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# Don’t Stop Me Now: Gender Attitudes in Academic Seminars Through Machine Learning

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# Don’t Stop Me Now: Gender Attitudes in Academic Seminars Through Machine Learning

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## Abstract

This study, utilizing a novel dataset from economic seminar audio recordings, investigates gender-based peer interactions, structured around five key findings: (i) Female speakers are interrupted more frequently, earlier, and differently than males; (ii) the extra interruptions largely stem from female, not male, audience members; (iii) male participants pose fewer questions but more comments to female presenters; (iv) audience members of both genders interrupt female speakers with a more negative tone; (v) less senior female presenters receive more interruptions from women. Control variables include seminar series, presentation topic, and factors like presenter affiliation, seniority, and department ranking.

**Keywords**: Gender, Academic Environment, Machine Learning, Audio Processing.

**JEL-classification**: A1, C8, C45, J4, J7.

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# 1 Introduction

It has been well-established that men and women differ in their attitudes toward various dimensions of life, such as work, education, family arrangements, and financial decisions (Bursztyn and Jensen, 2017; Goldin, 2014; Bertrand et al., 2010; Altonji and Blank, 1999). This is particularly relevant in highly skilled and demanding professions with uncertain career prospects, such as academia, where women are still underrepresented (Sattari and Sandefur, 2019; Harris and Jenkins, 2006). One manifestation of these attitudes is through interactions between peers, particularly through conversational dynamics. A commonly accepted finding in this field is that men interrupt women more often than women interrupt men (Carli, 2017; West and Zimmerman, 2009; Tannen, 1993). In this paper, I present evidence disputing this view.

For that, I analyze 1,712 recordings of economic seminars investigating whether female presenters are interrupted more often and receive more questions than their male counterparts do. This is done by means of machine learning and audio processing algorithms, which identify interruptions in speech flow by detecting any voice change and predict the gender of each speaker based on their vocal characteristics. In addition, deep learning methods are also used to examine how interruptions are expressed and whether emotional cues conveyed through voice tone vary depending on the gender of the presenter. This topic seems particularly pressing, given the under-representation of women in the profession and the distinctively aggressive culture of economics seminars (Boustan and Langan, 2019).

The baseline findings point to a differential treatment of female and male presenters during seminars, with female presenters being interrupted more frequently and earlier than males. Building on this result, the study contributes five key findings to the literature on how the behavior of individuals is affected by the presence of peers.

First, it shows that those extra interruptions received by female presenters are not entirely due to men in the audience but also to females. In particular, women in the audience tend to contribute to a higher proportion of interruptions when the seminar is presented by a woman, as compared to when a man is presenting.

As the dependent variable, referred to as "interruptions," is operationalized as every change of speaker in a given talk, I supplement the previous results by analyzing the type of interruption, i.e. whether they are questions or comments.[1] In that sense, the second key finding is that the gender of the presenter is associated with the number of interruptions identified as questions, with female presenters receiving a higher proportion of questions from female audience members and a lower proportion from male audience members. In contrast, the gender of the presenter has no effect on the number of comments made by female audience members, but an increase in comments made by male audience members when the presenter is female is observed.

As conversational interactions can reflect broader issues of power and dominance in social life (West and Zimmerman, 2009), this paper also makes a third key contribution by examining the way in which the interruption takes place. Specifically, it analyzes whether the interruption occurs through a smooth transition or a speech overlap between speakers. Smooth transition interruptions are characterized by a seamless transition between speakers, while speech overlap interruptions occur when the interrupter begins speaking while the original speaker is still talking. The results indicate that female presenters are more likely to be interrupted via voice overlap. In particular, the evidence

1. Even if this use of "interruptions" is accepted in the literature (e.g. Schegloff, 2001), other expressions such as "interaction" are also possible.

suggests that men tend to increase the use of this interruption method when the presenter is a woman, while findings are less clear on whether women in the audience alter their behavior similarly. Although not all instances of overlapping interruptions convey a negative meaning (e.g., they can be used to provide support and foster collaboration in concept constructions), the focus here is on successful overlapping interruptions, where the interrupter takes control of the conversation from the interrumpee by preventing them from finishing their statement. In such cases, a larger consensus in the literature exists regarding the negative connotation of these types of interruptions (Schegloff, 2001; Tannen, 1993).

The fourth key finding of this study pertains to the emotional tone of voice utilized in interruptions. The results indicate that female presenters are more likely to be interrupted with negative tones of voice such as anger, by both male and female interrupters. Furthermore, interruptions directed at female presenters are less likely to include positive tones, such as happiness.

Finally, although female presenters experience more interruptions from female audience members, it is found that female interruptions decrease with more senior presenters.

This analysis was made possible due to the virtualization of most academic activity during the COVID-19 outbreak of 2020. Among those activities, academic seminars—one of the main instances for researchers to present their findings, as well as a place for socializing among faculty members—were moved to a virtual setting and, in many cases, also made publicly available afterward. This study analyzes talks that were web-streamed between 2020 and 2022, featuring speakers predominantly from the top 320 ranked universities worldwide. The information gathered from these recordings was assembled in two steps. Using an audio processing technique known as "speaker diarization," I associated each speech segment with a speaker, based on estimated number of speakers in an audio stream (Park et al., 2022; Dadvar, 2011). After determining "who spoke when," I identified the gender of the speakers based on their voices. Although such techniques are commonly applied by various devices used in daily life (e.g., mobile phones), their use in the domain of social science is rare and a novel feature of this paper. Data on interruptions and the gender of the speakers are complemented by additional information on the length of the seminar, the speaker's economic department affiliation, number of citations, seniority, and other relevant information about the presenter available on Google Scholar and the Research Papers in Economics (RePEc) database. Additionally, the topic of the presentation and the seminar series to which the presentation belongs were used as control variables.

The results presented in this paper contribute to the growing body of evidence documenting gender discrimination in the academic profession, particularly within the field of economics.[2] In addition, it expands the available literature on how women and men are treated differently when presenting their research. Dupas et al. (2021) analyzed hand-coded data from 460 seminars, mostly in the applied micro field, and found that women are subjected to more questions and patronizing/hostile treatment than men during these events. Similarly, research from other disciplines also sheds light on this issue. Using transcribed audio recordings from medical conferences, Salem et al. (2021) finds that women are less likely than men are to interrupt the presenter. Hand-coding videotaped conferences (mostly medical and psychological), Jarvis et al. (2022) report that women are less likely than men to ask ques-

2. See Lundberg and Stearns (2019) for an overview. Paredes et al. (2020) provide evidence that undergraduate students exhibit more gender bias after studying economics. Wu (2018) documents an unwelcoming and stereotypical culture using online economic forums. Card et al. (2020) and Hengel (2022) provides evidence on how women are held to higher standards of writing and research than men are. Even if this can be seen as part of a larger problem, the disparities exhibited in academic economics are greater than those observed in other scientific areas (e.g., engineering), as well as those in other fields of the social sciences (Ginther and Kahn, 2004).

tions, and they are likely to feel more anxious about asking questions. Finally, in a study of gender balance at the American Astronomical Society, Davenport et al. (2014) observe that women were asked slightly more questions than men were, interpreting this as an age effect, as senior scientists may be more likely to ask questions, and they are more commonly men.

A primary benefit of this methodology is its objectivity and reproducibility. In contrast, relying on human classification is not only costlier but may also introduce judgment, biases, conflicting interpretations, and excessive reliance on "reading between the lines." Nonetheless, humans might excel at recognizing subtle tone variations and contextual nuances within seminar interruptions.

This paper is composed of six sections. In the following section, I present the data used in the study and in Section 3, I introduce the machine-learning algorithms used for speaker diarization and gender recognition as well as the text-analysis tools used for the seminar transcripts. Section 4 presents the econometric model. Section 5 present the main results and Section 6 formulates conclusions and avenues for further research.

## 2 Dataset

The data analyzed in this study was gathered from economic seminars that were streamed online and conducted between 2020 and 2022. Figure A.1 in the Appendix A shows the year and month frequency of these seminars. Specifically, the seminars were hosted on YouTube, and were readily available to the public. In order to be included in the dataset, each seminar has to be part of a seminar series organized or sponsored by an economics department based in either the United States or Europe. Additionally, seminars hosted or sponsored by highly regarded research institutions such as the National Bureau of Economic Research (NBER), the American Economic Association (AEA), and the Centre for Economic Policy Research (CEPR) were also considered.

To obtain additional information about the seminars, YouTube metadata and natural language processing (NLP) techniques developed in Qi et al. (2020) were leveraged. The seminar's title and description, video comments, and number of likes it received, as well as the date it was posted, were directly obtained from YouTube. The video's title and description were analyzed using NLP to extract the presenter's name. Using this information, Google Scholar was queried to obtain additional details about the presenter, such as their affiliation, number of citations, and the year of their first paper's publication. The year of the presenter's first paper was used as a proxy for their level of seniority. Additionally, the affiliated department's ranking was obtained from a query on RePEc.

The sample consisted of 1,712 seminars featuring 1,547 different presenters.[3] Table 1 presents summary statistics for the database. The mean duration of the seminars was 62.3 minutes, with most seminars falling between 45 and 70 minutes. Interruptions occurred with an average of 11.0 interruptions per seminar, and most interruptions were less than 30 seconds. The average number of questions per seminar was 7.9 and the average number of comments was 3.1. A large proportion of presenters are affiliated with top economics departments, with around two-thirds coming from the top ten departments and less than 10% coming from departments ranked in the first 100 positions. This is detailed in Figure A.2.

3. A list of all presenters and their affiliated departments is included in the Appendix D of the paper

TABLE 1: SAMPLE CHARACTERISTICS

| | Mean/Percentage | SD |
|---|---|---|
| ***Interruptions*** | | |
| Interruptions (total) | 11.0 | 8.6 |
| Interruptions from males | 8.2 | 7.9 |
| Interruptions from females | 2.7 | 4.2 |
| Inter. 30 sec or less | 6.5 | 6.6 |
| Inter. between 30 and 60 sec | 2.6 | 2.5 |
| Inter. between 60 and 120 sec | 1.3 | 1.4 |
| Inter longer than 120 sec | 0.5 | 0.8 |
| ***Questions and comments*** | | |
| Questions | 7.9 | 6.3 |
| from males | 6.0 | 5.9 |
| from females | 2.0 | 3.2 |
| Comments | 3.1 | 4.6 |
| from males | 2.3 | 4.1 |
| from females | 0.8 | 1.8 |
| ***Duration*** | | |
| Duration (in min.) | 62.4 | 16.4 |
| Less than 45 min | 13.9% | 14.1% |
| Between 45min and 70 min | 55.9% | 20.5% |
| Between 70min and 90 min | 27.2% | 18.4% |
| More than 90 min | 3.0% | 7.1% |
| ***Ranking*** | | |
| Dept. ranking < 10 | 28.2% | 16.4% |
| Dept. ranking between 10 and 20 | 12.6% | 11.7% |
| Dept. ranking between 20 and 50 | 18.0% | 13.7% |
| Dept. ranking between 50 and 100 | 10.7% | 10.8% |
| Dept. ranking >100 | 30.5% | 16.9% |
| ***Emotions*** | | |
| Angry tone | 0.3 | 0.3 |
| Boredom tone | 0.1 | 0.1 |
| Sad tone | 0.1 | 0.1 |
| Neutral tone | 0.1 | 0.1 |
| Calm tone | 0.1 | 0.1 |
| Pls. Surprised tone | 0.0 | 0.0 |
| Happy tone | 0.3 | 0.1 |
| ***Other*** | | |
| Sem. without inter. | 8.3% | 10.5% |
| Sem. only w/host inter. | 10.1% | 11.8% |
| Sem. w/inter. from one pers. | 22.0% | 16.8% |
| Female presenters | 36.1% | 48.0% |
| Female chairs | 25.3% | 43.3% |
| Seminar series | 89 | |
| Presenters | 1,547 | |
| Observations | 1,712 | |

Note: Emotions were computed in such a way that each emotion was assigned a non-negative probability that sums to 1 across the seven emotions.

From the emotional spectrum considered in seminar interruptions, namely anger, boredom, sadness, neutrality, calmness, surprise, and happiness, both anger and happiness emerged as the most prominent. Each of these emotions accounted for around 30% of the model's emotional output. However, happiness exhibited a standard deviation of 0.1 points lower, indicating a more consistent presence compared to the somewhat variable occurrence of anger. The remaining emotional tones – boredom, sadness, neutrality, and calmness – were less pronounced, each representing approximately 10% of the output. The incidence of surprise (pleasant) was nearly negligible, with both mean and variability close to zero. This emotional landscape within the seminar environment underscores a compelling mix of negative (anger, boredom, sadness) and positive (happiness, calmness) emotions, with a notable inclination towards the extremes of anger and happiness. This information is complemented in the next section where the machine learning algorithm for predicting emotional tone in the voice is introduced.

In addition, Table A.1 and Figure A.3 present the locations of the economics departments to which the presenters are affiliated. Approximately two-thirds of the presenters are affiliated with economics departments in the US, while European countries and the United Kingdom constitute 12.0% and 9.2% of the sample, respectively. Among the European countries, Italy, France, and Germany have the highest representation. The proportion of female presenters does not appear to vary significantly by the location of the department, as it remains consistent at around one-third of the presenters in the USA, Europe, and the UK.

