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Research article

Exploring gender stereotypes in financial reporting: An aspect-level sentiment analysis using big data and deep learning

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ABSTRACT

This study delves into the intricate interplay between gender stereotypes and financial reporting through an aspect-level sentiment analysis approach. Leveraging Big Data comprising 129,251 human face images extracted from 2085 financial reports in Chile, and employing Deep Learning techniques, we uncover the underlying factors influencing the representation of women in financial reports. Our findings reveal that gender stereotypes, combined with external economic factors, significantly shape the portrayal of women in financial reports, overshadowing intentional efforts by companies to influence stakeholder perceptions of financial performance. Notably, economic expansion periods correlate with a decline in women's representation, while economic instability amplifies their portrayal. Furthermore, the financial inclusion of women positively correlates with their presence in financial report images. Our results underscore a bias in image selection within financial reports, diverging from the neutrality principles advocated by the International Accounting Standards Board (IASB). This pioneering study, combining Big Data and Deep Learning, contributes to gender stereotype literature, financial report soft information research, and business impression management research.

1. Introduction

This study highlights the significant role of appearance-based stereotypes in shaping the representation of women in financial reports, particularly through the depiction of facial expressions. Women are frequently shown with youthful and positive emotions, such as happiness and surprise, especially during periods of negative macroeconomic indicators, including lower GDP growth and increased economic uncertainty. Conversely, men are more often portrayed with serious expressions linked to negative emotions and are depicted as older. Our research demonstrates that the choice of women's images in financial reports is predominantly influenced by external economic conditions and societal stereotypes rather than deliberate corporate strategies aimed at shaping stakeholders' perceptions of financial performance. Additionally, this study seeks to understand the underlying principles guiding the selection of these images in corporate financial communications, exploring the intricate relationship between gender stereotyping, economic performance, and impression management within the context of financial reporting. The results align with prior research [1–3], which

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indicates that the traditional portrayal of women has characterized them as caring, trustworthy, kind, and skilled in fostering positive interpersonal connections. Furthermore, these scholars say this portrayal frequently represents women as exuberant and content.

This subject is relevant as there has been a noticeable increase in expectations for implementing policies that promote the inclusion of women in business, not just as employees but as leaders in the decision-making process. Given these conditions, analyzing business financial reports becomes crucial as they serve as the primary means through which firm management communicates with stakeholders.

Within these reports, firms have significant latitude in including unaudited information and effectively employing visual elements such as images, colors, and design to convey their intended message. Given this perspective, financial reports serve as a rich source of information to discern the gender roles and stereotypes that firms choose to present to their stakeholders.

Prior research suggests that managers play an active role in preparing financial reports, strategically using the sentiments expressed in these documents to convey desired information. Previous studies have shown that the tone and sentiment of financial reports can be used to gain insights into a firm's current and future performance, predict short-term stock returns, assess stock return volatility, influence trading volumes, and even anticipate unexpected earnings [4,5]. These findings underscore the importance of sentiment analysis in financial reporting as a tool for understanding market reactions and firm performance.

Nevertheless, evidence suggests that tone modulation can be used to hide and obfuscate crucial information. Yuan et al. [6] discovered that an excessively optimistic tone in financial reports can indicate negative future earnings and cash flows. Recently, Hardy et al. [7] demonstrated that companies in the mining sector tend to adopt a more pessimistic (optimistic) tone preceding periods of commodity price increases, suggesting that managers may manipulate investor expectations to mitigate overreactions to positive news (See. Figs 1–5)

While extensive literature analyzes the sentiments conveyed in textual reports, there needs to be more research concerning the images used in financial reports. Given that financial reports comprise numbers, letters, and images, with the numerical aspect extensively studied and the textual aspect to a lesser extent, there is a critical need for image studies. This need is accentuated because images can convey a wealth of information about trait impressions that is difficult to express verbally [3].

According to previous evidence, only a small portion of financial reports consists of numerical data, while the majority is composed of textual elements. For instance, Dyer et al. [8] demonstrate that informative numbers account for less than 1 % of the total words in financial reports. Similarly, Loughran and McDonald [9] highlight the predominance of textual content over numerical data in these documents. However, researchers have paid little attention to images in financial reports, underestimating the importance of examining their visual components.

In addition, sentiment analysis derived from financial reports suggest that some companies choose to use images rather than text to convey sensitive information or express sentiments and expectations. Strategic communication decisions are frequently made to minimize the possibility of facing legal consequences from investors due to failure to meet their expectations [10]. Despite these research opportunities, Ang et al. [11] highlight the need for more research on the use of photographs in corporate reporting and emphasize their role as a form of impression management.

The increasing promotion of gender equality by international organizations has garnered significant visibility and recognition in recent decades. These initiatives, although relatively recent—having been actively pursued for less than thirty years [12,13]—have prompted a closer examination of gender representation in various domains, including financial reporting. A seminal study by Kuasirikun [14] have manually analyzed images from 75 financial reports of Thai companies over three distinct years (1993, 1998, and 2007) and revealed a notable presence of women, albeit primarily in subsidiary roles. This finding underscores the importance of investigating gender representation in corporate financial communications, particularly in diverse cultural and economic contexts where the impact and effectiveness of gender inclusion and equity policies may vary significantly.

Given the advancements in big data analytics, a critical question arises: Is there gender stereotyping in the portrayal of women in

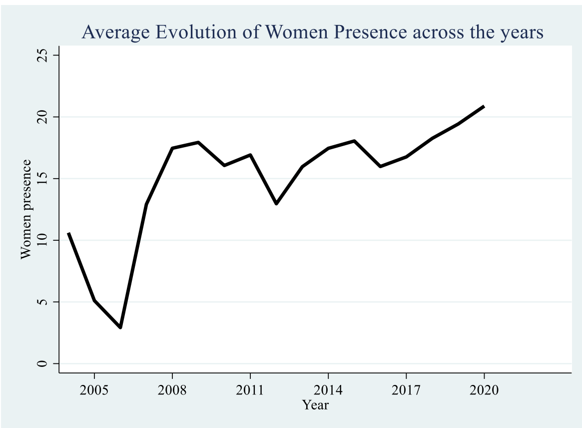

Fig. 1. This figure shows the average evolution of women's presence in financial reports. It highlights the fluctuations and growth trends, depicting the involvement and representation of women in corporate reports over these years.

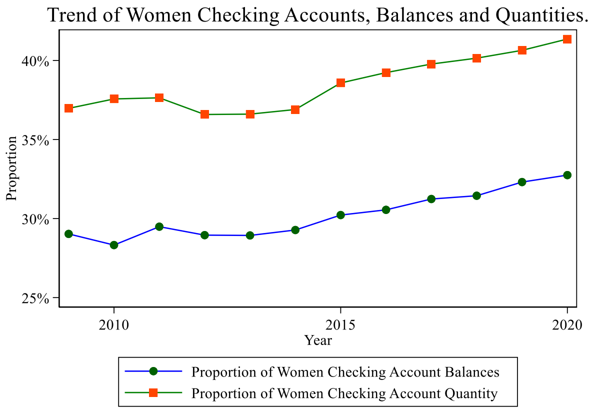

Fig. 2. This figure illustrates the trend in the proportion of women's checking account balances and quantities, reflecting financial inclusion metrics specific to women in the banking sector.

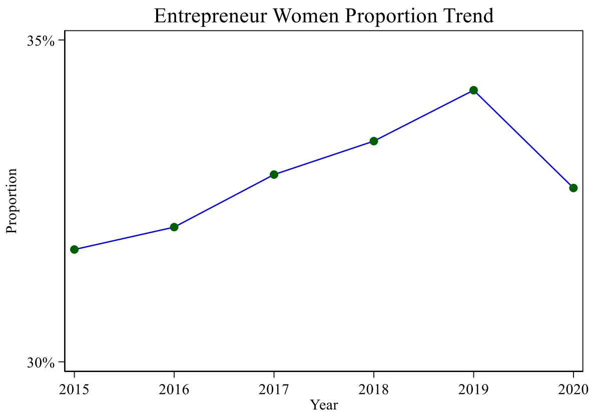

Fig. 3. This figure presents the trend of the proportion of entrepreneurial women, providing insights into women's entrepreneurial activities and representation in the business landscape.

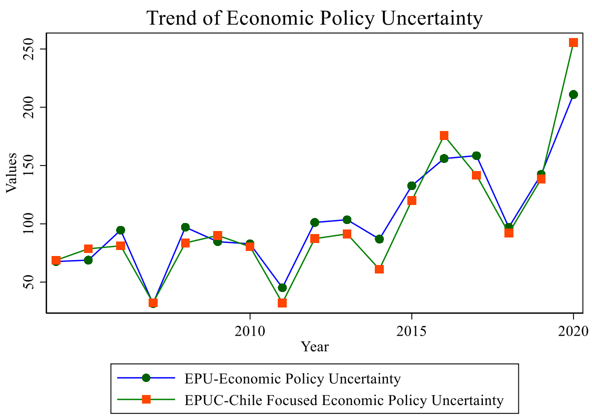

Fig. 4. The figure compares trends in Economic Policy Uncertainty (EPU) globally and specifically within Chile to assess the influence of economic stability on gender representation in corporate financial reporting.

financial reports, especially using images depicting facial expressions? Furthermore, what underlying principles influence companies' selection of these images, including the facial expressions depicted in their financial reports? Understanding these dynamics is crucial for assessing the extent of gender bias and stereotyping in corporate communication practices.

This study aims, on one hand, to determine whether stereotypical representations of women are observed in corporate financial

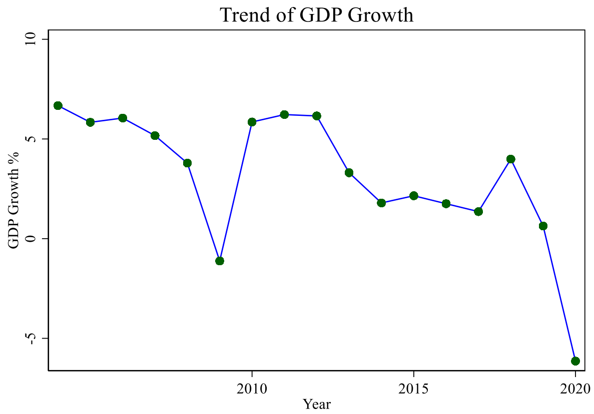

Fig. 5. This figure demonstrates the trend in GDP growth, showing how macroeconomic conditions impact corporate dynamics, including the representation of gender in financial documents.

reports. On the other hand, it seeks to identify the underlying principles behind such representations in these reports.

To answer these questions, we based ourselves on two theories. First, on the "doing gender" perspective proposed by Candace West and Don Zimmerman [15], which posits gender as an active and everyday construction within social interactions. We seek to explain how companies do gender. Second, on the theory of impression management [16], which suggests that companies can manage their impressions to create a desirable and different corporate image depending on the situation and context.

Given the recent advancements in artificial intelligence, deep learning tools, and enhanced computing capabilities, this study adopts a mixed-methods approach, combining qualitative and quantitative methods with AI and big data techniques. We leverage a substantial Big Data sample of 129,251 images extracted from 2085 PDF financial reports of Chilean companies. By employing advanced Deep Learning methodologies, we analyze these images to extract and examine facial features, providing insights into the visual representation of individuals in corporate financial communications.

Due to various factors, Chile offers a distinctive and interesting setting for conducting such research. Chile is one of two Latin American countries that are members of the Organization for Economic Co-operation and Development (OECD) and has entered into many agreements to increase gender diversity [13]. Chile has implemented regulations to promote gender equality, including creating the Ministry of Women and Gender Equality in 2015, to design policies to promote gender equality. In addition, Law 20.840 of the same year introduced quotas to increase female political representation, improving Chile's position in international rankings of gender parity in Congress [17]. Furthermore, Chile is making regulatory efforts regarding the presentation of annual report emphasizing improvements in the information contained in Social Responsibility and Sustainable Development reports [18].

