the language used in earnings press releases (Arslan-Ayaydin, 2020; Davis & Tama-Sweet, 2012; Henry & Leone, 2016), media news (Tetlock, 2007; Tetlock et al., 2008), conference calls (Frankel et al., 1999; Price et al., 2012), management, discussion and analysis (MD&A) disclosures (Audi et al., 2016; Davis & Tama-Sweet, 2012), and corporate social responsibility reports (Soliman & Ben-Amar, 2022; Du & Yu, 2021). The results of this research are consistent with the view that managers use the tone of corporate disclosures to convey private information about current and future performance, but the effect of operational performance on a firm's communication has not been investigated. We use an alternative multidimensional measure of performance, technical efficiency, to address the gap in literature. We contend that given the importance of the operational aspects of performance, which add to and complement financial performance, the effect of technical efficiency should also be considered.

Our results confirm our expectation that operational performance, measured by input-output technical efficiency, permeates the content of corporate reports and is reflected in the disclosure tone used by managers in their communications. In particular, better operational performance is related to higher levels of positive tone (generated from less negativity), less uncertainty, and less hesitancy in corporate disclosures.[2] More interestingly, balanced/unbalanced

[2] Following prior literature (Garcia, 2013), we define *Net Positivity* as a net tone of the narrative (i.e. the difference between positive and negative words scaled by the length of the reports). *Positivity* (*Negativity*) focuses on one dimension of tone measured as the number of the positive (negative) words divided by the total number of words. *Uncertainty* and *Hesitancy* tone are measured using the lists of uncertainty words and weak modal words in Loughran and McDonald (2011). These lists provide an additional means to analyze sentiment in corporate narratives. *Uncertainty* and *Hesitancy* have a similar flavor reflecting the unintentional information conveyed by the company by the text signaling troubles for the firm. The difference between *Uncertainty* and *Hesitancy* is subtle but likely identifies different unintentional messages with the difference that *Uncertainty* is more general than *Hesitancy* (Loughran & McDonald, 2011). *Uncertainty* indicates imprecision while *Hesitancy* indicates a reduction in the level of confidence.

levels between input-oriented and output-oriented technical efficiency are reflected in the tone of corporate report narratives. In particular, balanced levels between input efficiency and output efficiency (e.g., high input efficiency combined with high output efficiency or low input efficiency combined with low output efficiency) appear to reflect actual performance (Allee & Deangelis, 2015; Clarkson et al., 2013; Davis et al., 2015; Huang et al., 2014; Mensah & Chaing, 1996). Further, when an imbalance is present (e.g., high input efficiency combined with low output efficiency or low input efficiency combined with high output efficiency), the disclosures seem to reflect a more opportunistic managerial disclosure approach, that is, the narrative tone does not reflect actual corporate performance (Huang et al., 2014; Li, 2008; Schrand & Walther, 2000; Wild, 1992).

This paper makes several contributions to the business and accounting literature. We add to the literature on corporate performance and how it reflects on disclosure tone by demonstrating that narrative tone is affected not only by managerial judgment of financial performance, as demonstrated in the existing literature, but also by operational performance, as evidenced by efficient utilization of company resources (Chen et al., 2015). In this sense, we explore potential linkages between methodologies from different disciplines by responding to the general question of whether efficiency indicators explain corporate tone beyond profitability indicators. Further, we show whether input and output efficiencies are transmitted through corporate report narratives to users of these reports. Specifically, we demonstrate that management reporting behavior varies for the different scenarios faced by the company in relation to combinations of input and output efficiency. In particular, we provide evidence on how the effect of a balanced/unbalanced level of input efficiency and output efficiency is present in corporate narratives, potentially reflecting management concerns, which would be useful for investors and potential investors beyond that revealed by financial performance. However, 10K users cannot differentiate whether a positive or uncertain tone derives from operational or financial performance. Thus, regulation could mandate issuance of operational performance disclosures clearly separated from financial performance disclosures. Considering and measuring efficiency balance and imbalance in relation to corporate report tone is new to this area of research; this adds to the strength of our research.

This paper proceeds as follows. Next section reviews the relevant literature and develops our hypotheses. Section "Database and sampling period" and Section "Tested models and operationalization of variables" present the database and econometric models, respectively. The empirical results are described in the Results Section. The final section offers concluding comments.

2. Literature review and hypothesis development

The agency problem between managers and stakeholders is a central topic in the business and accounting literature (Abrahamson & Park, 1994; Chen, 2015; Lambert et al., 2007). Executives possess superior information relative to stakeholders and have incentives and ample scope to exercise their discretion when making disclosure choices. Further, voluntary disclosure theory is uncertain about whether managers disclose useful information and their incentives. Two competing views have been proposed in relation to discretionary disclosure strategies: the informativeness perspective and the opportunistic perspective. Agency theory suggests that disclosure mitigates information asymmetry (Verrecchia, 2001). Along this line, the informativeness perspective suggests that managers use their discretion in corporate narratives to convey value-relevant information to mitigate adverse selection problems (Baginski et al., 2016; Grossman, 1981; Grossman & Hart, 1980; Milgrom, 1981), to increase the market value of the firm, and to reduce capital costs (Healy & Palepu, 2001). Other related models assume that managers generally disclose good news (Dye, 1985; Verrecchia, 1983). In contrast to the above-described models, which are based on signaling prediction, where managers disclose good news to signal their superior performance (e.g. Nam et al., 2014; Park & Patel, 2015), other authors put forward the litigation risk hypothesis, where companies voluntarily disclose bad news to reduce the risk of litigation (Skinner, 1997; Trueman, 1997). The litigation risk hypothesis assumes that managers do not have incentive to engage in opportunistic disclosure, because the market can see through this potentially misleading behavior and penalize it (Donoher et al., 2007). Finally, another strand of literature argues that managers report both good and bad news to meet market demands for information and to align investor expectations with their own (Ajinkya & Gift, 1984;

Lang & Lundholm, 1996; McNichols, 1989). Alternatively, the opportunistic (strategic) perspective assumes that managers use their private information to strategically obfuscate investors and obtain revenue for their own benefit.

A wide stream of literature in line with the opportunistic behavior approach, also called impression management research (Neu, 1991), investigates whether and how managers use narrative documents to influence third party impressions (see Merkl-Davies & Brennan, 2007 for a literature review). The implicit assumption in impression management research is the inconsistency between information in the narratives and in the financial statements, which is linked to the intention to influence users, usually to mislead them in relation to actual corporate performance (e.g. An et al., 2024; Clatworthy & Jones, 2003; 2006; Merkl-Davies & Brennan, 2007; Yekini et al., 2016). The assumption is that negative company outcomes lead to conflicts with stakeholders and, therefore, managers have incentives to engage in impression management. Another possibility is that both truthful and strategic disclosures co-exist as investors are temporarily misled by tone management, but the market subsequently corrects the effect and reacts negatively to the misleading tone (Huang et al., 2014). The same negative effect to abnormal positive tone is observed from other users of corporate information in the context of crowdfunding (Cumming et al., 2024).

Given evidence of the negative market reaction if managers engage in opportunistic disclosure and the subsequent loss of reputation for the company and for the manager, we assume that company reports reflect truthful operational performance. Moreover, we do not assume that managers have the intention of misleading or not using operational performance, but that the reality of this performance reflects the characteristics of 10-K narratives. This assumption leads to our hypotheses that are formulated below.

2.1. The relation between financial and operational performance

Following the business and accounting research perspective, corporate information quality is assessed by considering only financial measures of performance; however, from an operational perspective, this is not accurate (Avkiran, 2011; Morrison-Paul & Siegel, 2006). Appendix A provides details about the comparison between operational and financial performance. The literature demonstrates that operational performance adds incremental information to the evaluation of corporate performance (Campisi et al., 2019; Curtis et al., 2020; Feroz et al., 2003; Thanassoulis et al., 1996; Yeh, 1996). Operational performance measures recognize the opportunity costs of inputs and capital accumulation by considering technological and economic relationships between output production and input demand (Morrison-Paul & Siegel, 2006). The business literature emphasizes the need for multidimensional conceptualization of performance (Richard et al., 2009). Operational performance has a distinct advantage over traditional financial performance as it is able to capture the interactions among multiple inputs and multiple outputs in a single measure (Avkiran, 2011; Beccalli et al., 2006). Specifically, prior research states that focusing only on financial measures can overlook the importance of firm efficiency in transforming resources as a major source of competitive advantage (Chen et al., 2015). Therefore, operational performance gives a broader view of performance measurement than the traditional profitability ratio analysis (Chen et al., 2015). Profitability ratio analysis related to financial performance is also often criticized for being subjectively chosen by analysts to assess overall performance. In addition, several ratios are necessary to capture all dimensions of firm performance, and it is possible that each of these ratios provides different views of a firm's current performance (Feroz et al., 2003). Further, the application of DEA in the assessment of operational performance and efficiency provides the benefit of obtaining relative firm performance that is compared and assessed in relation to other firms in the sample. Hence, it provides information relevant to benchmarking purposes.

An example from the automobile industry clearly illustrates the relation between US producers earning high returns by dominating attractive (albeit protected) market segments, and Japanese producers, such as Toyota and Honda, earning their returns through greater efficiency. Another example is from bank management and its measurement of performance (Athanassopoulos & Giokas, 2000; Sherman & Zhu, 2006). A bank branch may be considered more profitable for having large deposits and generating high levels of interest income while another branch may have lower cash deposits because it serves a different type of customer. While high-profit branches are the most desired, high profit does not necessarily mean a branch is well managed. The high-profit branch may be quite inefficient in processing transactions, which may not be apparent from financial measures, and the efficiency could be increased if the branch were managed and operated more efficiently (Sherman & Ladino, 1995).

Measures of operational performance are based on evaluating outputs and inputs, which raises questions about how this performance might be reflected in essential financial corporate documents. This is because operational performance concerns management assessment of corporate resources efficiency rather than attracting external capital, the main objective of financial performance information. This distinction is important because managers' performance explanations can influence investors' perceived persistence of earnings/revenue as well as shareholder judgment of executive performance and compensation. Therefore, if operational performance is reflected in the overall tone used by managers when discussing firm performance, we can say that both operational and financial performance affect company communications and are likely to drive market reaction. This could hold further implications for the necessity of potential disclosure of operational performance measures separately from financial measures.

