Deep Speech Embeddings of Earning Calls Predict Future Stock Returns

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Abstract

When CEOs report on the status of their company, it is not only important what they say but also *how* they say it. The tone of a CEO's voice may reflect certainty or uncertainty, optimism or pessimism, and many other social signals. Current AI methods for speech representation can pick up subtle vocal cues related to a CEO's tone of voice. These methods translate an audio file into a numerical representation, called an *embedding*. In this paper we conduct an empirical study to determine to what extent state-of-the-art deep speech representations of Quarterly Earnings Calls contain cues that reveal the future economic status of S&P 500 companies. We rely on high-dimensional embeddings consisting of 1024 numbers and on low-dimensional embeddings consisting of three numbers. The latter are interpretable and represent three measures of vocal expression: *arousal*, the intensity of the vocal expression, *dominance*, the degree of exerted control by the vocal expression, and *valence*, the degree of pleasantness of the vocal expression.

We collected 734 recordings of the introduction sessions (typically scripted) and Q&A sessions (unscripted) from the earnings calls, along with the associated future stock returns. Using high- and low-dimensional speech embeddings from the state-of-the-art TRILLsson and W2V2 models, we trained a simple linear classifier for a binary classification task to predict stock return increases or decreases after *d* days. Our results indicate that the W2V2 embeddings of CEO speeches produce future return predictions with an average success rate exceeding the chance level of 54% to 59%. No predictions of this kind were obtained for the TRILLsson embeddings. Only low-dimensional embeddings for the introduction sessions resulted in successful predictions, while both low- and high-dimensional embeddings were effective for the Q&A sessions. The low-dimensional Q&A embeddings enable us to understand how the three emotional dimensions contribute to predicting an increase in stock returns. We found that *arousal* and *dominance* have a positive contribution, while *valence* has a negative contribution to predicting a return increase.

Our results show that: (i) W2V2 embeddings combined with a linear classifier can extract subtle vocal cues from CEO QECs to predict their company's future economic state, (ii) the explicit (interpretable) low-dimensional W2V2 embeddings are effective for achieving above-chance level predictions specifically for the Q&A sessions, and (iii) the TRILLsson embeddings do not succeed in the prediction task. We conclude that W2V2 models can capture subtle vocal cues useful for various tasks involving human speech data. We also examine a model that includes macroeconomic variables such as S&P 500 index levels and inflation rates to determine if vocal embeddings offer any additional return predictive power beyond existing predictive models. The macroeconomic model alone achieves average prediction accuracies ranging from 57.9% to 80.5%, and the addition of low-dimensional vocal embeddings does not result in any significant improvement. In contrast, incorporating high-dimen-

sional vocal embeddings into the macroeconomic model improves the prediction of future stock return directions by about 1.3% to 3.4%. These findings indicate that the predictive capability of vocal sentiment, best captured through high-dimensional representations, is closely tied to underlying macroeconomic conditions.

Samenvatting

Wanneer CEO's verslag uitbrengen over de status van hun bedrijf is het belangrijk wat ze zeggen, maar ook hoe ze het zeggen. De stem van de CEO kan zekerheid of onzekerheid, optimisme of pessimisme en vele andere sociale signalen weerspiegelen. AI-modellen voor spraakrepresentatie, zoals zoals TRILLsson en W2V2, kunnen subtiele spraaksignalen oppikken die gerelateerd kunnen zijn aan de toon van de stem van de CEO. We voeren een empirisch onderzoek uit om te bepalen in hoeverre geavanceerde spraakrepresentaties van kwartaalcijfergesprekken aanwijzingen bevatten die de toekomstige economische status van SP 500-bedrijven onthullen. De AI-modellen vertalen een audiobestand in een hoog-dimensionale of laagdimensionale getalsrepresentatie, een zogenaamde embedding. We maken gebruik van hoog-dimensionale embeddings bestaande uit 1024 getallen en laag-dimensionale embeddings bestaande uit 3 getallen. De laatstgenoemde is interpreteerbaar en vertegenwoordigt drie maten van vocale expressie: arousal (de intensiteit van de vocale expressie), dominantie (de mate van uitgeoefende controle door de stem) en valentie (de mate van aangenaamheid van de vocale expressie).

Het empiriche onderzoek is uitgevoerd met een dataset van 734 audio opnames van de besprekingen van de kwartaalrapportages (Quarterly Earning Calls) van S&P 500 bedrijven. De opnames omvatten de introductiesessies (meestal gescript) en Q&A sessies (ongescript) van de QECs. Met behulp van de AI embeddings trainen we een eenvoudig lineair classificatiealgoritme op de binaire taak om de stijging of daling te voorspellen van de aandelenrendementen na *d* dagen.

Onze resultaten laten zien dat de W2V2 embeddings van de CEO toespraken toekomstige rendementsvoorspellingen opleveren tussen 54% en 59%. Voor de TRILLsson embeddings is dat niet het geval. Voor de introductiesessies leidden enkel de hoogdimensionale embeddings tot succesvolle voorspellingen, terwijl voor de Q&A sessies zowel de laag- als hoogdimensionale embeddings succesvol zijn. De laag-dimensionale embeddings stellen ons in staat om te interpreteren hoe de drie emotionele dimensies bijdragen aan de voorspelling van een stijging van het aandelenrendement. We vinden dat de dimensies *arousal* en *dominance* positief bijdragen, en *valence* negatief bijdraagt aan de voorspelling van een stijging van het rendement. Onze resultaten laten zien dat: (i) W2V2 embeddings in combinatie met een lineair classificatiealgoritme subtiele vocale signalen kunnen onttrekken aan de spraak van CEOs om de toekomstige economische staat van hun bedrijf te voorspellen, (ii) de expliciete interpreteerbare W2V2 laag-dimensionale embeddings alleen geschikt zijn om voorspellingen te doen boven het kansniveau voor de Q&A sessies, en (iii) de TRILLsson embeddings niet succesvol zijn in de voorspellingstaak. We concluderen dat W2V2-modellen in staat zijn om subtiele vocale aanwijzingen te extraheren die van nut kunnen zijn voor veel taken waarbij menselijke spraakgegevens worden gebruikt.

We hebben ook een model met alleen macro-economische variabelen zoals SP 500-indexniveaus en inflatiepercentages gebruikt om te onderzoeken of vocale embeddings extra voorspellende waarde hebben. Het macro-economische model behaalt gemiddelde voorspellingsnauwkeurigheden tussen 57.9% en 80.5% en het toevoegen van laag-dimensionale vocale embeddings levert geen significante verbetering op. Daarentegen verbetert het toevoegen van hoog-dimensionale vocale embeddings aan het macro-economische model de voorspelling van toekomstige richtingen van aandelenrendementen met ongeveer 1.3% tot 3.4%. Deze bevindingen suggereren dat de voorspellende kracht van vocale sentimenten het best wordt vastgelegd via hoog-dimensionale representaties en nauw verbonden is met onderliggende macro-economische omstandigheden.

1. Introduction

Every quarter, CEOs or CFOs report on their company's status during quarterly earnings conference (QEC) calls. Typically, during the introductory session of a QEC call, CEOs provide a general report on their company's status and outlook. In the following Q&A session, financial analysts and investors pose potentially challenging questions that the senior management team, including the CEOs, must address. During QEC calls, CEOs share information that may present an overly optimistic view of the company's condition. Their tone of voice, however, may provide an honest signal as to the true state of affairs [1, 2]. In this paper, we use deep-learning models to analyze CEO speeches and investigate whether they can help predict the direction of future stock returns.

The analysis of nonverbal behavior using digital signal processing methods has given rise to the field of social signal processing [3, 4]. With the emergence of advanced deep-learning techniques in AI, the digital analysis of subtle vocal patterns became possible. Several deep-learning models are now available for tasks related to speech prediction. Such models are typically pre-trained on extensive vocal datasets for various tasks, including automatic speech recognition [5] and inferring the sentiment of speech [6]. Two notable examples of such models are wav2vec [6] and TRILLsson [7]. These pre-trained models can convert audio files into numerical representations known as *embeddings*, which capture vocal features. The models vary in their neural architecture, training procedures, and the data used for pre-training. The wav2vec model was trained on audiobooks, crowd-sourced collected read-out text snippets, and (noisy) telephone speech [5]. The TRILLsson model was trained on three million hours of audio taken from "speech-heavy" YouTube videos (YT-U) [8] and 60,000 hours of audiobooks (Libri-Light) [9]. The TRILLsson model was specifically trained on paralinguistic tasks—those where meaning is conveyed not by the words and sentences themselves, but by their expression, such as tone of voice, pitch, and loudness.

In speech emotion recognition, emotional expressions are predominantly represented in two ways: categorical and dimensional. In categorical representation, emotional expressions are represented in terms of categories, such as *happy*, *sad*, or *angry* [10]. In the dimensional representation of emotional expressions, they are depicted along three dimensions: *arousal*, which refers to the intensity of the vocal expression; *dominance*, indicating the degree of control exerted by the vocal expression; and *valence*, reflecting the degree of pleasantness of the vocal expression. In this paper, we use both ways of representing emotions: the categorical representation is used to demonstrate vocal TRILLsson embeddings in Section 2, and the dimensional representation is used in our experiments with TRILLsson and a variant of the wav2vec model.

In contrast to TRILLsson, the wav2vec variant produces two embeddings: a high-dimensional embedding (1024D) and a low-dimensional embedding (3D). These enable the creation of embeddings that provide interpretable estimates of *arousal, dominance*, and *valence*.

To focus on affective expressions in speech and compare the virtues of using implicit and explicit embeddings, we use the wav2vec variant developed by Wagner *et al.* [6]. They performed additional supervised training on the wav2vec 2.0 model to tune it to affective speech tasks producing what we refer to as the W2V2 model.

As previously stated, the model produces a clear three-dimensional embedding (3D) that includes estimates for *arousal*, *dominance*, and *valence*. The model also offers high-dimensional implicit embedding (1024D) of speech, which may lead to better predictions; however, due to the high dimensions, these predictions are not easily interpretable on their own.

Embeddings can serve as input for a linear classification or regression algorithm trained on one of various vocal classification tasks. For instance, it is possible to automatically detect specific speaking styles, such as off-putting, using pre-trained speech embeddings with an accuracy of approximately 70 to 80% [11]. In most cases, the embeddings obtained from pre-training are high-dimensional and represent abstractions that are hard to interpret [5, 7].

Our considerations pose two questions regarding QECs: First, how much does a CEO's tone of voice provide insights into the company's future state? Secondly, to what extent can these cues be explained? We collected N = 734 audio recordings of QECs and extracted thin slices – short segments of a few seconds of each QEC – from the CEO audio recordings to address these questions. We also collected associated company stock returns measured at 5, 10, 20, 40, 80, and 160 days after the day of the QEC. These returns are then converted into binary labels based on whether they are positive (1) or less than or equal to 0 (0). The labels are expected to serve as a valid indicator of the company's financial condition as presented by the CEO. While the tone of voice is just one of several factors involved in the assessment, our aim is to evaluate whether there is a measurable effect on the ability to estimate return values based on the vocal characteristics of the CEO's QEC.