Furthermore, Figure A.4 shows that the majority of presenters published their first paper between 2000 and 2020, whereas a few more senior presenters made their first publication in the 80s. The proportion of female presenters has increased over the last decades, shifting from approximately 10% in the

80s and 90s, to nearly two-thirds of the presenters between 2010 and 2020.

Figure A.5 reveals that the kernel density distribution of interruptions made during seminars presented by female scholars is marginally right-skewed relative to that of their male counterparts, indicating that potential outliers are improbable to exert a substantial impact on the frequency of interruptions during academic talks.

Finally, Figure A.6 displays a plot of the average number of interruptions during a seminar over time, along with the associated confidence intervals. As anticipated, the initial minutes of the seminars witness a low average number of interruptions, a figure that escalates as the seminar progresses. It is notable that an average of more than two interruptions is recorded between the 50th and 60th minutes of the seminar, contrasting sharply with the 0.5 interruptions typically noted during the seminar's first ten minutes.

## 2.1 Topic Modeling and Identification of Seminar Topics

The identification of seminar topics employed a topic modeling approach applied to audio transcripts of the seminars. Prior to analysis, the transcripts underwent pre-processing for text analysis.[4]

Topic modeling is an unsupervised machine learning technique utilized to identify distinctive concepts or topics from an extensive collection of documents. In this study, the pre-processed transcripts served as the corpus data for topic extraction. A "topic" represents a group of words that frequently co-occur. The analysis employed Mallet, a topic modeling toolkit that encompasses sampling-based implementations of Latent Dirichlet Allocation (Mc-

4. The transcripts underwent pre-processing for text analysis, including the removal of punctuation and *stop words* that lack intrinsic meaning, such as "and" or "the." The remaining words were lemmatized to group all inflected f orms o f a w ord, a nd o nly n ouns, a djectives, v erbs, and adverbs were retained. As an illustration, "policies" was transformed into "policy," and "were" was converted to "be."

Callum, 2002). Coherence scores for models trained with different numbers of topics are shown in Figure B.1 in the Appendix B. Despite the coherence score seeming to increase further when trained with 40 topics, the model with 15 topics was selected based on the highest coherence value before the curve flattened (Röder et al., 2015).

The word clouds in Figure A.7, display the most probable words for each topic. Each topic was associated with a category from the JEL classification system to enhance conceptual understanding.[5] Once the topics were generated, the specific topic of a given seminar was identified by determining the topic number with the highest percentage contribution in the seminar transcript. This information is presented in Table A.2, where the share of each topic, the percentage of female presenters, and the JEL category associated with each topic are shown. In addition, the table reports the first five words that best describe the content of each topic. Notably, female presenters commonly partake in discussions related to education and inequality (topic 13) and health and welfare (topic 2) but are less prevalent in discussions about industrial organization (topics 4 and 14) and macroeconomics (topic 6).

Figure A.8 shows the average number of interruptions during academic presentations across four broader topic categories.: Microeconomics, Macroeconomics, Development, Education, and Others, and Econometrics.[6] Although the mean number of interruptions is comparable across topics, ranging from 9.9 to 10.8, the data reveals topic-specific patterns of interruptions. Specifically, in the Development, Education, and Other topics, male voices accounted for 67.5% of interruptions, while female voices contributed only 32.5%. In the

5. This was accomplished by querying the words of each topic in Chat GPT, after which the JEL category that they were most likely to belong to was assigned.

6. The Micro group includes topics 4, 5, 10, 11, 12, and 14. The Macro group includes topics 1, 6, 8, and 9. The Development, Education, and Others group comprises topics 2, 3, 8, and 13. The Econometrics group includes topic 15.

Macro and Micro topics, women make up just 22% of interruptions, with men constituting 78%. Interestingly, in the Econometrics topic, women account for nearly 30% of interruptions, with men making up the remainder.

### 2.2 Identification of Interruptions as Questions

To identify questions within the seminar interruptions, it was employed a gradient boosting algorithm that was applied to the transcript of each interruption. This algorithm was trained using a corpus of over 10,000 human-annotated posts from online forums, which were made available by Forsythand and Martell (2007). These posts contain dialogue-act tagged information about whether a sentence is interrogative or not.[7] This methodology has been used in the field of natural language processing, such as in Wu (2018), who employed deep learning techniques, including convolutional and recurrent neural networks, to classify dialogue acts such as questions in multi-turn conversation settings. For the purpose of this study, interruptions were deemed questions if a question was identified at any point during the interruption, irrespective of whether it appeared at the beginning or end of the interruption. Any interruptions not recognized as questions were classified as comments.

## 3 Machine Learning Algorithms for Audio Processing

The audio data processing comprises two primary steps. Firstly, the speaker diarization technique is employed to construct a map of all speakers present in the audio signal. Secondly, the gender of each identified speaker is predicted based on their voice.

7. The dialogue-act tags comprise of "Wh" questions (questions that start with "what," "when," "where," "who," "whom," "which," "whose," "why," and "how") and closed questions, which can only be answered with "yes" or "no."

Building on earlier research on voice recognition (e.g., Gorodnichenko et al., 2023; Bai and Zhang, 2021; Sell et al., 2018), a standard and widely-used approach to extracting audio features is followed. Initially, the analysis involves extracting 128 Mel Spectrogram Frequencies (Mel), enabling the assessment of loudness for specific frequencies at given time instances. Subsequently, a Chroma coefficients (Chromagram) comprising 12 chroma coefficients is derived, representing the energy distribution across 12 chroma bands over time, capturing the melodic and harmonic features of the audio. Lastly, 40 Mel Frequency Cepstral Coefficients (MFCC) are obtained, which are the result of applying discrete cosine transformations to the Mel Spectrogram Frequency. All these short-term acoustic signal features are commonly utilized to extract information regarding a speaker's vocal tract characteristics (Müller, 2021; Anguera et al., 2012). These features are incorporated into both speaker diarization and gender prediction, as well as the identification of emotions. Appendix C provides further details about these features.

### 3.1 Speaker Diarization

For speaker diarization, a three-stage audio processing pipeline is implemented. In the first stage, the diarization system differentiates between speech and non-speech segments, which serves also as a preliminary step necessary for other activities such as gender prediction and emotion prediction based on the voice. During the second stage, changes in speakers are detected, and the audio data is segmented accordingly. Finally, these segmented regions are grouped into homogeneous speaker clusters, with each cluster associated with a different speaker, as described in Pulkki et al. (2017).

The process of identifying speech segments and excluding background noise and silence is known as voice activity detection (VAD). The use of VAD improves output quality by masking silent frames and noise and speeds up signal processing by eliminating unnecessary runs on uninformative frames. To detect and eliminate non-speech segments, I leverage the assumption that voiced frames exhibit higher energy levels than silent ones. Regions of the signal with high energy levels can be linked to voice activity.

The detection of change points in the audio signal is achieved by relying on a Gaussian Mixture Model (GMM), as discussed in Weninger et al. (2016) and Moattar and Homayounpour (2012). To determine the number of segments in the signal, the Bayesian Information Criterion (BIC) is used. This approach segments the audio signal within a millisecond window. It utilizes a penalized likelihood ratio test to determine whether the data in the window is better modeled by a single distribution or by two distinct distributions. The null hypothesis is that there is no speaker change point at time $t_j$. The data, denoted as $Z = X + Y$, is modeled by a multivariate Gaussian probability density function with a set of parameters $\theta_Z$ and a log-likelihood $L_0$, defined as follows:

$$L_0 = \sum_{i=1}^{n_X} \log N(x_i|\theta_Z) + \sum_{i=1}^{n_Y} \log N(y_i|\theta_Z), \tag{1}$$

where $n_X$ represents the length of the window, and $X$ and $Y$ denote the two segments of the window.

Under the alternative hypothesis, a speaker change point exists at time $t_j$, and the windows $X$ and $Y$ are modeled by two multivariate Gaussian densities, each having its own set of parameters $\theta_X$ and $\theta_Y$. The log-likelihood $L_1$ is then obtained as follows:

$$L_1 = \sum_{i=1}^{n_X} \log N(x_i|\theta_X) + \sum_{i=1}^{n_X} \log N(y_i|\theta_Y). \tag{2}$$

To estimate the set of parameters Θ, the Expectation Maximization (EM) algorithm is utilized (Gales, Young, et al., 2008). This iterative algorithm compares two adjacent sliding windows of audio data, calculates the distance between them, and determines if they are from the same speaker. To measure the dissimilarity between the windows, the ΔBIC metric is used, defined as

$$\Delta BIC = L_1 - L_0 - \lambda R, \tag{3}$$

where the penalty term $R$ adjusts for the excess of parameters in the alternative hypothesis model compared to the null hypothesis model, and the fine-tuning factor $\lambda$ is used in this calculation. If the ΔBIC is positive, a local maximum is identified, and the time point $t_j$ is marked as a speaker change point. Conversely, if the ΔBIC is not positive, no speaker change point exists at time $t_j$. This process is repeated for multiple samples within the analysis window to identify potential boundary points.

In this study, the identified audio segments are grouped by speaker identity using a similarity-based approach, which involves comparing speaker similarity between all clusters. In that sense, new speakers are assigned new identification numbers while similar speakers are assigned the same identification number. To compute voice similarities, I relied in Ravanelli et al. (2021) and Desplanques et al. (2020), which utilizes an ECAPA-TDNN model to compute voice similarity between different audio signals.[8]

For the main results of the paper, no restrictions regarding the length of the interruptions were imposed. However, when extremely short interruptions

8. ECAPA-TDNN, or "Efficient Convolutional Attention with Pooled Aggregation Time Delay Neural Network," is a neural network architecture to process sequences of data, such as audio signals or natural language text. The architecture uses convolutional blocks and attentive statistical pooling to better capture important information from the input data and improve performance. It is also based on the Time Delay Neural Network (TDNN) model, which is designed to process sequences of data using a series of hidden layers with time delay units.

(i.e. shorter than three seconds) are removed the conclusions presented here remain unchanged.

Upon completion of the diarization process, the presence of speech overlaps was examined by comparing the start and end times of consecutive speaker turns. Building upon the work of Bredin and Laurent (2021), an end-to-end model was utilized to detect overlapping speech in 5-second audio chunks at a high temporal resolution. Through extensive training involving permutation-invariant training and data augmentation, the model achieves accurate identification of speech overlaps using refined multi-label classification techniques.

### 3.2 Gender Prediction

The prediction of gender was based on Mozilla's Common Voice Dataset (Ardila et al., 2020). After data cleaning and filtering, 6,995 male and 5,662 female audio files were included in the dataset, comparable with previous works that utilized the same data (Alnuaim et al., 2022; Chachadi and Nirmala, 2022; Sánchez-Hevia et al., 2019).

Following Alnuaim et al. (2022) and Chachadi and Nirmala (2022), a deep feed-forward neural network with five hidden layers was employed. To enhance the model's performance, a 30% dropout rate was applied as a regularization technique, effectively reducing overfitting (Chollet, 2021). This model attained a 90.95% accuracy on a separate validation set.

As described in Section 2, the metadata gathered from the video included the speaker's name. To enhance the accuracy of the gender predictions, the results obtained by predicting the gender based on the voice were compared to those based on the name of the presenter. This involved querying each name in Chat GPT and inquiring about its gender association, specifically whether the name was more likely to be associated with a masculine or feminine identity.

The results presented in Table A.3 reveal that, of all the presenters predicted to be male based on their voice, 94.7% were also predicted to be male based on their name. For those predicted to be female based on their voice, there was a 91.0% correspondence with the prediction based on their name. Considering the accuracy of the pre-trained model for voice gender prediction, this consistency suggests that the voice-based gender prediction model performs well in conjunction with the name-based prediction, demonstrating a strong agreement between the two methods.[9] As only online seminars are considered to construct the database, the voice quality and recording characteristics from the voices for which the names are available, and those for which are not, are assumed to be similar. While name-based gender predictions were only possible for the presenters, this assumption allows to suggest that the strong agreement between voice-based gender prediction and name-based gender prediction observed in the subsample can be generalized to the rest of the dataset, which includes both presenters and interrupters.

### 3.3 Emotions Prediction

The emotion recognition algorithm used in this study was developed using three publicly available datasets: RAVDESS, TESS, and Emo-DB. These datasets include audio recordings of actors speaking emotionally. RAVDESS (Livingstone and Russo, 2018) has 12 actors and 12 actresses expressing eight emotions, TESS (Dupuis and Pichora-Fuller, 2011) features two actresses articulating 200 words in seven emotions, and Emo-DB (Burkhardt et al., 2005) includes emotional utterances from five male and five female actors of varying lengths. These datasets are widely used in computer science for speech

9. It should be noted that gender prediction based on names is not exempt from error. For example, names commonly used for females, such as “Camille” or “Ariel”, appeared in the database as being associated with male economists. Similarly, “Daron” is a unisex name.

emotion recognition systems (Gorodnichenko et al., 2023; Zisad et al., 2020; Bhavan et al., 2020; Choudhury et al., 2018; Verma and Mukhopadhyay, 2016). The combined datasets consist of approximately 8,500 short recordings representing happy, surprised (pleasantly), neutral, sad, and angry emotions. As in Gorodnichenko et al. (2023), emotions of fear and disgust were not considered due to their unlikely occurrence during seminar interruptions.