2.2. Testing the association between corporate report tone and operational performance using textual analysis

As argued in agency theory, separation of ownership and control leads to asymmetry of information and sometimes the use of superior information by managers for their own benefit. Discretionary disclosures can contribute to overcoming information asymmetries and to incremental information between managers and outsiders (Baginski et al., 2000; Kanto & Schadewitz, 2000); or, it can be used to opportunistically mislead users, engaging in impression management (Abrahamson & Park, 1994; Brennan et al., 2009).[3]

Analysis of corporate reports is essential to assess whether managers are providing the right information to users (Ignatov, 2023). The information is appropriate if it reflects the financial but also the operational performance of the firm. Prior literature establishes the link between financial performance and disclosure content, but the link between operational performance and disclosure content has not been investigated.

Prior research examines narrative disclosure and its relationship with firm performance using content analysis and, in particular, textual analysis. Textual analysis is a subset of content analysis and is widely used to analyze the style of corporate reports (Breton & Taffler, 2001; Kothari et al., 2009). Research in accounting, finance, and business has generally analyzed multiple linguistic features in corporate reports (e.g. Hasan & Habib, 2020; Cho et al., 2024; Li, 2008; Lim et al., 2018; Loughran et al., 2009; Twedt & Rees, 2012), press releases (Arslan-Ayaydin, 2020; Davis & Tama-Sweet, 2012; Henry & Leone, 2016), news media (Johnman et al., 2018; Tetlock, 2007), MD&A disclosures (Audi et al., 2016; Davis & Tama-Sweet, 2012), and corporate social responsibility reports (Soliman & Ben-Amar, 2022; Du & Yu, 2021) or environmental reports (Beck et al., 2010). Besides analyzing corporate disclosure, research has also used different methodologies of textual analysis. For example, some studies analyze the frequency of particular words, such as risk-related words or uncertainty-related words (Hope et al., 2016; Kravet & Muslu, 2013; Lim et al., 2018), while others analyze the overall positive or negative tone (Twedt & Rees, 2012).

Some studies employ readily available dictionaries to count words that reflect particular characteristics of the text, such as the General Inquirer or the Harvard list, while others use hand-collected customized lists. Another methodological approach is to apply text classifiers from computational linguistics (e.g., using a naïve Bayesian algorithm) (Antweiler & Frank, 2004; Li, 2010a; Ryans, 2016). A few papers also examine readability (Li, 2008; Lim et al., 2018).

Corporate performance measures are related to several aspects of corporate activity, including accounting, finance, operations, marketing, and corporate social responsibility (Chen et al., 2015). Despite the different methodologies, most research in this area analyzes the link between linguistic cues and firm performance, but the focus is on financial performance (e.g. González et al., 2021; Li, 2010b) and social performance (e.g. Cho et al., 2010; Nazari et al., 2017). In the present paper, we stipulate that if the analysis of operational performance, and specifically technical efficiency, complements the analysis of financial performance (Chen et al., 2015; Feroz et al., 2003), then there should be a relationship between the tone of information included in corporate reports and operational performance. We posit that if corporate narratives reflect corporate performance, then a positive, negative, or uncertain and hesitant tone is likely to reflect good or bad operational performance measured as technical efficiency.

In particular, one would expect that companies with better technical efficiency, similarly to companies with better financial performance, will show a higher level of positive tone, as well as lower levels of negativity, uncertainty, and hesitancy. Technical efficiency measures several aspects of firm performance and specifically information addressed mainly to internal parties. But given the relevance of technical efficiency to management analysis of internal efficiency in transforming resources as a source of competitive advantage (Chen et al., 2015), it should also be of interest to external parties. It is not clear whether operational performance is embedded in the tone of corporate report narratives. Thus, whether this information is reflected in corporate narrative tone is an empirical question. Thus, we pose the following hypothesis.

> ***Hypothesis 1*** The level of positive (negative) tone in corporate reports is higher (lower) for companies with better technical efficiency.

Textual analysis studies focus on the positive/negative dichotomy of sentiment analysis, which is argued to have low power (Loughran & McDonald, 2016). Loughran and McDonald (2011) created word lists for uncertainty and weak modal (the basis for our measure of hesitancy), among others. These lists could provide additional means of analyzing sentiment in narrative disclosures. An economic hypothesis suggested by Loughran and McDonald (2016) is analysis of whether the level of uncertainty and hesitancy affects market reaction. High levels of uncertainty or hesitancy likely indicate a low probability of the company completing an economic event, resulting in a negative outcome (Loughran & McDonald, 2016). Moreover, Bonsall and Miller (2017) speculate that if optimistic language is less credible than neutral to pessimistic language, this could create more uncertainty. These authors, therefore, make a connection between positive/negative tone and uncertainty in a negative association. In line with these arguments, we hypothesize that efficiency should be negatively associated with the level of uncertainty and hesitancy. Thus, our second hypothesis is posed as follows.

Hypothesis 2 The level of uncertainty/hesitancy in corporate reports is lower for companies with better technical efficiency.

2.3. Unbalanced and balanced operational performance and disclosure tone

Operational performance can be defined as input-output technical efficiency that considers improvements in both inputs and outputs, but that also can be measured as an oriented measure of technical efficiency that treats optimization of inputs and outputs separately.

Prior literature investigates and compares input- and output-oriented measures of technical efficiency both theoretically and empirically (Berger et al., 1993; Coelli & Perelman, 1999; Kapelko et al., 2019; Ray, 2008). Our focus on technical efficiency allows us to explore not only the association between disclosure tone and performance but also whether the tone of corporate narratives reflects the balances and imbalances of technical efficiency differently. Previous research suggests that input technical efficiency is not the only factor that should be considered in efficiency studies, but that output efficiency is a dimension of technical efficiency that is at least as important as input efficiency (Berger et al., 1993; English et al., 1993). We go a step further and not only consider input and output dimensions of technical efficiency, but also imbalances between them.

On the one hand, when there is an unbalanced level of technical efficiency dimensions, the previous literature shows that firms would need to restructure their scale of operations (Atkinson & Cornwell, 1994; Ray, 2008). An imbalance occurs when input technical efficiency is high and output is low, or the opposite, where input is low, and output is high. For example, Ray (2008) concludes that when input-oriented technical efficiency is higher than output-oriented technical efficiency, the firm would need to increase its output scale to attain the most productive scale size after eliminating input inefficiency. But when output efficiency is higher than input efficiency, the firm needs to scale down its activities after output inefficiency is eliminated. Also, Atkinson and Cornwell (1994) conclude that when output efficiency is less than input efficiency, such a situation is consistent with an industry that functions under increasing returns to scale, and this industry would need to increase the scale of activity. This implies that given that the company has to engage in structural operational changes, the level of uncertainty should increase and corporate reports should reflect this uncertainty. Similarly, given the need to carry out these changes to achieve efficiency, it is likely that managerial concerns about firm operational performance increase, which should be reflected in the negativity and uncertainty embedded in corporate reports. Therefore, we expect that, generally, when imbalance is present between input and output efficiency, the tone of corporate reports will reflect less positivity and greater negativity, uncertainty, and hesitancy. This should be particularly relevant for the case of high input efficiency combined with low output efficiency where companies are showing are not able to achieve a good outcome even though the input was good.

Ray (2008) and Atkinson and Cornwell (1994) also imply that changes in scale to eliminate inefficiencies lead to more balanced input and output efficiency. Balance in technical efficiency dimensions can be assessed from two scenarios: both efficiencies (input and output efficiency) are high or both are low. Our argument is then that this balanced state is desirable, specifically when both inputs and outputs efficiency are high.

Thus, according to informative theory, when both input and output efficiencies for a firm are high, the narrative tone will be more positive and less uncertain, but when both input and output efficiencies are low, the narrative tone will be less positive and more uncertain, showing corporate disclosure transparency.

Prior literature investigates technical efficiency dimensions and compares input- and output-oriented efficiency. However, it does not assess the effect of the different imbalances on corporate disclosure. Adding to this literature, our work investigates management corporate disclosure in relation to balance and imbalance in input and output efficiency.

Thus, our third and fourth hypotheses are posed as follows.

> ***Hypothesis 3*** The level of positive (negative) tone in corporate reports is higher (lower) depending on the balanced level of input and output efficiency.
>
> ***Hypothesis 4*** The level of positive (negative) tone in corporate reports is higher (lower) depending on the unbalanced level of input and output efficiency.

To test Hypotheses 3 and 4, we identify four scenarios of high and low input and output efficiency levels. This allows us to operationalize the testing of Hypotheses 3 and 4 into four sub-hypotheses each (3a, 3b, 3c, 3d, 4a, 4b, 4c, 4d). The specific sign of each sub-hypothesis is detailed in Figure 1. Details are provided in Section "Balance and imbalance in technical efficiency" and in Figure 1.