1.1 Related Work

Over the past 30 years, many studies have revealed the relevance of vocal cues in various contexts. In 1993, Ambady and Rosenthal [12] found that reliable evaluations of teachers could be made from so-called *thin slices* of video clips. In finance, machine learning has become an important tool for analyzing social signals (see, e.g., [13]). Hobson, Mayew, & Venkatachalam found that "vocal markers of cognitive dissonance" could be used to detect financial misreporting [14]. Price, Seiler & Shen investigated to what extent investors infer vocal cues from CEOs [15]. Qin and Yang studied risk-level prediction from speech and text in QEC calls [16]. Favaro et al. [17] used speech embeddings to assess Parkinson's disease automatically. They compared interpretable speech features (e.g., features related to the pitch, energy, or rhythm of the voice) with non-interpretable speech embeddings. In the health domain, interpretable features are crucial for diagnostic purposes. The results showed that the non-interpretable embeddings are superior to the interpretable features in assessing the disease. In summary, the relevance of nonverbal vocal cues is well established in the domain of finance and beyond.

1.2 Outline of the Paper

The outline of the remainder of the paper is as follows. We start by illustrating the nature of vocal embeddings in Section 2. Then, in Section 3 we describe our approach. Section 4 outlines the methodology of our experiments. The results of the experiments are presented in Section 5. Finally, in Sections 6 and 7 we discuss our results and present our conclusions.

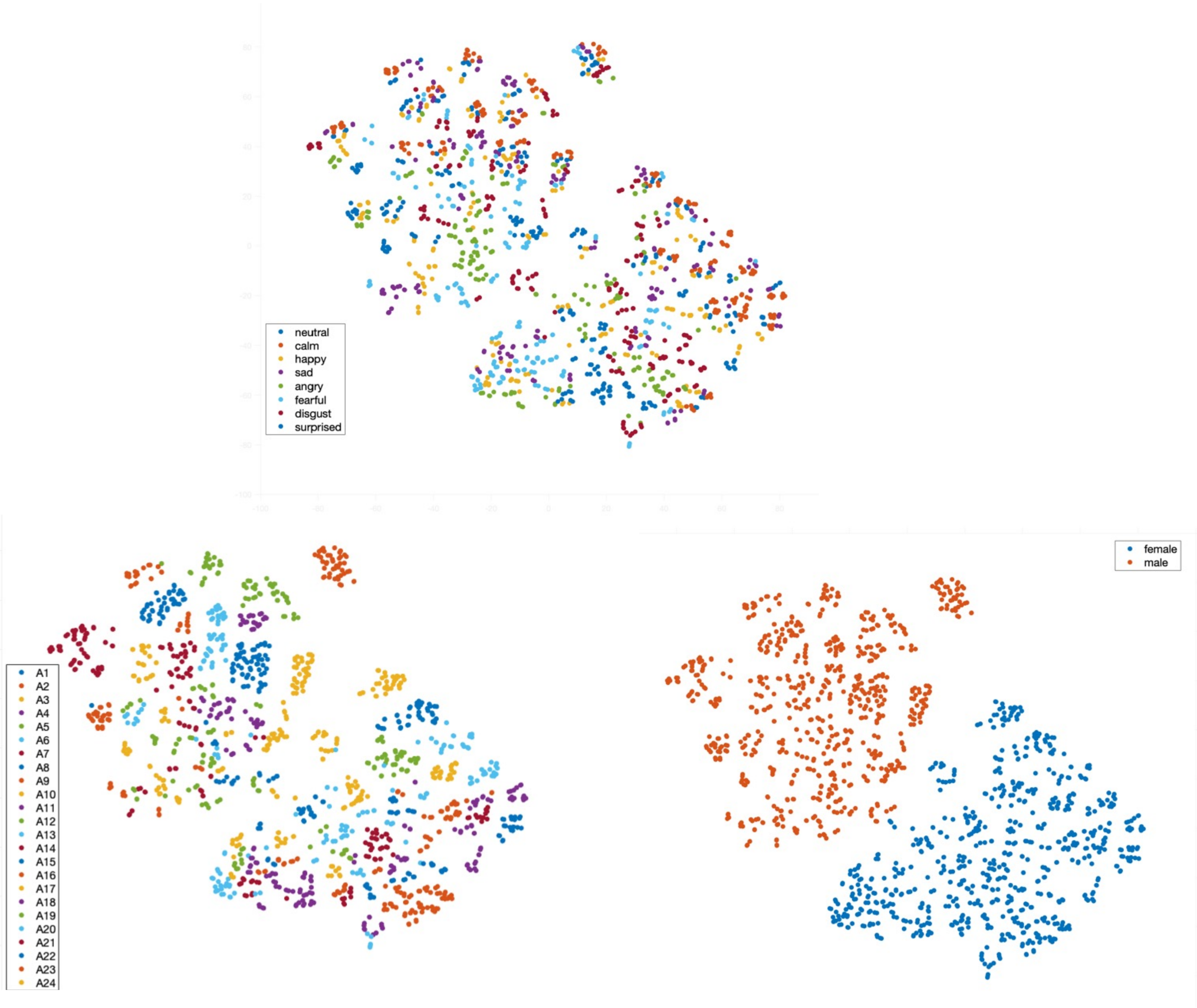
2. Deep Embeddings of Speech: An Example

Deep-learning models are currently the most powerful available machine-learning models. Provided that ample training data are available, these models can deliver the best predictions on a wide range of tasks. In cases where limited amounts of data are available, transfer learning provides an effective method to leverage the power of deep models. In transfer learning, a so-called foundation model, a deep-learning model successfully trained on a classification (or regression) task T involving a large dataset, is utilized on a related task T′ for which only a small dataset is available. In training on task T′, the deep-learning network benefits from the pre-trained foundation model's knowledge already gained on task T. Typically, in transfer learning, the entire pre-trained model is retained except for the top, constituting a classification layer that outputs the classes of task T. The output of the pre-trained model, without its classification layer, consists of a high-dimensional vector that provides a suitable representation for all kinds of tasks related to task T and is often referred to as an embedded representation or simply embedding. We provide an example to illustrate the effectiveness of such embeddings.

For this example, we use the RAVDESS dataset to generate embeddings. The RAVDESS dataset of emotional speech [18] is trained on a categorical representation of emotions. It consists of audio fragments of 24 (12 female) professional North American actors, vocalizing lexically matched statements expressed in one of seven emotional classes: calm, happy, sad, angry, fearful, surprise, and disgust. As a foundation model, we use TRILLsson [7], a deep-learning model for speech developed to create a deep representation of speech for "paralinguistic" tasks. We fed the RAVDESS audio fragments into the TRILLsson foundation model to obtain embeddings. An illustration of the nature of these embeddings is shown in Figure 1. The figure illustrates the embeddings of emotional speech in terms of two-dimensional projections using t-SNE [19]. This nonlinear dimensionality reduction method projects high-dimensional vectors on a 2D representation while preserving (to a certain extent) their relative distances.

In our case, the high-dimensional vectors are 1024D, and their low-dimensional projections are 2D to allow for visualization. In the 2D projections, each colored dot represents an embedding of an audio fragment. The distance between dots (embeddings) is roughly proportional to their dissimilarity in terms of vocal characteristics. The three scatter plots are identical; only the colored labels are different. The top plot is labeled according to the seven emotions expressed by the RAVDESS actors. Although some degree of clustering is visible, the class separation is not strong. The middle plot is labeled according to the actor who vocalized the emotions. The TRILLsson mappings cluster utterances by the same actor. The labels in the bottom plot represent gender. The TRILLsson embeddings for male and female actors show an almost perfect separation. Presumably, the difference in average

Figure 1: Visualizations of t-SNE mappings of the TRILLsson embeddings of the RAVDESS dataset. The three mappings are identical but labeled according to emotion (top), actor (middle), and sex (bottom). The embeddings reveal the actor, especially his or her gender, more prominently than emotion.

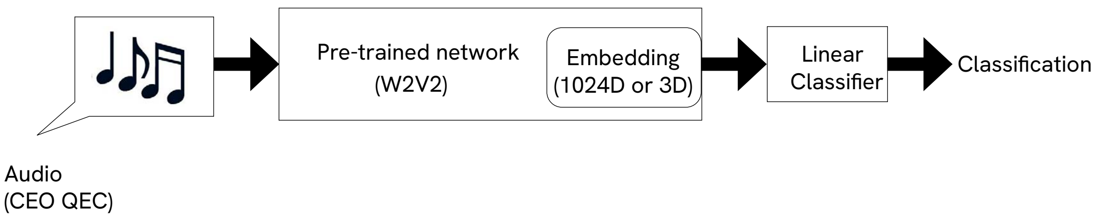


pitch in males and females is responsible for the separation. As the figure illustrates, the TRILLsson embeddings contain information about emotions, actor identity, and actor gender. Automatic recognition of emotions, identity, or gender from the TRILLsson embeddings can be done by training a machine-learning algorithm on the embeddings. More importantly pre-trained deep-learning models such as TRILLsson can capture subtle vocal characteristics that can be used in any task to detect affective states from speech.

3. Our Approach

Since our dataset of CEO speeches is relatively small (for a description of the data, we refer to the next section), we rely on transfer learning by utilizing two of the currently best pre-trained models for speech representation: the W2V2 model and the TRILLsson model. In line with standard practice in transfer learning, the pre-trained model remains frozen, while one or more dense layers are trained on a new task. A single dense layer is often sufficient to represent a linear classifier or a linear regression layer. In principle, the pre-trained model can also be fine-tuned for the new task, potentially yielding modest performance improvements (see, e.g. [6]). In this paper, we avoid fine-tuning the pre-trained network and instead use the W2V2 embeddings as inputs to train a support vector machine (SVM) classifier. Figure 2 illustrates our approach. The box on the left represents the audio input, which is an audio file containing a fragment (i.e., a "thin slice") of a company's QEC . The audio signal is processed by a pre-trained network, either W2V2 or TRILLsson, yielding a 1024D embedding and, for W2V2, an additional 3D embedding. Either embedding provides the input for a linear binary classifier that predicts the company's future state. The classifier is trained in a supervised manner using a large set of embeddings and evaluated on embeddings that were not included in the training, i.e., out-of-sample testing.

Figure 2: Illustration of our approach. Audio fragments of the CEO's Quarterly Earnings Calls are processed by a pre-trained network (W2V2 or TRILLsson) to obtain two embeddings: a high-dimensional (1024D) embedding and (for W2V2) a low-dimensional (3D) embedding. A linear binary classifier is trained to map either embedding onto a change in stock returns: increase (1) vs no increase (0), *d* days after the date of the QEC.



