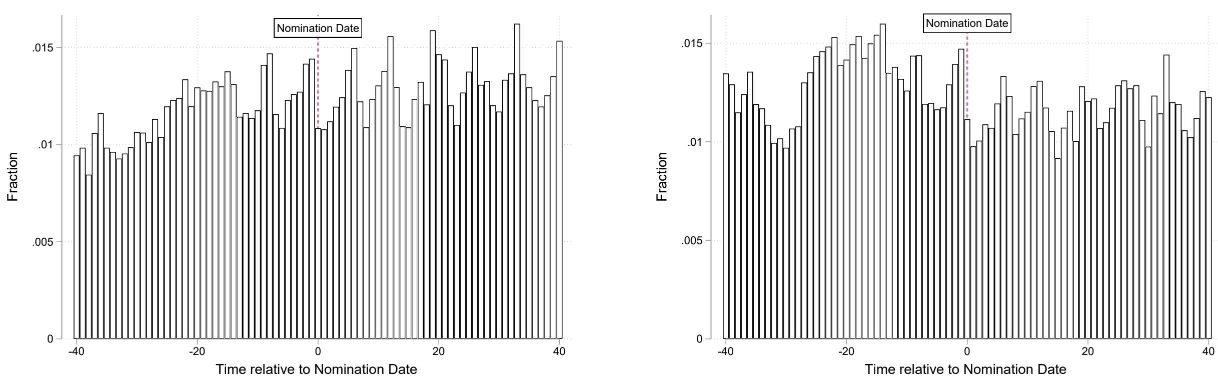
# APPENDIX - Quality Disclosures and Disappointment: Evidence from the Academy Awards by Michelangelo Rossi and Felix Schleef

## A APPENDIX - Empirical Setting and Dataset

**Table A1.** Summary Statistics: Non-Nominated Movies

| | Mean | SE | Min | Max |
|---|---|---|---|---|
| *Average Ratings* | | | | |
| All | 3.212 | .0047 | .8548 | 4.483 |
| Before Nom. | 3.182 | .0063 | .5 | 5 |
| After Nom. | 3.213 | .0048 | .8929 | 4.48 |
| *Number of Ratings* | | | | |
| All | 1221 | 35.5011 | 30 | 72674 |
| Before Nom. | 127.2 | 5.23 | 1 | 15200 |
| After Nom. | 1085 | 32.0367 | 4 | 68582 |
| *Average Ratings (80-days window)* | | | | |
| All | 3.205 | .0071 | .5 | 5 |
| Before Nom. | 3.197 | .0082 | .5 | 5 |
| After Nom. | 3.221 | .0083 | .5 | 5 |
| *Number of Ratings (80-days window)* | | | | |
| All | 43.45 | 1.206 | 0 | 2827 |
| Before Nom. | 23.55 | .6598 | 0 | 1454 |
| After Nom. | 20.31 | .5767 | 0 | 1373 |

*Note*: The table presents descriptive statistics on all 9,397 movies, non-nominated for AMPAS awards, included in our sample. We report the average ratings and the number of ratings both before and after the nominations. The first two panels include all available ratings without any time restrictions, while the second two panels focus on ratings within a 80-day window surrounding the nominations.




**(a)** Nominated

**(b)** Non-Nominated

**Figure A1.** Arrival of Ratings for Nominated and Non-Nominated Movies

*Notes*: The two figures show the amount of ratings that are displayed over time for not nominated and nominated movies. On the x-axis, time is measured in terms of days of distance from the nomination dates.

**Table A2.** User Selection Before and After the Nominations: All Ratings

| | Mean | SE | Min | Max |
|---|---|---|---|---|
| *Average User Ratings* | | | | |
| All | 3.456 | .0012 | 2.956 | 3.946 |
| Before Nom. | 3.411 | .0022 | 1.038 | 5 |
| After Nom. | 3.459 | .0013 | 2.65 | 3.955 |
| *Number of User Ratings* | | | | |
| All | 758.5 | 3.99432 | 62.09 | 2927.1 |
| Before Nom. | 813.5 | 6.457 | 1 | 17502 |
| After Nom. | 766.6 | 4.35713 | 62.17 | 5602 |
| *Average User Stringency* | | | | |
| All | .0794 | .001 | -.5153 | .6804 |
| Before Nom. | .1101 | .0024 | -2.243 | 2.2 |
| After Nom. | .0768 | .0011 | -.4975 | 1.149 |
| *Average Share of User Ratings for Current-Year Releases* | | | | |
| All | .041 | .000271 | .0055 | .427 |
| Before Nom. | .1072 | .00116 | 0 | .8587 |
| After Nom. | .03 | .000134 | .0047 | .2183 |