Our findings reveal that companies "doing gender" in their financial reports by reinforcing (rather than challenging) conventional gender stereotypes. Traits such as youthfulness, happiness, and surprise, significantly influence the presence of women's images in financial reports. Conversely, the depiction of negative sentiments like sadness, anger, fear, and disgust corresponds to a decrease in the use of women's images (and consequently an increase in men's images).

Our research reveals that the selection of women's images in financial reports is primarily influenced by external economic factors and societal stereotypes, rather than being a deliberate strategy by companies to shape stakeholders' perceptions of their financial performance. We also document that the structural financial inclusion of women is positively linked to their presence in images featured in financial reports.

Interestingly, we observed that during periods of higher economic growth, the representation of women in these reports tends to decrease, while the representation of men increases. Conversely, during times of economic instability, the portrayal of women in financial reports rises. This pattern suggests that the fluctuations in gender representation are more closely linked to macroeconomic conditions than to intentional impression management by companies related to their financial performance.

This study represents an initial foray into exploring the use of human images in financial reports leveraging Big Data and Deep Learning tools. While our findings offer valuable insights, we acknowledge the preliminary nature of our contribution. Our findings significantly enrich the ongoing discourse concerning gender inclusivity, the integration of soft information in financial reporting, and the strategic management of business impressions. By illuminating the nuanced interplay of gender representation, including facial expressions, our study advances the application of theories in this area.

Moreover, our research extends beyond mere identification, delving into the Aspect level sentiments conveyed through financial report images, thereby enhancing the depth and breadth of existing literature. Furthermore, our insights provide valuable guidance for organizations grappling with gender-related challenges, offering actionable strategies to optimize communication tactics and foster greater inclusivity within financial reporting practices. We recognize that there is still much to learn in this complex and evolving field, and we hope our study will inspire further research and refinement of methodologies in this area.

Our findings indicate that businesses are not fully adhering to the IASB's principles of neutrality and unbiased financial reporting, as gender representation in financial reports often reflects societal stereotypes rather than objective standards. We recommend that the Chilean Financial Market Commission (CMF) take steps to address this by promoting guidelines that encourage gender-neutral imagery, monitoring corporate practices, and fostering greater awareness of the need for unbiased financial communications. By doing so, the CMF can help ensure that Chilean companies align with international standards and promote a more inclusive approach to financial reporting.

The subsequent sections of the paper are organized as follows: Section 2 reviews the existing literature and develops our hypothesis. Section 3 outlines the methodology employed in the study. Section 4 presents and interprets the results obtained. Section 5 conducts a robustness analysis to validate the findings. Section 6 discusses the findings and implications of the results, and finally, Section 7 concludes the study, summarizing the key insights and offering directions for future research.

2. Literature review and hypothesis development

2.1. Sentiment analysis research on business communication

It is widely recognized that financial reports are essential for analyzing figures related to companies' resources, obligations, and results. Although textual analysis of these documents is not a widespread practice, it has gained interest in the academic community. Through the underlying narratives, researchers have identified sentiments within financial reports that predict various business outcomes, including investor behavior, future earnings performance, short-term stock returns, stock return volatility, trading volume, and the likelihood of unexpected earnings or bankruptcy [19–23].

Lopatta et al. [24] discovered that companies at higher risk of bankruptcy use more negative language in their 10-K filings than healthy ones. Gandhi et al. [25] found that negative sentiment in US banks' 10-K annual reports is associated with increased delisting probabilities, lower dividend payout odds, higher loan loss provisions, and lower future return on assets. Martikainen et al. [26] found that directors' gender, education, financial expertise, and board turnover lead to negative disclosure in 10-K annual reports, while age is associated with less negative disclosure. They also document a correlation between a negative disclosure tone and lower bid-ask spread, indicating that a more negative tone conveys more descriptive information.

Despite the extensive literature on sentiments derived from the text in financial report, there is a notable lack of research on the images within these reports. Image analysis is crucial in the examination of financial reports because these documents consist of numerical data, textual information, and visual representations. However, the focus of the analysis mainly focuses on the numerical data rather than the textual content [9,27].

A study conducted by Ben-Raphael et al. [28] reveals that a rise in the prominence of visual elements and the extent to which images in annual reports convey reinforcing information is linked to higher analyst forecast accuracy and lower forecast dispersion in the following quarters, as well as reduced risk. The study also demonstrates that companies enhance their utilization of visual aids in response to an external decrease in analyst coverage. The researchers conclude that visual informativeness helps individuals better understand and absorb information. Ronen et al. [29] provide evidence, using theoretical imagery constructs, that certain image characteristics, including additivity, as well as factors derived from psychology, computer science, marketing, and related literature, such as colorfulness and non-complexity, have a predicted impact on equity funding.

In this context, Ang et al. [11] emphasize the importance of understanding the emotions triggered by different photographs in corporate reporting. They argue that we currently lack knowledge about the types of emotionally loaded information frequently used in corporate reporting and the effectiveness of photographs in eliciting target emotions. Their call for research highlights the need to investigate emotive photographs as a significant research inquiry.

2.2. The (mis)representation of women in financial-related contexts

The issue of women being underrepresented in the business context is widely acknowledged and can be observed prominently in education, particularly in business schools. A report has brought attention to the misrepresentation of gender in economics textbooks, revealing that out of the 2800 mentions of individuals, 75 % were men, while women were portrayed as leaders in only 6 % of the cases, economists in 7 % of the cases, and policymakers in 8 % of the cases [30]. This finding emphasizes that specific portrayals can exacerbate the gender disparity [31]. The presence of unequal gender representation in economic texts, as highlighted by Stevenson and Zlotnick [30], emphasizes the interconnection between gender stereotypes and economic and academic narratives, which subtly contribute to the perpetuation of the gender gap.

Similarly, gender representation in financial reporting has been identified. An interesting case study examining Thai corporate annual reports over three years (1993, 1997, and 2007) revealed a predominant portrayal of women in subsidiary roles [14]. The authors conclude that financial reports can inadvertently reinforce gender stereotypes rather than challenge them.

Today, the promotion of gender equality by international organizations enjoys increasing visibility and recognition. However, it should be noted that these initiatives are relatively recent, starting less than thirty years ago. Notable examples include the NGO Forum on Women in 1995, the launch of the UN WomenWatch website in 1997, the creation of the Bureau for Gender Equality by the ILO in 1999, the Global March of Women in 2001, and the World Bank's Gender Action Plan in 2006; Inauguration of UN Women in 2010; NGO participation in Beijing +15 in 2011; UN Women Civil Society Advisory Groups in 2012; Emergence of gender experts in 2013; Beijing +20 in 2015 and SDGs and 2030 Agenda in 2016 [13].

For its part, the OECD, like other organizations, has played a crucial role in promoting gender equality, particularly through initiatives such as the DAC Gender Equality Network (GenderNet), which supports the 2030 Agenda [12]. These efforts focus on improving policies and practices to strengthen gender equality, highlighting initiatives such as regional dialogues, annual meetings, and the publication of the Global SIGI Report, which assesses progress on key aspects related to gender equality in areas such as access to productive and financial resources since 2019 [12].

Amidst the global drive for gender equality, a critical examination of gender representation in corporate financial communications is imperative. The business sphere serves as a pivotal arena for advancing gender inclusion initiatives, making it essential to scrutinize how companies portray gender in their financial communications.

2.3. Gender stereotype

Gender stereotypes are neither random nor arbitrary. From a cultural perspective, gender stereotypes emerge from historically assigned roles and collective beliefs [2]. This assignment not only reflects but also shapes social reality, entrenching the stereotypes prevalent today. This leads us to identify stereotypes associated with masculinity and femininity, encompassing, among other components, physical appearance (characteristics), feelings, age, and behavior [32]. In particular, the media often use gender stereotypes in physical representation, with an idealized female image, with slim and toned bodies and emphasizing strength and muscularity in the male image [33,34].

Regarding emotions (or feelings), stereotypes often assign and limit the expression of feelings according to gender. Traditionally, the female image has been created as caring, trustworthy, kinder, and with the ability to maintain good relationships and represents the happier, smiling woman [1–3]. On the other hand, the male image is dominant and prone to anger [1,2] These expectations not only restrict the authenticity of expressing individuals' emotions regardless of gender but also perpetuate outdated notions of masculinity and femininity.

Similarly, there are gender stereotypes that often impose age-related expectations in both professional and social settings. Carlsson and Eriksson [35] suggest that employers prefer younger employees because of their learning ability, flexibility, and ambition, a phenomenon more pronounced in women. Sutherland and Young [3] add that youthful attractiveness is especially valued in women as a romantic ideal in heterosexual couples. This trend extends to advertising, which emphasizes female youth [36].

Based on the literature, it is evident that women who do not conform to stereotypes of appearance, feeling, or age are often invisibilized and underrepresented, reflecting a biased view of society. This perpetuates gender stereotypes and hinders the appreciation of human diversity.

Business financial reports, which include visuals and text, can either reinforce or challenge these stereotypes. Idealized depictions of femininity and masculinity could reinforce norms related to appearance, emotions, and age.

On the other hand, Methods for measuring gender stereotypes vary, focusing on both perceptions and underlying biases. Questionnaires like the Bem Sex Role Inventory (BSRI) and the Personal Attributes Questionnaire (PAQ) are commonly used to assess masculine and feminine traits across contexts [37]. Additionally, interviews and focus groups offer deeper insights into how people perceive and experience gender stereotypes in work and educational settings [38]. To examine underlying stereotypes, content analysis is used to identify and quantify gender stereotypes in language and images within various communications, such as job ads and reports. For example, De Gioannis [39] investigates how cultural norms shape gender perceptions across countries. Some researchers have used the "Symons test" to assess gender equality in textbooks, focusing on female representation in leadership roles and business discussions [30]. Using manual image analysis techniques, Kuasirikun [14] analyzed women's representation in Thai company annual reports over three years.

2.4. Methods review

Methods for measuring gender stereotypes are varied, addressing both perceptions and underlying biases. Questionnaires are commonly used to assess stereotypes, with tools like the Bem Sex Role Inventory (BSRI) and the Personal Attributes Questionnaire (PAQ) frequently employed to measure perceptions of masculine and feminine traits in different contexts [37]. Additionally, interviews and focus groups can provide deeper insights into how individuals perceive and experience gender stereotypes in work and educational settings [38]. Content analysis of communication materials, such as job advertisements and reports, has also been used to identify and quantify the presence of gender stereotypes in language and imagery to observe underlying stereotypes. For instance, research explores how cultural norms shape gender perceptions across countries [39]. Some researchers have applied the "Symons test" to evaluate gender equality in textbook examples, focusing on female representation in leadership roles and their involvement in business discussions [39]. Kuasirikun [14] analyzed the portrayal of women in Thai companies' annual reports over three years using manual image classification and analysis techniques. In summary, methods for measuring gender stereotypes are diverse, incorporating both quantitative and qualitative approaches such as questionnaires, interviews, content analysis, and specific tools like the Symons test. While these methods provide valuable insights, they are labor-intensive, often susceptible to researcher bias or individual subjective bias, and pose significant challenges regarding replicability and scalability, particularly when dealing with large datasets.

To address these limitations, more robust tools like deep learning can be employed. For instance, machine learning classifications, convolutional neural networks (CNNs), and advanced models such as RetinaFace [40] offer enhanced accuracy and scalability, enabling more efficient analysis across extensive datasets while reducing the influence of subjective biases.