4. Methodology

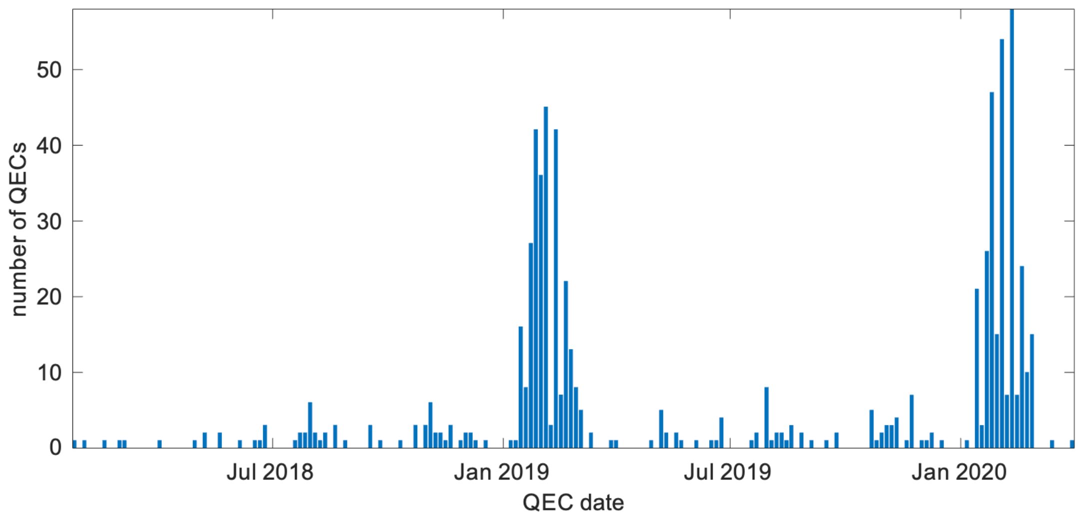
The methodology employed involves the preparation of the data, the training procedure, and the evaluation procedure. These are described in the following sub- sections.

4.1 Data

Our dataset contains 734 recordings of annual report editions of Quarterly Earnings Calls held by CEOs (including 39 female CEOs) of S&P 500 companies (see the Appendix). These data were obtained from LSEG, previously known as Refinitiv.[1] We extracted the first four-second segments of the introduction session of each call and the first ten-second segments of the Q&A session. CEOs typically make statements in the introductory segments such as: *"Thank you Bruce. Good morning everyone and thank you for joining us."* (Michael Roman, 3M, 29-01-2019) and *"Thank you Laura and good afternoon to all listening in today."* (Lisa Su, AMD, 28-01-2020). While these verbal statements do not indicate anything about the company's state, the tone of voice and other vocal characteristics may provide relevant cues for our prediction task. Inthe Q&A sessions, the verbal information may be more pertinent to the company's future direction because, the CEO can address critical questions about the company within the first 10 seconds.

Using the W2V2 and TRILLsson models, we generated N_{intro} = 734 pairs of 1024D and 3D (for W2V2) embeddings for the introduction sessions, and $N_{Q\&A}$ = 654 pairs for the Q&A sessions. Using a Python script and Yahoo Finance, we obtained the labels for our classification task, i.e., the closing stock prices of each of the companies included in the dataset

Figure 3: Histogram illustrating the dates of the QECs included in the experiment. The four dates represent the first day of each month.



1 https://www.lseg.com/en/data-analytics

Table 1: Specification of the labeled embeddings in our dataset for the four-second fragments of the introductory sessions.

Days after QEC d	Negative instances (0) $V_d \leq V_{QEC}$	Positive instances (+) $V_d > V_{QEC}$	Total instances *N*
5	312	402	714
10	313	401	714
20	367	347	714
40	394	320	714
80	395	319	714
160	327	387	714

Table 2: Specification of the labeled embeddings in our dataset for the 10-second segments of the Q&A sessions.

Days after QEC d	Negative instances (0) $V_d \leq V_{QEC}$	Positive instances (+) $V_d > V_{QEC}$	Total instances *N*
5	282	372	654
10	283	371	654
20	327	327	654
40	349	305	654
80	353	301	654
160	293	361	654

at d days after the date of the QEC, with $d \in \{5, 10, 20, 40, 80, 160\}$[2]. Next, we calculated the *daily* (log) returns. Stock return data were available for all companies except 20, which were excluded due to corporate events like mergers and acquisitions, resulting in a final dataset of 714 valid observations. Figure 3 illustrates the dates of the QECs. The histogram shows that the dates span from early 2018 to midway through 2020. Most QECs occurred in February and March of 2019 and 2020. The Appendix contains a comprehensive list of the companies, CEOs, and dates of the QECs.

We prepared binary labels for classification based on the comparison of the stock value on the day (closing price) of the QEC[3], $V_{QEC} = V_0$ and the future value V_d with $d \in \{5, 10, 20, 40, 80, 160\}$. Each binary label was defined by $H(V_d - V_0)$, where $H()$ represents the Heaviside step function and $H(0) = 0$.

Table 1 displays the number of embeddings for each label, specifically the negative and positive returns of the stocks for each of the future days examined. All recordings from the introduction section were truncated to four seconds, creating a thin slice that ensures that the verbal contents are similar across the QECs (i.e., welcoming words). Table 2 presents the same information for the Q&A session. All Q&A recordings are limited to 10 seconds to ensure that some non-scripted interactions are captured.

2 The prediction results for d ∈ 1, 2, 3, 4, 5 are quite similar. As our focus is not on real-time post-QEC predictions, we only report d = 5 to simplify the representation of short-term outcomes.

3 Experiments showed that choosing the day before or after the QEC (V_{-1} or V_1) did not influence the pattern of results.

4.2 Training Predictive Models

All embeddings were generated using Python scripts to read the audio files and save the embeddings. The embeddings were generated using Tensorflow and Keras. We trained linear (SVM) classifiers on the embeddings and associated binary labels.

All classification experiments were conducted in Matlab R2023a using the *fitclinear (X,Y,'Learner','svm')* function, which implements the linear SVM classifier without optimizing parameters. As shown in Table 1, the positive and negative classes are unbalanced. We decided to randomly under-sample the majority class to achieve an equal number of positively and negatively labeled instances. According to Table 1, when $d = 5$, this involves selecting a random subsample of size 312 from the majority class (positive instances) to balance the positive and negative instances. Random undersampling is a common technique for dealing with imbalanced classes but it may discard instances from the majority class that are crucial for the prediction task. To mitigate this risk, we utilize an comprehensive variant of *EasyEnsemble* [20, 21], where we repeat each experiment 100 times, using a different random subsample of the majority class each time. The impact of the various repetitions will be evident through the standard deviations (SDs) and box plots presented in the results below.

In each experiment, we trained the SVM classifier using the balanced dataset. Additionally, we conducted a control experiment using the same instances but with randomly permuted labels to identify any hidden biases in the data or training algorithm. These would manifest as a noticeable deviation from the chance level in the predictions of classifiers trained on the permuted label data.

4.3 Evaluation

The SVM classifier was trained using a leave-two-out cross-validation scheme. In each fold, with M instances, the classifier was trained on $M - 2$ instances and tested on the remaining single pair of positive and negative instances. The cross-validation consists of $M/2$ folds, each containing a unique pair of test instances. The prediction accuracy is defined as the total number of correct predictions across folds divided by M.

We assessed the prediction results for various values of d by comparing them to the chance level performance of 50%, which will be verified to align with the classifier's performance when trained with randomly permuted labels.

5. Empirical Results

5.1 Voice Only Embeddings

Table 3 lists the main results of our experiment. For each value of *d* (row), the table displays the mean prediction accuracies (averaged over 100 replications) and standard deviations (in parentheses) for the W2V2 and TRILLsson embeddings. The results for high-dimensional embeddings (1024D) for both foundation models and low-dimensional embeddings (3D) for W2V2 only are included. The highest accuracy for each row is printed in bold.

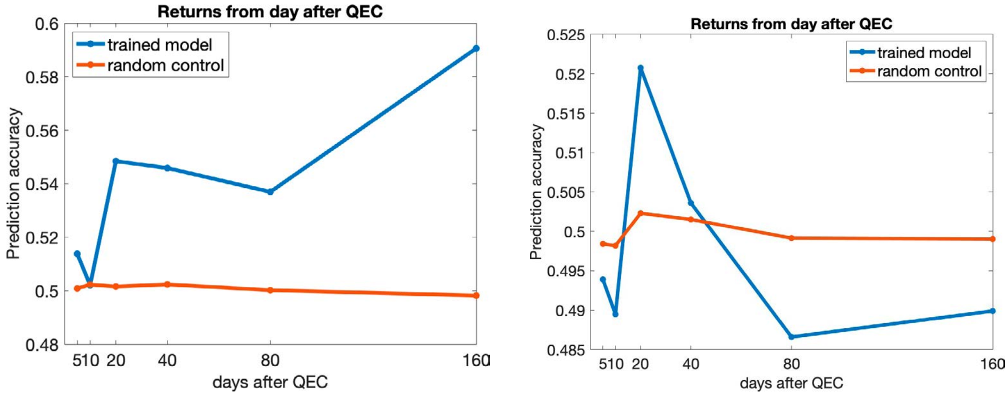
All control results (obtained with randomly permuted labels) were at the baseline (mean 0.5, standard deviation 0.02), confirming the validity of our code and setup. The key observation is that the embeddings of W2V2 1024*D* lead to above-chance predictions for all values of *d* except for *d* = 10. In contrast, the W2V2 3D embeddings achieve only a small above-chance prediction accuracy for *d* = 20. Surprisingly, the TRILLsson embeddings operate at the chance level across all values of *d*. Given the strong results obtained with TRILLsson embeddings in other studies [11, 17, 22], this is unexpected. This may be attributed to the fact that, unlike the TRILLsson model, which is trained on diverse YouTube audio, the W2V2 model we use was pre-trained on speech data—including audiobooks, read speeches, and, in some cases, conversational recordings—that more closely resemble the style and structure of earnings conference call audio recordings. The W2V2 model, therefore, excels at extracting vocal embeddings in this context.

Table 3: Mean accuracies (SDs between parenthesis) for returns prediction for the initial four seconds of the introduction session of the QEC. Binary prediction labels $V_d > V_0$.

Days after QEC Intro (4 sec.)	W2V2 embedding		TRILLsson embedding
d	1024D	3D	1024D
5	**0.51** (0.02)	0.49 (0.01)	0.50 (0.01)
10	0.50 (0.02)	0.49 (0.01)	0.50 (0.01)
20	**0.55** (0.02)	0.52 (0.02)	0.50 (0.01)
40	**0.55** (0.02)	0.50 (0.01)	0.50 (0.01)
80	**0.54** (0.02)	0.49 (0.01)	0.50 (0.01)
160	**0.59** (0.02)	0.49 (0.01)	0.50 (0.01)

Figure 4 plots the results for QEC introductions showing the average prediction accuracies obtained with the W2V2 embeddings 1024 D and 3 D. We have added a line through the six data points to improve readability. The chance prediction results, especially those of the 1024D embeddings, indicate that vocal cues in the first four seconds of QEC introductions can predict future returns. The accuracy of the predictions improves with *d*. For small values of *d*, such as *d* = 5 or 10, the accuracy is approximately at the chance level, respectively. This indicates that vocal cues are more dependable for longer-term predictions. For

Figure 4: Illustration of the W2V2 prediction accuracies for the 1024D and 3D embedding of the introduction session (initial 4 seconds). Please note the different y-axis ranges.



(a) 1024D embeddings

(b) 3D embeddings

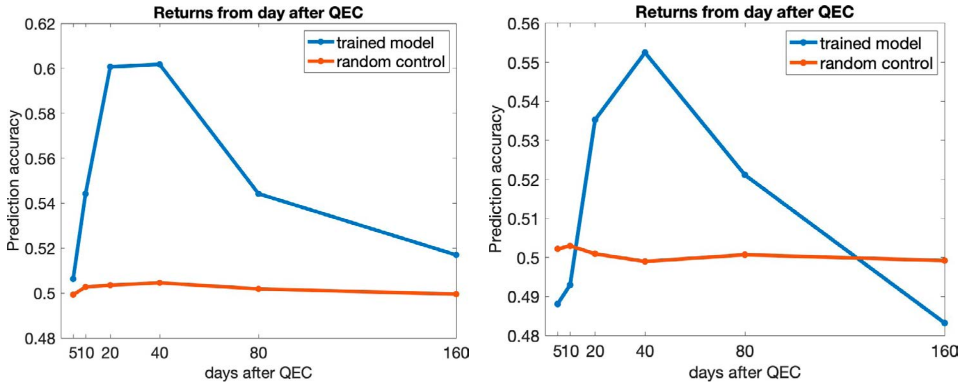
small values of *d*, there is likely too much noise and too little signal in the market. For larger values of *d*, this pattern may be reversed.