*Note*: The table presents descriptive statistics of users who rated movies nominated for AMPAS Awards included in our sample, with no time restrictions. We report the average user rating, the average number of ratings per user, the average rating stringency (a measure of how strictly users rate, based on how their ratings compare to the average rating of the movie at the time), and the average share of ratings for movies produced in the same year as the rating. The stringency of a user is defined as a moving average of the stringency of their past five ratings. These statistics are presented separately for users who rated the movies before and after the nominations.

# B APPENDIX - Conceptual Framework

## Signals Between Watching and Rating Decisions

In our framework, the decisions to watch and to rate a movie are closely linked: users receive signals about a movie's quality either before or after both actions and form expectations accordingly. In practice, however, it is reasonable to assume that users may often rate a movie days or even weeks after watching it. This temporal gap introduces a crucial nuance, namely, that a new quality signal, such as an AMPAS nomination, may arrive after the user has seen the movie but before they submit a rating.

Our data capture only the timing of the rating, not the moment of consumption. As a result, we cannot directly observe whether a user watched the movie before or after receiving the signal. Nevertheless, we can articulate two competing hypotheses regarding how such signals might affect evaluations when they arrive after viewing but prior to rating.

**Hypothesis 1: Primacy of First Experience.** According to this hypothesis, users who watch a movie before any nomination signal are unaffected by that signal, even if it precedes their rating. This view draws on the notion of primacy or confirmation bias (Lange, Chattoraj, Beck, Yates and Haefner, 2021), where the initial experience (here, the act of watching the film) anchors the user's evaluation. Since expectations were formed without knowledge of the nomination and the film's quality has already been directly experienced, the rating reflects that unmediated encounter. In this case, nominations would not influence ratings, and these users would resemble those who both watched and rated the film before the signal emerged.

**Hypothesis 2: Retrospective Signal Adjustment.** An alternative possibility is that users who watched the movie before the nomination may still be influenced by the nomination if it arrives before they submit their rating. In this view, the evaluation is not solely a function of an objective memory of the film's quality, or the expectations held at the time of viewing. Rather, it is also shaped by the user's psychological and cognitive state at the moment of rating (Parkinson, Briner, Reynolds and Totterdell, 1995), an internal context that may have been altered by the arrival of the signal. A nomination can thus serve as a reframing cue, prompting the user to reassess the film not in isolation but in light of its new categorization as an "Academy-nominated" movie (Mitchell, Thompson, Peterson and Cronk, 1997). The result may be a shift in perceived standards or reference points, leading to a revised rating that reflects a discrepancy between the remembered experience and the elevated status suggested by the nomination. In line with this, Brandes and Dover (2022) demonstrate that a reviewer's offline context at the time of review provision systematically affects online review content for hotels: they use weather conditions at the time of reviewing and show that 6.5% more reviews are written on rainy days, and that these reviews are 0.1 points lower on average. This mechanism implies that post-viewing signals can retroactively reshape evaluations by influencing how users interpret and contextualize their memories, rather than by modifying expectations beforehand.

These opposing hypotheses illustrate the complexity introduced by the unobserved timing of consumption. Without data on when users watched the movie, we cannot definitively determine which mechanism prevails. However, this distinction becomes especially relevant when we explore heterogeneity in the nomination effect over time, as discussed in Sections 4 and 5. Observing how the size of the effect evolves in the weeks following the nomination may offer indirect evidence on whether such post-viewing, pre-rating influence exists.

Ultimately, resolving this question remains an important avenue for future research. One promising direction would be to leverage belief data as in Aridor, Gonçalves, Kong, Kluver and Konstan (2024) to study how expectations adjust after a signal changes but before a rating is submitted.