For this study, a Multilayer Perceptron (MLP) model was utilized to predict the emotions contained in the audio data. MLPs are a type of feed-forward neural network that have demonstrated success in various classification tasks, including audio emotion recognition (Mishra et al., 2022).

The training sample consisted of 80% of the recordings from RAVDESS, TESS, and Emo-DB, leaving 20% for testing. The model's performance was evaluated on this testing set, yielding a test score of 81.4%.

The input for the classifier was each full-length interruption.[10] The classifier produces a distribution of probabilities across the seven emotions considered, which sum up to 1. Those probabilities are then averaged across all interruptions received by the presenter. This average distribution per seminar is the variable used to analyze the tone in seminars.

The kernel distribution of the seven emotions considered for male and female interrupters is shown in Figure A.9. Overall, the distributions for male and female emotions did not differ significantly. However, the kernel distribution for angry emotions exhibited a mountain shape with a plateau for both males and females, with the female distribution also exhibiting a valley and appearing to be slightly shifted downward compared to the male distribution. Conversely, the kernel distribution for happy emotions for female interrupters appeared to be slightly shifted upward compared to the male distribution, with

10. Results were unchanged when several random samples of 5 and 3 seconds per interruption were taken and then averaged instead of considering the full length of this one.

the male distribution shifted upward before the female peak. These suggest that there may be slight gender-based differences in the expression of those feelings during interruptions.

## 4 Econometric Model

To investigate the relationship between the gender of presenters and the number of interruptions they receive in a seminar, a linear model is employed, as specified below:

$$Y_i = \beta_0 + \beta_1 \text{FemalePresenter}_i + Xi\gamma + Z_i\lambda + \epsilon_i, \tag{4}$$

where $Y_i$ represents the number of interruptions in seminar $i$, and $\beta_1$ indicates the effect of being a female presenter on the number of i nterruptions. A positive $\beta_1$ implies that female presenters receive more interruptions. The vector $X_i$ includes presenter characteristics such as citations, university ranking, and years since the first p ublication. The vector $Z_i$ includes characteristics related to the seminar such as duration, gender of interrupters, seminar series, and presentation topic. The error term is denoted by $\epsilon_i$.

It is important to note that audience composition and the number of attendees for each seminar are unobserved, which may introduce potential confounding factors into the analysis. Therefore, it is crucial to consider seminar series and presentation topic as controls, under the assumption that audience characteristics remain consistent within the same seminar series and presentation topic.

The same model specification is also used to explain the number of questions and comments received by a presenter, the predicted emotion embedded in the tone of voice of the interrupters, and the time elapsed before the first interruption. In the latter, the duration in minutes from the start of the presenter's talk to the first interruption is measured. A negative $\beta_1$ indicates that being a female presenter is associated with a shorter time before the first interruption. When questions or comments are used as the dependent variable, a positive $\beta_1$ indicates that female presenters receive more questions or comments.

In the case of the predicted emotions, the same model specification is applied to each of the seminar-averaged emotions, which take values between 0 and 1. Specifically, it is estimated the effect of presenter gender on the probability of the presence of a particular emotion across the interruptions of the seminar. An increase in $\beta_1$ is associated with an increase in the probability of the presence of that emotion across the interruptions of the seminar.

In all the specifications, robust standard errors were employed.

# 5 Results

This study's outcomes are structured in three parts. The initial part discusses the correlation between the gender of the presenter and the number of interruptions encountered during a seminar. The subsequent part examines the involvement of female attendees in creating disparities in interruption rates between male and female presenters. Finally, the last part provides supplementary findings supporting the existence of gender-based inequities in the academic environment.

## 5.1 The effect of being a female presenter on seminar interruptions

Panel A of Table 2 presents the baseline results of this paper. The OLS estimation of Equation 4 with the number of interruptions as the dependent variable is carried out there. Across all specifications, the variable of interest, the gender of the presenter, is found to be positively significant, with the size of this effect remaining relatively constant. This suggests that on average, female presenters experience between 1.3 and 1.7 more interruptions in seminars compared to their male counterparts. The effect of seminar duration is also found to be significant and positive. As the seminar duration increases, the number of interruptions also increases, with an increase of 0.16 to 0.23 interruptions per minute. The influence of being a female presenter on the number of interruptions decreases slightly when seniority and citations are added as controls (Column 2). This same trend continues when both variables are considered together along with the seminar's topic (Column 3). The most comprehensive specification includes as well the location of the speaker's department and the seminar series as controls. According to this specification, a female speaker receives, on average, nearly 1.36 additional interruptions during a presentation compared to a male presenter.

These numbers are smaller than the ones of Dupas et al. (2021), where it is found that on average, a female presenter receives around 3.8 extra interruptions during a seminar. However, the percentage difference in interruptions received by female presenters of 12.7% reported in their study is remarkably similar to the one found in this paper of 12.3%. It is possible that the difference in the number of interruptions found in both studies is due to differences in the sample selection, with Dupas et al. (2021) focusing mostly on applied micro seminars while this study considers a broader set of economic fields. Additionally, the seminars in this study were held online rather than in-person, which may have affected the dynamics of interruptions. In this context, when selecting seminars that appear to be closer to applied micro topics, such as 2, 3, 8, 11, and 13, it is observed an increase in both the average number of interruptions received in a seminar and the coefficient associated with a female presenter.[11]

TABLE 2: DETERMINANTS OF NUMBER OF INTERRUPTIONS

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: All interruptions*** | | | | |
| Female presenter | 1.74 | 1.57 | 1.35 | 1.36 |
| | (0.38) | (0.43) | (0.44) | (0.38) |
| Duration | 0.23 | 0.23 | 0.22 | 0.16 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Citations | | -0.12 | -0.09 | -0.03 |
| | | (0.05) | (0.05) | (0.03) |
| Seniority | | -0.03 | -0.03 | -0.01 |
| | | (0.03) | (0.03) | (0.02) |
| R2 | 0.20 | 0.20 | 0.26 | 0.51 |
| Observations | 1,712 | 1,456 | 1,391 | 1,391 |
| ***Panel B: Controlling by proportion of females' interruptions*** | | | | |
| Female presenter | 0.60 | 0.31 | 0.11 | 0.10 |
| | (0.51) | (0.58) | (0.59) | (0.50) |
| Prop. Female Inter. | -3.93 | -4.33 | -4.32 | -2.83 |
| | (0.57) | (0.63) | (0.67) | (0.70) |
| Fem. Present x Prop. Fem. Inter | 3.57 | 3.99 | 4.27 | 4.58 |
| | (1.09) | (1.26) | (1.34) | (1.25) |
| Duration | 0.21 | 0.21 | 0.20 | 0.16 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Citations | | -0.11 | -0.09 | -0.05 |
| | | (0.05) | (0.05) | (0.04) |
| Seniority | | -0.02 | -0.02 | 0.00 |
| | | (0.03) | (0.03) | (0.03) |
| R2 | 0.18 | 0.18 | 0.22 | 0.47 |
| Observations | 1,592 | 1,348 | 1,292 | 1,292 |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |

Note: Robust standard errors in parentheses.

11. The topics considered are Topic 2 (Health, Education, and Welfare), Topic 3 (Economic Development, Innovation, Technological Change, and Growth), Topic 8 (Urban, Rural, Regional, Real Estate, and Transportation Economics), Topic 11 (Industrial Org). and Topic 13 (Health, Education, and Welfare).

This is presented in Table A.4 where the coefficient associated with being female presenter is 1.86 in the most comprehensive specification.

### 5.2 Who is behind those interruptions?

There is a substantial body of literature on conversation dynamics that reports men frequently interrupting women more than women interrupt men.[12] Given this, it is relevant to question to what extent this pattern holds in the present study. Table A.6 provides a preliminary glimpse into whether interruptions during seminars are made by males or females in the audience. Since men usually make up a higher share of attendees at economic seminars, it is not surprising that they ask more questions overall than women. However, it is worth noting that both male and female attendees contribute to the higher number of interruptions received by female presenters: male attendees make 0.6 more extra interruptions to female presenters than to male presenters, while female attendees make 0.8 extra interruptions to female presenters than to male presenters.

Considering this, the results presented in Panel B of Table 2 indicate that the effect of presenter gender on the number of interruptions is moderated by the proportion of interruptions made by female audience members. Specifically, the coefficient on the female presenter variable becomes statistically insignificant on its own when the proportion of female interruptions in the seminar is included as an interaction term in Equation 4. This suggests that the relationship between presenter gender and interruptions is conditional on the proportion of female interruptions. Moreover, the coefficient on the interaction term is positive and statistically significant, indicating that the impact of female interruptions on the total number of interruptions is more pronounced

12. This topic has been previously explored in the works of Carli (2017), Hancock and Rubin (2015), West and Zimmerman (2009), Tannen (1993), Holmes (1992), and Rosenblum (1986)

when the presenter is female.

Notably, although the duration of the seminar continues to exhibit a positive correlation with a higher frequency of interruptions, both citations and seniority retain their negative sign, indicating that greater citation counts and seniority are associated with fewer interruptions. However, the significance of their effect appears to be somewhat reduced, particularly in the case of citation count, when compared to the results presented in the panel A of Table 2.

To further validate the results, Table A.7 presents an alternative strategy in which the dependent variable is the difference between the proportion of interruptions made by females during the seminar series and the proportion of interruptions made by females in each individual seminar. All the specifications consistently show that being a female presenter is positively related to the dependent variable. This indicates that, on average, when the presenter is female, there is an increase in the difference between the proportion of interruptions made by females during the seminar series and within each seminar.

In addition to these results, in many seminar series, a seminar's chair is responsible for overseeing the seminar and introducing the speaker, and in some cases, also moderates the chat and poses questions on behalf of attendees. The chair of a seminar was identified as the individual who speaks at the beginning of the seminar and briefly introduces the speaker before yielding the floor to them. Table A.5 presents the results obtained when estimating Equation 4 without considering interruptions from the seminar chair. The coefficients for female presenters and their interactions with the proportion of female interruptions, with exclusions for those from the chair, remain significant. This suggests that the additional interruptions received by female presenters are not solely driven by factors such as the seminar chair reading questions or comments posted in the chat. However, as expected, these coefficients are lower than those obtained in analyses where the chair's interruptions were included.

### 5.3 Additional results and robustness checks

This final part of the Results section provides supplementary findings regarding seminar interactions and the impact of the presenter's gender. Initially, the role of questions and comments is discussed. Subsequently, interruptions are classified according to the way in which they are conducted. The emotion embedded in the tone of voice is then considered. Next, an analysis is performed on the role of the presenter's seniority and citations in relation to the interruptions received. Finally, the relationship between the gender of the presenter and the time that passes before the first interruption occurs is examined.

**Questions and comments:** Table A.8 reports the estimation results of Equation 4 with the dependent variable being the number of questions, specifically the interruptions identified as questions according to the procedure outlined in Section 2.2. The results are presented separately for the overall number of questions asked during the seminar (Panel A), male questions (Panel B), and female questions (Panel C). The data does not conclusively show a significant effect of a female presenter on the overall number of questions received. However, this is primarily due to the divergent effects observed in male and female questions, as shown in Panel A. Specifically, Panel B shows that male participants ask approximately 0.7 fewer questions when the presenter is a woman, whereas Panel C reveals that female participants ask approximately 0.5 more questions.

In a similar way, Table A.9 reports the estimation of Equation 4, where the dependent variable is the number of comments received during the seminar, i.e. all interruptions not labeled as questions. The results reveal a significant and positive effect of a female presenter on the total number of comments, mainly due to an increase in comments made by male attendees (Panel B). On the other hand, the data shows no significant effect of presenter gender on the number of comments made by female attendees (Panel C).

**Interruptions by voice overlapping:** As outlined above, interruptions during spoken interactions can be characterized by either smooth transitions between speakers or overlapping speech. Tables A.10 and A.11 present the estimated effects of speaker gender on the number of overlapping interruptions that occur in a seminar. Table A.10 reports the number of smooth interruptions, which are defined as interruptions in which the interrupter spoke over the voice of the original speaker no more than once during the interruption due to overlapping speech. While the findings in Panel A do not indicate a significant change in the overall audience behavior based on presenter gender, Panels B and C reveal notable differences in behavior between male and female attendees. Specifically, male attendees reduce the number of interruptions by smoothly transitioning voices, while female attendees increase this method of conducting interruptions when the presenter is female.

Table A.11 reveals that overlapping interruptions, defined as interruptions in which the interrupter spoke over the voice of the original speaker at least twice to conduct the interruption, were more frequent when the presenter is female. Specifically, Panel A of the table shows that female presenters were interrupted almost an extra time due to persistent speech overlap compared to male presenters. Furthermore, Panel B of the table suggests that male attendees tended to increase their use of this method of interruption when the presenter was female. In contrast, evidence suggesting a change in the behavior of female attendees is less strong. It is found that they also tended to increase interruptions through overlapping voices in the two most basic specifications (columns 1 and 2). However, when additional control variables, such as the seminar's topic and series, as well as the department's location, were included in the model specifications, no significant effects were observed.