<Please insert Figure 1 here>

3. Database and sampling period

We use the Loughran and McDonald (2011) database, which was developed using textual analysis for annual reports (so-called 10-K filing) of US companies included on the EDGAR website. This database has been validated through its use in prior research in finance, accounting, and business (e.g. Garcia, 2013; Garcia Osma & Guillamon-Saorin, 2011; Lim et al., 2018; Park & Patel, 2015; Twedt & Rees, 2012). We obtained the Loughran and McDonald wordlist from the authors' website.[4] We use four-word lists: positive (Fin-Pos); negative (Fin-Neg); uncertainty (Fin-Unc); and weak modal words (MW-Weak).[5]

Public firms are required to report a comprehensive review of firm business operations and financial conditions. The most important of the corporate reports in the US is the 10-K, which must be filed as required by the Securities Exchange Act of 1934 (Loughran & McDonald, 2014); it is used by managers to communicate with investors and analysts. 10-Ks are an important source of information for external stakeholders to understand the strategies and operations of the firm (Guo et al., 2017). The 10-Ks contain detailed information about a firm's financial resources, strategies, potential risks, and sources of income (SEC, 2011). Moreover, 10-Ks include a management discussion of the results of operations, changing business strategies, competition, resource utilization, and cost management. All of this information is vital for users to understand

[4] We appreciate McDonald sharing this dataset based on the 10-K summary file to construct our sample at *https://sraf.nd.edu/sec-edgar-data/*. Each observation in the summary file represents a 10-K filing record acquired from EDGAR database. The parsing procedure of the 10-K fillings is detailed in (Loughran & McDonald, 2011). The Loughran and McDonald's dataset is based on the textual analysis of the whole 10-K. This dataset has been used in prior research as proxy of the tone of the 10-K report (Law & Mills, 2015).
[5] Other widely used word lists for positive and negative words in the accounting literature include Henry (2008) and Harvard's General Inquirer (GI). We use the Loughran and McDonald (2011) database because it was created specifically for 10-Ks and therefore, customized to the terminology included in the documents. The Fin-Pos list includes words such as achieve, efficient, increase, improve, profitable. The Fin-Neg list includes words such as bad, bankruptcy, damage, deceived. The Fin-Unc list includes words denoting uncertainty such as approximate, contingency, uncertainty, variability (in total 285 words) with emphasis on the concept of imprecision rather than risk. The MW-Weak list is a reduced list based on Fin-Unc with more emphasis on expressing levels of confidence, with words such as could, might, possibly (in total 26 words which are also included in the Fin-Unc list are part of this list).

the firm. Evidence indicates that multiple stakeholders, including investors, journalists, and competitors, regularly review the annual reports of companies of interest to gather intelligence and inform their decisions (Guo et al., 2017).

Among its different sections, the 10-K includes a management discussion of the results of operations, changing business strategies, competition, resource utilization, and cost management. We do not specifically analyze operations technical efficiency related matters as this would be difficult to achieve. Specific analysis of operations technical efficiency would imply development of a specific list of words and a methodology to carry out a content analysis. This is a completely different task that is outside the scope of this study. Another option is to focus on the MD&A section of the 10-K (e.g. Feldman et al., 2010; Li, 2010a), which includes management discussion of company general performance. However, the MD&A or any other section of the 10-K does not specifically focus on operational performance. Thus, we analyze the entire 10-K document to assess whether the narrative tone reflects operational performance. In measuring sentiment, Loughran and McDonald (2011) report that focusing on the MD&A section does not provide more powerful statistical results. We assume that users' assessment of firm operational performance goes well beyond a specific section of the 10-K filing. This is also the approach taken in prior research, whereby the whole report is analyzed to link the linguistic characteristics of narratives to financial performance (e.g. Loughran & McDonald, 2016). Therefore, we follow a methodology widely accepted in textual analysis research.

In this study, whose period of analysis is 1993–2021, Central Index Key (CIK) and fiscal year-end date are used as unique identifiers to combine 10-K filings with financial data from Compustat 10-K files. After merging the information from the databases, we removed firms with missing information on the variables of interest. Finally, because it is well known that the DEA method is very sensitive to the presence of outliers in the sample, we detected and removed them following the Simar (2003). The final sample consists of 29,598 firm–year observations on 4,348 firms (unbalanced panel).

4. Tested models and operationalization of variables

The models used to test our hypotheses are described below via the following three equations.

$$\textbf{Narrative Tone}_{\textbf{it}} = \beta_0 + \beta_1 \mathit{Tech\_eff}_{it} + \beta_2 \mathit{Loss}_{it} + \beta_3 \mathit{Cfo}_{it} + \beta_4 \mathit{ROE}_{it} + \beta_5 \mathit{Leverage}_{it} + \beta_6 \mathit{Equity\_Assets}_{it} + \beta_7 \mathit{MTB}_{it} + \beta_8 \mathit{ROA}_{it} + \sum \beta_9 \mathrm{Industry\_Controls}_{it} + \sum \beta_{10} \mathrm{Year\_Controls}_{i} + u_{it} \quad (1)$$

$$\textbf{Narrative Tone}_{\textbf{it}} = \beta_0 + \beta_1 \mathrm{Balance}_{it} + \beta_2 \mathit{Loss}_{it} + \beta_3 \mathit{Cfo}_{it} + \beta_4 \mathit{ROE}_{it} + \beta_5 \mathit{Leverage}_{it} + \beta_6 \mathit{Equity\_Assets}_{it} + \beta_7 \mathit{MTB}_{it} + \beta_8 \mathit{ROA}_{it} + \sum \beta_9 \mathrm{Industry\_Controls}_{it} + \sum \beta_{10} \mathrm{Year\_Controls}_{i} + u_{it} \quad (2)$$

$$\textbf{Narrative Tone}_{\textbf{it}} = \beta_0 + \beta_1 \mathrm{Imbalance}_{it} + \beta_2 \mathit{Loss}_{it} + \beta_3 \mathit{Cfo}_{it} + \beta_4 \mathit{ROE}_{it} + \beta_5 \mathit{Leverage}_{it} + \beta_6 \mathit{Equity\_Assets}_{it} + \beta_7 \mathit{MTB}_{it} + \beta_8 \mathit{ROA}_{it} + \sum \beta_9 \mathrm{Industry\_Controls}_{it} + \sum \beta_{10} \mathrm{Year\_Controls}_{i} + u_{it} \quad (3)$$

Below, we explain in detail how each variable in the models is operationalized.

4.1. Operationalization of dependent variables

Narrative tone in equations (1)–(3) is allowed to vary to refer to *Net Positivity*, *Positivity*, *Negativity*, *Uncertainty*, and *Hesitancy*. Positive tone in narratives is captured by two variables: *Net Positivity* and *Positivity*. We evaluate managers' language (narrative tone) using frequency counts of "positive," "negative," "uncertainty," and "hesitancy." Using these frequency counts, we create our proxies for disclosure tone: *Net Positivity*, *Positivity*, *Negativity*, *Uncertainty*, and *Hesitancy*.

Net Positivity, Positivity, and *Negativity* are measured using a pre-established list of positive and negative words created by Loughran and McDonald (2011). *Net Positivity* is measured as the number of positive words minus the number of negative words divided by the total number of words in an annual report and reflects the net tone between positive and negative words. The ratio of positive minus negative words scaled by total words or scaled by positive plus negative words better captures the positivity in the content of corporate narratives as it is a relative measure that compensates the lack of meaning of positive words per se. *Positivity* is calculated as the number of positive words divided by the total number of words. The third proxy of disclosure tone reflects only the negativity in the text. *Negativity* is calculated as the number of negative words divided by the total number of words (Wisniewski & Moro, 2014). For this proxy, our focus is exclusively on negative words, because negative information creates a stronger effect on readers (Garcia, 2013; 2014; Tetlock, 2007).

Two proxies for uncertain and hesitant tone are also measured, as in Loughran and McDonald (2011). *Uncertainty* (*Hesitancy*) is calculated as the number of uncertainty (weak modal) words from the Loughran and McDonald (2011) list scaled by the total number of words in each document.

4.2. Operationalization of the main independent variables

4.2.1. Technical efficiency

Tech_eff in equation (1) represents the values of input-output technical efficiency, with values between 0 and 1, where value 1 reflects 100% efficiency. Technical efficiency refers to the distance from the point of the company's current input-output combination to the efficient frontier. Its three versions are input-oriented, output-oriented, and input-output technical efficiency measures. The potential for reducing inputs while maintaining the output constant reflects input orientation. Similarly, potential increase in output while maintaining the originally specified input levels signifies output orientation. Input-output technical efficiency is measured by simultaneous reduction in input quantities and increase in output quantities. Technical efficiency scores determine in their input- or output- or input-output-oriented dimensions, respectively, the percentage by which the unit inputs should be decreased or the unit output production should be increased, or simultaneously a unit input reduction and output production increase, to reach an efficient frontier. Details on mathematical formulations for these measures are described in Appendix B.

To create the relative input-, output-, and input-output-oriented efficiency measures of the firms, we use the data-oriented non-parametric method of DEA. DEA is applied widely in business and accounting research (Burnett & Hansen, 2008; Demerjian et al., 2012; Demerjian et al., 2013; Yang & Basile, 2022).[6] Details on DEA and the specifics of its application in this paper,

[6] An alternative and competing possibility would be the estimation of efficiency measures via parametric methods, that is stochastic frontier method (Aigner et al., 1977). The advantages of DEA over stochastic frontier include its flexibility as it does not impose specific functional forms on the technology as well as distribution assumption on the data, and thus avoids the misspecification errors. Also, statistical inference

as well as the DEA models for calculating input-oriented, output-oriented, and input-output measures are given in Appendix C. To estimate efficiency measures with DEA, one needs information on inputs and outputs of firm production processes. To measure input and output variables, we use accounting data measured in financial terms, a very common strategy in the efficiency literature since quantity data are often not available. Following accounting research and particularly Demerjian et al. (2012), we distinguish one output and seven inputs. Output is proxied by firm total sales, which are deflated using the producer price index supplied by International Monetary Fund statistics.[7] The inputs consist of: (1) costs of goods sold (*CoGS*), (2) selling general and administrative expenses minus current operating lease expense and research and development expense (*SG&A*), (3) property, plant and equipment (*PP&E*), (4) operating leases (*Ops Lease*), (5) net value of research and development expenses (*Net R&D*), (6) goodwill (*Goodwill*), and (7) other intangible assets (*OtherIntan*). *CoGS* are deflated using producer price index for primary goods, *SG&A*, *Ops Lease*, and *Net R&D* by the producer price index for intermediate goods, while *PP&E*, *Goodwill*, and *OtherIntan* by the producer price index for investment goods; all indices are obtained from the OECD dataset. Our input-output variables approximate the quantity measures because we use implicit quantity indexes generated as the ratios of value to the price index (Silva et al., 2015).

Table 1 provides descriptive statistics of our input-output data for the study period, 1993–2021. The data in Table 1 show a wide variation in the sample for all input-output variables, as shown by high values of standard deviations relative to their respective means. In particular, the largest variation is presented by inputs like *CoGS*, *PP&E*, *Net R&D*, *Goodwill*, and *OtherIntan*. The mean is much higher than the median, suggesting that the data are skewed to the right (more values on the lower end of the scale).

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in DEA is now available through for example the usage of bootstrap methods that allow for statistical inference and robust assessment of efficiency, which mitigate the main disadvantage of DEA as being a non-stochastic method. These reasons lead us to choose DEA and not stochastic frontier as the method for the assessment of efficiency used in this paper.