Table 4 lists the results for the W2V2 embeddings of the first 10 seconds of the Q&A sessions. Figure 5 visually shows the same results. Both embeddings exhibit a similar

Table 4: Mean accuracies for returns prediction for the initial 10 seconds of the Q&A session of the QEC. Binary prediction labels $V_d > V_0$.

Days after QEC Q&A (10 sec.)	W2V2 embedding	
d	1024D	3D
5	**0.51** (0.03)	0.49 (0.01)
10	**0.53** (0.03)	0.49 (0.01)
20	**0.58** (0.03)	0.54 (0.02)
40	**0.59** (0.03)	0.55 (0.02)
80	**0.54** (0.03)	0.52 (0.02)
160	**0.50** (0.03)	0.48 (0.01)

Figure 5: Illustration of the W2V2 prediction accuracies for the 1024D and 3D embedding of the Q&A session (first 10 seconds). Please note the varying ranges of the y-axes.



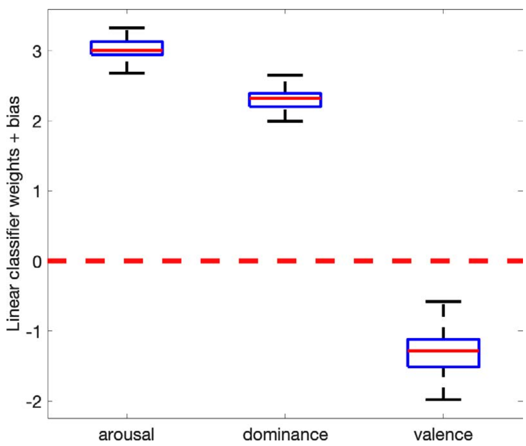
(a) 1024D embeddings

(b) 3D embeddings

prediction accuracy pattern, peaking between d = 20 and 40, and declining to or below chance level for larger values of d. The main results are that the mean accuracies are higher compared to the QEC introduction dataset and that, unlike the 3 D embeddings of the introduction session, those of the Q&A session do show a clear deviation from the chance level, although slightly lower than for the 1024D embeddings. This implies that the information contained in the vocal cues of (the first 10 seconds of) Q&A sessions has some predictive power regarding the sign of future returns.

To gain a clearer understanding of the emotional characteristics that contribute to the predictive performance of the 3D embeddings, we analyzed the weights (β values) of the logistic classifiers trained with d = 40, the interval with the highest mean precision. Considering all classifiers trained during the folds and repetitions, we created box plots for each of the three weights. Figure 6 displays the three box plots that represent the weights assigned to each of the three emotional dimensions. We have added the bias value to each weight to indicate their value with respect to the zero level clearly. The confined boxes indicate that all classifiers reached closely similar weight values, converging on the same solution. The relative position regarding the zero level (horizontal dashed red line) indicates the contribution to the classification of an embedding (representing the initial 10 seconds of the Q&A session of the QEC) as "1" (an increase in returns after d = 40 days). The relative positions of the boxes reveal that *arousal* and *dominance* contribute positively to an increase in returns, while *valence* contributes negatively.

Figure 6: Box plots showing the weight distributions of all classifiers trained on the W2V2 3D embeddings of the Q&A session at d = 40 (i.e., the peak in Figure 5b).



5.2 **Macroeconomic Variables and Vocal Cues**

In the financial literature, macroeconomic variables such as risk-free rate, stock market indices, price-earnings ratios, dividend yields, and inflation rates are widely recognized as informative indicators to predict future stock prices [23]. To evaluate the additional predictive power of vocal cues versus financial variables, we begin by analyzing their performance with a low-dimensional W2V2 (3D) model. This approach provides interpretable vocal features and reduces potential biases that may arise from the high dimensionality of the W2V2 (1024D) model when incorporating multiple macroeconomic variables. Finally, we expand our analysis to incorporate financial variables along with vocal embeddings derived from the high-dimensional W2V2 (1024D) model, as these embeddings capture more detailed information and yield better predictions of future stock returns.

All macroeconomic indicators in this study are measured at monthly frequencies and lagged by one month in the prediction experiments. The variables consist of the long-term interest rate for 10-year U.S. government bonds, inflation-adjusted metrics for the S&P 500 index, dividends, and earnings. Additionally, we incorporate the Cyclically Adjusted Price-to-Earnings (CAPE) ratio, a valuation measure that smooths earnings over a ten-year period, as well as the excess earnings yield over bond yields, following the methodology of [24]. We also include the inflation- adjusted U.S. Treasury Bill Rate Index. Finally, we monitor overall price levels using the Consumer Price Index (CPI) and the inflation rate, offering insights into broader economic trends.

Marquering (2001) uses a linear OLS model based on macroeconomic variables to predict the return signs of the market index for the next period, attaining a mean accuracy of about 57%. Considering this benchmark, our out-of-sample prediction accuracy of 51% to 59%—derived exclusively from brief clips of vocal information—demonstrates economic significance. The ability of vocal sentiment alone to achieve predictive power similar to that of macroeconomic models indicates that CEO speech embeddings hold valuable forward-looking information.

Moreover, in comparison to Marquering (2001), the financial models demonstrate even greater predictive accuracy, averaging between 58% and 81% across various time horizons. This highlights the strength of our approach in capturing the relationship between macroeconomic conditions and stock returns more effectively than traditional linear models.
The increase in prediction accuracy when using vocal cues from the introduction or Q&A sessions—compared to a random model benchmark—further emphasizes the informational value contained in vocal sentiment. This is especially clear during spontaneous, unscripted moments when CEOs may unintentionally convey implicit signals about future firm performance or the overall macroeconomic outlook. However, in Table 5, when comparing models that combine vocal and financial characteristics (Vocal + Financial) with those that use financial characteristics alone, we do not observe a significant improvement in predictive performance based on low-dimensional (3D) vocal embeddings extracted from our W2V2 model.
A possible explanation for this result is that there is a correlation between vocal sentiment and macroeconomic conditions. In that case, vocal sentiment already reflects macroeconomic conditions or market sentiment, resulting in overlapping information with financial variables and therefore no additional explanatory power for vocal sentiment.

Table 5: This table presents the mean prediction accuracies for binary targets derived from cumulative gross returns over the first 10 seconds of a CEO's response during the Q&A session of earnings conference calls, utilizing 3D models. The table compares various input combinations: financial features alone (*Financial*) and vocal features combined with financial data (*Vocal+Financial*). Results are presented for different time horizons (*d*) ranging from 5 to 160 days. The baseline performance (*Random*) refers to models trained using random firm performance labels. The "Diff." column indicates the mean difference in prediction accuracy between *Vocal+Financial* models and *Financial* models. All standard deviations not reported are smaller than 0.01, indicating that the variability is due solely to subsampling in the cross-validation process rather than significant variance in model performance.

Days after QEC Q&A (10 sec.)		W2V2 embedding (3D)		
d	Random	Financial	Vocal + Financial	Diff.
5	0.498	0.579	0.578	-0.001
10	0.501	0.649	0.650	+0.001
20	0.503	0.796	0.796	0.000
40	0.501	0.805	0.809	+0.004
80	0.501	0.663	0.666	+0.003
160	0.502	0.644	0.643	-0.001

To explore the potential explanation mentioned above, we further examine the relationship between vocal embeddings and macroeconomic indicators using high-dimensional (1024D) vocal embeddings. As shown in Table 6, the combined model (Vocal + Financial) outperforms the financial-only model across all time horizons in our experiments, with prediction accuracy improvements ranging from approximately 1.3% to 3.4%. These results suggest that high-dimensional vocal embeddings capture more detailed information related to firm-specific signals rather than macroeconomic sentiment. This contrasts with low-dimensional embeddings, making high-dimensional vocal embeddings more effective for forecasting future firm performance.

Table 6: This table presents the mean prediction accuracies for binary targets based on cumulative gross returns from the first 10 seconds of a CEO's response during the Q&A session of earnings conference calls using 3D models. The table compares various input combinations: financial features alone (*Financial*) and vocal features combined with financial data (*Vocal + Financial*). Results are presented for different time horizons (*d*) ranging from 5 to 160 days. The baseline performance (*Random*) refers to models trained on randomly assigned firm performance labels. The "Diff." column shows the difference in mean prediction accuracy between *Vocal+Financial* models and *Financial* models. All standard deviations, which are not reported and are smaller than 0.01, reflect variability due solely to subsampling in the cross-validation process rather than significant variance in model performance.

Days after QEC Q&A (10 sec.)		W2V2 embedding (1024D)		
d	Random	Financial	Vocal + Financial	Diff.
5	0.503	0.582	0.616	+0.034
10	0.501	0.653	0.685	+0.032
20	0.499	0.799	0.826	+0.027
40	0.503	0.804	0.817	+0.013
80	0.503	0.667	0.691	+0.024
160	0.501	0.633	0.663	+0.030

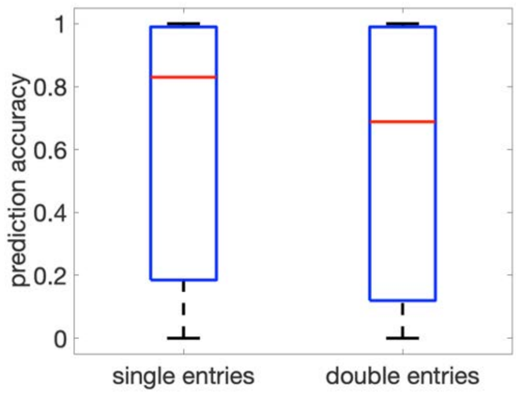
6. Discussion

The discussion of our experiments covers four topics: the impact of pairs from the same company in the dataset, the trade-off between explainability and prediction accuracy, the observed superiority of W2V2 over TRILLsson, and the relevance of our findings to the pension sector.

6.1 Effect of Same-Company Pairs in the Dataset

A potential alternative explanation for our results could stem from the presence of QECs from the same company and, often, the same CEO. These same-company pairs may have influenced our results, particularly when one QEC's embedding is in the training set and the other is in the test set. Any correlation in terms of company success (returns) will provide a signal that has nothing to do with tone of voice but with detecting the CEO's identity (which deep-learning models are very able to detect, as shown in the middle of Figure 1). This advantage should manifest as a benefit for both the single and double entries in our dataset. (We left out the single instance of triple entries.) Figure 7 shows separate box plots of the prediction accuracies for the single and double entries. There is no advantage for double entries. Instead, the single entries yield better predictions, as reflected in the higher median (red horizontal line in the box plot). Therefore, there is no evidence supporting this alternative explanation for our results.