2.5. Hypothesis development

We assume that the inclusion of images of human faces in companies' financial reports, designed to communicate financial information to stakeholders, is not a random act, and that the faces depicted reflect specific gender characteristics. To understand this phenomenon, our study is based on two theories that explain how and when the representation of women is used in financial reports.

a) Doing gender theory

According to West and Zimmerman [15], this theory postulates that gender is not a static or inherent characteristic of people, but rather a social activity that is carried out through social interactions and daily practices. In other words, for these authors, gender is not something that "is" but rather something that is "done." The theory maintains that how gender is conceived is a social construction that is cemented to the extent that people act in accordance with gender norms and expectations that are socially defined [15]. Cultural expectations about how men and women should act establish gender norms that are learned and reinforced through socialization and social interaction.

In the organizational context, it has been observed that mostly stereotypical gender norms are constructed and reinforced, for example, by employee behavior, corporate narrative or communications, or by the community. The perception of people's roles in the workplace and in society responds to the daily practices of "doing gender" [37]. Companies "do gender" when they represent men and women in roles consistent with cultural expectations that maintain the idea of stereotypical gender capabilities and roles that limit the opportunities and promotion of women to leadership positions [14,41]. In the scientific community, "doing gender" allows us to understand how gender expectations influence the lower participation of women in the scientific field [39]. However, the social construction of gender can change in response to contextual factors or by challenging established gender norms and thus reconfiguring gender identity [38,42].

Accordingly, the way the company presents women in its statements could reflect how it "does gender", that is, how it reproduces or defies gender norms. When the company aligns with cultural gender expectations and presents images of men with traits that symbolize power and control, their faces project a strong, muscular and serious image. In contrast, representations of women tend to focus on objectification and present faces that respond to the judgment they often face for their beauty and appearance. With these representations, the company's communication perpetuates gender stereotypes. Alternatively, the company could take a defiant stance against gender norms, and "do gender" by responding to contextual demands [37], promoting a break from conventional gender stereotypes. In this way, companies depending on the industrial context in which it operates could communicate in their reports, though, the faces of women and men empathizing with those who challenge gender norms and pursue the reconfiguration of identity.

With this, we put forward the following hypotheses.

H1. Companies that "do gender" through their corporate reporting by perpetuating conventional gender norms present women under gender stereotypes of beauty and appearance

b) Impression management

For Goffman [16], people present different "faces" in various social situations to influence the perception of others. This perspective suggests that individuals, in order to achieve the desired goal, present an image that is congruent with the image necessary for that purpose [43]. Although this theory arises in social psychology, it has been widely used to explain phenomena at the corporate level. Companies can manage their impressions to create a desirable and different corporate image depending on the situation and context. For example, companies can use impression management tactics to create an attractive corporate image, protect and restore their reputation, and influence the perception of stakeholders [44,45]. In addition, they can use certain rhetorical expressions in letters to shareholders to legitimize their actions [46]. Photographs also play a crucial role as an impression management tool in corporate reporting, influencing investor decisions [11].

Thus, companies might be expected to use images of women in financial reports as an impression management strategy. This suggests a deliberate effort to influence stakeholder's perceptions of the company's financial performance by using depictions that reinforce traditional gender stereotypes, such as young, positive-feeling women, which is appealing to the audience [47]. Furthermore, from the glass cliff perspective [48], it is observed that the presence of women in senior positions is often associated with situations of crisis or stress, both in the company's performance and the country's economic context [49,50]. There is a possibility that companies may introduce images of women in corporate communications during these periods as a strategy to manage stakeholder perception.

Based on the previous premises, we postulate the following hypothesis.

H2. There is an association between the financial performance of the company and the use of women's faces under gender stereotypes.

H3. There is a positive association between the context of economic crisis and uncertainty faced by the company and the use of female faces under gender stereotypes.

3. Methodology

3.1. Financial report dataset definition

Financial data from the firms were obtained from the Economatica^{R} Database. The dataset of financial reports was obtained through the process of web scraping annual reports from the CMF website[1] spanning from 2004 to 2020. Out of these reports, we successfully extracted faces from 3670 PDFs of financial reports. Subsequently, information from 2085 annual reports was matched with Economatica^{R}, constituting our initial firm-year sample comprising 234 unique firms.

To begin our analysis, we converted each page of the financial reports into PNG images. We then utilized the Python libraries DeepFace and RetinaFace to extract faces from these images. DeepFace serves as a versatile interface that provides access to a range of facial analysis algorithms, including RetinaFace. RetinaFace is particularly noted for its cutting-edge deep learning capabilities, allowing it to detect faces and facial landmarks with remarkable accuracy, even under challenging conditions such as varied lighting, poses, and occlusions [40].

The choice of RetinaFace is critical given its robustness in handling the diverse image qualities encountered in our dataset, which includes scanned financial reports from different years and companies. According to the original RetinaFace paper, the model excels at detecting faces across multiple scales and angles, making it well-suited for our large-scale analysis of financial reports where image quality can be inconsistent.

By leveraging RetinaFace through DeepFace, we were able to extract essential features for each detected face, including face size, pixel dimensions, estimated age, gender classification, and emotional expressions. The emotions analyzed include happiness, surprise, sadness, anger, fear, and disgust. This comprehensive feature extraction allowed us to systematically quantify the presence and portrayal of women in these financial documents, ensuring a robust and accurate analysis of gender representation across the reports.

Recognizing that the impact of each feature can be modulated by the size of each face, we introduced a size ratio to standardize the features of each image. This ratio is calculated by dividing the area size of each image by the total area size of all faces within each report. Subsequently, we computed the average of each feature per report to generate the final variables utilized in the analyses.

3.2. Discussion on the assumptions and limitations of the models used

In this study, we utilize advanced deep learning models, specifically DeepFace and RetinaFace, to extract and analyze facial images from financial reports in a Big Data context. While these models provide robust capabilities to analyze a large number of images, certain assumptions and limitations inherent in our methodology could impact the findings.

When comparing the application of convolutional neural networks (CNNs) in gender identification from facial images across various studies, several key insights emerge. Zhou et al. [51] focused on developing a face and gender recognition system utilizing CNNs, emphasizing the system's ability to classify gender with high accuracy in real-time applications. The study highlights the effectiveness of CNNs in recognizing gender across a wide array of facial features, demonstrating the robustness of the model under various conditions. However, the approach is primarily tailored for practical implementation in specific environments, such as security systems, rather than generalizability across diverse datasets. Khan et al. [52] explored automatic gender classification through face segmentation using CNNs, addressing the challenges of accurately segmenting faces before applying gender classification algorithms. This study emphasizes the importance of preprocessing steps in improving classification accuracy, particularly in cases where the image quality may be compromised or when the face is partially obscured. The segmentation step adds complexity but results in enhanced accuracy, especially in scenarios involving low-resolution images.

Özbulak et al. [53] investigated the transferability of CNN-based features for age and gender classification, analyzing how well CNN features trained on one dataset can be applied to another. The study underscores the versatility of CNNs but also points out that the performance can degrade when the model is applied to datasets with different characteristics than those it was trained on. This limitation suggests that while CNNs are powerful, their effectiveness can be highly dependent on the diversity and representativeness of the training data.

In contrast, RetinaFace [40] offers a more comprehensive solution by integrating multi-task learning for face detection and landmark localization, allowing it to perform exceptionally well across a variety of challenging conditions, such as varying poses, scales, and occlusions. Unlike the previously mentioned studies, which focus on specific aspects of gender classification, RetinaFace provides a holistic approach that enhances both face detection and subsequent gender classification. Its robustness in detecting faces even in high-density scenes and its resilience to image quality variations make it a superior tool for large-scale applications, particularly in analyzing financial reports where image quality and consistency may vary significantly.

By comparing these approaches, it becomes clear that while CNNs offer powerful solutions for gender classification, the comprehensive capabilities of models like RetinaFace [40] provide enhanced performance, especially in complex real-world scenarios. Integrating these advanced models into gender identification tasks ensures more accurate, scalable, and reliable outcomes across diverse datasets.

1 Image Quality and Detection Limitations:

[1] The reports are available at https://www.cmfchile.cl/portal/principal/613/w3-propertyvalue-18591.html. On Appendix, sectionA1, we provide detailed explanation for the process of obtaining the PDF dataset.

Assumption: The models assume that the facial images within the PDFs are of sufficient quality for accurate detection and analysis.

Limitation: Some financial reports were scanned from physical copies, resulting in lower image quality. Blurry or low-resolution images can impede the ability of the models to detect faces accurately. Consequently, faces that are present in these reports might not be recognized, leading to potential underestimation of women's presence in the dataset.

2 Facial Alignment and Recognition Challenges:

Assumption: The models assume that the faces within the images are aligned correctly and are free from significant distortions.

Limitation: Some faces, particularly those of women, may not be perfectly aligned due to the scanning process, page orientation, or other distortions. While a human observer might still recognize these faces, the model may fail to do so. This misalignment can result in the omission of certain faces from the analysis, potentially biasing the results.

3 Bias in Gender Detection Algorithms:

Assumption: The models used for gender detection are presumed to be unbiased and accurate across different demographics.

Limitation: Deep learning models for facial recognition, including gender detection, can exhibit biases depending on the training data used. If the models were trained on datasets that are not fully representative of the diversity in the financial reports (e.g., in terms of race, age, or gender presentation), there is a risk that the gender of some individuals, particularly women, may be misclassified. This could lead to inaccurate estimates of women's presence in the reports, thereby affecting the validity of our conclusions.

4 Gender Misclassification in Ambiguous Cases:

Assumption: The model assumes that gender is binary and can be accurately classified based solely on facial features without considering the diversity of gender expressions, non-binary identities, and cultural variations in appearance.

Limitation: Gender classification models often struggle with ambiguous cases, such as individuals with non-binary gender expressions, androgynous features, or certain cultural norms of dress and appearance. These models typically rely on binary gender classification, which may not accurately reflect the diversity of gender identities. As a result, the misclassification of gender can occur, leading to biased estimates and interpretations of gender presence in the dataset.

5 Age Estimation Errors Due to Diverse Facial Characteristics:

Assumption: The model assumes that facial features provide a consistent and accurate indication of age across all individuals, regardless of factors like ethnicity, facial expressions, or environmental influences such as lighting and makeup.

Limitation: Age estimation models are sensitive to a variety of factors, including facial expressions, lighting, makeup, and even the presence of facial hair. Additionally, factors such as ethnicity and genetic diversity can lead to significant errors in age estimation. For example, certain ethnic groups may naturally have features that cause them to appear younger or older than they are, leading to inaccuracies in age detection. These errors could skew the analysis, especially when aggregating age-related data.

6 Emotion Recognition Variability and Context Dependence:

Assumption: The model assumes that facial expressions are universal indicators of emotion, accurately reflecting a person's true emotional state without accounting for cultural differences, context, or subtle nuances in expression.

Limitation: Emotion recognition algorithms often rely on facial expressions, which may not accurately capture the true emotional state of an individual. Cultural differences in expressing emotions, contextual factors, and subtle expressions can all contribute to misinterpretation by the model. For example, a neutral expression might be misclassified as sadness or anger depending on the context, or a smile may not necessarily indicate happiness. This can introduce noise into the sentiment analysis, potentially leading to incorrect conclusions about the emotional tone of the financial reports.

7 Impact of Environmental Factors on Detection Accuracy:

Assumption: The model assumes that facial detection and analysis models operate effectively regardless of variations in lighting, shadows, or background complexity, without the need for preprocessing or adjustments to improve image quality.

Limitation: Environmental factors such as lighting, shadows, and background clutter in the images can adversely affect the performance of face detection and analysis models. Poor lighting or shadows on the face can lead to inaccurate gender, age, and emotion detection. Similarly, complex or cluttered backgrounds might introduce noise, causing the model to miss or incorrectly analyze faces.