# C APPENDIX - Comparing Ratings for Nominated and Non-Nominated Movies

**Table C1.** Difference-in-Differences: Removing Days Right After the Nominations

| | (All) | (5 Days After) | (10 Days After) | (15 Days After) |
|---|---|---|---|---|
| $Nominated_j \times post_t^{Nom}$ | -0.018** | -0.019** | -0.024*** | -0.033*** |
| | (0.007) | (0.008) | (0.008) | (0.009) |
| Movie FEs | ✓ | ✓ | ✓ | ✓ |
| Date FEs | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.21 | 0.21 | 0.21 | 0.21 |
| N | 497,266 | 469,327 | 437,886 | 405,986 |
| Mean Dep. Var. | 3.503 | 3.502 | 3.503 | 3.502 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. Column 1 (All) reports results based on all ratings in the window. Columns 2 to 4 (5 Days After; 10 Days After; 15 Days After) restrict the sample to ratings posted within 5, 10, and 15 days following the nomination date, respectively. Standard errors, clustered by movie, are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table C2.** Difference-in-Differences: Varying Non-Nominated Movies in the Control Group

| | (All) | ($n_i^{critics} > 0$) | ($\bar{r}_i^{critics} > 50$ ) | ( $\bar{r}_i^{IMDb} > 5$ ) |
|---|---|---|---|---|
| $Nominated_j \times post_t^{Nom}$ | -0.018** | -0.015** | -0.013* | -0.016** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Movie FEs | ✓ | ✓ | ✓ | ✓ |
| Date FEs | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.21 | 0.20 | 0.16 | 0.18 |
| N | 497,266 | 467,818 | 397,498 | 484,683 |
| Mean Dep. Var. | 3.503 | 3.511 | 3.628 | 3.532 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. Column 1 (All) reports results based on all ratings in the window. Columns 2 to 4 ($n_i^{critics} > 0$, $\bar{r}_i^{critics} > 50$, and $\bar{r}_i^{IMDb} > 5$) restrict the sample to movies with at least one professional review on the Metacritic website, those with an average Metacritic score above 50 (out of 100), and those with an average IMDb rating above 5, respectively. Standard errors, clustered by movie, are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table C3.** Difference-in-Differences: Nominated Movie Heterogeneity

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $Nominated_j^{=1} \times post_t^{Nom}$ | -0.012 | | | |
| | (0.011) | | | |
| $Nominated_j^{>1} \times post_t^{Nom}$ | | -0.021** | | |
| | | (0.008) | | |
| $Nominated_j^{award=0} \times post_t^{Nom}$ | | | -0.018** | |
| | | | (0.009) | |
| $Nominated_j^{award>0} \times post_t^{Nom}$ | | | | -0.018* |
| | | | | (0.011) |
| Movie FEs | ✓ | ✓ | ✓ | ✓ |
| Date FEs | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.19 | 0.21 | 0.19 | 0.20 |
| N | 429,955 | 458,487 | 455,277 | 433,165 |
| Mean Dep. Var. | 3.421 | 3.475 | 3.451 | 3.446 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. In all specifications, the control group of non-nominated movies remains unchanged, while the treated group varies across columns. In Column (1), the variable $Nominated_j^{=1}$ identifies movies that received exactly one nomination. In Column (2), $Nominated_j^{>1}$ captures movies with more than one nomination. In Column (3), $Nominated_j^{award=0}$ refers to nominated movies that did not win any award. In Column (4), $Nominated_j^{award>0}$ includes nominated movies that won at least one award. Standard errors, clustered by movie, are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table C4.** Difference-in-Differences: Controlling for User Selection

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $Nominated_j \times post_t^{Nom}$ | -0.018** | -0.018** | -0.016** | -0.017** | -0.027*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| $\bar{r}_i^j$ | 0.689*** | 0.693*** | 0.244*** | 0.244*** | -0.156*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.015) |
| $N_i^j$ | | 0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | | (0.000) | (0.000) | (0.000) | (0.000) |
| $\bar{s}_i^j$ | | | -0.520*** | -0.521*** | -0.201*** |
| | | | (0.005) | (0.005) | (0.006) |
| $Share_i^j$ | | | | -0.189*** | -0.258*** |
| | | | | (0.022) | (0.049) |
| Movie FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Date FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| User FEs | | | | | ✓ |
| $R^2$ | 0.30 | 0.30 | 0.33 | 0.33 | 0.43 |
| N | 496,044 | 496,044 | 493,817 | 493,817 | 487,847 |
| Mean Dep. Var. | 3.502 | 3.502 | 3.503 | 3.503 | 3.498 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. Standard errors, clustered by movie, are shown in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# D APPENDIX - A Recommendation-based Matching Design

## D.1 Computation of User Embeddings for Recommendation System Matching

To implement our recommendation system matching approach, we construct user embeddings that reflect individual preferences over time. We present here in detail the procedure used to compute these embeddings, which are later used in our matching algorithm.