Figure 7: Box plots depicting the prediction accuracies for single and double entries in our QEC introduction dataset. The horizontal red lines indicate the median values. The box plot for single entries is based on 167 instances, while the one for double entries is based on 544 instances.



6.2 Explainability vs Prediction Accuracy

What cues in the data enable subtle predictions? For the embeddings of 3D extracted from the Q&A sessions (cf. the 3D results in Table 2), the weight of the three emotional dimensions offers a clear interpretation. Due to their high dimensionality, the 1024D embeddings likely contain additional information. The results of the introduction session listed in Table

1 show that this is the case: The 1024D embeddings give rise to predictions, whereas the 3D embeddings do not. Even for the Q&A session results, listed in Table 4, where the 3D embeddings do give rise to predictions, the 1024D predictions outperform the 3D ones, which indicates that there is some additional vocal information that is predictive but cannot be expressed in terms of the three emotional dimensions. Moreover, it is difficult to express the results of the introduction sessions in terms of the three dimensions.

6.3 TRILLsson vs W2V2

Why do the W2V2 embeddings succeed while the TRILLsson embeddings fail to make accurate predictions? The key difference is that the original wav2vec2 model (which W2V2 is based on) was trained for automatic speech recognition (ASR), while TRILLsson was specifically trained for paralinguistic tasks. While the W2V2 model was fine-tuned on the three emotional dimensions, it is fundamentally more capable than TRILLsson at extracting words from the QEC sessions. Therefore, one possible explanation for the W2V2 model's predictive ability is that it extracts linguistic information rather than paralinguistic information from the QEC segments. As we have argued, the words spoken during the four-second introduction segments lack any valuable information about the company's current or future state. Thus, this explanation is not valid, though it may apply to some extent to the 10-second Q&A fragments that sometimes include words supporting predictions. Whatever the nature of the cues the W2V2 model extracts from the QEC introductions, they cannot be explained solely in terms of the three emotional dimensions: arousal, dominance, and valence, because the corresponding 3D embeddings did not show predictive abilities (see the 3D column of Table 1). Fortunately, during the longer 10 second segments of the QEC's Q&A session, the 3D embeddings made a small but significant predictive contribution, peaking on day d = 40. We cannot dismiss the possibility that the linguistic information in the 10-second segments contributed to the performance of the 3D embedding.

The ability to predict future return signs does not indicate a causal relationship between speech information and stock movements. There may be another factor influencing the CEO and future stock performance. If that is true, the actual cause occurred prior to the QEC. It is also possible that the market picks up on the CEO's tone during the QEC, in which case the call itself is the cause. Examples of variables that were not accounted for include CEO gender (which affects speech pitch), the specific words spoken, and model imperfections (such as TRILLsson's failure regarding W2V2, which may indicate the types of cues captured).

6.4 Economic Interpretations

In this paper, we primarily focus on predicting future firm performance through vocal cues using deep-learning models as an initial step. Rather than concentrating on investors' real-time understanding of a company's speech, our study analyzes the overall "vibe" or sentiment expressed in the speech. We investigate the predictive power of essential macroeconomic variables, including S&P 500 index levels, dividends, earnings, and inflation rates. While financial models trained on these variables demonstrate strong performance, achieving average precisions of 57.9% to 80.5% in predicting future stock return directions, our results show that low-dimensional (3D) vocal sentiment offers limited predictive value. These empirical results indicate that the predictive ability of 3D vocal sentiment is associated with macroeconomic indicators. A possible explanation is that both investors and CEOs are shaped by the same prevailing macroeconomic sentiment. Alternatively, CEOs may possess a greater ability to process macroeconomic information and evaluate its implications for firm performance, which is subtly reflected in their vocal expressions. The results show that our models' predictive power is strongest approximately 20 to 40 days after the earnings conference call. This indicates that the market's response to the information conveyed in the speech during these calls is not immediate. Instead, investors may take time to process this information, especially considering that the audio recordings of earnings calls are often made available online only two weeks after the live stream. This delay may well influence how and when the market incorporates the information into stock prices, resulting in the observed lag in predictive accuracy.

Concerning the economic interpretation of speech-predicting returns, we discover that for speech features to be predictive, investors must eventually interpret and act on these differences. However, our results suggest that this interpretation may not happen in real time, but rather over an extended period. This delayed response may result from further analysis by market participants, the spread of insights via financial media, or the gradual acknowledgment of the speech's implications within the context of changing market conditions. This observation supports the idea that some insights from earnings calls may only become actionable or fully understood after further processing or contextualization.

Nonetheless, models that integrate high-dimensional (1024D) vocal embeddings with financial variables consistently exceed the performance of financial-only models. This suggests a promising avenue for future research designed to reveal the informational content embedded in high-dimensional vocal representations.

To investigate how speech features affect immediate investor behavior, we need high-frequency trading data to analyze real-time market reactions. Revisiting this approach is a promising direction for future research, but it is outside of the scope of this paper.

6.5 Relevance to the Pension Sector

In this paper, we explore a straightforward application of how state-of-the-art speech foundation models can predict future economic outcomes, specifically future stock returns. Our findings imply that vocal features extracted from CEOs' speech are correlated with macroeconomic indicators, an area that warrants further investigation and may be of interest to long-term investors, such as the pension sector. For example, Gorodnichenko et al. (2023) demonstrate that a positive tone in speeches by the Federal Reserve chairperson leads to significant increases in share prices, illustrating the market's sensitivity to vocal cues. Similarly, it would be valuable to explore how CEOs' speeches influence broader economic indicators. Another potentially interesting avenue for exploring vocal analytics is investigating firms' commitment to ESG-related policies. When CEOs are questioned about their firms' ESG policies, vocal analytics may be able to determine the sincerity of their proposals and intentions. Once more, this can aid in guiding investment decisions.

7. Conclusion

This empirical study on deep speech representations of earnings calls demonstrates that embeddings generated by the W2V2 model capture cues that aid in predicting future returns and, to a lesser extent, the trading volumes of companies. Unlike the TRILLsson model, the W2V2 model effectively captures subtle vocal signals from Quarterly Earnings Calls that reflect a company's prospects. These findings underscore the W2V2 model's potential to enhance investment decisions and company-customer interactions, especially for institutional investors such as pension funds. However, the generalizability of these results, both within the domain of stock return prediction and across other applications, remains an area for future research.

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Appendix

The table below lists the contents of the dataset used for the results reported in Tables 3 and 4. Each entry of the table lists the company name (first column), the name of the CEO giving the QEC (second column), and the date of the QEC (third column, format “yyyymmdd”). Each company has one or two entries, except for *Copart* that is the only company with three entries.

Company	CEO	Date
3M	Michael F. Roman	20190129
3M	Michael F. Roman	20200128
A. O. Smith	Kevin J. Wheeler	20190129
A. O. Smith	Kevin J. Wheeler	20200128
ADM	Juan Ricardo Luciano	20190205
ADM	Juan Ricardo Luciano	20200130
AES Corp	Andres Ricardo Gluski Weilert	20190227
AT&T	Randall L. Stephenson	20190130
AT&T	Randall L. Stephenson	20200129
AbbVie	Richard A. Gonzalez	20190125
AbbVie	Richard A. Gonzalez	20200207
Abbott Laboratories	Miles D. White	20190123
Abbott Laboratories	Miles D. White	20200122
Abiomed	Michael R. Minogue	20190502
Accenture	Pierre Nanterme	20180927
Adobe	Shantanu Narayen	20181213
Adobe	Shantanu Narayen	20191212
Advance Auto Parts	Thomas R. Greco	20190219
Advance Auto Parts	Thomas R. Greco	20200218
Advanced Micro Devices	Lisa T. Su	20190129
Advanced Micro Devices	Lisa T. Su	20200128
Aflac	Daniel Paul Amos	20190201
Aflac	Daniel Paul Amos	20200205
Agilent Technologies	Michael R. McMullen	20181119
Agilent Technologies	Michael R. McMullen	20191125
Air Products Chemicals	Carlos A. Rodriguez	20180801
Air Products Chemicals	Seifollah Ghasemi	20191107
Akamai Technologies	F. Thomson Leighton	20190212
Akamai Technologies	F. Thomson Leighton	20200211
Alaska Air Group	Bradley D. Tilden	20190124
Alaska Air Group	Bradley D. Tilden	20200128
Albemarle Corporation	Luther C. Kissam	20190221
Albemarle Corporation	Luther C. Kissam	20200220
Alexandria Real Estate Equities	Stephen A. Richardson	20190205
Align Technology	Joseph M. Hogan	20190129
Align Technology	Joseph M. Hogan	20200129
Allegion	David D. Petratis	20190219
Alliant Energy	Patricia Leonard Kampling	20190222
Allstate Corp	Thomas Joseph Wilson	20190206
Allstate Corp	Thomas Joseph Wilson	20200205
Alphabet (Class A)	Sundar Pichai	20190204
Alphabet (Class A)	Sundar Pichai	20200203
Altria Group	Howard A. Willard	20190131
Ameren Corp	Warner L. Baxter	20190214
Ameren Corp	Warner L. Baxter	20200226

Company	CEO	Date
American Airlines Group	William Douglas Parker	20190124
American Airlines Group	William Douglas Parker	20200123
American Electric Power	Nicholas K. Akins	20190124
American Electric Power	Nicholas K. Akins	20200220
American Express	Stephen Joseph Squeri	20190117
American Express	Stephen Joseph Squeri	20200124
American International Group	Brian Charles Duperreault	20200213
American Tower	James D. Taiclet	20190227
American Tower	James D. Taiclet	20200225
American Water Works	Susan N. Story	20190220
American Water Works	Susan N. Story	20200219
Ameriprise Financial	James M. Cracchiolo	20190131
Ameriprise Financial	James M. Cracchiolo	20200130
AmerisourceBergen	Steven H. Collis	20181106
AmerisourceBergen	Steven H. Collis	20191107
Ametek	David A. Zapico	20190205
Ametek	David A. Zapico	20200205
Amgen	Robert A. Bradway	20190129
Amgen	Robert A. Bradway	20200130
Amphenol	Richard Adam Norwitt	20190123
Amphenol	Richard Adam Norwitt	20200122
Analog Devices	Vincent T. Roche	20181120
Analog Devices	Vincent T. Roche	20191126
Ansys	Ajei S. Gopal	20190228
Ansys	Ajei S. Gopal	20200227
Anthem	Gail Koziara Boudreaux	20190130
Aon	Gregory C. Case	20190201
Apple	Timothy D. Cook	20181101
Apple	Timothy D. Cook	20191030
Applied Materials	Gary E. Dickerson	20181115
Aptiv	Kevin P. Clark	20190131
Arista Networks	Jayshree V. Ullal	20190214
Arista Networks	Jayshree V. Ullal	20200213
Arthur J. Gallagher & Co.	J. Patrick Gallagher	20190131
Arthur J. Gallagher & Co.	J. Patrick Gallagher	20200130
Assurant	Alan B. Colberg	20190213
Assurant	Alan B. Colberg	20200212
Atmos Energy	Michael E. Haefner	20181108
Atmos Energy	John Kevin Akers	20191107
AutoZone	William C. Rhodes	20180918
AutoZone	William C. Rhodes	20190924
Autodesk	Andrew Anagnost	20180306
Autodesk	Andrew Anagnost	20190228
Automatic Data Processing	Carlos A. Rodriguez	20180801
Automatic Data Processing	Carlos A. Rodriguez	20190731
AvalonBay Communities	Timothy J. Naughton	20190205
AvalonBay Communities	Timothy J. Naughton	20200206
Avery Dennison	Mitchell R. Butier	20190130
Avery Dennison	Mitchell R. Butier	20200129
BNY Mellon	Charles W. Scharf	20190116
BNY Mellon	Thomas P. Gibbons	20200116
BSX	Michael F. Mahoney	20200205
Baker Hughes	Lorenzo Simonelli	20190131
Ball Corp	John A. Hayes	20190131
Ball Corp	John A. Hayes	20200206
Bank of America	Brian Thomas Moynihan	20190116
Bank of America	Brian Thomas Moynihan	20200115
Baxter International	Jos, E. Almeida	20190131
Baxter International	Jos, E. Almeida	20200317