[7] It resulted impossible to apply price index specific for each industry as in the main source of price indices for USA that is in the US Bureau of Labor Statistics there were no data or time series were incomplete for some industries. Therefore, to have the price index uniform between industries, we applied a general producer price index.

<Please insert Table 1 here>

4.2.2. Balance and imbalance in technical efficiency

To measure balance and imbalance as shown in equations (2) and (3), we split the companies in our sample into those with: (1) high level of efficiency in inputs and high level of efficiency in outputs (*Input_High-Output_High*), (2) high level of efficiency in inputs and low level of efficiency in outputs (*Input_High-Output_Low*), (3) low level of efficiency in inputs and high level of efficiency in outputs (*Input_Low-Output_High*), and (4) low level of efficiency in inputs and low level of efficiency in outputs (*Input_Low-Output_Low*). (1) and (4) represent a balance in input and output efficiency, while (2) and (3) are considered imbalanced. Moreover, (1) is considered the best-case scenario, where high input efficiency is transformed into high output efficiency, and (4) is the worst-case scenario, reflecting a situation where low input efficiency leads to low output efficiency. We subsequently assess the level of disclosure tone and uncertainty tone of disclosures included in the 10-K for companies in groups (1) through (4) and compare them. In particular, as shown in the hypotheses, we expect that (1) when the level of efficiency in inputs is high and the level of efficiency in output is high, the disclosure tone in corporate reports tends to be more positive, less negative, less uncertain, and displays a lower level of hesitancy (reflecting a lack of managerial concern); (2) when the level of efficiency in inputs is high and the level of efficiency in output is low, the disclosure tone in corporate reports tends to be less positive, more negative, and tends to reflect uncertainty and hesitancy (reflecting a certain level of managerial concern); (3) when the level of efficiency in inputs is low and the level of efficiency in output is high, the disclosure tone tends to be less positive, more negative, more uncertain, and more hesitant (reflecting a certain level of managerial concern); and (4) when the level of efficiency in inputs is low and the level of efficiency in output is low, the disclosure tone in corporate reports tends to be less positive, more negative, more uncertain, and more hesitant (reflecting a high level of managerial concern). *Input_High-Output_High*, *Input_High-Output_Low*, *Input_Low-Output_High*, and *Input_Low-Output_Low* are dummy variables with values of 1, indicating the firms in the sample with a high level of efficiency in both inputs and outputs, a high level of efficiency in inputs and a low level of efficiency in outputs, a low level of efficiency in inputs and a high level of efficiency in outputs, and a low level of efficiency in both inputs and outputs, respectively, and values of 0 otherwise. High (Low) level of inputs or outputs is measured as being above (below) the annual average of the whole population and of the industry. Figure 1 shows the four possible scenarios, hypotheses, and expected signs.

4.3. Control variables

As our primary interest is the effect of operational performance on corporate narrative tone, we add controls for a variety of factors that may affect this relationship. Following prior literature (Davis & Tama-Sweet, 2012; Lang & Lundholm, 1993), we control for variables that may affect cross-sectional variation in disclosure tone. For financial structure we use two variables, leverage and cash flow (Bonsall & Miller, 2017). *Leverage* is a ratio calculated by dividing a firm's total debt by a firm's total assets in year *t*. *Cfo* is cash flow from a firm's operations in year *t* scaled by total assets. To control for company profitability, we include *ROE*, *ROA*, and losses (Irani & Oesch, 2013). *ROE* is calculated by dividing earnings before extraordinary items by shareholder equity, all in year *t*. *ROA* corresponds to earnings before extraordinary items of a firm in year *t* scaled by total assets. *Loss* is a dummy variable that equals 1 if a firm presents a net loss in year *t*, and 0 otherwise. Momentum in firm performance suggests that the tone in 10-Ks should be more positive for firms performing well. *Equity_Assets* is the value of a firm's stockholder equity in year *t* scaled by total assets in year *t*.[8] *MTB* is the ratio corresponding to market value of a firm divided by book value of a firm in year *t*. Firms with high *MTB* are different from those with low *MTB* in relation to investment opportunities and potential for growth (Lawrence, 2013; Miller, 2010). As companies with high *MTB* are expected to face uncertain growth opportunities, the expectation would be a negative association between *MTB* and tone. Finally, we supplement these controls by including year and industry dummies in all models (Campbell et al., 2014). Industry dummies are constructed according to the main SIC codes, with value 1 indicating the industry under analysis, and 0 otherwise. For example, the variable *Construction* takes the value 1 when a

[8] If we use *Log_Equity* as control (value of a firm's stockholders' equity in year t in logs), the results remain unchanged. We include *Equity_Assets* as control as we lose less observations.

firm belongs to the construction industry, 0 otherwise. Year dummies indicate the year of observation.

4.4. Descriptive statistics of regression variables

Table 2 summarizes the descriptive statistics of the variables used in the regressions to test our hypotheses. The mean of *Net Positivity* is negative, indicating that the 10-Ks in our sample generally have a low level of positive words in relation to the negative words included in our lists. The mean of *Uncertainty* is larger than the mean of *Hesitancy*. The values of *Tech_eff* indicate that, on average, firms in the sample are 92.6% efficient; that is, they can improve operational performance by increasing output by 7,99% ((1/0.926)-1)*100, while simultaneously reducing inputs by 7.4% (1-0.926)*100. The descriptive statistics on *Input_High-Output_High*, *Input_High-Output_Low*, *Input_Low-Output_High*, and *Input_Low-Output_Low* indicate that the majority of firms in the sample have a high level of efficiency in inputs and a high level of efficiency in outputs (38.5% of sample observations) or a high level of efficiency in inputs and a low level of efficiency in outputs (21.7% of sample observations). The statistics also indicate some variability in the sample regarding most control variables, for which we find large standard deviations relative to their respective means and, as a result, a relatively high coefficient of variation.

<Please insert Table 2 here>

5. Results

5.1. Hypotheses testing

To test our hypotheses, we run a pooled panel data linear regression, with robust standard errors, clustered by firm (Petersen, 2009), controlling for both industry and year dummies.[9]

Table 3 (Models 1, 2, and 3) presents the results on the association between positive and negative words in disclosures reported in the corporate 10-K and operational performance. As expected from Hypothesis 1, we find that operational performance as measured by input-output

[9] Regressions are calculated substituting missing variables (because of controls' missing values) by zero. A total of 824 observations are replaced by zero. Main results remain unchanged if this replacement is not done or if the missing control values are replaced by the annual industry median or average.

technical efficiency is positively associated with *Net Positivity* and negatively associated with *Negativity*. As shown in Models 1 and 2, *Positivity* is non-significant while *Net Positivity* is positive and significant. This shows that the effect of technical efficiency on narrative tone is likely to be generated by a decrease in the level of negativity rather than by an increase in positivity. Prior research argues in favor of the lack of predictability of positive words per se and that positive words tested in isolation are weaker than negative words (Tetlock, 2007; Tetlock et al., 2008). *Loss* is negatively associated with *Net Positivity* and positively related to *Negativity*, as expected (Huang et al., 2014). *Leverage* is negatively associated with *Positivity* and *Negativity*, indicating that companies with higher debt issue more neutral corporate narratives. *Cfo* is significant for *Net Positivity* (negative sign), *Positivity* (negative sign), and *Negativity* (positive sign). Similar to prior research (Huang et al., 2014), *ROE* is not statistically significant and the remaining control variables are not significant but present the expected sign from the literature.[10]

In Table 3 (Models 4 and 5), we test the relationship between uncertainty and hesitancy in 10-K reports and operational performance as measured by input-output technical efficiency. Consistent with our expectations in Hypothesis 2, *Uncertainty* and *Hesitancy* tone is negatively associated with operational performance. Again, the findings for the control variables are in line with prior research. *Loss* is significantly and positively associated with *Uncertainty* and *Hesitancy*, showing that companies with higher losses are more likely to have an uncertainty and hesitancy tone in their corporate reports. On the contrary, *Leverage* is significant and negatively associated with *Uncertainty* and *Hesitancy*, indicating that companies with higher debt levels include more uncertain and hesitant corporate report narratives. *MTB* is also significant and positively associated with *Uncertainty*.

<Please insert Table 3 here>

In Tables 4 and 5, we look into the specific cases of balances and imbalances between input and output efficiencies (Hypotheses 3 and 4). We start by analyzing the scenarios of

[10] The effects of *Tech_eff* on *Net Positivity, Positivity*, *Negativity*, *Uncertainty* and *Hesitancy* remain unchanged when (1) we include in the regression models only *ROE* or only *ROA*, (2) we include revenue or revenue growth as extra controls and (3) we include the three components of *ROE* instead of *ROE* itself (i.e., earnings/sales, sales/assets, and assets/equity).

balances related to Hypotheses 3a, 3b, 3c, and 3d, with respect to scenarios (1) and (4). The first balanced scenario (1) occurs when the level of efficiency in inputs is high and the level of efficiency in outputs is high, which is considered the best-case scenario. In this case, the disclosure tone in corporate reports is found to be more positive (as measured using the variable *Net Positivity*), less negative, less uncertain, and less hesitant, as expected from Hypotheses 3a and 3b (see Figure 2 and Models 1-2-3 in Table 4 and Models 1-2 in Table 5). Again, here the results for the effect of technical efficiency on narrative tone are likely to be generated by a decreased level of negativity rather than by an increase in positivity; this is why the variable that shows a positive association is *Net Positivity* rather than *Positivity*. The second balanced scenario, (4), occurs when the level of efficiency in inputs is low and the level of efficiency in output is low. This is the worst-case scenario, when both input and output efficiencies are low. In this scenario, the disclosure tone in the narratives of corporate reports is shown to be less positive (as derived from the negative and significant coefficient in Model 10 in Table 4 based on the variable *Net Positivity*), more negative, more uncertain, and more hesitant (as summarized in Figure 2 and Models 10–12 in Table 4 and Models 7–8 in Table 5), which is line with our expectations from Hypotheses 3c and 3d.