We rely on a standard matrix factorization technique based on singular value decomposition (SVD), as implemented in the `scikit-surprise` python package. This algorithm decomposes the user-item rating matrix into low-dimensional latent factors, which we interpret as embeddings of user tastes and item characteristics. The performance and hyperparameter settings of this algorithm are discussed in Appendix D.2.

The construction of time-varying user embeddings proceeds as follows:

- We loop over all nomination dates between 1995 and 2019, which corresponds to the time span covered by the Movielens 25M dataset. For users who are active in multiple nomination periods, we compute a separate set of embeddings for each period.
- In each iteration of the loop, we restrict the rating data to include only ratings up to 40 days before the respective nomination date. This ensures that user preferences are estimated based only on information available prior to each nomination period.
- We then train the SVD algorithm on the windowed rating data and recover the user embeddings.
- Lastly, we merge the resulting user embeddings with the rating data. Each film in the dataset is assigned a nomination reference date (i.e., the date at which it would have been eligible for nomination, regardless of whether it was actually nominated). For each rating, we assign the embedding corresponding to the nomination period in which the film falls.

This procedure allows user embeddings to evolve across time, reflecting changing preferences or reactions to past outcomes. In particular, we allow ratings from the previous nomination period to enter the training data of the subsequent period. This design choice ensures that prior disappointment from award outcomes can influence the embedding used for future matching, capturing potential dynamics in user tastes.

**Table D1.** Recommender Algorithm Performance with Different Specifications

| **No. of Epochs = 10** | | | | |
|---|---|---|---|---|
| **No. of Factors** | (LR=0.002, RR=0.02) | (LR=0.002, RR=0.01) | (LR=0.005, RR=0.02) | (LR=0.005, RR=0.01) |
| 10 | .8586 | .8689 | .8185 | .864 |
| 20 | .8561 | .8688 | .8128 | .8623 |
| 50 | .8513 | .8688 | .8074 | .8598 |
| 100 | .8487 | .8686 | .8035 | .8582 |
| 200 | .8457 | .8684 | .801 | .8566 |
| **No. of Epochs = 20** | | | | |
| **No. of Factors** | (LR=0.002, RR=0.02) | (LR=0.002, RR=0.01) | (LR=0.005, RR=0.02) | (LR=0.005, RR=0.01) |
| 10 | .8268 | .8644 | .7903 | .847 |
| 20 | .8226 | .8635 | .7836 | .8461 |
| 50 | .8162 | .8617 | .7789 | .8449 |
| 100 | .8118 | .86 | .7779 | .8439 |
| 200 | .8088 | .8578 | .7781 | .8427 |

*Note*: The sample includes all MovieLens ratings from 1995 to 2019, posted up to 40 days before the nomination date of each year. The table displays the average root-mean-squared error (RMSE) obtained via 5-fold cross-validation across a range of hyperparameter values: the number of factors (embedding dimensions), the number of training epochs, the learning rate (LR), and the regularization rate (RR).

## D.2 The Hyperparameter Choice for the Recommender Algorithm and its Efficiency

The calculation of embedding values for the matching procedure involves several degrees of freedom, governed by four key hyperparameters: the number of embedding dimensions, the number of training epochs, the learning rate (LR), and the regularization rate (RR). The number of embedding dimensions determines the size of the vector that encodes a user's preferences. The number of epochs indicates how many iterations the optimization routine performs to update and refine these embeddings. The learning rate controls the step size of these updates, affecting the speed and stability of convergence. Finally, the regularization rate penalizes large parameter values, helping to prevent overfitting.