Company	CEO	Date
Becton Dickinson	Vincent A. Forlenza	20181106
Becton Dickinson	Vincent A. Forlenza	20191105
Best Buy	Hubert Joly	20180301
Best Buy	Hubert Joly	20190227
Bio-Rad Laboratories	Norman D. Schwartz	20190228
Bio-Rad Laboratories	Norman D. Schwartz	20200213
Biogen	Michel Vounatsos	20190129
Biogen	Michel Vounatsos	20200130
BlackRock	Laurence Douglas Fink	20190116
BlackRock	Laurence Douglas Fink	20200115
Boeing	Dennis A. Muilenburg	20190130
Boeing	David L. Calhoun	20200129
Booking Holdings	Glenn D. Fogel	20190227
Booking Holdings	Glenn D. Fogel	20200226
BorgWarner	Frederic B. Lissalde	20190214
BorgWarner	Frederic B. Lissalde	20200213
Boston Properties	Owen David Thomas	20190130
Boston Properties	Owen David Thomas	20200129
Boston Scientific	Michael F. Mahoney	20190206
Bristol Myers Squibb	Giovanni Caforio	20190124
Bristol Myers Squibb	Giovanni Caforio	20200206
Broadcom	Hock E. Tan	20181206
Broadcom	Hock E. Tan	20191212
Broadridge Financial Solutions	Richard J. Daly	20180807
Broadridge Financial Solutions	Timothy C. Gokey	20190801
C. H. Robinson	John P. Wiehoff	20190130
C. H. Robinson	Robert C. Biesterfeld	20200129
CBRE	Robert E. Sulentic	20190213
CBRE	Robert E. Sulentic	20200227
CDW	Christine A. Leahy	20190207
CDW	Christine A. Leahy	20200206
CF Industries	W. Anthony Will	20190214
CF Industries	W. Anthony Will	20200213
CI	David Michael Cordani	20190201
CME Group	Terrence A. Duffy	20190214
CME Group	Terrence A. Duffy	20200212
CMS Energy	Patricia Kessler Poppe	20190131
CMS Energy	Patricia Kessler Poppe	20200130
CSX	James M. Foote	20200116
CVS Health	Larry J. Merlo	20190220
CVS Health	Larry J. Merlo	20200212
Cadence Design Systems	Lip-Bu Tan	20190219
Cadence Design Systems	Lip-Bu Tan	20200212
Campbell Soup	Keith R. McLoughlin	20180830
Campbell Soup	Mark A. Clouse	20190830
Capital One Financial	Richard D. Fairbank	20190122
Capital One Financial	Richard D. Fairbank	20200121
CarMax	William D. Nash	20180404
CarMax	William D. Nash	20190329
Cardinal Health	Michael C. Kaufmann	20180806
Cardinal Health	Michael C. Kaufmann	20190808
Carnival Corporation	Arnold W. Donald	20181220
Carnival Corporation	Arnold W. Donald	20191220
Catalent	John R. Chiminski	20190827
Caterpillar	D. James Umpleby	20190128
Cboe Global Markets	Edward T. Tilly	20190208
Cboe Global Markets	Edward T. Tilly	20200207
Centene Corporation	Michael Frederic Neidorff	20200204
CenterPoint Energy	John William Somerhalder	20200227

Company	CEO	Date
Charles River Laboratories	James C. Foster	20200211
Charter Communications	Thomas M. Rutledge	20190131
Chevron Corporation	Mike Wirth	20190201
Chipotle Mexican Grill	Brian R. Niccol	20190206
Chipotle Mexican Grill	Brian R. Niccol	20200204
Chubb	Evan G. Greenberg	20190206
Church & Dwight	Matthew Thomas Farrell	20190205
Cincinnati Financial	Steven J. Johnston	20190207
Cincinnati Financial	Steven J. Johnston	20200206
Cisco Systems	Charles H. Robbins	20180815
Cisco Systems	Charles H. Robbins	20190814
Citigroup	Michael L. Corbat	20190114
Citigroup	Michael L. Corbat	20200114
Citizens Financial Group	Bruce Winfield Van Saun	20200117
Clorox	Benno O. Dorer	20180802
Clorox	Benno O. Dorer	20190801
Coca-Cola Company	James Robert B. Quincey	20190214
Cognizant Technology Solutions	Francisco D'Souza	20190206
Cognizant Technology Solutions	Brian Humphries	20200205
Colgate-Palmolive	Ian M. Cook	20190125
Comcast	Brian L. Roberts	20190123
Comcast	Brian L. Roberts	20200123
Comerica	Ralph W. Babb	20190116
Comerica	Curtis Chatman Farmer	20200121
Conagra Brands	Sean M. Connolly	20180627
Conagra Brands	Sean M. Connolly	20190627
ConocoPhillips	Ryan Lance	20200204
Constellation Brands	William A. Newlands	20190404
Copart	A. Jayson Adair	20180919
Copart	A. Jayson Adair	20190905
Copart	A. Jayson Adair	20190919
Corning	Wendell P. Weeks	20190129
Corning	Wendell P. Weeks	20200129
Crown Castle	Jay A. Brown	20190124
Crown Castle	Jay A. Brown	20200227
Cummins	N. Thomas Linebarger	20190206
Cummins	N. Thomas Linebarger	20200204
D. R. Horton	David V. Auld	20181108
D. R. Horton	David V. Auld	20191112
DTE Energy	Gerard M. Anderson	20190207
DTE Energy	Gerardo Norcia	20200205
DXC Technology	John Michael Lawrie	20190523
DaVita	Kent J. Thiry	20190214
DaVita	Javier J. Rodriguez	20200210
Danaher Corporation	Thomas P. Joyce	20190129
Danaher Corporation	Thomas P. Joyce	20200130
Darden Restaurants	Eugene I. Lee	20180621
Darden Restaurants	Eugene I. Lee	20190620
Delta Air Lines	Edward H. Bastian	20190115
Delta Air Lines	Edward H. Bastian	20200114
Dentsply Sirona	Donald M. Casey	20190301
Devon Energy	David A. Hager	20190220
Devon Energy	David A. Hager	20200219
DexCom	Kevin R. Sayer	20190221
DexCom	Kevin R. Sayer	20200213
Diamondback Energy	Travis D. Stice	20190220
Diamondback Energy	Travis D. Stice	20200219
Digital Realty Trust	Arthur William Stein	20190205
Digital Realty Trust	Arthur William Stein	20200213

Company	CEO	Date
Discover Financial Services	Roger Crosby Hochschild	20190124
Discover Financial Services	Roger Crosby Hochschild	20200123
Dollar General	Todd J. Vasos	20190314
Dollar Tree	Gary M. Philbin	20190306
Dominion Energy	Thomas F. Farrell	20200211
Domino's Pizza	Richard E. Allison	20200220
Dover Corporation	Richard Joseph Tobin	20190129
Dover Corporation	Richard Joseph Tobin	20200130
DuPont	Edward D. Breen	20190131
DuPont	Edward D. Breen	20200130
Duke Energy	Lynn J. Good	20190214
Duke Energy	Lynn J. Good	20200213
EOG Resources	William R. Thomas	20200228
Eastman Chemical	Mark J. Costa	20190201
eBay	Devin N. Wenig	20190129
eBay	Scott F. Schenkel	20200128
Ecolab	Douglas M. Baker	20190219
Ecolab	Douglas M. Baker	20200218
Edison International	Pedro J. Pizarro	20190228
Edison International	Pedro J. Pizarro	20200227
Edwards Lifesciences	Michael A. Mussallem	20190131
Edwards Lifesciences	Michael A. Mussallem	20200130
Electronic Arts	Andrew Wilson	20180508
Electronic Arts	Andrew Wilson	20190507
Eli Lilly & Co	David A. Ricks	20190206
Emerson Electric Company	David N. Farr	20181106
Emerson Electric Company	David N. Farr	20191105
Enphase Energy	Badrinarayanan Kothandaraman	20190226
Enphase Energy	Badrinarayanan Kothandaraman	20200218
Entergy	Leo P. Denault	20200219
Equifax	Mark W. Begor	20190221
Equifax	Mark W. Begor	20200213
Equinix	Charles J. Meyers	20190213
Equinix	Charles J. Meyers	20200212
Equity Residential	Mark J. Parrell	20200129
Essex Property Trust	Michael J. Schall	20200130
Estee Lauder Companies	Fabrizio Freda	20180820
Estee Lauder Companies	Fabrizio Freda	20190819
Etsy	Joshua G. Silverman	20190225
Etsy	Joshua G. Silverman	20200226
Everest Re	Dominic James Addesso	20190212
Eversource Energy	James J. Judge	20190221
Eversource Energy	James J. Judge	20200220
Exelon	Christopher Mark Crane	20200211
Expedia Group	Mark D. Okerstrom	20190207
Extra Space Storage	Joseph D. Margolis	20200219
ExxonMobil	Darren W. Woods	20190201
F5 Networks	Fran‡ois Locoh-Donou	20181024
F5 Networks	Fran‡ois Locoh-Donou	20191023
FMC Corporation	Pierre R. Brondeau	20190212
FMC Corporation	Pierre R. Brondeau	20200206
Facebook	Mark Elliot Zuckerberg	20190130
Facebook	Mark Elliot Zuckerberg	20200129
Fastenal	Daniel L. Florness	20200117
FedEx	Frederick W. Smith	20190625
Federal Realty Investment Trust	Donald C. Wood	20200211
Fidelity National Information Services	Gary Adam Norcross	20190212
Fidelity National Information Services	Gary Adam Norcross	20200213