8 Dependence on the Quality of Pretrained Models:

Assumption: The model assumes that pretrained models are sufficiently diverse and representative of the population in the financial reports, leading to accurate and unbiased predictions across different demographics and contexts.

Limitation: The accuracy of gender, age, and emotion detection is heavily dependent on the quality of the pretrained models used in DeepFace and RetinaFace. If the models were trained on datasets that are not diverse or representative of the population in the financial reports, the predictions could be biased or inaccurate. This includes potential overfitting to certain demographics or underrepresentation of others, which would limit the generalizability of the findings.

These limitations underscore the importance of carefully interpreting our results and acknowledging potential biases inherent in the models used. While advanced models like DeepFace and RetinaFace allow to perform our analysis in a Big Data context, they are not without challenges. On the conclusions section, we outline a few improvements that future research could do to help reduce these challenges.

3.3. Research design

To investigate the factors influencing the depiction of women in financial reports, we will employ the following models:

$$Women\ Presence_{it} = \beta_0 + \beta_1 sentiments_{it} + \beta_2 Tangibility_{it} + \beta_3 Size_{it} + FEs + \varepsilon_{it} \quad (1)$$

$$Women\ Presence_{it} = \beta_0 + \beta_1 Youth_{it} + \beta_2 Tangibility_{it} + \beta_3 Size_{it} + FEs + \varepsilon_{it} \quad (2)$$

$$Women\ Presence_{it} = \beta_0 + \beta_1 Youth_{it}\#sentiments_{it} + \beta_2 Youth_{it} + \beta_3 sentiments_{it} + \beta_4 Tangibility_{it} + \beta_5 Size_{it} + FEs + \varepsilon_{it} \quad (3)$$

$$Women\ Presence_{it} = \beta_0 + \beta_1 GDP\ Growth_t + \beta_2 Tangibility_{it} + \beta_3 Size_{it} + FEs + \varepsilon_{it} \quad (4)$$

$$Women\ Presence_{it} = \beta_0 + \beta_1 EPU_t + \beta_2 Tangibility_{it} + \beta_3 Size_{it} + FEs + \varepsilon_{it} \quad (5)$$

$$Women\ Presence_{it} = \beta_0 + \beta_1 Women\ financial\ inclusion_t + \beta_2 Tangibility_{it} + \beta_3 Size_{it} + FEs + \varepsilon_{it} \quad (6)$$

$$Women\ Presence_{it} = \beta_0 + \beta_1 ROA_{it} + \beta_2 Loss_{it} + \beta_3 Delta\ earnings_{it} + \beta_4 MTB_{it} + \beta_5 Tangibility_{it} + \beta_6 Size_{it} + FEs + \varepsilon_{it} \quad (7)$$

Where each variable is defined as follows:

Women Presence: represents the ratio of scaled faces depicting women to the total number of scaled images depicting both women and men. **Age:** denotes the average age of all extracted faces, adjusted by their size. **Youth:** derived by multiplying the "Age" variable by negative one, thereby increasing on its magnitude and facilitating interpretation.

Sentiments: Neutrality, Happiness, Sadness, Angryness, Surprise, Fear or Disgustness. These sentiments were measured using a scoring system that assessed the intensity of each emotion present in the extracted facial expressions. This scoring system assigned a numerical value to each sentiment, indicating its level of prominence or intensity in the facial expressions detected. These numerical values were then averaged across all extracted facial expressions within each financial report, providing a comprehensive overview of the sentiment distribution within the images. Additionally, to account for variations in the size of the facial expressions, the scores were adjusted based on the size of each individual face, ensuring a more accurate representation of the sentiments portrayed.

GDP Growth: This represents the annual growth rate of Chile's Gross Domestic Product (GDP) expressed as a percentage. **EPU:** Is Economic Policy Uncertainty for Chile, which is measured using a news-based approach developed by Cerda et al. [54], following the methodology of Baker et al. [55]. Cerda et al. [54] provide two indices: one that concentrates on articles related to economic policy uncertainty (EPU) and another that specifically targets articles related to domestic sources of economic policy uncertainty in Chile (EPUC).[2] Both definitions will be utilized in the analysis.

Women financial inclusion is measured by the two following indicators, separately: **Proportion of Women Checking Account Balances:** This is the average yearly ratio of the balance in checking accounts held by women divided by the total balance of all individuals. **Proportion of Women Checking Account Quantity**: the average yearly ratio of the number of checking accounts held by women compared to the total number of individuals. The data for calculating these variables were sourced from the Chilean Central Bank.[3]

ROA: Return on Assets, a financial metric indicating a company's profitability relative to its total assets defined as Net income divided by total assets, multiplied by 100. **Tangibility:** Refers to the proportion of tangible assets within a company's total assets, providing insight into its asset composition, defined as Property, Plant & Equipment divided by total assets. **Size:** Represents the natural logarithm of a company's total assets, often used as a proxy for firm size in financial analysis. **Delta Earnings:** Represents the yearly change in a company's net income multiplied by 100. **Loss:** Is a dummy variable that indicates whether a company has experienced negative net income in a given year (equal 1 on this case). **MTB:** Is Market-to-book, which represents the ratio of a company's market value to its book value.

FEs represent a set of fixed effects controls used in regression models to account for unobserved heterogeneity across units—in this case, industries—while allowing for differences that are constant over time. By including industry fixed effects, we ensure that any time-invariant characteristics specific to an industry are controlled for, reducing the potential bias in our estimates. Additionally, we control for year fixed effects to account for time-related shocks or trends that could affect all units, similarly, ensuring that our results

[2] The dataset is openly available at https://www.policyuncertainty.com/chile_monthly.html.

[3] The dataset is openly available at https://si3.bcentral.cl/Siete/ES/Siete/Cuadro/CAP_ESTADIST_GENERO/MN_GENERO1/EST_GEN_POB_01.

are not driven by such external factors. The use of fixed effects assumes that the independent variables are uncorrelated with time-varying unobserved effects, which is critical for producing unbiased and consistent coefficient estimates. However, it is important to note that fixed effects models rely on sufficient within-unit variation in the independent variables over time [56,57]. This approach strengthens the validity of our inferences by mitigating confounding from unobserved time-invariant factors. The interpretation of our results is made within these constraints, ensuring robustness and reliability in our analysis.

4. Results and discussion

4.1. Descriptive statistics

Table 1, Panel A, displays summary statistics. There are certain notable features. The mean representation of women in the images used in financial reports is 16.16 %, with a notable standard deviation of 20.5 %. This illustrates a substantial disparity in gender representation, with a higher number of men compared to women.[4] The average age of the individuals portrayed in the reports is 35.04 years, with a standard deviation of 4.76 years, suggesting a rather low level of age variation.

Happiness is the most frequently depicted emotion, with an average occurrence rate of 36.59 % and a standard deviation of 23.32 %. Sadness follows as the second most common emotion, with an average score of 17.51 % and a standard deviation of 15.19 %. The high standard deviations for these two emotions indicate a wide variation in how they are portrayed across the sample. Other emotions, such as anger, surprise, fear, and disgust, are also depicted but to a lesser extent, with average scores ranging from 1.13 % to 10.5 %. The standard deviations for these emotions indicate important variability in how they are portrayed. The Return on Assets (ROA) shows an average of 4.55 % with a standard deviation of 7.13 %, suggesting importance variance in the profitability of the firms analyzed.

Throughout the analyzed sample period, 39 % of all checking accounts in the country were owned by women, with minimal fluctuation across the years, as reflected by a standard deviation of 2 %. However, women held only 30 % of the total checking account balances, with similarly negligible variation over the years, showing a standard deviation of just 1 %. Additionally, the proportion of women entrepreneurs during this period averaged 33 %, with a slight fluctuation indicated by a 1 % standard deviation.[5]

In terms of the macroeconomic environment, the country witnessed significant fluctuations in Economic Policy Uncertainty (EPU), with a standard deviation of 44.76 considering an average value of 111.86. Additionally, GDP Growth exhibited variability, with a standard deviation of 3.27, despite an average growth rate of 2.61 %.[6]

Notably, as shown in Panel B of Table 1, women's appearance in financial report imagery correlates positively with youth and negatively with neutrality. This suggests that companies are more likely to depict women displaying emotions that are not neutral when selecting images for their reports. Additionally, there is a positive association between the presence of women and positive sentiments such as happiness and surprise. In contrast, negative sentiments like sadness, anger, and disgust are negatively associated with women's presence.

Firms with higher levels of tangibility, which indicates a greater reliance on tangible fixed assets like Property, Plant, and Equipment—known for their intensive use of manual labor—show a negative association with the presence **of** women in financial reports. Conversely, larger firms with greater assets tend to feature more women. Additionally, the results suggest that during periods of higher GDP growth, the use of images depicting women decreases, whereas during times of elevated uncertainty regarding the country's economic policy, there is an increase in the depiction of women in financial reports.

Panel C of Table 1 reveals intriguing insights into the average presence of women, age, and happiness levels across various industries. For instance, the Electroelectronics and Commerce sectors stand out, featuring the highest levels of women in their financial reports, with averages of 36.59 % and 36.25 %, respectively. These sectors also exude strong sentiments of happiness, averaging 46.11 % and 41.24 %, respectively, while maintaining a slightly below-average age profile of around 33 years old, compared to the sample average of 35.

In stark contrast, the Vehicles & Parts and Iron & Steel industries present a different picture. These sectors exhibit the lowest levels of women's presence in their financial reports, with percentages of 2.64 and 6.24 %, respectively. They also tend to have higher-than-average age profiles, approximately 37 years old for both sectors, and below-average levels of happiness, at 20.15 % and 29.55 %, respectively.

The higher representation of women in end-consumer-oriented sectors, such as Electroelectronics and Retail—both of which show high levels of happiness—suggests that these industries may leverage gender stereotypes to connect emotionally with the public and potentially influence consumer behavior. On the other hand, sectors with lower female representation, such as Vehicles & Parts and Iron & Steel, reflect a trend toward more neutral or negative imagery, possibly due to their more technical and less consumer-oriented nature.

Furthermore, the observation that female representation increases during periods of economic uncertainty and decreases during times of economic growth suggests that companies may use the image of women strategically to counteract the negative effects of

[4] Fig. 1 illustrates the average trend of women's presence across the sample years.

[5] Fig. 2 illustrates the trends of the Proportion of Women Checking Account Balances and the Proportion of Women Checking Account Quantity across the sample period. Fig. 3 depicts the trend of the Proportion of Entrepreneur Women.

[6] Fig. 4 illustrates the trends of Economic Policy Uncertainty (EPU) and Economic Policy Uncertainty focused on Chile (EPUC), while Fig. 5 depicts the trend of GDP Growth.

Table 1
Panel A: Summary statistics.