Appendix Table D1 reports the average root-mean-squared error (RMSE) obtained via 5-fold cross-validation across a range of hyperparameter values. The results indicate that a learning rate of 0.005 and a regularization rate of 0.02 yield the best predictive performance. While increasing the number of epochs from 10 to 20 does lead to some improvement, the RMSE is less sensitive to this change than to variations in the learning and regularization rates. Similarly, expanding the number of embedding dimensions from 50 to 100 or 200 yields only marginal gains. Based on these findings, we adopt the following hyperparameter configuration for all embedding calculations used in the matching estimations: LR = 0.005, RR = 0.02, number of epochs = 20, and number of embedding = 50. The chosen values for learning rate, regularization rate, and number of epochs coincide with the default settings of the `scikit-surprise` library. The only deviation from the default is the number of embeddings, which we set to 50 instead of the default of 100.

### D.3 Embedding Distances and Rating Similarity

A key assumption underlying our identification strategy is that the user embeddings produced by the recommendation model meaningfully reflect users' tastes and preferences. While the model's predictive accuracy (e.g., RMSE) validates the overall quality of the rating predictions, it does not guarantee that the learned embeddings capture behaviorally-relevant preference structures. Here, we present a validation exercise designed to test whether users who express more similar opinions on specific movies also tend to have more similar embeddings.

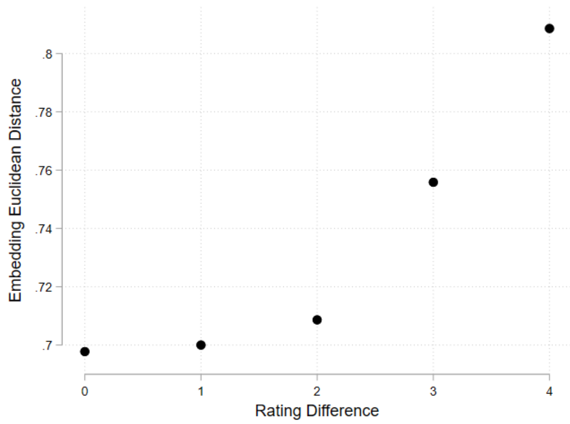
We focus on the 50 most-rated movies in our dataset, as these ensure a large and diverse set of users for comparison. For each movie $j$ and user $i$, we compute the absolute difference between user $i$'s rating and the rating of every other user $k$ who also rated movie $j$: $\delta_{ik} = |r_{ij} - r_{kj}|$. This measure, $\delta_{ik}$, captures the degree of rating similarity between users $i$ and $k$ for movie $j$. By construction, $\delta_{ik}$ takes values ranging from a minimum of 0, when users give the same rating, to a maximum of 4, corresponding to the largest possible difference in ratings (e.g., one user gives a 5 and the other a 1).[1]

We then compute the Euclidean and Mahalanobis distances between the embedding of user $i$ and that of user $k$, for all pairs of users who rated the same movie. If embeddings reflect preferences, we should observe that smaller values of $\delta_{ik}$ are associated with smaller distances in embedding space.

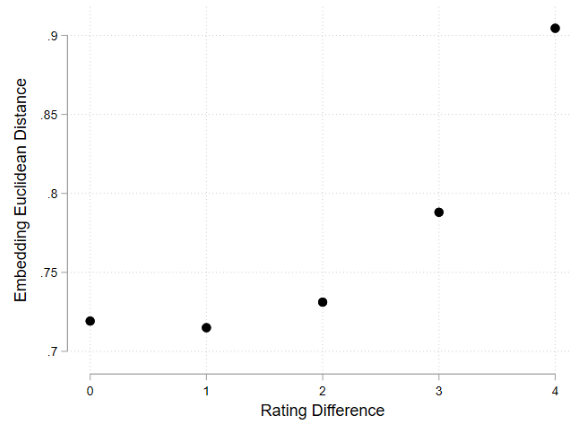
Appendix Figures D1 and D2 show the average Euclidean and Mahalanobis distances, respectively, between users' embeddings as a function of $\delta_{ik}$. Each point in the plot represents the average embedding distance for all user pairs $(i,k)$ with a given $\delta_{ik}$ value.