We next move to the analysis of imbalances related to Hypotheses 4a, 4b, 4c, and 4d. The imbalances are related to scenarios (2) and (3), which are considered moderate scenarios. The first case of imbalance happens with scenario (2) where the level of efficiency in inputs is high and the level of efficiency in output is low, that is, high efficiencies in inputs are transformed into low efficiencies in outputs. We find a positive and significant relationship between this imbalance and disclosure *Net Positivity* and *Positivity* and a negative and significant relationship with *Negativity*. The association is also positive and significant for *Hesitancy* (see Figure 2 and Models 4-5-6 in Table 4 and Models 3–4 in Table 5). These results would be contrary to informative theory and more in line with an opportunistic disclosure approach. According to the informative theory, one would expect positivity to be low and a negative, uncertainty, and hesitancy tone to be embedded in the narratives, reflecting the fact that companies need to change the scale of activity to achieve a balance between input and output efficiency (Atkinson & Cornwell, 1994;

Ray, 2008). Although there is some level of hesitancy, we find more positive tone in the narratives of these companies than expected. These results mean that, generally, we do not find support for Hypotheses 4a and 4b which would be in line with informative hypothesis. Thus, our results are more in line with the opportunistic disclosure view.

The second case of imbalance occurs when in scenario (3) the level of efficiency in inputs is low and the level of efficiency in outputs is high. In this second scenario of imbalance, the disclosure tone in corporate reports is found to display a higher level of *Net Positivity* and *Positivity* and a lesser degree of uncertainty and hesitancy. Also, we find no significant relationship with *Negativity*, as summarized in Figure 2 and Models 7-8-9 in Table 4 and Models 5–6 in Table 5. These results would be contrary to the expectations from Hypotheses 4c and 4d and thus also more in line with an opportunistic disclosure approach. Again, according to Ray (2008), firms would need to increase their input scale to obtain the most productive scale size and to achieve a balance between input and output efficiency.

The results of unbalanced scenario (2) are more controversial than those of scenario (3). In scenario (2) the use of high input efficiency leads to a low output efficiency, but still the tone of the corporate reports is, generally, positive, contrary to what one would expect according to the informative theory (i.e., less positive tone). Also, in scenario (3), we observe a general reduction of uncertainty and hesitance in corporate narratives. Thus, both scenarios (2) and (3) show more positive tone than expected in line with opportunistic managerial disclosure practices.

These results indicate that corporate narratives in 10-Ks correctly reflect balanced technical efficiency. However, they also show that the narratives do not reflect both balanced scenarios equally. For the case of imbalances, narrative tone does not contain the negativity and uncertainty that would give some indication to the reader that the company needs to deal with this imbalance in operational performance. These results may be interpreted as going against the informative argument and are more in line with opportunistic disclosure.

<Please insert Tables 4 and 5 here>
<Please insert Figure 2 here>

Throughout, all our results for *Uncertainty* and *Hesitancy* are similar. If we consider the differences in meaning between these two variables, we could investigate whether managers tend to emphasize a tone that indicates a reduced level of confidence (*Hesitancy*) or a tone that indicates imprecision (*Uncertainty*). This is a significant and interesting result that deserves further investigation.

5.2. Robustness checks

To address potential endogeneity issues, we run several robustness checks. First, in line with previous research such as Lim et al. (2018) and Fich and Shivdasani (2006) we adopt a lead-lag regression approach with the main goal of mitigating the potential concern of reverse causality. For this, we run our main regression lagging each independent variable (including our main variable of interest, efficiency) one year. The main results for Tables 3, 4, and 5 remain unchanged. Second, to check that firm size is not driving our results, we follow previous research (Bentley et al., 2013; Carson & Fargher, 2007; Lim et al., 2018) and create firm size quintiles. In particular, we calculate firm size quintiles by industry and year and create interactions with our efficiency variable. We add interactions between our efficiency variable and the lowest, medium, and largest firm quintiles. *Firm Size* is calculated as the logarithm of total assets. Our main results in Table 3 hold (except for *Hesitancy*, where the coefficient is not statistically significant but shows the expected sign). Most of our main results remain for Tables 4 and 5. Third, to check that firm age is not driving our results, we follow previous research (Higgins et al., 2015; Lim et al., 2018) and create the variable *Older*, which equals 1 for companies with age higher than the median firm age at the industry-year level, and 0 otherwise. In particular, we create interactions of *Older* with our efficiency variable. Our main results in Table 3 hold. Most of our main results remain for Tables 4 and 5. Finally, we adjust all our narrative variables by subtracting the industry-year average. The main results hold for Tables 3, 4, and 5.[11] Detailed results (tables) with robustness checks can be obtained upon request.

[11] It is also important to highlight that the use of industry and year fixed effects applied in the paper allows mitigating to some extent the endogeneity problem related with omitted variable that is time-invariant (Antonakis et al., 2010).

6. Conclusions

This study focuses on operational performance measured as technical efficiency and how it is reflected in the tone of corporate narratives. We study different dimensions of technical efficiency and investigate whether firms, in pursuing good performance outcomes, target reduction in inputs (input efficiency) or increase in outputs (output efficiency).

Operational performance helps to determine corporate efficiency and the ability of a firm to compete in the market (European Commission, 2009). Operational performance focuses on the efficient use of corporate resources based on transformation of inputs and outputs under the control of firm management. Thus, operational performance and its technical efficiency measurement provide indications of resource inefficiencies not realized by financial performance measures (Avkiran, 2011). This means that operational performance measurement may detect issues and inefficiencies not captured by financial performance, thereby adding new and valuable information for corporate disclosure users.

This study contributes to the literature on disclosure tone by demonstrating that positive/negative tone, uncertainty, and hesitancy are affected by technical efficiency, revealing managerial concern about imbalances in technical efficiency. Hence, we add to the literature by introducing operational performance, evidenced by efficient utilization of resources, as an important determinant of corporate disclosure tone. We also document evidence on the reflection of a balanced/unbalanced level of input and output technical efficiency in the narratives of corporate reports.

We find that technical efficiency is positively related to positive tone and negatively to negativity, uncertainty and hesitancy in corporate disclosure tone. This general finding is further elaborated by examining situations of balances/imbalances between input and output technical efficiency. In particular, we find that a balanced level between input and output efficiency, that is, when both input and output efficiencies are high, leads to a disclosure tone in corporate reports that is more positive (through use of less negativity), less uncertain, and less hesitant. When both input and output efficiencies are low, the disclosure tone in corporate reports is shown to be less positive (through use of more negativity), more uncertain, and more hesitant. On the contrary, we find that in situations of imbalance between input and output efficiency, managers do not generally disclose higher negativity, uncertainty, and hesitancy as one would expect in an uncertain situation. Considering efficiency balances and imbalances and measuring their relationship with narrative tone is a new approach to analyzing corporate performance and corporate narratives. This approach adds further value and contributes to the literature.

Our findings hold important implications for managers, who can improve corporate reports to better reflect operational performance and further reduce asymmetries of information that lead to agency costs. Also, policy makers and market participants are increasingly concerned about the content of 10-Ks, which underpins the relevance of the decision usefulness of the information contained therein. This is in line with the need for policymaking decisions that could consider the relevance of the transparency of corporate reports reflecting both operational and financial performance. This paper also holds relevant implications for users of corporate reports. From corporate disclosure narratives, users can derive information on firms' technical efficiency that complements views supported by financial performance. Specifically, users of corporate reports should be aware that managers, intentionally or unintentionally, reflect their concerns about imbalances of technical efficiency in corporate narratives, providing relevant insights on how efficient companies are in their use of resources. Indeed, a higher level of uncertainty, hesitance, and negativity, together with a lower level of positive tone, is clearly indicative of low input and low output efficiency; therefore, users can make decisions accordingly. However, 10-K users may not be able to differentiate whether the different aspects of narrative tone (*Net Positivity*, *Positivity*, *Negativity*, *Uncertainty*, *Hesitance*) derive from operational or financial performance. Thus, regulators could consider mandating operational performance disclosures separately from financial performance disclosures to allow users to better identify and use disclosures in their decision-making process.

We limit our analysis to indices of technical efficiency as measures of operational performance and their reflection in corporate disclosure tone. Future research could extend such analysis to other types of operational performance, analyzing not only conversion of inputs into outputs, but also the optimality of allocation of resources (allocative efficiency) or efficiency in terms of cost minimization (cost efficiency), revenue maximization (revenue efficiency), and profit maximization (profit efficiency). Another limitation of this study refers to our measures of narrative tone. Despite wide use of the Loughran and McDonald (2011) database, it should be noted that not all information presented in 10-Ks and in this database is necessarily related to operational performance and technical efficiency. Hence, our narrative tone measures could be considered noisy in this respect. Future research could use narrative tone measures based on words that exclusively refer to operational performance and efficiency. This would require self-creation of such measures or the use of newer approaches based on machine learning to identify and extract operational-specific textual cues (Bochkay et al., 2023). In this way, future research could consider the research question of whether technical efficiency is being communicated through more direct language that specifically addresses operational efficiency or operational improvements that have been made. Finally, another interesting future line of research could analyze how personal CEO characteristics moderate the relationship between disclosure tone and operational performance.

Figures and Tables

Fig. 1. Summary of different scenarios and hypothetical relationships.

Hypothesis 3 to test scenarios (1) and (4)

Hypothesis 3a: The level of positive (negative) tone in corporate reports will be higher (lower) for companies where input efficiency is high and output efficiency is high.

Hypothesis 3b: The level of uncertainty/hesitancy in corporate reports will be lower for companies where input efficiency is high and output efficiency is high.

Hypothesis 3c: The level of positive (negative) tone in corporate reports will be lower (higher) for companies where input efficiency is low and output efficiency is low.

Hypothesis 3d: The level of uncertainty/hesitancy in corporate reports will be higher for companies where input efficiency is low and output efficiency is low.

Hypothesis 4 to test scenarios (2) and (3)

Hypothesis 4a: The level of positive (negative) tone in corporate reports will be lower (higher) for companies where input efficiency is high and output efficiency is low.

Hypothesis 4b: The level of uncertainty/hesitancy in corporate reports will be higher for companies where input efficiency is high and output efficiency is low.