The literature on conversation dynamics has pointed out how the prevalence of interruptions during spoken interactions can hinder effective communication and be perceived as impolite or disrespectful (Kendrick and Torreira, 2015; Tannen, 1993). While some overlapping speech is inevitable in group discussions, excessive or prolonged interruptions can negatively affect the quality and flow of the conversation, especially in academic settings where the exchange of ideas is crucial for knowledge advancement.

**Emotion embedded in the tone of voice:** To gain further insight into the emotional dynamics of interruptions during presentations, it is analyzed the average emotional tone of interruptions using the predictive model described in Section 3. The dependent variable, the average emotional tone of interruptions during presentations, is calculated by averaging the probabilities assigned to the seven discrete emotions (anger, boredom, sadness, neutrality, calmness, surprise, and happiness) for each interruption. Specifically, for each interruption, the predictive model assigns a probability to each emotion, with the probabilities for all seven emotions summing to one. These probabilities are then averaged across all interruptions in each seminar to obtain a single value for each emotion, representing the overall emotional tone of the interruptions during that seminar.

In the regression analysis in Table A.12, the average probability of a given emotion serves as the dependent variable, capturing the overall level of that emotion expressed during interruptions across all presentations. For instance, in Panel A, the coefficient for "female presenter" under the "anger" column is statistically significant at the 1% level. This suggests that female presenters receive interruptions that, on average, have a higher probability of being associated with anger compared to interruptions received by male presenters.

The regression results reveal differences in the average probability of certain emotions during interruptions between men and women. Interruptions directed toward female presenters by male audience members are more likely to express anger compared to those aimed at male presenters. In contrast, male audience members express less neutral and calm tones when interrupting female presenters than when they interrupt male presenters.

Similarly, interruptions directed towards female presenters by female audience members have a higher average probability of expressing anger and a lower average probability of expressing happiness. Conversely, when female audience members interrupt female presenters, they are less likely to express boredom.

**Interruptions, seniority and citations of the presenter:** Tables A.13 and A.14 present the results of estimating Equation 4 by interacting seniority and citations of the presenter with their gender. Each of the tables' three panels displays the main equation estimated with the total number of interruptions (panel A), interruptions made by males (panel B), and interruptions made by females (panel C).

In both tables, female presenters continue to be significantly associated with an increase in the total number of interruptions when male and female interruptions are pooled together (panel A). Notably, controlling for seniority renders the coefficient of female presenter insignificant in explaining an increase in male interruptions (panel B of Table A.13). By contrast, panel B of Table A.14 shows that the interaction term of citations remains significant at the 1% level, indicating that the impact of female presenters on increasing male interruptions can be mitigated by their academic achievements. Moreover, the results shows a decrease in interruptions made by female audience members when more senior female speakers are presenting, as observed in panel C of

Table A.13. A similar effect is observed in Table A.14 for explaining male interruptions, although the effect is less robust and appears at the 10% confidence level in six out of eight specifications. Finally, no significant effect is found when interruptions made by females is used as the explained variable.

**Time before the first interruption:** Table A.15 presents the results obtained by estimating Equation 4 with the time elapsed before the presenter receives the first interruption as the dependent variable. The results indicate that female presenters tend to receive the first interruption between 1 and 3 minutes earlier than male presenters. Additionally, a higher number of citations in the presentation is associated with a delayed onset of the first interruption, while no significant effect of seniority is observed.

## 6 Concluding Remarks

Yes, female presenters in economic seminars are interrupted more frequently than their male counterparts. On average, they experience nearly 15% more interruptions, with a higher number of comments coming from male attendees and more questions posed by females. Additionally, these interruptions occur earlier in their presentations and are often delivered differently: the presenter's speech is more commonly overlapped by the interrupter's voice, and the tone of the interruptions is typically more negative.

The findings of this study offer support for a less commonly discussed observation: the additional interruptions experienced by female presenters are not exclusively caused by male attendees but also by female participants. Specifically, the proportion of interruptions made by women does not have a significant impact on the overall number of interruptions in a seminar, unless the presenter is a woman. This suggests that when the presenter is female, interruptions from female audience members contribute more to the total number of interruptions compared to when the presenter is male.

Two mechanisms could potentially explain this pattern of female-to-female interruptions. One mechanism refers to interruption behavior as a measure of dominance, disruption, or obstruction. Even if commonly associated with male-to-female interaction,[13] evidence suggests that the balance of power between participants—and not the gender of the participants—is the main driver of these type of interruptions (Hancock and Rubin, 2015; Kollock et al., 1985). Given both the potentially aggressive culture of economics seminars and the under-representation of women in the professional field of economics (Boustan and Langan, 2019), it is plausible that women may feel greater legitimacy to take the floor from other women (of less senior status) than they do to take the floor from men. That female presenters are being interrupted with a more negative tone of voice and by speech overlap from other women in the audience supports the existence of this mechanism. Similar to minority students who adapt their behavior by "acting white," thereby improving their standing with peers (Austen-Smith and Fryer Jr, 2005), female attendees might try to improve their acceptance within the academic community by behaving as their male peers (i.e., "acting male").

A second mechanism is related to the use of an interruption as a way of providing support, adding positively to what is being said in a cooperative way. In this context, women in the audience may feel more comfortable and eager to take the floor when interacting with female peers or within environments characterized by a high proportion of women (Ford et al., 2017; Dasgupta et al., 2015). This may be due to lower levels of intimidation and anxiety about participating (Wey, 2009). Given that seminars are opportunities that researchers use to improve their work, it could also reflect a desire to help

13. In an article in Times, Bennett (2015) coined the term "manterruption" to refer to the unnecessary interruption of women by men in order to silence them and discredit their expertise.

in this regard. This effect could be reinforced by the fact that women are more likely to share common research interests and to work together (Card et al., 2020; Ductor et al., 2018) suggesting that some interruptions could be made by coauthors or colleagues from the same research group. Female presenters receiving more questions from other women in the audience suggests that female-to-female interruptions also serve as a means of "working together to produce shared meanings" (Coates, 2015) than as an attempt to take the floor from another speaker.

These explanations should nevertheless be approached with caution. It does not necessarily follow that interruptions intended to express agreement or ask for clarification always constitute attempts to seize the floor. As noted by Hutchby and Wooffitt (2008) and Dindia (1987), agreement with what is being said can be a precursor to taking over the floor. Conversely, interrupting to disagree is not necessarily disruptive. Even in collaborative, rapport-building simultaneous talk, one speaker gently express disagreement with another (Coates, 2015; Tannen, 1993). For example, the negative relationship found when female presenters interact with seniority to explain the number of interruptions received could work as evidence of both mechanisms. One possibility is that less senior female presenters are interrupted more often by female attendees who use it as a way to exert power. However, it is also possible that these interruptions are made with the intention of offering help and support to younger colleagues.

A similar complexity could arise in the interpretation of questions and comments in seminars. For instance, attendees may pose questions or make comments to demonstrate their knowledge, challenge the presenter's assumptions, or genuinely seek clarification. These actions can be perceived as supportive or combative, depending on the tone, phrasing, and context. The results are nevertheless in line with considerable evidence that women are more likely to express interest in the opinions of others through such means as asking questions (Wodak and Benke, 2017; Mulac et al., 2001; Cameron et al., 1993).

Lastly, it should be noted that results reported in studies of interruptions are sometimes inconsistent, due to differences in the methodologies employed. For instance, the manner in which interruptions are counted may vary across studies. Nevertheless, the definition employed in this work is tractable and provides a clear way to identify and count interruptions, thereby allowing for an easy extension of this work to other domains. Other inconsistencies among previous studies have to do with unrepresentative subject samples, the absence of statistical testing, and faulty statistical methods, which call the reliability of the results of some studies into question. The present study has resulted in the creation of a relatively large dataset that is representative of the various sub-fields of economics, while also including dialogues between individuals who were not affected by any external observer coding or analyzing their interactions.

In that sense, this study is among the first to leverage algorithmic techniques for audio processing in the social sciences, and to the best of my knowledge, offers one of the most comprehensive examinations of audience participation and academic interactions. The growing availability of publications, video and audio recordings, and other materials suggests that such techniques will likely be used in future studies to explore individual behaviors. This method is also easy to replicate and extend to other domains, such as TV interviews or political discussions.

This study evidences significant gender differences in audience participation in academic settings. Addressing this issue calls for interventions to increase awareness of these differences and promote more equitable participation. In the case of economics, in recent years, various academic actors have begun to take steps to enhance understanding of the problem and to facilitate changes that will make the profession more welcoming to women. Understanding the documented differences in the participation of men and women in these types of events is a necessary step toward designing interventions that could positively affect the participation of under-represented groups. For example, differences in the behavior patterns of men and women (e.g., female-to-female interruption vs. male-to-female interruption) or the lower visibility of women in academic activities might affect their roles as role models, potentially perpetuating this cycle. These interventions could include fostering a culture that values inclusive dialogue in seminars, educating moderators and participants to recognize and refrain from unwarranted interruptions, ensuring equal opportunities for everyone to voice their perspectives, and increasing the visibility of women in academic activities. Taking steps to address these disparities can help create more inclusive academic environments that benefit all participants.

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## Appendix A Figures and Tables