Variable	Observations	Mean	Standard Deviation	0.25	Mdn	0.75
Women Presence	2085	16.16	20.5	0.1	8.09	24.22
Age	2085	35.04	4.76	31.84	34.49	37.9
Youth	2085	−35.04	4.76	−37.9	−34.49	−31.84
Neutrality	2085	26.3	18.43	14.25	22.84	34.15
Happiness	2085	36.59	23.32	18.77	36.09	52.89
Sadness	2085	17.51	15.19	7.11	14.09	23.52
Angryness	2085	7.73	9.96	1.8	4.81	10.07
Surprise	2085	1.13	3.06	0.04	0.21	0.82
Fear	2085	10.5	11.94	3.24	7.34	13.34
Disgustness	2085	0.23	1.27	0	0.01	0.05
ROA	2085	4.55	7.13	1.41	3.72	6.92
Tangibility	2085	0.4	0.28	0.14	0.4	0.63
Size	2085	12.77	1.74	11.63	12.78	13.85
Delta Earnings	1993	0.45	5.8	−1.12	0.22	1.7
Loss	2085	0.42	0.49	0	0	1
Market-to-book	906	1.48	1.36	0.72	1.1	1.82
GDP Growth	2085	2.61	3.27	1.36	2.15	5.84
EPU	2085	111.86	44.76	84.69	101.19	142.34
EPUC	2085	108.86	56.42	80.37	91.36	138.57
Proportion of Women Checking Account Balances	1710	0.30	0.01	0.29	0.30	0.31
Proportion of Women Checking Account Quantity	1710	0.39	0.02	0.37	0.39	0.40
Proportion of Entrepreneur Women	965	0.33	0.01	0.32	0.33	0.33

Table 1 Panel B: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Women Presence	1									
(2) Age	0.285*	1								
(3) Neutrality	−0.144*	−0.171*	1							
(4) Happiness	0.250*	−0.178*	−0.451*	1						
(5) Sadness	−0.115*	0.267*	−0.195*	−0.503*	1					
(6) Angryness	−0.111*	0.022	−0.167*	−0.287*	−0.019	1				
(7) Surprise	0.114*	0.074*	−0.104*	−0.056*	−0.052*	−0.003	1			
(8) Fear	−0.053*	0.239*	−0.245*	−0.360*	0.042*	0.006	0.083*	1		
(9) Disgustness	−0.047*	−0.051*	−0.025	−0.032	−0.026	0.032	−0.009	0.004	1	
(10) ROA	−0.028	−0.009	0.061*	−0.074*	0.006	0.004	−0.026	0.048*	−0.002	1
(11) Tangibility	−0.112*	−0.048*	0.044*	−0.086*	0.060*	0.042*	−0.006	−0.007	−0.011	−0.003
(12) Size	0.108*	−0.037*	−0.079*	0.128*	−0.049*	0.006	0.003	−0.071*	0.004	−0.02
(13) Delta Earnings	−0.014	0.03	0.018	−0.029	0.011	0.008	0.024	0.001	0.01	0.454*
(14) Loss	0.015	−0.015	−0.026	0.022	−0.005	0.002	−0.025	0.009	−0.011	−0.263*
(15) Market-to-book	0.051	0.002	0.169*	−0.139*	−0.022	−0.021	0.014	0.054	−0.012	0.545*
(16) GDP Growth	−0.116*	0.03	0.050*	−0.061*	0.017	0.017	−0.033	0.011	0.032	0.143*
(17) EPU*	0.086*	−0.035	−0.050*	0.075*	−0.044*	−0.008	0.039*	−0.011	−0.037*	−0.140*
(18) EPUC**	0.078*	−0.011	−0.051*	0.049*	−0.017	−0.003	0.039*	0.002	−0.03	−0.128*
(19)Proportion of Women Checking Account Balances	0.062*	−0.009	−0.070*	0.072*	−0.009	−0.004	0.002	−0.018	−0.016	−0.101*
(20)Proportion of Women Checking Account Quantity	0.065*	−0.022	−0.062*	0.074*	−0.009	−0.007	0.01	−0.036	−0.025	−0.120*
(21)Proportion of Entrepreneur Women	0.03	−0.071*	−0.034	0.075*	−0.03	0.014	−0.043	−0.069*	0.003	−0.044

(*continued on next page*)

Table 1 (*continued*)

Table 1 Panel B: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(11) Tangibility	1										
(12) Size	−0.059*	1									
(13) Delta Earnings	−0.073*	−0.046*	1								
(14) Loss	0.044*	0.018	−0.544*	1							
(15) Market-to-book	0.199*	−0.067*	−0.034	−0.038	1						
(16) GDP Growth	0.048*	−0.077*	0.069*	−0.162*	0.116*	1					
(17) EPU*	−0.062*	0.085*	−0.054*	0.147*	−0.096*	−0.808*	1				
(18) EPUC**	−0.054*	0.075*	−0.045*	0.144*	−0.089*	−0.833*	0.966*	1			
(19)Proportion of Women Checking Account Balances	−0.025	0.069*	−0.047*	0.102*	−0.073*	−0.589*	0.738*	0.745*	1		
(20)Proportion of Women Checking Account Quantity	−0.018	0.075*	−0.063*	0.119*	−0.105*	−0.656*	0.750*	0.736*	0.965*	1	
(21)Proportion of Entrepreneur Women	−0.001	0.034	−0.053	−0.008	0.053	0.033	−0.214*	−0.208*	0.654*	0.688*	1

Table 1 Panel C: Summary statistics by industry

	Mean			N
Industry	Women Presence	Age	Happiness	
Agribusiness & Fisheries	15.63	34.28	32.59	198
Chemicals	13.05	33.27	28.73	55
Commerce	36.25	33.23	41.24	150
Construction	8.22	35.69	35.14	59
Electric Power	11.92	36.23	32.40	194
Electroelectronics	36.59	32.85	46.11	3
Finance & Insurance	17.57	36.25	42.40	269
Food & Beverages	17.99	34.16	39.23	129
Funds	10.05	35.83	36.52	189
Iron & Steel	6.24	36.32	29.55	75
Mining	10.33	35.10	30.31	40
Non-Metallic Minerals	7.80	36.43	36.05	57
Oil & Gas	14.35	33.62	32.17	43
Other	19.14	33.75	38.49	343
Paper & Pulp	6.43	37.12	31.68	21
Software & Data	13.21	34.41	37.56	5
Telecommunication	23.52	32.23	33.89	33
Transport Services	14.49	36.24	37.52	213
Vehicles & Parts	2.64	36.59	20.15	9
			Total	2085

*$p < 0.1$.

Table 2
All regressions are estimated independently. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Neutrality	−0.131***	−0.082*												
	(0.028)	(0.044)												
Happiness			0.173***	0.123***										
			(0.022)	(0.035)										
Sadness					−0.107***	−0.105**								
					(0.029)	(0.041)								
Angryness							−0.166***	−0.143						
							(0.054)	(0.138)						
Surprise									0.629***	0.907***				
									(0.181)	(0.266)				
Fear											−0.072**	−0.061		
											(0.031)	(0.055)		
Disgustness													−0.472**	−0.652***
													(0.204)	(0.228)
Market-to-book		0.307		0.377		0.083		0.082		0.080		0.146		0.111
		(0.423)		(0.394)		(0.409)		(0.415)		(0.405)		(0.409)		(0.411)
Tangibility	−3.705**	−3.086	−3.394*	−2.630	−3.606**	−1.862	−3.675**	−2.715	−3.721**	−2.461	−3.874**	−2.462	−3.829**	−2.515
	(1.849)	(3.084)	(1.804)	(2.981)	(1.776)	(2.982)	(1.824)	(2.978)	(1.802)	(2.952)	(1.786)	(2.999)	(1.789)	(2.997)
Size	0.944***	2.003***	0.796***	1.800***	1.060***	2.082***	1.101***	2.077***	1.106***	2.140***	1.053***	2.078***	1.091***	2.128***
	(0.312)	(0.452)	(0.296)	(0.454)	(0.307)	(0.440)	(0.308)	(0.435)	(0.311)	(0.445)	(0.308)	(0.441)	(0.311)	(0.444)
Observations	2085	906	2085	906	2085	906	2085	906	2085	906	2085	906	2085	906
R2	0.170	0.244	0.193	0.255	0.163	0.245	0.163	0.243	0.166	0.257	0.159	0.241	0.158	0.241
Adjusted R2	0.155	0.216	0.178	0.228	0.148	0.217	0.148	0.215	0.151	0.230	0.144	0.213	0.143	0.213
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

adverse economic news. This highlights the importance of images as a component of impression management and suggests that decisions about gender representation in financial reporting are influenced by external economic factors and social stereotypes.

These findings underscore the need for corporate policies and accounting regulations that promote more equitable and accurate gender representation in financial reporting, considering the economic and social complexities underlying these decisions.

In summary, these descriptive findings suggest that firms operating in end-consumer-oriented industries demonstrate distinct patterns in gender representation compared to those primarily engaged in Business-to-Business transactions, which are characterized by a heavier reliance on manual labor.

4.2. Regression models results

Table 2 highlights the relationship between sentiments and the presence of women images in financial reports, as illustrated in Model 1. Each column corresponds to a distinct regression model, with the odd-numbered columns including the market-to-book variable as an additional control.

In Columns 1 and 2, the negative beta coefficient for Neutrality suggests that higher levels of neutrality in financial reports are associated with lower levels of women's representation. This finding indicates that financial reports conveying a more neutral tone tend to feature fewer images of women.

Conversely, the positive beta coefficients for Happiness in Columns 3 and 4 indicate a direct relationship between higher levels of happiness in financial reports and an increased presence of women. Financial reports with higher happiness are more likely to include images depicting women. A similar trend is observed for surprise in Columns 9 and 10.

Interestingly, negative emotions such as Sadness, Anger, Fear, and Disgust are associated with negative beta coefficients in Columns 5–8 and 11–14. This implies that an increase in negative sentiment within financial reports corresponds to a decrease in the inclusion of images of women.

Overall, these findings suggest that financial reports characterized by higher levels of negativity tend to have a lower representation of women in images. In contrast, reports with more positivity are associated with a higher representation of women.

Table 3 presents the results from Model 2, which examines the relationship between the degree of youthfulness depicted in financial reports and the presence of women. Column 2 includes the market-to-book ratio as an additional control variable. In both models, the 'Youth' variable shows positive and statistically significant coefficients at the 1 % level, indicating that greater levels of youthfulness in financial reports are associated with a higher presence of women.

Table 4 provides further insights into how sentiments and Youth interact to influence the depiction of women in financial reports, according to model 3. Columns 1 and 2 reveal a statistically significant negative coefficient for Neutrality, suggesting that a higher proportion of young individuals in financial reports strengthens the negative association between neutrality and women's representation. Conversely, Columns 3 and 4 show positive coefficients for the interaction between Youth and Happiness, indicating that as financial reports depict more youthful individuals, there is a greater representation of women alongside positive sentiments like happiness. A similar trend is observed for surprise in Column 10. These interactions indicate that positive emotions and youthfulness are closely linked, both contributing to the increased selection of women's images in financial reports.

However, the interaction between youthfulness and negative emotions such as sadness, fear, and disgust show negative and

Table 3
All regressions are estimated independently. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

	(1)	(2)
Youth	1.207***	1.214***
	(0.108)	(0.149)
Market-to-book		0.332
		(0.377)
Tangibility	−2.615	−1.740
	(1.869)	(3.028)
Size	1.100***	2.221***
	(0.302)	(0.426)
Observations	2085	906
R2	0.227	0.309
Adjusted R2	0.213	0.284
Firm-level controls	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes

Table 4
All regressions are estimated independently. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Youth # Neutrality	−0.009***	−0.005												
	(0.003)	(0.006)												
Youth # Happiness			0.028***	0.020***										
			(0.003)	(0.005)										
Youth # Sadness					−0.020***	−0.018***								
					(0.004)	(0.006)								
Youth # Angryness							−0.011	0.009						
							(0.007)	(0.024)						
Youth # Surprise									0.003	0.116*				
									(0.036)	(0.067)				
Youth # Fear											−0.020***	−0.008		
											(0.005)	(0.005)		
Youth # Disgustness													−0.072**	−0.101
													(0.029)	(0.074)
Observations	2085	906	2085	906	2085	906	2085	906	2085	906	2085	906	2085	906
R2	0.235	0.311	0.316	0.365	0.256	0.335	0.235	0.316	0.233	0.326	0.241	0.318	0.228	0.311
Adjusted R2	0.221	0.284	0.303	0.340	0.241	0.309	0.221	0.289	0.219	0.300	0.227	0.292	0.213	0.284
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

significant coefficients in Columns 5, 6, 11, and 13. This suggests that negative emotions and youthfulness do not align in the same direction. Specifically, even with an increase in youthfulness, the presence of sadness still tends to reduce the selection of women's images in financial reports.