Hypothesis 4c: The level of positive (negative) tone in corporate reports will be lower (higher) for companies where input efficiency is low and output efficiency is high.

Hypothesis 4d: The level of uncertainty/hesitancy in corporate reports will be higher for companies where input efficiency is low and output efficiency is high.

Input efficiency/output efficiency	**High output efficiency**		**Low output efficiency**	
High input efficiency	*(1) Best scenario*		*(2) Moderate scenario*	
Narrative Tone	**Hyp.**	**Exp. sign**	**Hyp.**	**Exp. sign**
Positive tone	*H3a*	+	*H4a*	–
Negative tone	*H3a*	–	*H4a*	+
Uncertainty	*H3b*	–	*H4b*	+
Hesitancy	*H3b*	–	*H4b*	+
Low input efficiency	*(3) Moderate scenario*		*(4) Worst scenario*	
Narrative Tone	**Hyp.**	**Exp. sign**	**Hyp.**	**Exp. sign**
Positive tone	*H4c*	–	*H3c*	–
Negative tone	*H4c*	+	*H3c*	+
Uncertainty	*H4d*	+	*H3d*	+
Hesitancy	*H4d*	+	*H3d*	+

Scenarios (1) and (4) reflect a balance between input and output efficiency. Scenarios (2) and (3) reflect an imbalance between input and output efficiency.

Fig. 2. Summary of results for different scenarios.

Input efficiency/output efficiency	**High output efficiency**	**Low output efficiency**
High input efficiency	*(1) Best scenario*	*(2) Moderate scenario*
Narrative Tone Variables	**Results**	**Results**
Net Positivity	More positive	More positive
Positivity	Less positivity	More positivity
Negativity	Less negativity	Less negativity
Uncertainty	Less uncertainty	NS
Hesitancy	Less hesitancy	More hesitancy
Low input efficiency	*(3) Moderate scenario*	*(4) Worst scenario*
Narrative Tone Variables	**Results**	**Results**
Net Positivity	More positive	Less positive
Positivity	More positivity	NS
Negativity	NS	More negativity
Uncertainty	Less uncertainty	More uncertainty
Hesitancy	Less hesitancy	More hesitancy

Scenarios (1) and (4) represent a balance between input and output efficiency and reflect operational performance embedded in the tone of corporate narratives. Scenarios (2) and (3) represent an imbalance between input and output efficiency reflecting the managerial disclosure approach.

In Figure 2, we have included two measures of positive tone that is "Net Positivity" measured as positive minus negative words divided by total words and "Positivity" measured as positive words divided by total words, as explained in Section "Operationalization of Dependent Variables".

Table 1
Descriptive statistics of input-output data, 1993-2021.

VARIABLES	Mean	Median	Std. dev.	CV
Inputs				
CoGS	2,508.734	171.180	13,186.110	5.256
SG&A	748.248	94.560	3,504.816	4.684
PP&E	1,022.127	47.520	6,075.305	5.944
Ops Lease	108.652	11.580	446.722	4.111
Net R&D	374.306	22.333	1,955.959	5.226
Goodwill	768.912	14.343	4,069.365	5.292
OtherIntan	368.152	4.351	2,935.925	7.975
Output				
Sales	3,872.791	347.436	18,061.250	4.664

This table shows the descriptive statistics for the input-output data between 1993 and 2021. Std. dev. is the standard deviation, and CV is the coefficient of variation. Monetary values are in millions of US dollars, constant prices from 1993. All variables are defined in Appendix D.

Table 2
Descriptive statistics of regression variables.

VARIABLES	Mean	Median	Std. dev.	CV
	Dependent variables			
Narrative tone variables				
Net Positivity	-0.010	-0.010	0.004	-0.459
Positivity	0.007	0.007	0.002	0.237
Negativity	0.017	0.017	0.004	0.249
Uncertainty	0.013	0.013	0.003	0.262
Hesitancy	0.006	0.005	0.002	0.392
Efficiency indicators				
Tech_eff	0.926	0.964	0.087	0.094
(1) Input_ High-Output_High	0.385	0	0.487	1.264
(2) Input_High-Output_Low	0.217	0	0.412	1.900
(3) Input_Low-Output_High	0.190	0	0.392	2.064
(4) Input_Low-Output_Low	0.208	0	0.406	1.951
Control variables				
Loss	0.378	0	0.485	1.283
Cfo	-0.072	0.072	1.885	-26.178
ROE	-0.111	0.077	12.612	-113.655
Leverage	0.499	0.168	7.490	15.000
Equity_Assets	-0.481	0.491	26.854	-55.798
MTB	3.582	2.135	126.151	35.218
ROA	-0.394	0.028	15.234	-38.674
Industry				
Construction	0.003	0	0.055	18.209
Finance	0.011	0	0.103	9.581
Manufacturing	0.650	1	0.477	0.733
Mining	0.007	0	0.085	11.663
Trade	0.134	0	0.340	2.546
Services	0.181	0	0.385	2.125
Transportation	0.014	0	0.116	8.501
Year				
1993	0.004	0	0.062	16.082
1994	0.006	0	0.076	13.080
1995	0.016	0	0.124	7.907
1996	0.018	0	0.131	7.478
1997	0.018	0	0.134	7.336
1998	0.019	0	0.136	7.208
1999	0.017	0	0.130	7.560
2000	0.017	0	0.130	7.567
2001	0.021	0	0.145	6.754
2002	0.034	0	0.182	5.312
2003	0.044	0	0.206	4.640
2004	0.051	0	0.219	4.328
2005	0.051	0	0.219	4.328
2006	0.050	0	0.218	4.368
2007	0.046	0	0.210	4.538
2008	0.047	0	0.212	4.503
2009	0.048	0	0.213	4.471
2010	0.046	0	0.209	4.564
2011	0.046	0	0.209	4.566
2012	0.046	0	0.210	4.550
2013	0.044	0	0.204	4.685
2014	0.042	0	0.201	4.774
2015	0.042	0	0.201	4.776
2016	0.042	0	0.201	4.768
2017	0.044	0	0.205	4.656
2018	0.043	0	0.203	4.704
2019	0.044	0	0.205	4.671
2020	0.042	0	0.201	4.776
2021	0.013	0	0.112	8.792

This table shows the descriptive statistics for regression variables 1993 and 2021. Std. dev. is the standard deviation, and CV is the coefficient of variation. All variables are defined in Appendix D.

Table 3
Relationship between disclosure tone and technical efficiency.

	Model 1 *Net Positivity*	**Model 2** *Positivity*	**Model 3** *Negativity*	**Model 4** *Uncertainty*	**Model 5** *Hesitancy*
Tech_eff	0.495***	-0.028	-0.523***	-0.412***	-0.123***
	(9.449)	(-1.313)	(-10.418)	(-10.685)	(-4.412)
Loss	-0.170***	0.005	0.175***	0.023***	0.063***
	(-18.632)	(1.370)	(20.402)	(3.808)	(14.337)
Cfo	-0.007***	-0.002**	0.005**	0.002	-0.001
	(-3.288)	(-2.536)	(2.449)	(1.081)	(-0.781)
ROE	-0.000	-0.000	0.000	0.000	0.000
	(-1.083)	(-1.145)	(0.582)	(1.338)	(0.311)
Leverage	0.001	-0.000*	-0.001**	-0.002**	-0.001*
	(1.480)	(-1.866)	(-2.080)	(-2.503)	(-1.797)
Equity_Assets	0.000	-0.000	-0.000	-0.000	0.000
	(0.698)	(-0.202)	(-0.846)	(-0.729)	(0.375)
MTB	-0.000	-0.000	0.000	0.000*	0.000
	(-0.624)	(-0.843)	(0.327)	(1.890)	(1.361)
ROA	0.000	0.000	0.000	-0.000	0.000
	(0.041)	(0.886)	(0.073)	(-1.024)	(0.050)
Constant	-1.099***	0.682***	1.781***	1.119***	0.370***
	(-10.202)	(16.291)	(19.643)	(12.565)	(7.884)
Industry Effects	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES
Observations	29,598	29,598	29,598	29,598	29,598
Adj. R-sqr.	0.194	0.160	0.199	0.339	0.344
F-test	84.71***	104.43***	66.71***	198.06***	118.68***

This table presents the regression results between technical efficiency and narrative variables. Models are estimated using industry and year dummies. Standard errors are clustered by firm and t-statistics are in parentheses. ***, **, and * represent significance levels at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix D.

Table 4
Relationship between positivity/negativity and the difference between input and output efficiency.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
	Net Positivity	*Positivity*	*Negativity*	*Net Positivity*	*Positivity*	*Negativity*	*Net Positivity*	*Positivity*	*Negativity*	*Net Positivity*	*Positivity*	*Negativity*
Input_High_Output_High	0.030***	-0.014***	-0.044***									
	(3.197)	(-4.282)	(-4.957)									
Input_High_Output_Low				0.029***	0.011***	-0.018*						
				(3.011)	(2.741)	(-1.922)						
Input_Low_Output_High							0.021**	0.009**	-0.013			
							(2.095)	(2.396)	(-1.324)			
Input_Low_Output_Low										-0.088***	0.002	0.090***
										(-9.157)	(0.568)	(9.888)
Loss	-0.164***	0.002	0.166***	-0.180***	0.001	0.182***	-0.167***	0.006*	0.173***	-0.164***	0.005	0.169***
	(-18.119)	(0.508)	(19.434)	(-20.448)	(0.337)	(21.483)	(-17.955)	(1.839)	(19.794)	(-17.952)	(1.329)	(19.667)
Cfo	-0.008***	-0.002***	0.006***	-0.008***	-0.001**	0.006***	-0.008***	-0.001**	0.007***	-0.007***	-0.001**	0.006***
	(-3.494)	(-2.597)	(2.801)	(-3.433)	(-2.335)	(2.755)	(-3.475)	(-2.474)	(2.799)	(-3.417)	(-2.444)	(2.669)
ROE	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000
	(-1.061)	(-1.156)	(0.566)	(-1.112)	(-1.147)	(0.614)	(-1.121)	(-1.176)	(0.622)	(-1.143)	(-1.144)	(0.649)
Leverage	0.001	-0.000*	-0.001**	0.001	-0.000*	-0.001**	0.001	-0.000*	-0.001**	0.001	-0.000*	-0.001**
	(1.612)	(-1.948)	(-2.199)	(1.536)	(-1.946)	(-2.095)	(1.576)	(-1.877)	(-2.121)	(1.529)	(-1.877)	(-2.113)
Equity_Assets	0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(0.850)	(-0.332)	(-1.056)	(0.715)	(-0.320)	(-0.893)	(0.788)	(-0.213)	(-0.944)	(0.777)	(-0.219)	(-0.939)
MTB	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000
	(-0.537)	(-0.861)	(0.244)	(-0.590)	(-0.883)	(0.280)	(-0.548)	(-0.835)	(0.257)	(-0.578)	(-0.851)	(0.284)
ROA	0.000	0.000	-0.000	0.000	0.000	-0.000	0.000	0.000	-0.000	0.000	0.000	-0.000
	(0.168)	(0.922)	(-0.046)	(0.183)	(0.772)	(-0.091)	(0.209)	(0.855)	(-0.105)	(0.116)	(0.833)	(-0.010)
Constant	-0.629***	0.663***	1.292***	-0.612***	0.655***	1.267***	-0.615***	0.653***	1.269***	-0.589***	0.654***	1.243***
	(-6.877)	(18.847)	(17.568)	(-6.935)	(18.205)	(18.119)	(-6.956)	(18.188)	(18.113)	(-6.270)	(18.139)	(16.581)
Industry Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	29,598	29,598	29,598	29,598	29,598	29,598	29,598	29,598	29,598	29,598	29,598	29,598
Adj. R-sqr.	0.187	0.162	0.192	0.187	0.161	0.190	0.186	0.160	0.190	0.192	0.160	0.197
F-test	81.77***	104.27***	61.85***	83.91***	104.49***	63.01***	81.63***	104.57***	61.42***	84.28***	104.98***	65.59***