FIGURE A.1: LOCATION OF THE DEPARTMENT OF SEMINAR PRESENTERS

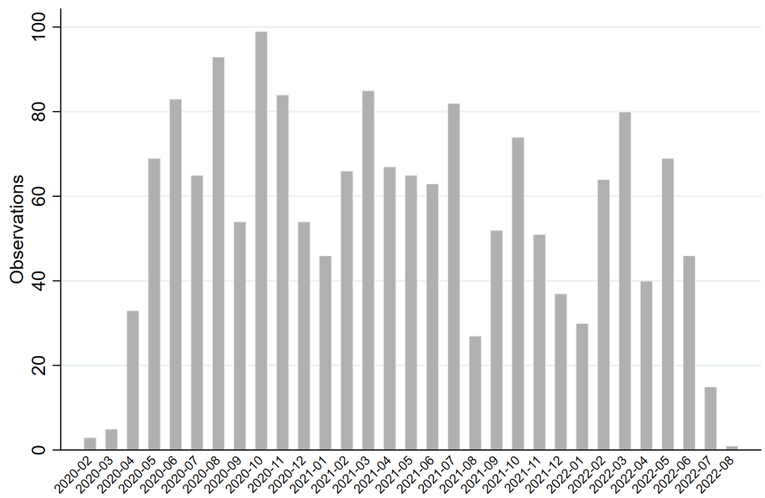



FIGURE A.2: RANKING OF ECONOMICS DEPARTMENT OF SPEAKER'S AFFILIATION

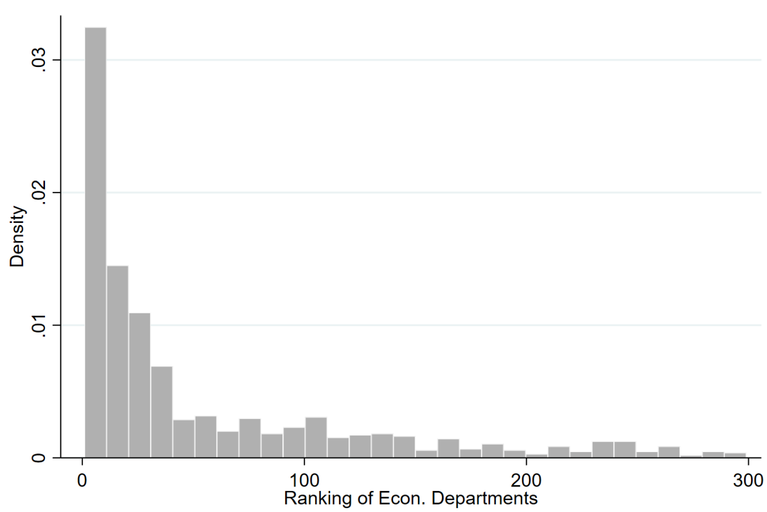


FIGURE A.3: LOCATION OF THE DEPARTMENT OF SEMINAR PRESENTERS

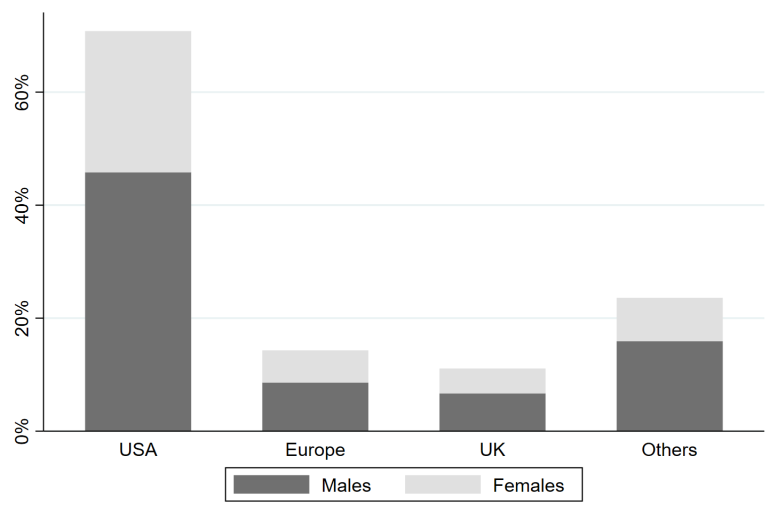



FIGURE A.4: YEAR OF SPEAKER'S FIRST PUBLICATION

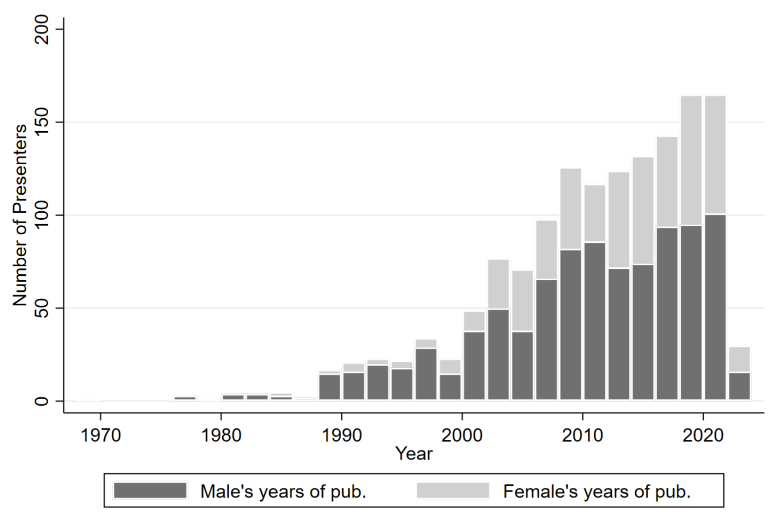


FIGURE A.5: DENSITY OF NUMBER OF INTERRUPTIONS BY GENDER OF THE PRESENTER

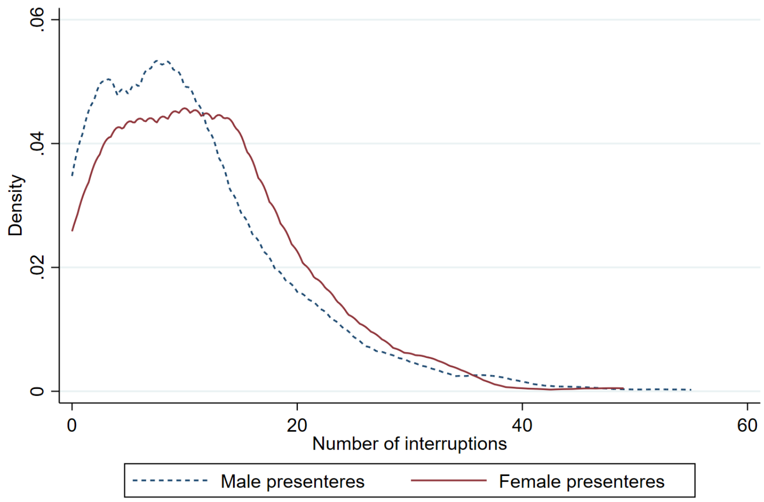



FIGURE A.6: AVERAGE INTERRUPTIONS AND SEMINAR'S DURATION

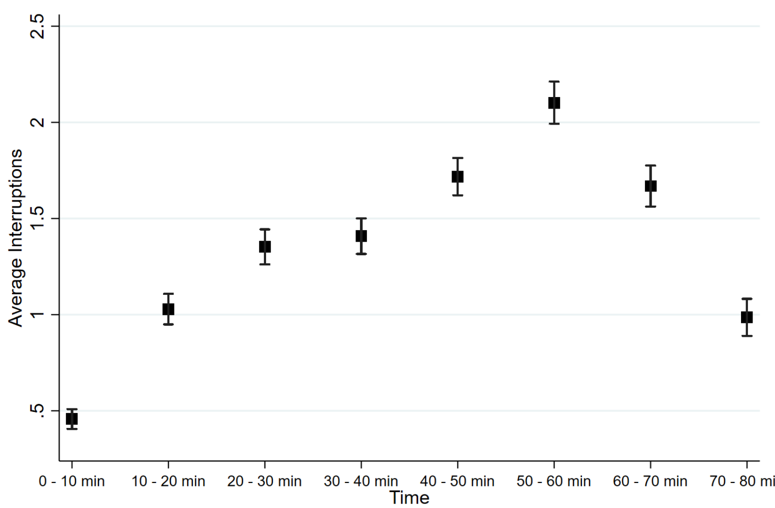


FIGURE A.7: TOPIC ANALYSIS RESULTS

FIGURE A.8: INTERRUPTIONS BY TOPIC

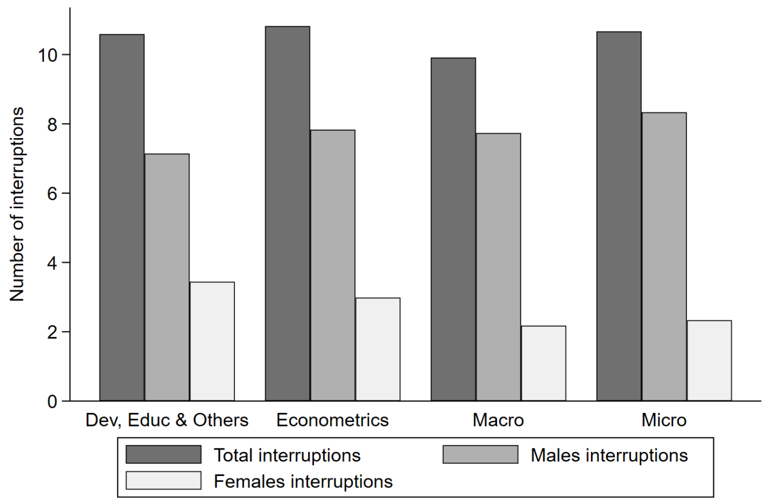
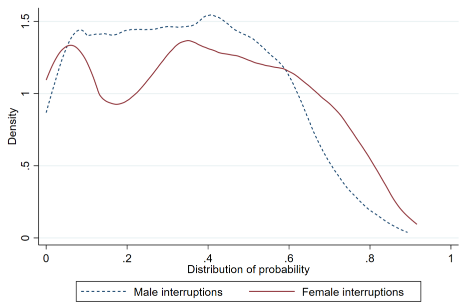
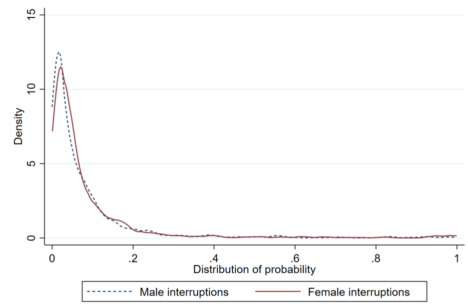


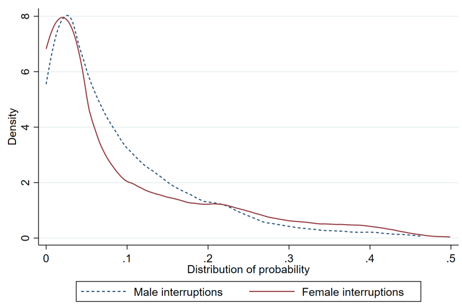
FIGURE A.9: DISTRIBUTION OF PROBABILITY OF EMOTIONS IN INTERRUPTIONS



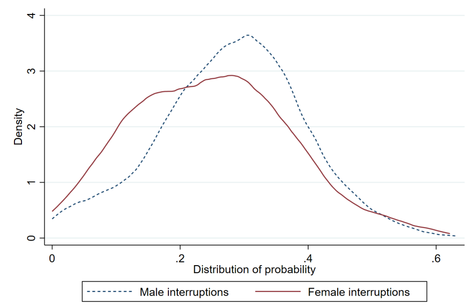

(a) Average probability of anger emotion in seminars.



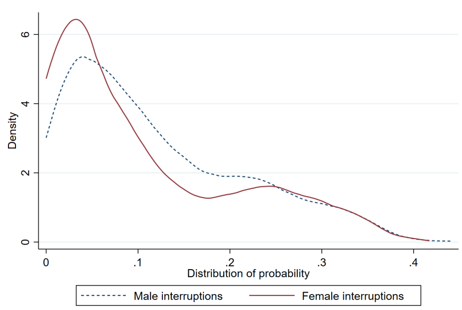

(b) Average probability of bored emotion in seminars.



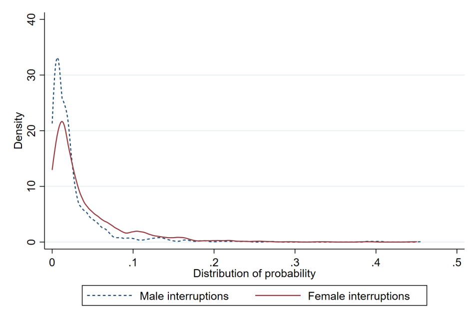

(c) Average probability of calm emotion in seminars.



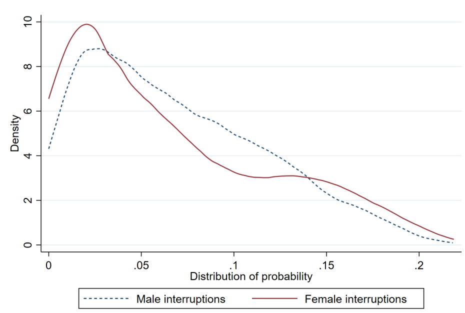

(d) Average probability of happy emotion in seminars




(e) Average probability of neutral emotion in seminars




(f) Average probability of pleasantly surprised emotion in seminars




(g) Average probability of sad emotion in seminars

## TABLE A.1: LOCATION OF THE DEPARTMENT OF SEMINAR PRESENTERS

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Australia | 1.9% | Denmark | 0.2% | Italy | 2.9% | Russia | 0.2% | Turkey | 0.1% |
| Austria | 0.3% | France | 2.2% | Japan | 0.3% | Singapore | 0.5% | USA | 67.4% |
| Belgium | 0.8% | Germany | 2.0% | Luxembourg | 0.9% | South Korea | 0.2% | United Kingdom | 10.6% |
| Brazil | 0.1% | Hong Kong | 0.3% | Netherlands | 1.0% | Spain | 0.9% | | |
| Canada | 3.3% | Ireland | 0.7% | New Zealand | 0.1% | Sweden | 1.4% | | |
| Colombia | 0.2% | Israel | 0.6% | Portugal | 0.4% | Switzerland | 0.8% | | |

## TABLE A.2: SUMMARY TOPIC MODEL

| Topic | Share of topics | Female presenters | JEL - Category | First 5 words of the topic |
|---|---|---|---|---|
| 1 | 7.0% | 27.5% | G -Financial Econ. | bank, financial, capital, risk, credit |
| 2 | 7.5% | 47.5% | I -Health, Edu. & Welfare | treatment, program, group, health, experiment |
| 3 | 6.9% | 38.5% | O- Dev, Innov & Growth | technology, innovation, research, company, patent |
| 4 | 4.7% | 25.6% | L - Industrial Org. | network, transaction, company, information, fund |
| 5 | 5.1% | 34.1% | D - Microeconomics | price, cost, market, consumer, firm |
| 6 | 6.6% | 26.6% | E - Macroeconomics | rate, consumption, model, shock, economy |
| 7 | 10.9% | 38.5% | F - International Econ. | firm, worker, trade, labor, country |
| 8 | 6.0% | 42.4% | R - Urban & Rural | city, area, local, location, population |
| 9 | 7.0% | 33.9% | H - Public Econ. | policy, political, state, country, government |
| 10 | 6.6% | 30.2% | D - Microeconomics | market, price, return, risk, asset |
| 11 | 4.8% | 47.5% | M - Industrial Org. | platform, product, state, policy, information |
| 12 | 4.7% | 41.0% | D - Microeconomics | game, player, choice, preference, set |
| 13 | 8.1% | 50.3% | I -Health, Edu. & Welfare | income, child, high, school, woman |
| 14 | 9.0% | 28.1% | L - Industrial Org. | model, agent, information, function, state |
| 15 | 4.3% | 20.8% | C - Econometrics | variable, effect, result, sample, estimate |

## TABLE A.3: GENDER PREDICTION BASED ON SPEAKER'S VOICE AND SPEAKER'S NAME

| | | Prediction based on the name | |
|---|---|---|---|
| | | Males | Females |
| Prediction based on the voice | Males | 94.7% | 9.0% |
| | Females | 5.3% | 91.0% |

**Results for Seminars More Closely Related to Applied Microeconomics**

The topics considered are the following with the most relevant words of the topic model appearing between parenthesis. Topic 2: Health, Education, and Welfare (treatment, program, group, health, experiment), Topic 3: Economic Development, Innovation, Technological Change, and Growth (technology, innovation, research, company, patent), Topic 8: Urban, Rural, Regional, Real Estate, and Transportation Economics (city, area, local, location, population), Topic 11: Industrial Org. (platform, product, state, policy, information) and Topic 13: Health, Education, and Welfare (income, child, high, school, woman).

TABLE A.4: INTERRUPTIONS IN SEMINARS RELATED TO THE APPLIED MICRO FIELD

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Female presenter | 1.69 | 1.59 | 1.39 | 1.81 |
| | (0.64) | (0.71) | (0.70) | (0.70) |
| Duration (in hs) | 0.20 | 0.19 | 0.17 | 0.13 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Citations | | -0.09 | -0.04 | 0.02 |
| | | (0.09) | (0.08) | (0.07) |
| Seniority | | -0.04 | -0.04 | 0.00 |
| | | (0.04) | (0.04) | (0.04) |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |
| Constant | -2.18 | -1.10 | 0.20 | 5.44 |
| | (1.71) | (1.97) | (2.23) | (5.96) |
| R2 | 0.15 | 0.13 | 0.18 | 0.46 |
| Observations | 548 | 476 | 476 | 476 |

Note: Robust standard errors in parentheses.