These findings highlight the complex relationship between age and sentiments in influencing how women are portrayed in financial reports. They underscore the importance of analyzing both age and sentiments together to fully understand their impact on gender diversity representation.

Table 5 presents the findings from models 4, 5, and 6, which incorporate key macroeconomic indicators and measures of women's financial inclusion, factors that are external to the firm and beyond management's direct control.

In Column 1, the coefficients are negative and statistically significant, indicating that higher GDP growth is associated with a decrease in the representation of women in financial report images. This suggests that during periods of economic prosperity, the portrayal of men tends to increase while the portrayal of women declines. This trend is consistent with the results in Columns 2 and 3, where higher levels of uncertainty regarding the country's economic policy are linked to an increase in the representation of women.

This indicates that during times of economic instability, there is a greater prevalence of women's images in financial reports. This phenomenon might be attributed to the strategic use of women's images to counteract the negative effects of economic uncertainty, possibly by leveraging stereotypes. Furthermore, higher representation of women in financial reports appears to be associated with increased participation and inclusion of women in financial matters. Columns 4 and 5 show that as the proportion of women's checking accounts and account balances increases relative to men's, there is a corresponding rise in the presence of women in financial report images.

These findings suggest that stereotypes may not solely drive the depiction of women in financial reports but could also reflect the growing integration of women into the workforce and financial activities.

Table 6 presents the results for Model 7, which includes additional variables related to firm financial performance, such as ROA (Return on Assets), Loss, Delta Earnings, Market-to-book ratio, Size, and Tangibility. Importantly, the analysis shows that the inclusion of women in financial report images is not directly related to the company's financial performance. The coefficients for ROA, Loss, Delta Earnings, and Market-to-book ratio all lack statistical significance in relation to the presence of women in these images. This suggests that the use of women's images in financial reports is not a strategy employed to mask poor financial performance or to soften the impact of negative news.

The findings also show that Tangibility consistently has a negative and statistically significant relationship across all columns (Columns 1 to 5). This indicates that higher levels of asset tangibility, which reflect a larger proportion of Property, Plant, and Equipment within total assets, are associated with a decrease in the portrayal of women in financial report images. Conversely, Size consistently exhibits positive and significant coefficients across all columns, suggesting that larger firms tend to include more images of women in their financial reports.

5. Robustness

In this section, we perform a robustness analysis to evaluate whether the previous results and conclusions remain consistent when additional control variables are introduced. This analysis focuses on assessing the impact of economic conditions on the portrayal of women in financial reports, ensuring the reliability of our findings.

First, we introduced four additional control variables: 1) GDP growth, 2) Economic Policy Uncertainty (EPU), 3) the proportion of women's checking account balances, and 4) the proportion of women entrepreneurs.

Next, we reduced the dimensionality of the data by combining GDP growth and EPU into a single variable using principal component analysis (PCA), labeled GDP-EPU-PCA. This was done because these variables may capture similar economic factors. For clarity, EPU was multiplied by -1 so that the PCA component increases with positive macroeconomic news.

We applied the same PCA approach to the variables representing the proportion of women's checking account balances and the proportion of women entrepreneurs, creating a combined component labeled Women-PCA.

Tables 1A and 1B replicate the results from Table 2, Model 1, incorporating each set of variables respectively. The results and overall conclusions remain largely consistent, though slightly less pronounced. Positive sentiments, such as happiness and surprise, continue to significantly explain the increased presence of women in financial report images, while negative sentiments, including sadness, anger, fear, and disgust, consistently reduce their presence. However, the neutrality sentiment lost its statistical significance in explaining the representation of women, suggesting that its influence may be less robust when additional economic conditions are considered.

Tables 2A and 2B, along with Table 3, present the results from Model 2, which includes the two sets of additional controls. The conclusions remain robust, confirming the relationship between the degree of youthfulness depicted in financial reports and the presence of women. This analysis reaffirms that greater levels of youthfulness in financial reports are associated with a higher presence of women.

Tables 3A and 3B replicate the results from Table 4, Model 3, incorporating the two sets of additional controls. The conclusions largely remain robust, indicating that the interaction between sentiments and youthfulness continues to significantly impact the depiction of women in financial reports. However, neutrality loses its significance in this context. These findings underscore the

Table 5
All regressions are estimated independently. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth	−0.623***					
	(0.141)					
EPU*		0.030***				
		(0.010)				
EPUC**			0.022***			
			(0.008)			
Proportion of Women Checking Account Balances				82.152***		
				(29.949)		
Proportion of Women Checking Account Quantity					66.749**	
					(25.980)	
Tangibility	−4.456**	−4.495**	−4.533**	−3.543*	−3.525*	0.474
	(1.840)	(1.844)	(1.853)	(2.003)	(2.005)	(2.352)
Size	1.190***	1.220***	1.239***	1.087***	1.097***	1.136**
	(0.304)	(0.308)	(0.306)	(0.340)	(0.339)	(0.468)
Observations	2085	2085	2085	1710	1710	965
R2	0.138	0.133	0.132	0.133	0.133	0.118
Adjusted R2	0.129	0.124	0.123	0.122	0.122	0.100
Year fixed effects	No	No	No	No	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 6
All regressions are estimated independently. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tangibility	−3.808**	−3.739**	−3.748**	−4.208**	−4.191**	−2.525	−2.505	−2.509	−2.127	−2.149
	(1.799)	(1.803)	(1.805)	(1.873)	(1.875)	(3.011)	(3.006)	(3.018)	(3.152)	(3.155)
Size	1.085***	1.097***	1.098***	1.086***	1.083***	2.115***	2.129***	2.130***	2.158***	2.165***
	(0.310)	(0.311)	(0.312)	(0.316)	(0.316)	(0.439)	(0.435)	(0.437)	(0.441)	(0.444)
ROA		0.056	0.057	0.061	0.061		0.092	0.093	0.028	0.027
		(0.065)	(0.067)	(0.072)	(0.072)		(0.123)	(0.129)	(0.134)	(0.133)
Loss			0.092		−0.385			0.044		0.882
			(0.872)		(1.064)			(1.110)		(1.401)
Delta Earnings				−0.017	−0.034				0.115	0.155
				(0.083)	(0.099)				(0.110)	(0.134)
Market-to-book						0.121	−0.143	−0.145	0.026	0.043
						(0.411)	(0.512)	(0.525)	(0.559)	(0.558)
Observations	2085	2085	2085	1993	1993	906	906	906	896	896
R2	0.157	0.157	0.157	0.155	0.155	0.240	0.240	0.240	0.236	0.236
Adjusted R2	0.142	0.142	0.142	0.139	0.138	0.213	0.212	0.212	0.207	0.206
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

complex relationship between age and sentiments in shaping gender representation, further confirming the robustness of the results even with the added economic controls.

Finally, Tables 4A and 4B replicate the results from Table 5, Model 4, incorporating the two sets of additional controls. The conclusions remain robust, confirming that the inclusion of women in financial report images is not directly linked to the company's financial performance. The coefficients for ROA, Loss, Delta Earnings, and Market-to-book ratio continue to lack statistical significance concerning the presence of women in these images. This consistency reinforces the notion that the use of women's images in financial reports is not strategically employed to conceal poor financial performance or to mitigate the impact of negative news about the firm's performance. It is worth noting that all robustness analyses include industry fixed effects and account for time fixed effects by incorporating annual variables consistent across all firms in a given year. Overall, the analysis suggests that while the relationship between positive and negative sentiments and the presence of women in financial report images is influenced by macroeconomic conditions and broader female inclusion in the financial system and business, the main findings remain robust for most sentiments. However, the explanatory power of neutrality sentiments in predicting women's presence weakens under these additional controls.

6. Discussion of findings and implications

6.1. Discussion of findings

Our results demonstrate that gender stereotypes significantly influence the depiction of women in financial reports. Women are underrepresented compared to men, and when they are featured, they are typically portrayed as younger and exhibiting positive emotions, such as happiness and surprise. Notably, these portrayals are more common during challenging economic conditions, such as periods of lower GDP growth or heightened economic policy uncertainty. This pattern aligns with the hypothesis that women are strategically used to mitigate the negative perception of exogenous poor macro-economic performance, serving as a subtle attenuator of bad news within the narrative of financial reports.

Our results strongly support the hypotheses grounded in the "Doing Gender" theory as proposed by West and Zimmerman [15]. This theory posits that gender is not an inherent characteristic but rather a social construct performed through daily interactions and practices. In the organizational context, companies "do gender" by reinforcing or challenging stereotypical gender norms through their communications and representations.

Our findings indicate that companies predominantly reinforce conventional gender norms in their financial reports. Women are underrepresented and, when depicted, are often shown in ways that emphasize youth and positive emotions, such as happiness and surprise. This aligns with H1, which suggests that companies perpetuate traditional gender stereotypes in their corporate reporting by focusing on women's beauty and appearance. The persistence of these patterns suggests that the corporate portrayal of women remains heavily influenced by societal expectations and norms, rather than reflecting a progressive stance toward gender equality. This outcome aligns with the findings of Lopez-Zafra et al. [37], Kuasirikun [14], and Van den Brink et al. [41], who argue that organizations often reinforce gender stereotypes through their narratives and practices.

Our analysis underscore how companies, through their financial reports, continue to "do gender" by reproducing cultural expectations that limit the depiction of women to stereotypical roles and appearances. This behavior perpetuates the existing gender biases, rather than challenging them to promote a more inclusive representation.

Our findings align closely with the principles of Impression Management Theory as articulated by Goffman [16]. This theory suggests that individuals—and by extension, organizations—craft specific "faces" to present in different situations to shape the perceptions of others.

At the corporate level, companies may engage in impression management to create a desirable image that aligns with their strategic objectives. This could involve using visual elements, such as photographs, to reinforce particular narratives or to influence stakeholder perceptions.

In the context of our study, the evidence does not fully support the hypothesis (H2) that companies use images of women in their financial reports as an impression management tool directly related to firm performance. However, the results do show that women are often depicted with positive facial expressions, such as happiness and surprise, particularly during times of economic downturn or uncertainty. This pattern suggests that companies may strategically choose these images to project optimism or resilience in challenging circumstances.

Additionally, the increased representation of women during periods of economic instability aligns with H3, indicating that companies might use these images to manage stakeholder perceptions during crises. Companies may use such imagery to evoke stability, distance themselves from the crisis, or signal resilience. However, these strategies risk reinforcing gender inequality by placing women in precarious positions, rather than advancing true gender equality [58].

The negative correlation between GDP growth and the representation of women indicates that companies tend to highlight men more during economic booms, while increasing the visibility of women during economic downturns. This strategic use of imagery likely stems from the perception that women evoke empathy and trust, which companies may leverage to cushion the impact of unfavorable economic news. This behavior reflects the "glass cliff" phenomenon, where women are more prominently featured in leadership roles during difficult times [48–50].

The results suggest that companies are not merely reflecting societal norms but are actively leveraging these stereotypes as part of their strategic communication efforts. By presenting women in roles that are traditionally associated with positivity and support during economic stress, companies may be attempting to mitigate negative perceptions and bolster their image in the eyes of stakeholders.

This behavior aligns with findings by Shafi [47], who highlights the appeal of using young, positive-feeling women in corporate communications to enhance the attractiveness of the company's image. In conclusion, the application of Impression Management Theory to our findings reveals a deliberate use of gendered images in financial reports to manage corporate image, especially during periods of economic difficulty. This strategic use of women's images highlights how gender stereotypes are not only perpetuated but are also manipulated to serve corporate objectives.