Company	CEO	Date
Fifth Third Bancorp	Gregory D. Carmichael	20190122
Fifth Third Bancorp	Gregory D. Carmichael	20200122
First Republic Bank	James H. Herbert	20200114
FirstEnergy	Charles E. Jones	20200207
Fiserv	Jeffery W. Yabuki	20200204
Fleetcor	James J. Cannon	20190206
Fleetcor	Ronald F. Clarke	20200206
Ford	James Patrick Hackett	20190123
Ford	James Patrick Hackett	20200204
Fortinet	Ken Xie	20200206
Fortive	James A. Lico	20200206
Fortune Brands Home & Security	Christopher J. Klein	20190131
Fortune Brands Home & Security	Nicholas Ian Fink	20200129
Franklin Resources	Gregory Eugene Johnson	20181025
Franklin Resources	Gregory Eugene Johnson	20191025
Freeport-McMoRan	Richard C. Adkerson	20190124
Gap	Arthur Peck	20190228
Garmin	Clifton Albert Pemble	20190220
Gartner	Eugene A. Hall	20190205
Gartner	Eugene A. Hall	20200204
Generac Holdings	Aaron P. Jagdfeld	20200213
General Dynamics	Phebe N. Novakovic	20190130
General Dynamics	Phebe N. Novakovic	20200129
General Electric	H. Lawrence Culp	20200129
General Mills	Jeffrey L. Harmening	20180627
General Mills	Jeffrey L. Harmening	20190626
General Motors	Mary T. Barra	20190206
Genuine Parts	Paul D. Donahue	20190219
Genuine Parts	Paul D. Donahue	20200219
Gilead Sciences	Daniel O	20200204
Global Payments	Jeffrey S. Sloan	20190213
Global Payments	Jeffrey S. Sloan	20200212
Globe Life	Gary Lee Coleman	20190206
Goldman Sachs	David Michael Solomon	20190116
Goldman Sachs	David Michael Solomon	20200115
HCA Healthcare	Samuel N. Hazen	20190129
HCA Healthcare	Samuel N. Hazen	20200128
HP	Dion J. Weisler	20181129
HP	Enrique J. Lores	20191126
Halliburton	Jeffrey Allen Miller	20190122
Halliburton	Jeffrey Allen Miller	20200121
Hanesbrands	Gerald W. Evans	20190207
Hanesbrands	Gerald W. Evans	20200207
Hasbro	Brian D. Goldner	20190208
Hasbro	Brian D. Goldner	20200211
Healthpeak Properties	Thomas M. Herzog	20190214
Healthpeak Properties	Thomas M. Herzog	20200212
Henry Schein	Stanley M. Bergman	20190220
Henry Schein	Stanley M. Bergman	20200220
Hess Corporation	John B. Ness	20190130
Hess Corporation	John B. Hess	20200129
Hewlett Packard Enterprise	Antonio Fabio Neri	20181204
Hewlett Packard Enterprise	Antonio Fabio Neri	20191125
Hilton Worldwide	Christopher J. Nassetta	20190213
Hilton Worldwide	Christopher J. Nassetta	20200211
Hologic	Stephen P. MacMillan	20181107
Hologic	Stephen P. MacMillan	20191106
Home Depot	Craig A. Menear	20190226
Home Depot	Craig A. Menear	20200225

Company	CEO	Date
Honeywell	Darius E. Adamczyk	20190201
Hormel	James P. Snee	20181120
Hormel	James P. Snee	20191126
Host Hotels & Resorts	James F. Risoleo	20190220
Host Hotels & Resorts	James F. Risoleo	20200220
Howmet Aerospace	John C. Plant	20200127
Humana	Bruce Dale Broussard	20190206
Humana	Bruce Dale Broussard	20200205
Huntington Bancshares	Stephen D. Steinour	20200123
Huntington Ingalls Industries	C. Michael Petters	20200213
IDEX Corporation	Andrew K. Silvernail	20200130
IPG Photonics	Valentin P. Gapontsev	20190212
IQVIA	Ari Bousbib	20200212
Idexx Laboratories	Jonathan W. Ayers	20190201
Illinois Tool Works	E. Scott Santi	20190201
Illumina	Francis A. deSouza	20190129
Illumina	Francis A. deSouza	20200129
Incyte	Hervé Hoppenot	20190214
Incyte	Hervé Hoppenot	20200213
Ingersoll Rand	Vicente Reynal	20190219
Ingersoll Rand	Vicente Reynal	20200218
Intel	Robert H. Swan	20190124
Intel	Robert H. Swan	20200123
Intercontinental Exchange	Jeffrey C. Sprecher	20190207
Intercontinental Exchange	Jeffrey C. Sprecher	20200206
International Flavors & Fragrances	Andreas Fibig	20200213
International Paper	Mark Stephan Sutton	20190131
Interpublic Group	Michael Isor Roth	20190213
Interpublic Group	Michael Isor Roth	20200212
Intuit	Brad D. Smith	20180823
Intuit	Sasan K. Goodarzi	20190822
Intuitive Surgical	Gary S. Guthart	20190124
Intuitive Surgical	Gary S. Guthart	20200123
Invesco	Martin L. Flanagan	20190130
Invesco	Martin L. Flanagan	20200129
Iron Mountain	William L. Meaney	20190214
J. B. Hunt	John N. Roberts	20200117
JM Smucker	Mark T. Smucker	20180607
JM Smucker	Mark T. Smucker	20190606
JPMorgan Chase	James Dimon	20200114
Jack Henry & Associates	David B. Foss	20180822
Jack Henry & Associates	David B. Foss	20190821
Jacobs Engineering Group	Steven J. Demetriou	20191125
Johnson & Johnson	Alex Gorsky	20190122
Johnson & Johnson	Alex Gorsky	20200122
Juniper Networks	Rami Rahim	20190129
Juniper Networks	Rami Rahim	20200127
KLA Corporation	Richard P. Wallace	20180730
KLA Corporation	Richard P. Wallace	20190805
Kellogg's	Steven A. Cahillane	20190207
Kellogg's	Steven A. Cahillane	20200206
KeyCorp	Beth E. Mooney	20190117
KeyCorp	Beth E. Mooney	20200123
Keysight Technologies	Ronald S. Nersesian	20181120
Keysight Technologies	Ronald S. Nersesian	20191126
Kimberly-Clark	Michael D. Hsu	20190123
Kimberly-Clark	Michael D. Hsu	20200123
Kinder Morgan	Steven J. Kean	20190116
Kinder Morgan	Steven J. Kean	20200122

Company	CEO	Date
Kraft Heinz	Bernardo Vieira Hees	20190221
Kraft Heinz	Miguel Patricio	20200213
Kroger	William Rodney McMullen	20190307
L3Harris Technologies	William M. Brown	20190731
L3Harris Technologies	William M. Brown	20200204
LKQ Corporation	Dominick P. Zarcone	20190228
LKQ Corporation	Dominick P. Zarcone	20200220
LabCorp	David P. King	20190207
LabCorp	Adam H. Schechter	20200213
Lam Research	Martin B. Anstice	20180726
Lam Research	Timothy M. Archer	20190731
Lamb Weston	Thomas P. Werner	20190723
Las Vegas Sands	Sheldon Gary Adelson	20200129
Leggett & Platt	Karl G. Glassman	20200204
Leidos	Roger A. Krone	20190219
Leidos	Roger A. Krone	20200218
Lennar	Richard Beckwitt	20190109
Lennar	Richard Beckwitt	20200108
Lincoln National	Dennis Robert Glass	20190207
Lincoln National	Dennis Robert Glass	20200206
Live Nation Entertainment	Michael Rapino	20200227
Lockheed Martin	Marillyn A. Hewson	20190129
Lockheed Martin	Marillyn A. Hewson	20200128
Loews Corporation	James S. Tisch	20200210
Lowe’s	Marvin R. Ellison	20190227
Lowe’s	Marvin R. Ellison	20200226
Lumen Technologies	Jeffrey K. Storey	20200212
MGM Resorts International	James Joseph Murren	20190213
MGM Resorts International	James Joseph Murren	20200212
MSCI	Henry A. Fernandez	20190131
Marathon Oil	Lee M. Tillman	20200213
Marathon Petroleum	Gary R. Heminger	20200129
MarketAxess	Richard Mitchell McVey	20200129
Marriott International	Arne M. Sorenson	20200227
Marsh & McLennan	Daniel S. Glaser	20190131
Martin Marietta Materials	C. Howard Nye	20190212
Martin Marietta Materials	C. Howard Nye	20200211
Masco	Keith J. Allman	20190207
Masco	Keith J. Allman	20200211
Mastercard	Ajaypal S. Banga	20190131
Mastercard	Ajaypal S. Banga	20200129
McCormick & Company	Lawrence E. Kurzius	20200128
McDonald’s	Stephen J. Easterbrook	20190130
McDonald’s	Christopher J. Kempczinski	20200129
McKesson Corporation	Brian S. Tyler	20190508
Merck & Co.	Kenneth C. Frazier	20190201
Merck & Co.	Kenneth C. Frazier	20200205
MetLife	Michel Abbas Khalaf	20200206
Mettler Toledo	Olivier A. Filliol	20200206
Microchip Technology	Stephen Sanghi	20190508
Micron Technology	Sanjay Mehrotra	20180920
Micron Technology	Sanjay Mehrotra	20190926
Microsoft	Satya Nadella	20180719
Microsoft	Satya Nadella	20190718
Moderna	Stephane Bancel	20200226
Mohawk Industries	Jeffrey S. Lorberbaum	20200214
Molson Coors Beverage Company	Mark R. Hunter	20190212
Molson Coors Beverage Company	Gavin D. K. Hattersley	20200212

Company	CEO	Date
Mondelez International	Dirk Van de Put	20190130
Mondelez International	Dirk Van de Put	20200129
Monster Beverage	Rodney Cyril Sacks	20200227
Moody's Corporation	Raymond W. McDaniel	20200212
Morgan Stanley	James Patrick Gorman	20200116
Motorola Solutions	Gregory Q. Brown	20190207
Motorola Solutions	Gregory Q. Brown	20200206
NOV	Clay C. Williams	20200207
NRG Energy	Mauricio Gutierrez	20190228
NRG Energy	Mauricio Gutierrez	20200227
Nasdaq	Adena T. Friedman	20190130
Nasdaq	Adena T. Friedman	20200129
NetApp	George Kurian	20180523
NetApp	George Kurian	20190522
Netflix	Wilmot Reed Hastings	20200122
Newell Brands	Michael B. Polk	20190215
Newell Brands	Ravichandra K. Saligram	20200214
Newmont	Gary J. Goldberg	20190221
Newmont	Thomas Ronald Palmer	20200220
News Corp (Class A)	Robert J. Thomson	20180809
News Corp (Class A)	Robert J. Thomson	20190808
NextEra Energy	James L. Robo	20200124
NiSource	Joseph J. Hamrock	20190220
NiSource	Joseph J. Hamrock	20200227
Nike	Mark G. Parker	20180628
Norfolk Southern	James A. Squires	20190124
Norfolk Southern	James A. Squires	20200129
Northern Trust	Michael G. O'Grady	20190123
Northern Trust	Michael G. O Grady	20200122
Northrop Grumman	Kathy J. Warden	20190131
NortonLifeLock	Richard S. Hill	20190509
Norwegian Cruise Line Holdings	Frank J. Del Rio	20190221
Nucor	John J. Ferriola	20190129
Nucor	Leon J. Topalian	20200128
Nvidia	Jen-Hsun Huang	20190214
O'Reilly Automotive	Gregory D. Johnson	20190207
O'Reilly Automotive	Gregory D. Johnson	20200206
Occidental Petroleum	Vicki A. Hollub	20190213
Occidental Petroleum	Vicki A. Hollub	20200228
Old Dominion Freight Line	Greg C. Gantt	20190207
Old Dominion Freight Line	Greg C. Gantt	20200206
Omnicom Group	John D. Wren	20190212
Omnicom Group	John D. Wren	20200211
Oneok	Terry K. Spencer	20200225
Oracle	Safra Ada Catz	20180619
Oracle	Safra Ada Catz	20190619
PNC Financial Services	William S. Demchak	20200115
PPG Industries	Michael H. McGarry	20200116
PPL	William H. Spence	20190214
PPL	William H. Spence	20200214
PTC	James E. Heppelmann	20191023
PVH	Emanuel Chirico	20200402
Paccar	Ronald E. Armstrong	20190129
Paccar	R. Preston Feight	20200128
Parker-Hannifin	Thomas L. Williams	20180802
Parker-Hannifin	Thomas L. Williams	20190801
PayPal	Earl C. Austin	20190130
PayPal	Daniel H. Schulman	20200129
Paychex	Martin Mucci	20190626