TABLE A.5: DETERMINANTS OF NUMBER OF INTERRUPTIONS EXCLUDING SEMINAR'S CHAIR

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: All interruptions*** | | | | |
| Female presenter | 0.77 | 0.76 | 0.75 | 0.81 |
| | (0.37) | (0.41) | (0.41) | (0.37) |
| Duration | 0.16 | 0.17 | 0.16 | 0.12 |
| | (0.01) | (0.01) | (0.01) | (0.02) |
| Citations | | -0.11 | -0.08 | -0.03 |
| | | (0.04) | (0.04) | (0.03) |
| Seniority | | -0.03 | -0.03 | -0.01 |
| | | (0.02) | (0.02) | (0.02) |
| R2 | 0.12 | 0.13 | 0.19 | 0.44 |
| Observations | 1,712 | 1,456 | 1,391 | 1,391 |
| | | | | |
| ***Panel B: Controlling by proportion of females' interruptions*** | | | | |
| Female presenter | -0.05 | -0.31 | -0.15 | -0.04 |
| | (0.54) | (0.60) | (0.60) | (0.53) |
| Prop. Female Inter. | -4.03 | -4.57 | -4.16 | -2.99 |
| | (0.56) | (0.60) | (0.62) | (0.64) |
| Fem. Present x Prop. Fem. Inter | 2.80 | 3.31 | 3.10 | 3.43 |
| | (1.03) | (1.16) | (1.20) | (1.14) |
| Duration | 0.15 | 0.16 | 0.14 | 0.11 |
| | (0.01) | (0.02) | (0.02) | (0.02) |
| Citations | | -0.10 | -0.08 | -0.05 |
| | | (0.04) | (0.04) | (0.03) |
| Seniority | | -0.03 | -0.03 | -0.02 |
| | | (0.03) | (0.03) | (0.03) |
| R2 | 0.12 | 0.14 | 0.19 | 0.42 |
| Observations | 1,435 | 1,224 | 1,179 | 1,179 |
| | | | | |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |

Note: Robust standard errors in parentheses.

TABLE A.6: Interruptions in total numbers and by gender of the interrupter

| | Interruptions by males | Interruptions by females | Total Interruptions |
|---|---|---|---|
| Male Presenters | 8.0 | 2.4 | 10.5 |
| Female Presenters | 8.6 | 3.2 | 11.8 |

TABLE A.7: CONTRASTING INTERRUPTIONS IN INDIVIDUAL SEMINARS WITH SEMINAR SERIES

Dep Var: Proportion Difference of Female Interruptions (Series vs. Specific Seminar)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Female presenter | 0.03 | 0.04 | 0.05 | 0.04 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Duration | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Citations | | -0.00 | -0.00 | -0.00 |
| | | (0.00) | (0.00) | (0.00) |
| Seniority | | -0.00 | -0.00 | 0.00 |
| | | (0.00) | (0.00) | (0.00) |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |
| R2 | 0.00 | 0.01 | 0.01 | 0.06 |
| Observations | 1,592 | 1,348 | 1,292 | 1,292 |

Note: Robust standard errors in parentheses.

TABLE A.8: NUMBER OF QUESTIONS

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: All questions*** | | | | |
| Female presenter | 0.23 | 0.07 | -0.08 | -0.06 |
| | (0.29) | (0.32) | (0.32) | (0.29) |
| R2 | 0.19 | 0.20 | 0.23 | 0.46 |
| Observations | 1,653 | 1,405 | 1,391 | 1,391 |
| ***Panel B: Males' questions*** | | | | |
| Female presenter | -0.59 | -0.64 | -0.62 | -0.47 |
| | (0.28) | (0.30) | (0.31) | (0.29) |
| R2 | 0.13 | 0.14 | 0.17 | 0.40 |
| Observations | 1,653 | 1,405 | 1,391 | 1,391 |
| ***Panel C: Females' questions*** | | | | |
| Female presenter | 0.81 | 0.71 | 0.53 | 0.40 |
| | (0.17) | (0.18) | (0.17) | (0.17) |
| R2 | 0.06 | 0.06 | 0.11 | 0.27 |
| Observations | 1,653 | 1,405 | 1,391 | 1,391 |
| Duration (in hs) | Yes | Yes | Yes | Yes |
| Citations | | Yes | Yes | Yes |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |

Note: Robust standard errors in parentheses.

TABLE A.9: NUMBER OF COMMENTS

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: All comments*** | | | | |
| Female presenter | 1.46 | 1.45 | 1.44 | 1.42 |
| | (0.32) | (0.37) | (0.39) | (0.29) |
| R2 | 0.08 | 0.08 | 0.12 | 0.25 |
| Observations | 1,653 | 1,405 | 1,391 | 1,391 |
| | | | | |
| ***Panel B: Males' comments*** | | | | |
| Female presenter | 1.37 | 1.34 | 1.36 | 1.39 |
| | (0.29) | (0.33) | (0.35) | (0.26) |
| R2 | 0.06 | 0.06 | 0.09 | 0.24 |
| Observations | 1,653 | 1,405 | 1,391 | 1,391 |
| | | | | |
| ***Panel C: Females' comments*** | | | | |
| Female presenter | 0.09 | 0.12 | 0.08 | 0.03 |
| | (0.11) | (0.13) | (0.12) | (0.12) |
| R2 | 0.03 | 0.04 | 0.06 | 0.14 |
| Observations | 1,653 | 1,405 | 1,391 | 1,391 |
| | | | | |
| Duration (in hs) | Yes | Yes | Yes | Yes |
| Citations | | Yes | Yes | Yes |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |

Note: Robust standard errors in parentheses.

TABLE A.10: INTERRUPTIONS MADE BY SMOOTH TALK

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: Smooth int. from all attendees.*** | | | | |
| Female presenter | -0.02 | -0.04 | -0.11 | -0.11 |
| | (0.09) | (0.10) | (0.11) | (0.11) |
| R2 | 0.05 | 0.04 | 0.06 | 0.21 |
| Observations | 1,712 | 1,456 | 1,391 | 1,391 |
| ***Panel B: Smooth int. from male attendees.*** | | | | |
| Female presenter | -0.22 | -0.23 | -0.28 | -0.27 |
| | (0.07) | (0.07) | (0.09) | (0.10) |
| R2 | 0.04 | 0.03 | 0.05 | 0.21 |
| Observations | 1,712 | 1,456 | 1,391 | 1,391 |
| ***Panel C: Smooth int. from female attendees.*** | | | | |
| Female presenter | 0.20 | 0.19 | 0.17 | 0.16 |
| | (0.06) | (0.06) | (0.05) | (0.06) |
| R2 | 0.03 | 0.03 | 0.05 | 0.13 |
| Observations | 1,712 | 1,456 | 1,391 | 1,391 |
| Duration (in hs) | Yes | Yes | Yes | Yes |
| Citations | | Yes | Yes | Yes |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |

Note: Robust standard errors in parentheses.

TABLE A.11: INTERRUPTIONS MADE BY OVERLAPPING TALK

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: Overlapping int. from all attendees.*** | | | | |
| Female presenter | 1.15 | 1.01 | 0.86 | 0.87 |
| | (0.26) | (0.29) | (0.29) | (0.26) |
| R2 | 0.18 | 0.19 | 0.24 | 0.49 |
| Observations | 1,712 | 1,456 | 1,391 | 1,391 |
| ***Panel B: Overlapping int. from male attendees.*** | | | | |
| Female presenter | 0.70 | 0.62 | 0.61 | 0.72 |
| | (0.25) | (0.27) | (0.28) | (0.24) |
| R2 | 0.12 | 0.13 | 0.17 | 0.44 |
| Observations | 1,712 | 1,456 | 1,391 | 1,391 |
| ***Panel C: Overlapping int. from female attendees.*** | | | | |
| Female presenter | 0.50 | 0.41 | 0.25 | 0.12 |
| | (0.18) | (0.19) | (0.19) | (0.19) |
| R2 | 0.05 | 0.05 | 0.10 | 0.25 |
| Observations | 1,712 | 1,456 | 1,391 | 1,391 |
| Duration (in hs) | Yes | Yes | Yes | Yes |
| Citations | | Yes | Yes | Yes |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |

Note: Robust standard errors in parentheses.

TABLE A.12: PREDICTED EMOTIONS IN THE TONE OF VOICE OF THE INTERRUPTIONS

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Angry | Boredom | Sad | Neutral | Calm | Pleas. Surprised | Happy |
| ***Panel A: All questions*** | | | | | | | |
| Female presenter | 0.05 | 0.00 | -0.01 | -0.01 | -0.02 | -0.01 | -0.00 |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) |
| R2 | 0.35 | 0.36 | 0.36 | 0.37 | 0.36 | 0.32 | 0.21 |
| Observations | 1,269 | 1,269 | 1,269 | 1,269 | 1,269 | 1,269 | 1,269 |
| ***Panel B: Males' questions*** | | | | | | | |
| Female presenter | 0.06 | 0.00 | -0.01 | -0.02 | -0.02 | -0.01 | -0.00 |
| | (0.01) | (0.01) | (0.00) | (0.01) | (0.00) | (0.00) | (0.01) |
| R2 | 0.37 | 0.38 | 0.40 | 0.40 | 0.39 | 0.36 | 0.23 |
| Observations | 1,170 | 1,170 | 1,170 | 1,170 | 1,170 | 1,170 | 1,170 |
| ***Panel C: Females' questions*** | | | | | | | |
| Female presenter | 0.06 | -0.03 | -0.01 | -0.01 | 0.01 | -0.00 | -0.02 |
| | (0.02) | (0.01) | (0.00) | (0.01) | (0.01) | (0.00) | (0.01) |
| R2 | 0.36 | 0.25 | 0.32 | 0.33 | 0.30 | 0.21 | 0.24 |
| Observations | 717 | 717 | 717 | 717 | 717 | 717 | 717 |

Note: All the specifications were estimated while controlling for seminar duration, speaker seniority and citations, topic of the presentation, speaker's department location, and seminar series. Robust standard errors in parentheses.

TABLE A.13: INTERRUPTIONS AND SENIORITY OF THE PRESENTER

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: All interruptions*** | | | | |
| Female presenter | 2.18 | 2.25 | 1.87 | 1.47 |
| | (0.70) | (0.70) | (0.71) | (0.61) |
| Seniority | -0.04 | -0.01 | -0.01 | -0.00 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Fem. presenter x Seniority | -0.05 | -0.06 | -0.05 | -0.01 |
| | (0.05) | (0.05) | (0.05) | (0.04) |
| R2 | 0.20 | 0.20 | 0.26 | 0.51 |
| Observations | 1,457 | 1,456 | 1,391 | 1,391 |
| ***Panel B: Males' interruptions*** | | | | |
| Female presenter | 0.60 | 0.68 | 0.34 | 0.32 |
| | (0.64) | (0.65) | (0.66) | (0.57) |
| Seniority | -0.04 | -0.01 | -0.02 | -0.02 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Fem. presenter x Seniority | 0.02 | 0.01 | 0.04 | 0.06 |
| | (0.05) | (0.05) | (0.05) | (0.04) |
| R2 | 0.14 | 0.14 | 0.19 | 0.46 |
| Observations | 1,457 | 1,456 | 1,391 | 1,391 |
| ***Panel C: Females' interruptions*** | | | | |
| Female presenter | 1.58 | 1.57 | 1.53 | 1.15 |
| | (0.37) | (0.37) | (0.38) | (0.37) |
| Seniority | 0.00 | 0.00 | 0.01 | 0.02 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Fem. presenter x Seniority | -0.07 | -0.07 | -0.09 | -0.07 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| R2 | 0.07 | 0.06 | 0.12 | 0.25 |
| Observations | 1,457 | 1,456 | 1,391 | 1,391 |
| Duration (in hs) | Yes | Yes | Yes | Yes |
| Citations | | Yes | Yes | Yes |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |

Note: Robust standard errors in parentheses.