This table presents the regression results between the difference between input and output efficiency and narrative variables. Models are estimated using industry and year dummies. Standard errors are clustered by firm and t-statistics are in parentheses. ***, **, and * represent significance levels at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix D.

Table 5
Relationship between uncertainty/hesitancy and the difference between input and output efficiency.

	Model 1 *Uncertainty*	**Model 2** *Hesitancy*	**Model 3** *Uncertainty*	**Model 4** *Hesitancy*	**Model 5** *Uncertainty*	**Model 6** *Hesitancy*	**Model 7** *Uncertainty*	**Model 8** *Hesitancy*
Input_High_Output_High	-0.045***	-0.015***						
	(-7.412)	(-3.523)						
Input_High_Output_Low			0.002	0.023***				
			(0.297)	(4.632)				
Input_Low_Output_High					-0.022***	-0.042***		
					(-3.430)	(-9.630)		
Input_Low_Output_Low							0.081***	0.038***
							(11.609)	(7.898)
Loss	0.014**	0.060***	0.023***	0.056***	0.019***	0.055***	0.017***	0.060***
	(2.252)	(13.355)	(3.755)	(12.803)	(3.219)	(12.905)	(2.856)	(13.680)
Cfo	0.003	-0.000	0.003	-0.000	0.003	-0.000	0.003	-0.001
	(1.467)	(-0.494)	(1.524)	(-0.223)	(1.548)	(-0.174)	(1.315)	(-0.717)
ROE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.305)	(0.303)	(1.369)	(0.315)	(1.405)	(0.391)	(1.419)	(0.350)
Leverage	-0.002***	-0.001*	-0.002**	-0.001*	-0.002**	-0.001*	-0.002**	-0.001*
	(-2.621)	(-1.876)	(-2.493)	(-1.913)	(-2.486)	(-1.835)	(-2.521)	(-1.814)
Equity_Assets	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(-0.994)	(0.246)	(-0.828)	(0.188)	(-0.825)	(0.298)	(-0.832)	(0.332)
MTB	0.000*	0.000	0.000*	0.000	0.000*	0.000	0.000*	0.000
	(1.679)	(1.307)	(1.748)	(1.277)	(1.752)	(1.319)	(1.817)	(1.350)
ROA	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(-1.340)	(-0.017)	(-1.408)	(-0.103)	(-1.438)	(-0.147)	(-1.220)	(0.041)
Constant	0.740***	0.258***	0.715***	0.249***	0.718***	0.255***	0.694***	0.239***
	(9.209)	(6.823)	(9.489)	(6.882)	(9.590)	(7.259)	(8.415)	(6.092)
Industry Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	29,598	29,598	29,598	29,598	29,598	29,598	29,598	29,598
Adj. R-sqr.	0.333	0.343	0.330	0.343	0.330	0.347	0.339	0.346
F-test	192.06***	116.68***	189.39***	114.11***	189.91***	114.36***	195.69***	119.92***

This table presents the regression results between input and output efficiency and uncertainty/hesitancy variables. Models are estimated using industry and year dummies. Standard errors are clustered by firm and t-statistics are in parentheses. ***, **, and * represent significance levels at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix D.

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APPENDICES

APPENDIX A. Comparing financial and operational performance

	Financial performance	Operational performance
Generally	Financial performance is considered as core indicator of firm's success.	Operational performance is an indicator of firm efficiency.
Objective	Obtain the highest profit. To attract external funds from the capital markets.	Produce more outputs with fewer inputs. Addressed to the management assessment of corporate resources efficiency.
General measurement	Corporate profitability. Financial performance is measured through the profitability or return on the business activities and the profit is primarily classified into economic and accounting profit (Hirsch, 1991).	Corporate efficiency. Operational performance measures recognize opportunity costs of inputs and capital accumulation by considering technological and economic relationships between output production and input demand (Morrison-Paul and Siegel, 2006).
Measurement issues (strengths and shortcomings)	Financial performance is usually measured via an elusive variable (March and Sutton, 1997) being affected by multiple variables simultaneously, making any investigation limited in terms of controls. Several ratios are necessary to capture all dimensions of firm's performance and each ratio may provide different views of the performance (Feroz et al., 2003). Accounting profits are measured either as operating income or net income (Meigs et al., 2002), these measurements represent the absolute values of profit but lack the property of comparison.	Operational performance identifies inefficiencies not captured by financial performance (Sherman and Zhu, 2006). It is able to capture the interactions among multiple inputs and multiple outputs in a single measure (Avkiran, 2011).
Target users	Accounting profit is targeted at corporate outsiders. i.e., the financial markets.	Traditionally, operational performance is considered a source of information for managers to make decisions on the use of resources. However, operational performance should also be useful for outsiders who decide whether the company may receive ¨license to operate¨.
Outcomes	The main outcome of financial performance are the financial statements and the accounting profit.	Some operational practices linked to operational performance may deliver positive outcomes in some settings, but negative outcomes in others, and identifying these interactions is not simple. Outsourcing is one example, as indicated by Rossetti and Choi (2005).
Link between financial and operational performance	Profitability is affected either by cost mismanagement or lack of desirable operational performance. Undoubtedly, improving organizational policies for operational performance could play a crucial role, which in turn will lead to improved financial performance.	In the industry view, industry structure drives profit while in the efficiency view companies achieve profits in a line of business when they operate more efficiently than their competitors (Chen et al., 2015). Assessing efficiency enables an understanding of firm performance that is deeper than a mere comparison of company profits (Chen et al., 2015).

APPENDIX B. Mathematical formulations of efficiency measures

Efficiency research includes a battery of mathematical measures with plenty of possibilities for determining input, output and input-output technical efficiencies. In this study we use the measures proposed by Shephard (1953) and Farrell (1957) to derive input- and output-oriented efficiencies, and the measure by Färe et al. (1985) to compute input-output efficiency, since there are the most widely used. In particular, we use the Farrell (1957) input-oriented efficiency, the Shephard (1953) output distance function, and the input-output measure of efficiency in order to have the same range of values for efficiency indicators, that is, the values that are smaller or equal to one. Let us now introduce the mathematical formulations for these measures and assume the data series of k DMUs (firms) that use n inputs $\mathbf{x} = (x_1,..., x_n) \in R_+^n$ to produce m outputs $\mathbf{y} = (y_1,..., y_m) \in R_+^m$. Production technology converting inputs into outputs is described:

$$T = \{(\mathbf{x}, \mathbf{y}) : \mathbf{x} \text{ can produce } \mathbf{y}\} \tag{B1}$$

Farrell (1957) provided the following definition of input-oriented measure of technical efficiency as the maximum reduction of the input vector (while maintaining the current output level) that places a given firm on the boundary of the technology *T*:

$$TE_I(\mathbf{x}, \mathbf{y}) = \min\{\delta : (\delta \mathbf{x}, \mathbf{y}) \in T\} \tag{B2}$$

where δ is the input-oriented efficiency score. This measure takes the values that are equal to or smaller than one, $TE_I(\mathbf{x}, \mathbf{y}) \leq 1$. The maximum value of this index is equal to one, which means that the firm is efficient, while values lower than one indicate the degree of efficiency achieved. For example, an input-oriented technical efficiency for inefficient firm of 0.8 implies that this firm can reduce inputs by 20%, at a given level of outputs. This measure is the reciprocal of the input distance function of Shephard (1953), which consequently will have the values that are greater than or equal to one, with values equal to one representing 100% of efficiency for the firm in question.

The output-oriented technical efficiency of Farrell (1957) measures the maximum expansion of the output vector (given the inputs) that places a given firm on the boundary of technology *T* and is defined as: $TE_O(\mathbf{x}, \mathbf{y}) = \max\{\theta : (\mathbf{x}, \theta \mathbf{y}) \in T\}$ (B3)

where θ is the output-oriented efficiency score. It takes values that are larger than or equal to one, $TE_O(\mathbf{x}, \mathbf{y}) \geq 1$. When it takes the maximum value of unity, the firm is considered output-efficient. For example, an output-oriented technical efficiency for inefficient firm of 1.2 implies that a firm can increase outputs by 20%, at a given level of inputs. This measure is a reciprocal of the Shephard (1953) output distance function, which gets values smaller or equal to one.[12] Finally, the input-output (hyperbolic) technical efficiency measures the maximum expansion of the output vector and reduction of the input vector that places a given firm on the boundary of technology *T* and is defined according to Färe et al. (1985) as:

$$TE_H(\mathbf{x}, \mathbf{y}) = \min\{\gamma : (x\gamma, y/\gamma) \in T\} \tag{B4}$$

where γ is the input-output efficiency score. By construction, $TE_H(\mathbf{x}, \mathbf{y}) \leq 1$ with values of one, indicating 100% efficiency has been achieved. If input-output efficiency score was equal to 0.8 it shows that outputs could be increased by 25% ((1/0.8)-1)*100, while inputs could be reduced by 20% (1-0.80)*100. Alternatively, one can consider input-output (hyperbolic) distance function, that is, the reciprocal of the measure described by (4), with values larger or equal to 1 (Simar et al., 2012).[13]

[12] Input- and output-oriented efficiency models estimate the same set of firms as being efficient but the efficiency measures of inefficient firms will differ between two models (Coelli and Perelman, 1999).