Our analysis also reveals notable differences in the use of stereotypical female images between B2C (Business to Consumer) and B2B (Business to Business) companies. B2C firms, which target individual consumers, more frequently employ images of young, happy women to establish an emotional connection, tapping into shared ideals of beauty and traditional gender roles to drive consumer engagement. Conversely, B2B companies, which prioritize professionalism and technical competence in their communications, are less likely to use such imagery. This distinction challenges the assumption of inherent sexism in B2B communications, although it remains essential to monitor for any reinforcement of gender stereotypes [59].

6.2. Discussion of implications

Our results underscore the need for companies to adopt a more mindful and equitable approach to gender representation in financial reporting. Our findings reveal a critical gap in how businesses adhere to the IASB's principles of neutrality and unbiased financial reporting.

The pervasive influence of societal stereotypes in the depiction of gender within financial reports highlights a misalignment with objective standards. To address this, we recommend that the CMF and similar regulatory bodies take proactive steps to promote gender-neutral imagery in corporate reporting.

This could involve developing clear guidelines, actively monitoring corporate practices, and raising awareness about the importance of unbiased financial communications. Such measures would not only help Chilean companies align with international standards but also foster a more inclusive and equitable approach to financial reporting.

In the realm of corporate governance, these findings underscore the importance of rethinking how gender is portrayed in financial communications. Instead of relying on traditional stereotypes to mitigate negative perceptions during economic downturns, companies should strive for a balanced and authentic representation of all genders. This shift requires a commitment to ongoing internal audits of visual communication strategies, ensuring that reports genuinely reflect diversity and inclusion. By doing so, companies can move beyond superficial representations and contribute to dismantling the entrenched gender biases that persist in corporate culture.

Moreover, regulatory bodies like the IASB should consider implementing stricter guidelines to ensure neutrality and fairness in non-financial information. This would not only enhance the credibility and transparency of financial reports but also challenge companies to rethink their visual strategies in ways that better reflect modern societal values. Such guidelines could mandate that companies provide more balanced gender representation, avoiding the use of stereotypical imagery as a tool for impression management, especially during times of economic uncertainty.

The insights from our findings point to an urgent need for reforms in corporate governance practices. By embracing gender neutrality in financial reporting and challenging the use of stereotypical imagery, companies can lead the way in fostering a more inclusive business environment. This not only enhances the credibility of financial reports but also aligns corporate practices with the evolving expectations of stakeholders and society at large.

7. Conclusion

Our analysis offers a comprehensive perspective on the factors influencing the portrayal of women in financial reports, emphasizing the persistence of gender stereotypes within corporate communications. The findings reveal notable yet limited diversity in gender representation, with women constituting a minority in facial images. The emotion of happiness is the most frequently depicted, while negative emotions such as sadness and anger also appear, reflecting a broad emotional range.

The study uncovers a complex interaction among sentiments, age, and external economic factors in the inclusion of women's images. Financial reports that feature positive sentiments and younger individuals tend to display more images of women, whereas neutral or negative sentiments correlate with fewer female representations. Additionally, our findings demonstrate a reinforcing effect between youthfulness and positive sentiments, indicating that portrayals of youth and positive emotions work together to enhance the visibility of women.

The analysis also reveals that periods of economic boom and stability correspond with a decrease in the presence of women and an increase in the presence of men, while times of economic instability see an increase in women's images. Moreover, a positive correlation exists between financial inclusion of women and their representation in financial report images, suggesting that broader societal changes influence corporate practices.

Importantly, the study finds no significant relationship between a company's financial performance and the inclusion of women in financial report images. Instead, the selection of women's images appears to be driven more by firm characteristics—such as size, tangibility—external economic conditions, and societal stereotypes, rather than by intentional efforts to influence stakeholder perceptions related to current financial performance.

In summary, this research underscores the complexity of gender representation in financial reports, where sentiments, age, economic factors, and financial inclusion all play critical roles. These findings deepen our understanding of the forces shaping gender diversity in corporate communications and suggest that images of women are often aligned with prevailing societal stereotypes rather than objective representations of corporate performance.

7.1. Future research directions

Future research could revisit the hypothesis concerning the use of women's images for impression management in relation to a company's financial performance, particularly in different countries and contexts. Expanding the scope to include other types of financial reports, such as sustainability, would also provide a broader understanding of how gender representation is utilized across various corporate communications.

To address the limitations identified in this study, future work could focus on refining the models, incorporating more diverse training data, using multi-class gender models, and applying domain-specific adjustments. Enhancing image preprocessing techniques and integrating manual validation steps could help to mitigate existing biases and improve the accuracy of findings.

Additionally, exploring other attributes of images, such as race and facial width-to-height ratio (FWHR), and their intersections with gender, age and sentiments, would offer a more nuanced perspective on human representation in financial reports. It would also be valuable to contrast insights from aspect-based sentiment analysis with ESG performance, national institutional contexts, and board diversity. These directions could significantly advance the understanding of how visual elements in corporate communications reflect and shape broader societal and organizational dynamics.

CRediT authorship contribution statement

Fabiola Jeldes-Delgado: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tiago Alves Ferreira:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Investigation, Formal analysis, Data curation. **David Diaz:** Visualization, Validation, Software, Methodology, Investigation, Data curation. **Rodrigo Ortiz:** Writing – original draft, Validation, Methodology, Investigation.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Section A1

In this section we provide detailed explanation for the process of obtaining the PDF dataset.

PDF Dataset Collection:

The dataset of financial reports was obtained by web scraping annual reports from the Financial Markets Commission (CMF) website. The process involved navigating to each company's page and locating the "Memoria Anual" tab to download the PDFs. Below is a pseudo-code that outlines this process:

Pseudo-Code for Finding and Downloading PDFs.

1. Navigate to the CMF Website:
   - URL: [CMF Chile - Memorias Anuales](https://www.cmfchile.cl/portal/principal/613/w3-propertyvalue-18591.html)
2. Select a Company:
   - Manually click on a company name to navigate to its specific page.
3. Locate the "Memoria Anual" Tab:
   - On the company's page, find and click the "Memoria Anual" tab.

4. Download the PDF:
   - Download the available PDF(s) for each year from 2004 to 2020.
5. Repeat for Each Company:
   - Iterate over each company listed on the CMF website.

Section A2

In this section we provide detailed python pseudo-code for extracting and analyzing the images from the Pdf financial reports. Pseudo-Code for Image Analysis.

1. Initialize the Deep Learning Models:
   - Import necessary libraries: 'deepface', 'pandas', 'pathlib', 'fitz', 'os', 'retinaface'.
   - Define backends for face detection: 'opencv', 'ssd', 'dlib', 'mtcnn', 'retinaface', 'mediapipe'.
2. Read PDF Files:
   - Recursively search for all PDF files in the specified directory.
   - Store the file paths in a list.
3. Extract Faces from Each PDF:
   - For each PDF file:
   - Open the file using 'fitz'.
   - For each page in the PDF:
   - Convert the page to an image (′pixmap').
   - Save the image temporarily.
   - Detect faces in the image using 'RetinaFace'.
   - For each detected face:
   - Analyze the face using 'DeepFace' for age, gender, and emotion.
   - Store the results in a DataFrame.
   - Append metadata (file name, page number, face number) to the DataFrame.
   - Save results to an Excel file.
4. Handle Exceptions:
   - Track and log any files that could not be processed.
5. Output:
   - Save the final DataFrame with all the results to an Excel file (′df_final_part2.xlsx').

Detailed Parameter Settings.

- Face Detection: 'RetinaFace.extract_faces(.)′ with 'align = True' to ensure faces are properly aligned.
- DeepFace Analysis: Analyze actions ′['age', 'gender', 'race', 'emotion']′ using 'enforce_detection = False' and 'detector_backend = 'retinaface'′.
- Output Files: Results are saved in 'df_final_part2.xlsx', and any unprocessed files are logged in 'no_procesados.xlsx'.

Table 1 A
All regressions are estimated independently and include industry fixed effects. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Neutrality	−0.099	−0.019												
	(0.064)	(0.077)												
Happiness			0.183***	0.102*										
			(0.035)	(0.052)										
Sadness					−0.144***	−0.100								
					(0.052)	(0.062)								
Angryness							−0.255**	−0.221						
							(0.123)	(0.277)						
Surprise									0.671**	0.793**				
									(0.289)	(0.385)				
Fear											−0.176***	−0.104		
											(0.051)	(0.108)		
Disgustness													−0.665	−0.847**
													(0.771)	(0.356)
Market-to-book		0.618		0.910		0.599		0.510		0.575		0.740		0.580
		(0.716)		(0.675)		(0.686)		(0.709)		(0.695)		(0.686)		(0.695)
Tangibility	0.823	0.311	1.458	0.656	0.837	1.265	0.899	−0.046	0.912	0.705	0.352	0.725	0.460	0.273
	(2.354)	(3.993)	(2.278)	(3.975)	(2.274)	(3.805)	(2.463)	(3.734)	(2.340)	(3.810)	(2.326)	(3.888)	(2.319)	(3.848)
Size	1.007**	1.897***	0.901**	1.714***	1.144**	1.896***	1.122**	1.873***	1.127**	1.973***	1.019**	1.831***	1.097**	1.897***
	(0.475)	(0.534)	(0.452)	(0.543)	(0.472)	(0.536)	(0.462)	(0.515)	(0.472)	(0.527)	(0.469)	(0.528)	(0.473)	(0.525)
GDP Growth	−1.902	0.501	−1.961	0.014	−1.803	0.411	−1.708	0.376	−1.682	0.491	−1.734	0.356	−1.870	0.353
	(1.261)	(1.895)	(1.281)	(1.917)	(1.255)	(1.865)	(1.315)	(1.961)	(1.202)	(1.908)	(1.238)	(1.920)	(1.291)	(1.955)
EPU*	−0.092*	−0.013	−0.087	−0.026	−0.095*	−0.020	−0.086	−0.011	−0.090*	−0.015	−0.091*	−0.018	−0.097*	−0.020
	(0.050)	(0.076)	(0.053)	(0.077)	(0.052)	(0.075)	(0.053)	(0.076)	(0.048)	(0.077)	(0.051)	(0.077)	(0.052)	(0.079)
Proportion of Women Checking Account Balances	−362.314	323.517	−376.609	169.210	−267.821	326.171	−285.558	251.431	−270.553	295.071	−261.679	291.508	−310.142	286.751
	(437.257)	(651.738)	(429.287)	(651.333)	(422.685)	(644.937)	(448.801)	(683.616)	(413.537)	(656.375)	(419.236)	(663.857)	(438.285)	(670.221)
Proportion of Entrepreneur Women	277.201	−312.860	264.941	−226.175	203.161	−324.899	232.300	−256.295	222.010	−282.666	193.643	−298.721	239.704	−291.577
	(310.874)	(476.245)	(293.164)	(471.431)	(293.117)	(468.877)	(317.482)	(502.106)	(294.340)	(480.000)	(292.657)	(480.796)	(307.510)	(487.782)
Observations	965	496	965	496	965	496	965	496	965	496	965	496	965	496
R2	0.127	0.222	0.157	0.232	0.130	0.227	0.134	0.230	0.129	0.233	0.129	0.224	0.122	0.223
Adjusted R2	0.105	0.185	0.135	0.195	0.108	0.189	0.112	0.192	0.107	0.196	0.107	0.187	0.100	0.185
Year fixed effects	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1B