TABLE A.14: INTERRUPTIONS AND CITATIONS OF THE PRESENTER

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ***Panel A: All interruptions*** | | | | |
| Female presenter | 1.78 | 1.73 | 1.53 | 1.35 |
| | (0.45) | (0.45) | (0.46) | (0.40) |
| Citations | -0.11 | -0.10 | -0.07 | -0.03 |
| | (0.05) | (0.05) | (0.05) | (0.04) |
| Fem. presenter x Citations | -0.13 | -0.13 | -0.14 | 0.01 |
| | (0.12) | (0.11) | (0.11) | (0.11) |
| R2 | 0.20 | 0.20 | 0.26 | 0.51 |
| Observations | 1,456 | 1,456 | 1,391 | 1,391 |
| ***Panel B: Males' interruptions*** | | | | |
| Female presenter | 0.94 | 0.93 | 0.89 | 0.98 |
| | (0.42) | (0.42) | (0.43) | (0.36) |
| Citations | -0.10 | -0.10 | -0.08 | -0.04 |
| | (0.04) | (0.05) | (0.04) | (0.03) |
| Fem. presenter x Citations | -0.14 | -0.14 | -0.12 | -0.04 |
| | (0.09) | (0.09) | (0.08) | (0.08) |
| R2 | 0.14 | 0.14 | 0.19 | 0.46 |
| Observations | 1,456 | 1,456 | 1,391 | 1,391 |
| ***Panel C: Females' interruptions*** | | | | |
| Female presenter | 0.84 | 0.81 | 0.63 | 0.37 |
| | (0.26) | (0.26) | (0.26) | (0.26) |
| Citations | -0.01 | 0.00 | 0.01 | 0.00 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Fem. presenter x Citations | 0.01 | 0.01 | -0.02 | 0.04 |
| | (0.08) | (0.08) | (0.08) | (0.09) |
| R2 | 0.06 | 0.06 | 0.11 | 0.25 |
| Observations | 1,456 | 1,456 | 1,391 | 1,391 |
| Duration (in hs) | Yes | Yes | Yes | Yes |
| Seniority | | Yes | Yes | Yes |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |

Note: Robust standard errors in parentheses.

TABLE A.15: TIME AT WHICH OCCURS THE FIRST INTERRUPTION.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Female presenter | -2.86 | -2.11 | -2.06 | -1.33 |
| | (0.81) | (0.90) | (0.92) | (0.82) |
| Duration (in hs) | 0.11 | 0.08 | 0.08 | 0.14 |
| | (0.03) | (0.03) | (0.03) | (0.04) |
| Citations | | 0.32 | 0.27 | 0.18 |
| | | (0.10) | (0.10) | (0.09) |
| Seniority | | 0.02 | 0.00 | -0.02 |
| | | (0.05) | (0.06) | (0.05) |
| Topic | | | Yes | Yes |
| Speaker's Dept. Locat. | | | | Yes |
| Seminar Series | | | | Yes |
| Constant | 18.40 | 18.47 | 22.32 | 13.56 |
| | (1.71) | (1.88) | (2.64) | (4.63) |
| R2 | 0.02 | 0.02 | 0.07 | 0.38 |
| Observations | 1,562 | 1,318 | 1,262 | 1,262 |

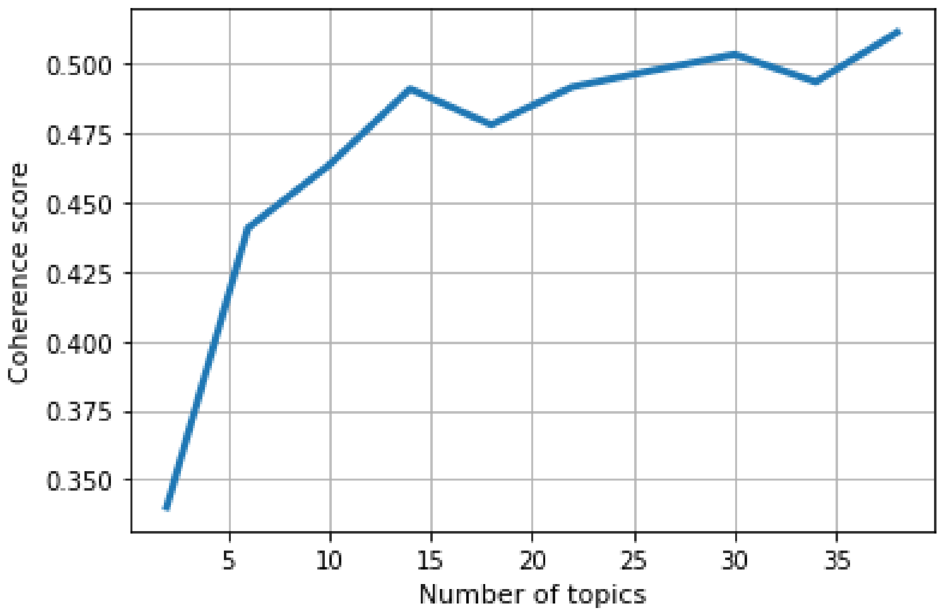
Note: Robust standard errors in parentheses.

## Appendix B Topic model

The coherence variance (CV) is a metric used to evaluate the quality of a topic model by measuring how well the words in each topic are related to each other. To compute the CV, the coherence score is calculated for each number of topics using a sliding window approach that measures the degree to which words in a topic co-occur with each other in the corpus. The CV plot is a visualization of the CV metric that shows the coherence score for different numbers of topics.

The CV plot indicates that the coherence scores increase rapidly from 1 to 10 topics and then plateau around 20 topics. This pattern suggests that the optimal number of topics for the corpus is likely between 10 and 20 topics. Overall, the CV plot provides valuable information about the quality of the topic model and can help identify the optimal number of topics that best captures the structure of the corpus.

FIGURE B.1: CHOOSING THE OPTIMAL MODEL WITH COHERENCE SCORE



## Appendix C Audio Signal Processing

Audio signal processing entails the extraction of essential features from audio data. This study extracts three primary features: Mel Spectrogram Frequencies (Mel), Chroma Coefficients (Chromagram), and Mel Frequency Cepstral Coefficients (MFCC). Their respective sizes - 128 for Mel, 12 for Chroma, and 40 for MFCC - are standard in the field of audio signal processing, although they are not fixed. These sizes are chosen to strike a balance between capturing sufficient detail and managing computational cost and complexity.

- **128 Mel Spectrogram Frequencies (Mel):** Mel Spectrograms convert the frequency scale to a Mel scale, a perceptual scale of pitches. While 128 is a common value, other values such as 64 or 96 may also be used depending on the task at hand. Using a higher number of Mel frequencies may capture more detail but at a higher computational cost.
- **12 Chroma Coefficients (Chromagram):** The number 12 corresponds to the 12 distinct semitones or pitch classes in the Western musical scale (C, C#, D, D#, E, F, F#, G, G#, A, A#, B). Chroma features are frequently used in music information retrieval applications such as chord detection and key detection.
- **40 Mel Frequency Cepstral Coefficients (MFCC):** MFCCs make up the Mel-frequency cepstrum (MFC). The number of MFCCs used is also a hyperparameter that can be tuned based on the specific task. In speech recognition, common choices are 13, 20, or 40 coefficients. In this study, 40 has been chosen to capture a broader range of voice characteristics.

These feature sizes represent a compromise between precision and computational expense. While these are common conventions that work well in many applications, it's critical to understand they are not strict rules. The optimal values may vary depending on the specifics of the problem under investigation.

# Appendix D Presenters and Affiliation

## List of all speakers identified (in parenthesis the number of seminars in which they took part).

Daron Acemoglu (7), Markus Brunnermeier (6), Esteban Rossi-Hansberg (5), Shengwu Li (5), Piotr Dworczak (5), Stephen Redding (4), Stefanie Stantcheva (4), Luigi Zingales (4), Darrell Duffie (4), Volker Wieland (4), Matthew Gentzkow (4), Jean Tirole (3), Douglas Bernheim (3), Shane Greenstein (3), Simone Bertoli (3), Alessandro Pavan (3), Amartya Se (3), Oleg Itskhoki (3), Harald Uhli (3), Pierre Collin-Dufresne (3), Harald Uhlig (3), Maria Cotofan (3), Melissa Dell (3), Marzena Rostek (3), Adrien Bilal (3), Susan Athey (3), Beata Javorcik (3), Avi Goldfarb (3), Brett Falk (2), Bruno Biais (2), Andrés Rodríguez-Clar (2), Ludwig Strau (2), Myra Samuels (2), Gurdip Bakshi (2), Luis Cabral (2), Randall Wright (2), James Read (2), Guido Imbens (2), Raj Chetty (2), Branko Milanovic (2), Jonathan Athow (2), Sonia Bhalotra (2), Nima Haghpanah (2), Raphael Espinoz (2), Edward Glaeser (2), Nicole Immorlica (2), Arjada Bardhi (2), Gilles Duranton (2), Jesse Schreger (2), Gianluca Violante (2), Nancy Qian (2), Swati Dhingra (2), Sydney Ludvigson (2), Giovanni Violant (2), Natalia Fabra (2), Arvind Krishnamurthy (2), Dave Donaldson (2), Steve Tadelis (2), Friederike Mengel (2), Antonio Andreon (2), Antoinette Schoar (2), Monica Morlacco (2), Annie Liang (2), Richard Blundell (2), Ruslan Goyenko (2), Ruslan Salakhutdinov (2), Stefano Giglio (2), Stefano DellaVigna (2), Fuhito Kojima (2), Renee Bowen (2), Andrei Hagiu (2), Jorge Guzman (2), Sara Signorelli (2), Juliet Schor (2), Kevin Fox (2), Edward Miguel (2), Yan Chen (2), Federico Echenique (2), Elhanan Helpman (2), Michel Beine (2), Yeon-Koo Che (2), Fabrizio Zilibotti (2), Ying Nian Wu (2), Yingni Guo (2), Paola Giuliano (2), Shota Ichihashi (2), Alan Blinder (2), Christian Krekel (2), Hélène Rey (2), Elliot Lipnowski (2), Hunt Allcott (2), Yuliy Sannikov (2), Sarah Flèche (2), Emmanuel Yimfo (2), Zibin Huan (2), Esther Duflo (2), Esen Onur (2), Matthieu Gomez (2), Barry Eichengreen (2), Laura Veldkamp (2), Pierre-Olivier Weill (2), Leonard Wantchekon (2), Dmitry Taubinsky (2), Doireann Fitzgerald (2), Leeat Yariv (2), Isabela Manelici (2), Nathan Nunn (2), Ana Maria Santacreu (2), Hanna Halaburda (2), Wei Xiong (2), Matthew Jackson (2), Michael Woodford (1), Michael Weber (1), Michael Luc (1), Mushfiq Mobarak (1), Michael Lee (1), Mikhail Chernov (1), Miguel Ferreira (1), Michelle Segovia (1), Michelle Reininge (1), Michael Kremer (1), Michael Kiley (1), Mushfiq Mobara (1), Michael Keen (1), Micheal Junho Lee (1), Michela Giorcelli (1), Michael Kearns (1), Michael Jordan (1), Mushtaq Khan (1), Micheala Giorcelli (1), Mikkel Plagborg-Møller (1), Mo Salah (1), Muly San (1), Michael Richards (1), Monica Martinez-Bravo (1), Mike Waugh (1), Michael Ostrovsky (1), Monica de Bolle (1), Morgan Frank (1), Moritz Schularick (1) , Mike Brewer (1), Morten Sorense (1), Michael Wittry (1), Moshe Tennenholtz (1), Michael Marder Upheaval (1), Michaela Kreyenfeld (1), Michael Smith (1), Motohiro Yogo (1), Muhammad Yasir Khan (1), Mike Andrews (1), Monica Bell (1), Nellie Liang (1), Myrna Wooders (1), Nachi Subramanian (1), Otmar Issing (1), Osea Giuntell (1), Oriana Bandiera (1), Ori Heffetz (1), Omer Tamuz (1), Olle Hammar (1), Olivier Daviaud (1), Olivier Darmouni (1), Olivier Blanchard (1), Oliver Levine (1), Oliver Hart (1), Olga Mikheev (1), Oleksiy Kryvstov (1), Odilon Câmara (1), Oded Galor (1), Ovanes Petrosian (1), Pablo Ottonello (1), Michael Clemens (1), Patrick Ferguson (1), Patrick Augustin (1), Patricia Cortes (1), Paschal Donohoe (1), Parag Pathak (1), Paolo Brunori (1), Pamela Campa (1), Paolina Medina (1), Paola Pederzoli (1), Paola Manzini (1), Paola Conconi (1), Pamela Medina Quispe (1), Pamela Medina