[13] There is a certain confusion in the literature as some authors like Zofio and Prieto (2006) define hyperbolic distance function in the same way as Färe et al. (1985), while other authors like Simar et al. (2012) distinguish between hyperbolic measure of efficiency and hyperbolic distance function. In this study, we follow the distinction proposed by Simar et al. (2012).

APPENDIX C. DEA and its application

The production technology in DEA is constructed empirically by enveloping the data on firms' inputs and outputs using linear programming techniques. An interesting issue when efficiency is to be measured via DEA, is the type of returns to scale imposed on the technology. Returns to scale measure the change in output levels resulting from the changes in input levels, and essentially two types of returns to scale can be assumed: (1) constant returns to scale (CRS) in which an increase in input levels leads to a proportional increase in output levels (Charnes et al., 1978), and (2) variable returns to scale (VRS), in which the output levels can increase or decrease by a different proportion than the increase in inputs (Banker et al., 1984). The application of the tests proposed by Kneip et al. (2016) and Simar and Wilson (2020) shows that our data exhibit VRS, hence this is the assumption maintained in this paper. In addition, it is worth pointing out that VRS assumption allows to control for the differences between firms in the sample with relation to firm size.[14]

The estimation of efficiency using DEA is done in the paper for all industrial sectors simultaneously. This is in differentiation to Demerjian et al. (2012) that estimate by industry since the aim of that study is to estimate managerial ability and measure efficiency attributed to both the firm and the manager. In our study, we aim for a broader meaning of efficiency in which we analyze the general technology as possibilities to make sales out of investments into major inputs regardless of particular managerial or firm features. In this way, we use a so-called metafrontier concept (O'Donnell et al., 2008) that is a common approach used in the efficiency analysis with data containing several groups of firms, such as different industries. Such pooling of the data over industries gives also more reliability to DEA estimations since it reduces the problem of dimensionality in DEA, which is related to having many input and output variables together with a limited number of observations. In fact, in our empirical analysis, some sectors have a limited number of observations. Moreover, in our empirical analysis we calculate efficiency separately for every year of the analyzed period to accommodate the potential changes in technology over time. It is widely known that if using the full dataset to construct a single intertemporal production set, one would make an assumption of no shift in the technology at all (Tulkens & Van den Eeckaut, 1995), which is rather unrealistic given our study covers 28 years of observations. Computation by year differs from Demerjian et al. (2012) that estimated pooling over time, but the main motivation for that was to enlarge a number of observations to obtain valid results. Overall, the estimation pooling over industries and by year is a common strategy in efficiency literature to analyze firms in different industries over time.

Traditionally, efficiency measures computed via DEA were considered to be deterministic; however, the bootstrap methods were developed for making statistical inferences about these measures. The idea of bootstrapping is based on randomly selecting a vast of pseudo-samples from the observed set of sample data, and then obtaining pseudo-estimates from each of these samples. These pseudo-estimates form an empirical distribution for the estimator of interest, which is then used as an approximation of the true underlying sampling distribution of the estimator. In this paper we follow the bootstrap algorithm, which was initially developed by Simar and Wilson (1998), which allows to obtain the bias-corrected estimates for DEA efficiency

[14] It is worth explaining that the comparison of input-oriented and output-oriented efficiency only makes sense when the underlying production technology is of VRS since under CRS input-oriented Farrell measure is basically a reciprocal of output-oriented Farrell measure (Fried et al., 2008).

scores.[15] The bias-corrected efficiency scores for input-, output- and input-output-oriented efficiency measures are used in this paper to test the hypotheses.[16]

Below we present the formulations of DEA models to estimate input, output and input-output efficiencies.

Table C.1. Formulation of DEA models.

Input efficiency	Output efficiency	Input-output efficiency
$TE_I = \min \delta$	$TE_O = \max \theta$	$TE_H = \min \gamma$
subject to	*subject to*	*subject to*
$\delta \cdot x_{n0} \geq \sum_{i=1}^{k} \lambda_i x_{ni}, \quad n = 1,\ldots,N$	$x_{n0} \geq \sum_{i=1}^{k} \lambda_i x_{ni}, \quad n = 1,\ldots,N$	$\gamma \cdot x_{n0} \geq \sum_{i=1}^{k} \lambda_i x_{ni}, \quad n = 1,\ldots,N$
$y_{m0} \leq \sum_{i=1}^{k} \lambda_i y_{mi}, \quad m = 1,\ldots,M$	$\theta \cdot y_{m0} \leq \sum_{i=1}^{k} \lambda_i y_{mi}, \quad m = 1,\ldots,M$	$y_{m0} / \gamma \leq \sum_{i=1}^{k} \lambda_i y_{mi}, \quad m = 1,\ldots,M$
$\sum_{i=1}^{k} \lambda_i = 1,$	$\sum_{i=1}^{k} \lambda_i = 1,$	$\sum_{i=1}^{k} \lambda_i = 1,$
$\lambda_i \geq 0.$	$\lambda_i \geq 0.$	$\lambda_i \geq 0.$

Notes: x_{ni} represents the quantity of input n consumed by DMU_i, y_{mi} indicates the quantity of output m produced by DMU_i, x_{n0} represents the quantity of input n consumed by DMU under analysis, y_{m0} indicates the quantity of output m produced by DMU under analysis, λ_i symbolizes the activity levels associated with inputs and outputs of DMU_i, while restriction $\sum_{i=1}^{k} \lambda_i = 1$ represents the VRS assumption. Since the model for input-output efficiency is nonlinear optimization problem, instead of solving it directly, we follow the bisection method described in Wilson (2011).

[15] The more recent review about the use of bootstrap methods to make inferences based on DEA can be found for example in Simar and Wilson, 2015).

[16] An important consideration is that the bias-corrected efficiency estimator should not be used when its mean-square error is higher than the traditional efficiency measure calculated without the application of bootstrap (Simar and Wilson, 2000). Our tests show that this is not the case in our study and consequently bias-corrected estimator is the most appropriate method. In this paper the computation of DEA input, output and input-output efficiency measures with bootstrap was undertaken using the library FEAR 3.1 in R (Wilson, 2008).

APPENDIX D. Variables definition

Variables	Definition	Database
Narrative tone variables		
Net Positivity	Number of positive words minus number of negative words scaled by total words.	Loughran & McDonald word list
Positivity	Number of positive words scaled by total words.	Loughran & McDonald word list
Negativity	Number of negative words scaled by total words.	Loughran & McDonald word list
Uncertainty	Number of uncertainty words scaled by total words.	Loughran & McDonald word list
Hesitancy	Number of weal-modal words scaled by total words.	Loughran & McDonald word list
Efficiency		
Tech_eff	Corporation efficiency measure that ranges between 0 (less efficiency) and 1 (more efficiency).	DEA analysis (*explained in Appendix C*)
Input_High-Output_High	Dummy variable that equals 1 if the company input and output is larger than the annual industry average; 0 otherwise.	DEA analysis (*explained in Appendix C*)
Input_High-Output_Low	Dummy variable that equals 1 if the company input (output) and is larger (lower or equal) than the annual industry average; 0 otherwise.	DEA analysis (*explained in Appendix C*)
Input_Low-Output_High	Dummy variable that equals 1 if the company input (output) and is lower or equal (larger) than the annual industry average; 0 otherwise.	DEA analysis (*explained in Appendix C*)
Input_Low-Output_Low	Dummy variable that equals 1 if the company input and output is lower or equal than the annual industry average; 0 otherwise.	DEA analysis (*explained in Appendix C*)
Controls		
Loss	Dummy variable that equals 1 if the company has negative earnings before extraordinary items; 0 otherwise.	COMPUSTAT
Cfo	Cash Flow from operating activities scaled by total assets.	COMPUSTAT
ROE	Earnings before extraordinary items scaled by shareholders' equity.	COMPUSTAT
Leverage	Total debt scaled by total assets.	COMPUSTAT
Equity_Assets	Shareholders' equity scaled by total assets.	COMPUSTAT
Log_Equity	Logarithm of shareholders' equity.	COMPUSTAT
MTB	Market value scaled by book value.	COMPUSTAT
ROA	Earnings before extraordinary items scaled by total assets.	COMPUSTAT
Inputs		
CoGS	Cost of goods sold.	COMPUSTAT
SG&A	Selling general and administrative expenses minus current operating lease expense and research and development expense.	COMPUSTAT
PP&E	Property, plant and equipment (at the beginning of the accounting period).	COMPUSTAT
Ops Lease	Discounted present value of the next five years of required operating lease payments (at the beginning of the accounting period). To calculate it we use the operating lease maturities (mrc) in years 1 to 5 as follows: $(mrc1/1.1)+(mrc2/(1.1^2))+(mrc3/(1.1^3))+(mrc4/(1.1^4))+(mrc5/(1.1^5))$	COMPUSTAT
Net R&D	The net value of research and development expenses equals $0.2R\&D_{t-5} + 0.4\ R\&D_{t-4} + 0.6R\&D_{t-3} + 0.8\ R\&D_{t-2} + R\&D_{t-1}$ (at the beginning of the accounting period).	COMPUSTAT
Goodwill	Goodwill (at the beginning of the accounting period).	COMPUSTAT
OtherIntan	Intangibles minus goodwill (at the beginning of the accounting period).	COMPUSTAT
Output		
Sales	Firm's total sales.	COMPUSTAT