All regressions are estimated independently and include industry fixed effects. Dependent variable is Women Presence. GDP-EPU-PCA is the first principal component of GDP growth and negative Economic Policy Uncertainty (EPU). Women-PCA is the first principal component of the proportion of women's checking account balances and the proportion of women entrepreneurs. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Neutrality	−0.100	−0.021												
	(0.064)	(0.077)												
Happiness			0.183***	0.102*										
			(0.035)	(0.052)										
Sadness					−0.142***	−0.097								
					(0.051)	(0.062)								
Angryness							−0.258**	−0.225						
							(0.123)	(0.276)						
Surprise									0.678**	0.800**				
									(0.291)	(0.385)				
Fear											−0.176***	−0.103		
											(0.051)	(0.108)		
Disgustness													−0.568	−0.826**
													(0.754)	(0.338)
Market-to-book		0.604		0.878		0.573		0.493		0.559		0.714		0.556
		(0.684)		(0.634)		(0.653)		(0.677)		(0.664)		(0.649)		(0.660)
Tangibility	0.841	0.186	1472	0.558	0.837	1119	0.913	−0.146	0.924	0.608	0.356	0.609	0.477	0.166
	−2358	−3985	−2282	−3974	−2282	−3794	−2466	−3753	−2346	−3800	−2335	−3882	−2327	−3845
Size	1.018**	1.900***	0.913**	1.721***	1.156**	1.902***	1.134**	1.876***	1.140**	1.978***	1.031**	1.837***	1.111**	1.903***
	(0.475)	(0.536)	(0.451)	(0.547)	(0.472)	(0.538)	(0.462)	(0.517)	(0.472)	(0.529)	(0.469)	(0.531)	(0.473)	(0.528)
Women-PCA	0.478	−0.209	0.342	−0.332	0.521*	−0.216	0.544*	−0.228	0.566*	−0.177	0.470	−0.236	0.537*	−0.213
	(0.292)	(0.459)	(0.286)	(0.434)	(0.290)	(0.444)	(0.308)	(0.447)	(0.286)	(0.454)	(0.287)	(0.456)	(0.297)	(0.458)
GDP-EPU-PCA	−0.312	−0.111	−0.617	−0.335	−0.419	−0.170	−0.302	−0.131	−0.185	0.077	−0.417	−0.207	−0.306	−0.114
	(0.424)	(0.749)	(0.387)	(0.737)	(0.411)	(0.741)	(0.421)	(0.755)	(0.417)	(0.750)	(0.403)	(0.755)	(0.427)	(0.751)
Observations	965,000	496,000	965,000	496,000	965,000	496,000	965,000	496,000	965,000	496,000	965,000	496,000	965,000	496,000
R2	0.126	0.222	0.155	0.231	0.128	0.226	0.133	0.229	0.127	0.232	0.127	0.223	0.120	0.222
Adjusted R2	0.105	0.187	0.136	0.197	0.108	0.191	0.112	0.195	0.107	0.198	0.107	0.189	0.100	0.188
Year fixed effects	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2 A
All regressions are estimated independently and include industry fixed effects. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)
Age	1.487***	1.434***
	(0.187)	(0.231)
Market-to-book		0.219
		(0.674)
Tangibility	1.708	1.370
	(2.518)	(4.084)
Size	0.899*	2.061***
	(0.469)	(0.521)
GDP Growth	−0.648	1.531
	(1.248)	(1.954)
EPU*	−0.044	0.044
	(0.050)	(0.076)
Proportion of Women Checking Account Balances	−17.969	530.406
	(425.348)	(677.044)
Proportion of Entrepreneur Women	107.546	−365.070
	(303.523)	(512.004)
Observations	965	496
R2	0.212	0.307
Adjusted R2	0.192	0.274
Firm-level controls	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes

Table 2 B
All regressions are estimated independently and include industry fixed effects. Dependent variable is Women Presence. GDP-EPU-PCA is the first principal component of GDP growth and negative Economic Policy Uncertainty (EPU). Women-PCA is the first principal component of the proportion of women's checking account balances and the proportion of women entrepreneurs. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)
Age	1.494***	1.430***
	(0.186)	(0.227)
Market-to-book		0.261
		(0.642)
Tangibility	1718	1299
	−2517	−4075
Size	0.904*	2.055***
	(0.469)	(0.519)
Women-PCA	0.786***	0.092
	(0.297)	(0.459)
GDP-EPU-PCA	0.136	0.173
	(0.391)	(0.701)
Observations	965	496
R2	0.212	0.307
Adjusted R2	0.193	0.276
Firm-level controls	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes

Table 3 A
All regressions are estimated independently and include industry fixed effects. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Youth # Neutrality	−0.010	−0.001												
	(0.007)	(0.010)												
Youth # Happiness			0.027***	0.013										
			(0.006)	(0.008)										
Youth # Sadness					−0.027***	−0.019**								
					(0.008)	(0.009)								
Youth # Angryness							−0.001	0.013						
							(0.029)	(0.039)						
Youth # Surprise									0.074	0.174**				
									(0.069)	(0.071)				
Youth # Fear											−0.026***	−0.008		
											(0.009)	(0.012)		
Youth # Disgustness													−0.542	−0.746**
													(0.433)	(0.303)
Observations	965	496	965	496	965	496	965	496	965	496	965	496	965	496
R2	0.215	0.307	0.291	0.346	0.248	0.334	0.226	0.320	0.219	0.326	0.238	0.319	0.214	0.309
Adjusted R2	0.193	0.271	0.271	0.311	0.228	0.298	0.205	0.284	0.197	0.290	0.217	0.283	0.192	0.273
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3 B

All regressions are estimated independently and include industry fixed effects. Dependent variable is Women Presence. This table includes as aditional controls: GDP-EPU-PCA, which is the first principal component of GDP growth and negative Economic Policy Uncertainty (EPU), and Women-PCA, which is the first principal component of the proportion of women's checking account balances and the proportion of women entrepreneurs. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Youth # Neutrality	−0.010	−0.000												
	(0.007)	(0.010)												
Youth # Happiness			0.027***	0.013										
			(0.006)	(0.008)										
Youth # Sadness					−0.026***	−0.019**								
					(0.008)	(0.009)								
Youth # Angryness							−0.001	0.013						
							(0.029)	(0.039)						
Youth # Surprise									0.073	0.175**				
									(0.069)	(0.071)				
Youth # Fear											−0.026***	−0.007		
											(0.009)	(0.012)		
Youth # Disgustness													−0.537	−0.749**
													(0.432)	(0.297)
Observations	965	496	965	496	965	496	965	496	965	496	965	496	965	496
R2	0.215	0.307	0.291	0.345	0.248	0.333	0.226	0.320	0.219	0.325	0.237	0.318	0.214	0.309
Adjusted R2	0.195	0.273	0.272	0.313	0.229	0.301	0.206	0.287	0.199	0.293	0.218	0.285	0.194	0.275
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4 A

All regressions are estimated independently and include industry fixed effects. Dependent variable is Women Presence. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tangibility	0.520	0.665	0.720	0.354	0.376	0.428	0.362	0.286	0.958	0.879
	(2.352)	(2.386)	(2.437)	(2.410)	(2.438)	(3.832)	(3.836)	(3.867)	(3.818)	(3.823)
Size	1.101**	1.116**	1.118**	1.110**	1.109**	1.911***	1.900***	1.898***	1.954***	1.955***
	(0.473)	(0.476)	(0.476)	(0.472)	(0.472)	(0.528)	(0.534)	(0.536)	(0.526)	(0.529)
ROA		0.070	0.060	0.067	0.065		−0.078	−0.064	−0.156	−0.153
		(0.094)	(0.097)	(0.110)	(0.110)		(0.156)	(0.155)	(0.175)	(0.175)
Loss			−0.467		−0.632			0.498		1.703
			(1.333)		(1.600)			(1.581)		(1.900)
Delta Earnings				0.008	−0.025				0.138	0.225
				(0.140)	(0.163)				(0.185)	(0.215)
Market-to-book						0.583	0.797	0.758	0.918	0.936
						(0.694)	(0.667)	(0.681)	(0.723)	(0.726)
GDP Growth	−1.787	−1.881	−1.900	−2.168*	−2.176*	0.527	0.594	0.618	0.321	0.317
	(1.257)	(1.264)	(1.263)	(1.229)	(1.227)	(1.899)	(1.900)	(1.922)	(1.870)	(1.874)
EPU*	−0.093*	−0.098*	−0.098*	−0.109**	−0.109**	−0.013	−0.010	−0.010	−0.025	−0.027
	(0.051)	(0.051)	(0.051)	(0.048)	(0.047)	(0.076)	(0.076)	(0.076)	(0.071)	(0.071)
Proportion of Women Checking Account Balances	−289.356	−308.095	−313.974	−393.238	−394.503	336.804	349.231	354.436	290.504	283.704
	(430.544)	(430.227)	(431.022)	(428.510)	(428.150)	(657.204)	(656.608)	(661.715)	(656.527)	(656.259)
Proportion of Entrepreneur Women	226.709	239.800	243.963	295.758	296.174	−321.603	−331.209	−336.343	−297.444	−294.787
	(304.217)	(303.993)	(305.194)	(309.055)	(308.907)	(480.823)	(479.609)	(484.697)	(489.817)	(490.133)
Observations	965	965	965	944	944	496	496	496	493	493
R2	0.122	0.122	0.122	0.119	0.119	0.222	0.223	0.223	0.216	0.217
Adjusted R2	0.100	0.100	0.099	0.095	0.094	0.186	0.185	0.183	0.176	0.175
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4 B

All regressions are estimated independently and include industry fixed effects. Dependent variable is Women Presence. GDP-EPU-PCA is the first principal component of GDP growth and negative Economic Policy Uncertainty (EPU). Women-PCA is the first principal component of the proportion of women's checking account balances and the proportion of women entrepreneurs. All errors are clustered at the industry-year level. Robust standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tangibility	0.527	0.642	0.696	0.338	0.361	0.315	0.247	0.175	0.855	0.777
	−2358	−2393	−2441	−2412	−2440	−3827	−3829	−3861	−3807	−3814
Size	1.114**	1.126**	1.128**	1.122**	1.121**	1.916***	1.903***	1.902***	1.959***	1.959***
	(0.473)	(0.476)	(0.476)	(0.472)	(0.472)	(0.530)	(0.536)	(0.537)	(0.527)	(0.531)
ROA		0.055	0.045	0.052	0.051		−0.080	−0.067	−0.162	−0.160
		(0.094)	(0.096)	(0.109)	(0.109)		(0.155)	(0.155)	(0.173)	(0.173)
Loss			−0.455		−0.640			0.471		1691
			−1319		−1585			−1571		−1905
Delta Earnings				0.005	−0.027				0.143	0.229
				(0.137)	(0.160)				(0.182)	(0.213)
Market-to-book						0.565	0.789	0.752	0.908	0.924
						(0.661)	(0.645)	(0.657)	(0.692)	(0.695)
Women-PCA	0.535*	0.548*	0.546*	0.537*	0.533*	−0.197	−0.212	−0.220	−0.202	−0.212
	(0.295)	(0.299)	(0.299)	(0.302)	(0.302)	(0.453)	(0.457)	(0.462)	(0.466)	(0.466)
GDP-EPU-PCA	−0.304	−0.322	−0.343	−0.330	−0.360	−0.106	−0.069	−0.041	−0.086	−0.003
	(0.425)	(0.430)	(0.420)	(0.430)	(0.423)	(0.750)	(0.766)	(0.759)	(0.757)	(0.757)
Observations	965	965	965	944	944	496	496	496	493	493
R2	0.120	0.120	0.120	0.117	0.117	0.221	0.222	0.222	0.215	0.216
Adjusted R2	0.100	0.100	0.099	0.094	0.094	0.189	0.187	0.186	0.178	0.177
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No	No	No	No	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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