Quisp (1), Pamela Jakiela (1), Nora Lustig (1), Nonso Obikili (1), Noam Yuchtman (1), Nava Ashra (1), Niall Hughes (1), Michael Grubb (1), Neil Thompson (1), Navin Kartik (1), Navin Kartik (1), Nava Ashraf (1), Nathaniel Hendren (1), Nicholas Kozeniauskas (1), Nathaniel Baum-Snow (1), Nathan Yang (1), Natalie Lee (1), Natalia Ordaz Reynoso (1), Nancy Rigotti (1), Nicholas Ashford (1), Nicholas Z. Muller (1), Nitya Pandalai-Nayar (1), Nikita Gaponiuk (1), Nishant Yonza (1), Nina Pavcnik (1), Nina Buchman (1), Nina Boyarchenko (1), Nina Balcan (1), Nimmi Patel (1), Nikolay Gatche (1), Nikhil Vellodi (1), Nicola Fuchs-Schundeln (1), Nicolás Ajzenman (1), Nicolas Ziebarth (1), Nicolas Vieille (1), Nicolas Treich (1), Nicolas Morales (1), Nicolas Lambert (1), Nicola Fusari (1), Michael Hallsworth (1), Matthew Elliott (1), Michael Greenstone (1), Leslie Marx (1), Ling Zhou (1), Linda Schilling (1), Linda Goldberg (1), Lin Tian (1), Liang Lu (1), Levent Altinoglu (1), Lester T. Chan (1), Leonhard Lades (1), Leah Bevis (1), Leonardo Melosi (1), Leonardo Madio (1), Leonardo Bursztyn (1), Leon Musolff (1), Leigh Shaw-Taylor (1), Leandro Navarro (1), Leah Platt Boustan (2), Lingfei Wu (1), Lint Barrag (1), Lisa Spantig (1), Liuren Wu (1), Maggie Jones (1), Madhuparna Ganguly (1), Maarten Lindeboom (1), M. Tivadar (1), Y. Schaeffer (1), M. Caridad Araujo (1), Léontine Goldzahl (1), Lynn Wu (1), Lukas Delgado-Prieto (1), Luisa Hammer (1), Luis Brites Pereira (1), Lucie Gadenne (1), Luciano Pomatto (1), Lorenzo Caliendo (1), Lorenz Götte (1), Lones Smith (1), Lloyd Dean (1), Ljubica Georgievska (1), Lawson Connor (1), Manju Pur (1), Kris Jacobs (1), L. Melon (1), L. Christensen (1), Kyungmin Kim (1), Kymberle Sterling (1), Kwabena Baah Donkor (1), Ksenia Shakhgildyan (1), Per Krusell (1), Krisztina Kis-Kato (1), Kose John (1), Lawrence Schmidt (1), Kosali Simon (1), Konstantin Sonin (1), Konrad Mierendorff (1), Klaus Desmet (1), Klaus Adam (1), Kitt Carpenter (1), Kirsten Slungaard Mumma (1), Kim Ruhl (1), Lara Bohne (1), Larry Hershfield (1), Larry Katz (1), Larry Summers (1), Lawrence Carin (1), Lavinia Piemontes (1), Laurent Mathevet (1), Laurent Clerc (1), Lauren Hoehn-Velasco (1), Lauren Chenarides (1), Laura Schechter (1), Laura Pilossoph (1), Laura Parisi (1), Laura Ogliari (1), Laura Doval (1), Laura Castillo Martinez (1), Laura Alfaro (1), Laszlo Tetenyi (1), Lasse Heje Pedersen (1), Lars Vilhuber (1), Lars Hansen (1), Miltiadis Makris (1), Manoj Pradhan (1), Michael Barnett (1), Massimo Anelli (1), Matthew Clair (1), Matteo Gamalerio (1), Matt Lasmanis (1), Matilde Bombardini (1), Mathilde Muñoz (1), Mathilde Emeriau (1), Massimo Morelli (2) , Masao Fukui (1), Martin Schmal (1), Marzena Rostek (1), Mary Barra (1), Mary Amiti (1), Martín Fernández-Sánchez (1), Martina Kirchberger (1), Martina Björkman Nyqvist (1), Martin Weale (1), Martin Spindle (1), Matthew Dene (1), Paul Collier (1), Matthew Gentzkow (1), Matthew Mitchell (1), Merrick Li (1), Meredith Crowley (1), Meredith Crowley (1), Melissa LoPalo (1), Melanie Wallsko (1), Melanie Meng Xue (1), Megna Chaudhuri (1), Meg Meyer (1), Maylis Avaro Seminar (1), Maya Rossin-Slater (1), Maximilian Kasy (1), Max Chomas (1), Maureen O'Hara (1), Maureen O'Hara (1), Mattia Fochesato (1), Matthias van den Heuvel (1), Matthew O. Jackson (1), Martin Schneider (1), Martin Ravallion (1), Manolis Galenianos (1), Maria Roche (1), Maria Petrova (2), Maria Marshall (1), Maria Kurakina (1), Maria Balgova (1), Margherita Giuzio (1), Margaret Meyer (1), Marco González-Navarro (1), Martin Ellison (1), Marco Avellaneda (1), Marcin Pęski (1), Marcel Fratzscher (1), Marc Melitz (1), Manuel Tong (1), Manuel Bautista-González Seminar (1), Manuel Adelino (1), Manolis Zampetakis (1), Maria Sole Pagliari (1), Maria Titova (1), Mariaflavia Harari (1), Mariana Gerstenbluth (1), Martin Elliso (1), Martin Eichenbaum (1), Martin Bodenstei (1), Martin Bichler (1), Martha Justus (1), Marta Prato (1), Marshall Burke (1), Markus Leippold (1), Mark Lowcock (1), Mark Bognann (1), Marius Busemeye (1), Marion Leroutier (1), Mario Molin (1), Mario Draghi (1), Marie Claire Villeval (1), Mariana Mazzucato (1), Mariana Khapko (1), Paul Belleflamme (1), - Michele Lenza (1), Paul Elhorst (1), Tamer Başar (1), Terry Hendershott (1), Ted Miguel

(1), Tayfun Sönmez (1), Tayfun Sonmez (1), Tatiana Rosá (1), Tarun Ramadorai (1), Tarun Kabiraj (1), Tamar Oostrom (1), Stijn Van Nieuwerburg (1), Syngjoo Choi (1), Sylvan Herskowit (1), Swapnika Rachapalli (1), Swapnendu Banerje (1), Svetlana Bryzgalova (1), Sven Rady (1), Sumit Agarwal (1), Sukwoong Choi (1), Theo Offerman (1), Thies Lindenthal (1), Thomas Crossley (1), Thomas Philippon (1), Toman Barsbai (1), Tobias Sichert (1), Tobias Salz (1), Tobias Klein (1), Tito Boeri (1), Timothy Besley (1), Timo Boppart (1), Tim Roughgarden (1), Tim Kriege (1), Tim Besley (1), Tim Armstrong (1), Tilman Börgers (1), Tijan Bah (1), Tianyi Wang (1), Thomas Sterner (1), Thomas Schmitz (1), Thomas Rivera (1), Suanna Oh (1), Steven Tadeli (1), Siddharth Suri (1), Simone Galperti (1), Srabashi Ray (1), Sophie Calder-Wan (1), Sonia Jaffe (1), Song Lin (1), Soeren Henn (1), Soares (1), Siyuan Li (1), Siyu Ma (1), Simone Galpert (1), Steven Stillman (1), Simon Mongey (1), Simon Maye (1), Simon Martin (1), Simon Loertscher (1), Simon Grant (1), Simon Franklin (1), Simon Deakin (1), Silvio Micali (1), Stefan G. Hofmann (1), Stefan Nagel (1), Stefania Albanes (1), Stefania Garetto (1), Steven Ruggles (1), Steven Rolf (1), Steven G. Rothmeie (1), Steven Durlauf (1), Steven Callander (1), Steve Redding (1), Steve Heston (1), Steve Callander (1), Stephen Morris (1), Stephen Machin (1), Stephen J. Terr (1), Stephen Figlewski (1), Stephane Wolton (1), Stephane Hallegatte (1), Stephan Meier (1), Stephan Lauermann (1), Steffan Mau (1), Tony Cookson (1), Torben Andersen (1), Yajna Govind (1), Yiling Chen (1), Yeon-Koo Che (1), Yannick Dillschneider (1), Yannay Spitzer (1), Yannai Gonczarowski (1), Yang Zhou: (1), Yang Li (1), Yan Ba (1), Xuhui (1), Trang Hoang (1), Xintong Zhan (1), Xiaotie Deng (1), Xiaosheng Mu (1), Xiaolan Fu (1), Xiao Lin (1), Xianwen Shi (1), Xiang Ha (1), Xiang Ding (1), Ying Yao (1), Yingni Guo - Project (1), Yingyan Zhao (1), Yoko Okuyama (1), Éva Tardos - Virtues (1), Éva Tardos (1), Jeffrey S. Skoll (1), Zoe Cullen (1), Zlatko Bodrozic (1), Ziad Obermeyer (1), Zhou Yu (1), Zhijun Chen (1), Yvonne Giesing (1), Yusuke Narita (1), Yuree Lim (1), Yuhta Ishii (1), Yuhei Miyauchi (1), Yuen Yuen Ang (1), Yu Na Lee (1), Yossef Rapoport (1), Yoram Halevy (1), Xi Xiong (1), Xavier Vives (1), Xavier Gabaix (1), Veronica Guerrieri (1), Verena Weber (1), Vassilis Zikas (1), Vasily Korovki (1), Vasiliki Skreta (1), Vasco Carvalho (1), Valerie Mueller (1), Vadim Elenev (1), Victoria Gregory (1), Utsav Sadana (1), Ulrike Malmendier (1), Ulrich Volz (1), Ulrich Laitenberger (1), Uday Rajan (1), Tyler Muir (1), Tuğba Bozçağ (1), Tristan Fitzgerald (1), Trish Greenhalgh (1), Vernon Henderson (1), Vic Adamowicz (1), Xavier Gabai (1), Victor Chernozhukov (1), Wolf-Hendrik Uhlbach (1), Wioletta Dziuda (1), William Cobbett (1), Willemien Kets (1), Will Gornal (1), Wenxin Du (1), Warwick McKibbin (1), Warwick McKibbi (1), Wagner F. Oliveira (1), Viviane Sanfelice (1), Vivian Lee (1), Vittorio Bass (1), Vincent Meisner (1), Vincent Anesi (1), Vili Lehdonvirta (1), Viktor Todorov (1), Victoria Barone (1), Silvia Peracchi (1), Shuaiqi Li (1), Paul Krugman (1), Ramon Faulí Oller (1), Rebecca Dizon-Ross (1), Raymond Fisman (1), Raoul van Maarseveen (1), Rann Smorodinsky (1), Randy Wright (1), Randall Akee (1), Ran Spiegler (1), Ran Spiegler (1), Ramanan Laxminarayan (1), Rachel Cummings (1), Ralph Koijen (1), Rakesh Vohra (1), Raissa Fabregas (1), Rahul Deb (1), Rahi Abouk (1), Raffaella Sadun (1), Rachid Laajaj (1), Rachel Griffith (1), Rebecca Henderson (1), Rebecca Myerson (1), Rebecca Sachs (1), Rema Hanna (1), Robert J. Lampman (1), Robert Inklaar (1), Robert Hill (1), Robert Hal (1), Robbie Butler (1), Rob Simmon (1), Rizki Siregar (1), Rick van del Ploeg (1), Richard Townsend (1), Richard Sylla (1), Richard Baldwi (1), Ricardo Reyes-Heroles (1), Ricardo Reis (1), Ricardo Correa (1), Renato Paes Leme (1), Renato Gomes (1), Renato Faccini (1), Rachel E. Kranton (1), Rachana Bhatt (1), Shouyong Shi (1), Penny Meal (1), Peter Hull (1), Peter Feldhutter (1), Peter Cramton - Lessons (1), Peter Carr (1), Peter Carr (1), Peter Buisseret (1), Peter Buhlmann (1), Pete Klenow (1), Pengpeng Xiao (1), Pawel Adrjan (1), Paula Vedoveli (1), Paula Bustos (1), Paul Romer (1), Paul Rodriguez-Lesmes

(1), Paul Novostad (1), Paul Milgrom (1), Paul Levine (1), Peter Nencka (1), Peter Rosendorff ( 1), Peter Taylor-Gooby (1), Peter Wendell (1), Quitzé Valenzuela-Stookey (1), Claudio Ferraz (1), Prachi Singh (1), Ponce Del Castillo (1), Pol Antras (2), Pietro Veronesi (1), Pierre-Louis Vézina (1), Pierre-François Weber (1), Pierre Yared (1), Piero Gottardi (1), Philippe Goulet (1), Philip Lane (1), Petra Vokata (1), Petra Todd (1), Petra Moser (1), Petra Mose (1), Robert J. Aumann (1), Robert Johnson (1), Robert Peel (1), Sarah Auster (1), Sathya Gopalakrishnan (1), Sascha Steffen ( 1), S arath B alachandran ( 1), S arah Ridout (1), Sarah Hawkes (1), Sarah Eichmeyer (1), Sara Lowe (1), Robert Pollin (1), Sara Giunti (1), Sang Byung Seo (1), Sandra Sequeira (1), Sandra Rosenbau (1), Sandra Mat (1), Sandip Sukhtanka (1), Samuel Marden (1), Samuel Bazz (1), Scott Duke Kominers (1), Scott Halpern (1), Sean Higgins (1), Sebastian Galiani (1), Sheri Berman (1), Sharon Traiberman (1), Sharat Ganapati (1), Sharada Davidson (1), Shaoying Ma (1), Sewon Hur (1), Sevgi Yuksel (1), Sevan Yesilta (1), Seth Benzell (1), Sergiu Hart (1), Sergei Guriev (1), Selçuk Bedü (1), Selina Gang (1), Sekou Keita (1), Seema Jayachandran (1), Sebnem Kalemli-Ozcan (1), Sebastián Álvarez (1), Samina Raja (1), Sam Kortum (1), Salvatore Carrozzo (1), Roland Strausz (1), Roger Farmer (1), Rod Garratt (1), Rod Garrat (1), Robtel Neajai Paile (1), Robin Schimmelpfenni (1), Robin Greenwood (1), Robin Burgess (1), Robin Burges (1), Robin Allen (1), Roberto Weber (1), Robert Zymek (1), Robert Wilson (1), Robert West (1), Robert Shimer (1), Robert Seamans (1), Robert Reich (1), Robert Ready (1), Rohini Pand (1), Romain Wacziarg (1), Saleh (1), Roman Kozha (1), Saleemul Huq (1), Saleem Baha (1), Sabrina Howell (1), S. Nageeb Ali (1), S. 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