Company	CEO	Date
Paycom	Chad Richison	20190205
Paycom	Chad Richison	20200205
Penn National Gaming	Jay A. Snowden	20200206
PepsiCo	Ramon Luis Laguarta	20190215
PepsiCo	Ramon Luis Laguarta	20200213
PerkinElmer	Robert F. Friel	20190131
PerkinElmer	Prahlad R. Singh	20200127
Pfizer	Albert Bourla	20190129
Pfizer	Albert Bourla	20200128
Philip Morris International	André Calantzopoulos	20200206
Pinnacle West Capital	Donald E. Brandt	20190222
Pioneer Natural Resources	Timothy L. Dove	20190214
Pioneer Natural Resources	Scott Douglas Sheffield	20200220
Pool Corporation	Peter D. Arvan	20190214
Pool Corporation	Peter D. Arvan	20200213
Principal Financial Group	Daniel Joseph Houston	20190130
Principal Financial Group	Daniel Joseph Houston	20200129
Procter & Gamble	David S. Taylor	20180731
Procter & Gamble	David S. Taylor	20190730
Prologis	Hamid R. Moghadam	20190122
Prologis	Hamid R. Moghadam	20200122
Prudential Financial	Charles Frederick Lowrey	20200205
Public Service Enterprise Group	Ralph Izzo	20190227
Public Service Enterprise Group	Ralph Izzo	20200226
Public Storage	Joseph D. Russell	20190227
Public Storage	Joseph D. Russell	20200226
PulteGroup	Ryan R. Marshall	20190129
PulteGroup	Ryan R. Marshall	20200128
Qorvo	Robert A. Bruggeworth	20180502
Qorvo	Robert A. Bruggeworth	20190507
Quanta Services	Murray S. Kessler	20190221
Quanta Services	Earl C. Austin	20200227
Quest Diagnostics	Stephen H. Rusckowski	20190214
Quest Diagnostics	Stephen H. Rusckowski	20200130
RFJ	Paul Christopher Reilly	20180125
Ralph Lauren Corporation	Patrice Jean Louis Louvet	20180523
Ralph Lauren Corporation	Patrice Jean Louis Louvet	20190514
Raymond James Financial	Paul Christopher Reilly	20191024
Realty Income Corporation	Sumit Roy	20200220
Regency Centers	Martin E. Stein	20190214
Regency Centers	Lisa Palmer	20200213
Regeneron Pharmaceuticals	Leonard S. Schleifer	20190206
Regeneron Pharmaceuticals	Leonard S. Schleifer	20200206
Regions Financial Corporation	John M. Turner	20190118
Regions Financial Corporation	John M. Turner	20200117
Republic Services	Donald W. Slager	20190207
Republic Services	Donald W. Slager	20200213
ResMed	Michael J. Farrell	20180802
ResMed	Michael J. Farrell	20190725
Robert Half International	Max Messmer	20190129
Rockwell Automation	Blake D. Moret	20181107
Rockwell Automation	Blake D. Moret	20191112
Rollins	Gary W. Rollins	20190123
Rollins	Gary W. Rollins	20200129
Roper Technologies	Laurence Neil Hunn	20190201
Ross Stores	Barbara Rentler	20190305
Royal Caribbean Group	Richard D. Fain	20190130
Royal Caribbean Group	Richard D. Fain	20200204

Company	CEO	Date
S&P Global	Douglas L. Peterson	20190207
S&P Global	Douglas L. Peterson	20200206
SBA Communications	Jeffrey A. Stoops	20190221
SBA Communications	Jeffrey A. Stoops	20200220
SGMO	Alexander D. Macrae	20200228
SVB Financial	Gregory W. Becker	20190125
SVB Financial	Gregory W. Becker	20200124
Salesforce	Marc R. Benioff	20190304
Schlumberger	Paal Kibsgaard	20190118
Schlumberger	Olivier Le Peuch	20200117
Seagate Technology	William David Mosley	20180730
Sealed Air	Edward L. Doheny	20190207
Sealed Air	Edward L. Doheny	20200211
Sempra Energy	Jeffrey Walker Martin	20190226
Sempra Energy	Jeffrey Walker Martin	20200227
ServiceNow	John J. Donahoe	20190130
ServiceNow	William R. McDermott	20200129
Sherwin-Williams	John G. Morikis	20190131
Simon Property Group	David E. Simon	20200204
Skyworks Solutions	Liam K. Griffin	20191112
Snap-on	Nicholas T. Pinchuk	20190207
Snap-on	Nicholas T. Pinchuk	20200206
Southern Company	Thomas A. Fanning	20200220
Southwest Airlines	Gary C. Kelly	20200123
Stanley Black & Decker	James M. Loree	20190122
Stanley Black & Decker	James M. Loree	20200129
Starbucks	Kevin R. Johnson	20181101
Starbucks	Kevin R. Johnson	20191030
State Street Corporation	Ronald Philip O Hanley	20190118
State Street Corporation	Ronald Philip O	20200117
Steris	Walter Rosebrough	20180509
Stryker Corporation	Kevin A. Lobo	20190129
Stryker Corporation	Kevin A. Lobo	20200128
Synchrony Financial	Margaret M. Keane	20190123
Synchrony Financial	Margaret M. Keane	20200124
Synopsys	Aart J. de Geus	20181205
Synopsys	Aart J. de Geus	20191204
Sysco	Thomas L. Bené	20180813
Sysco	Thomas L. Bené	20190812
T-Mobile US	John Legere	20190207
T-Mobile US	John Legere	20200206
TE Connectivity	Terrence R. Curtin	20181031
TJX Companies	Ernie L. Herrman	20190227
Take-Two Interactive	Strauss H. Zelnick	20190513
Tapestry	Victor Luis	20190815
Target Corporation	Brian C. Cornell	20190305
Teledyne Technologies	Aldo Pichelli	20190123
Teledyne Technologies	Aldo Pichelli	20200122
Teleflex	Liam J. Kelly	20190221
Teleflex	Liam J. Kelly	20200220
Teradyne	Mark E. Jagiela	20190124
Teradyne	Mark E. Jagiela	20200123
Texas Instruments	Rafael R. Lizardi	20190123
Textron	Scott C. Donnelly	20200129
The Cooper Companies	Albert G. White	20181206
The Cooper Companies	Albert G. White	20191205
The Hartford	Christopher Jerome Swift	20190205
The Hartford	Christopher Jerome Swift	20200204

Company	CEO	Date
The Hershey Company	Michele Gross Buck	20190131
The Hershey Company	Michele Gross Buck	20200130
The Mosaic Company	James C. O Rourke	20190226
The Mosaic Company	James C. O Rourke	20200220
The Travelers Companies	Alan David Schnitzer	20190122
The Travelers Companies	Alan David Schnitzer	20200123
Thermo Fisher Scientific	Marc N. Casper	20190130
Tractor Supply Company	Gregory A. Sandfort	20190131
TransDigm Group	Kevin M. Stein	20181106
TransDigm Group	Kevin M. Stein	20191119
Trimble	Steven W. Berglund	20190206
Trimble	Robert G. Painter	20200212
Truist Financial	Kelly Stuart King	20190117
Tyler Technologies	H. Lynn Moore	20190221
Tyler Technologies	H. Lynn Moore	20200213
Tyson Foods	Noel White	20181113
Tyson Foods	Noel White	20191112
U.S. Bancorp	Andrew Cecere	20190116
U.S. Bancorp	Andrew Cecere	20200115
UDR	Thomas W. Toomey	20190213
UDR	Thomas W. Toomey	20200212
UNM	Richard Paul McKenney	20200205
Ulta Beauty	Mary N. Dillon	20190314
Under Armour (Class A)	Patrik Frisk	20200211
Union Pacific	Lance M. Fritz	20200123
United Airlines	J. Scott Kirby	20190116
United Airlines	Oscar Munoz	20200122
United Parcel Service	David P. Abney	20190131
United Rentals	Michael J. Kneeland	20190124
United Health Group	David Scott Wichmann	20200115
VF Corporation	Steven E. Rendle	20190522
Valero Energy	Joseph W. Gorder	20190131
Ventas	Debra A. Cafaro	20190208
Ventas	Debra A. Cafaro	20200220
Verisign	D. James Bidzos	20190207
Verisign	D. James Bidzos	20200206
Verisk Analytics	Scott G. Stephenson	20190220
Verisk Analytics	Scott G. Stephenson	20200219
Verizon Communications	Hans Vestberg	20190129
Vertex Pharmaceuticals	Jeffrey Marc Leiden	20190205
ViacomCBS	Dow R. Wilson	20190214
ViacomCBS	Robert Marc Bakish	20200220
Visa	Alfred Francis Kelly	20181024
Visa	Alfred Francis Kelly	20191024
Vulcan Materials	Joseph W. Gorder	20190214
Vulcan Materials	James Thomas Hill	20200218
W. R. Berkley Corporation	William Robert Berkley	20190129
W. R. Berkley Corporation	W. Robert Berkley & Jr.	20200128
W. W. Grainger	Donald G. Macpherson	20190124
W. W. Grainger	Donald G. Macpherson	20200130
WEC Energy Group	Joseph Kevin Fletcher	20190212
Wabtec	Rafael O. Santana	20200218
Walgreens Boots Alliance	Stefano Pessina	20181011
Walgreens Boots Alliance	Stefano Pessina	20191028
Walmart	C. Douglas McMillon	20180220
Waste Management	James C. Fish	20190214
Waste Management	James C. Fish	20200213
Waters Corporation	Christopher James O	20190123
Waters Corporation	Christopher James O	20200204

Company	CEO	Date
Wells Fargo	Timothy J. Sloan	20190115
Wells Fargo	Charles W. Scharf	20200114
Welltower	Thomas J. DeRosa	20200213
West Pharmaceutical Services	Eric M. Green	20190214
West Pharmaceutical Services	Eric M. Green	20200213
Western Digital	Stephen D. Milligan	20180726
Western Digital	Stephen D. Milligan	20190731
Western Union	Hikmet Ersek	20190207
Western Union	Hikmet Ersek	20200211
Weyerhaeuser	Devin W. Stockfish	20190201
Whirlpool Corporation	Marc Robert Bitzer	20190129
Whirlpool Corporation	Marc Robert Bitzer	20200128
Williams Companies	Alan S. Armstrong	20200220
Wynn Resorts	Matthew Ode Maddox	20200206
Xcel Energy	Benjamin G. S. Fowke	20190131
Xylem	Patrick K. Decker	20200206
Yum! Brands	Giovanni G. Visentin	20190207
Yum! Brands	David W. Gibbs	20200206
Zebra Technologies	Anders Gustafsson	20200213
Zimmer Biomet	Bryan C. Hanson	20180201
Zimmer Biomet	Bryan C. Hanson	20200204
Zions Bancorp	Harris Henry Simmons	20190122
Zoetis	Juan Ramón Alaix	20190214
Zoetis	Kristin C. Peck	20200213

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