To provide granularity, Appendix Figures D1a—D1e and D2a—D2e show the same analysis separately for each of the five most-rated movies in the dataset (listed in chronological order): *Crouching Tiger, Hidden Dragon (2000)*; *Lord of the Rings: The Fellowship of the Ring (2001)*; *Lord of the Rings: The Return of the King (2003)*; *Avatar (2009)*; and *The Martian (2015)*. Finally, Appendix Figures D1f and D2f show the results for all top-rated 50 movies. Across all specifications, we observe a consistent monotonic relationship: as $\delta_{ik}$ increases, so does the average embedding distance. Specifically, we find that users with a rating difference of 0 or 1 tend to have relatively similar embeddings, indicating aligned preferences. In contrast, user pairs with the largest possible differences in ratings (such as one user loving and the other disliking the same movie) tend to have much larger distances in embedding space, suggesting that their overall movie preferences diverge substantially. This pattern holds for both Euclidean and Mahalanobis distances, both in individual movies and in the aggregated sample.

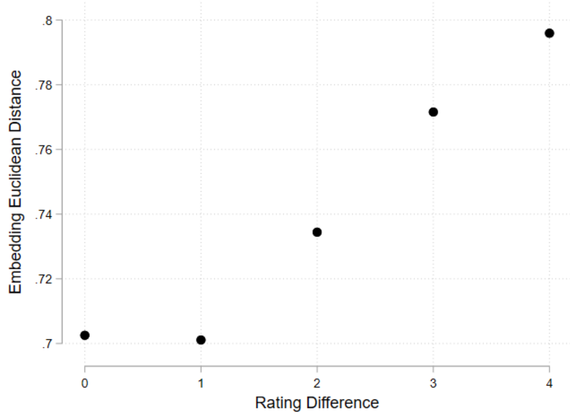
[1] To ensure consistency before and after the 2003 change in the rating system (Harper and Konstan, 2015), we restrict our analysis to ratings with integer values (i.e., full stars), excluding half-star ratings.



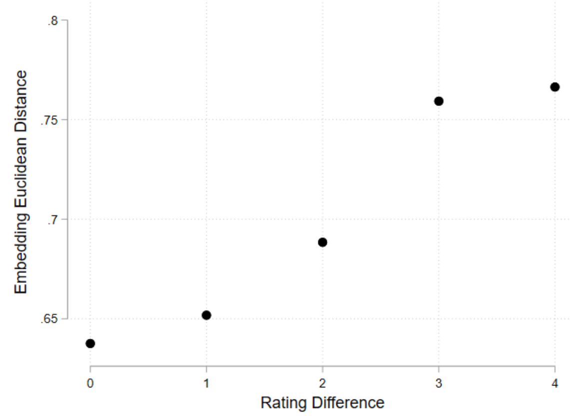

**(a)** *Crouching Tiger, Hidden Dragon (2000)*



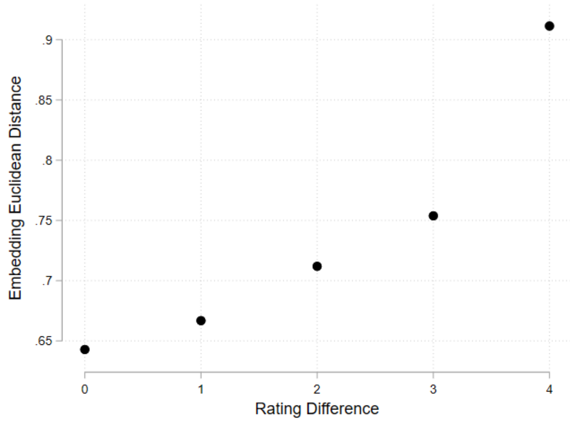

**(b)** *Lord of the Rings: The Fellowship of the Ring (2001)*



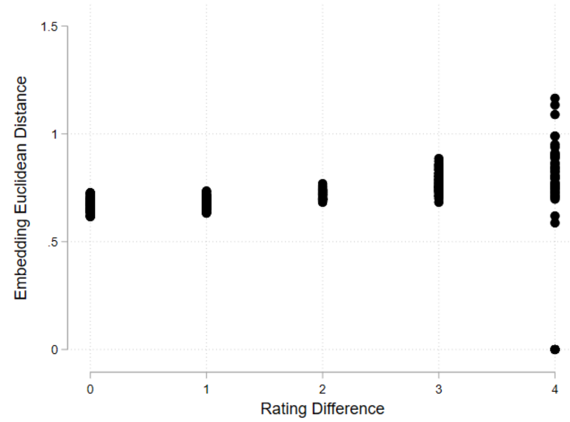

**(c)** *Lord of the Rings: The Return of the King (2003)*




**(d)** *Avatar (2009)*



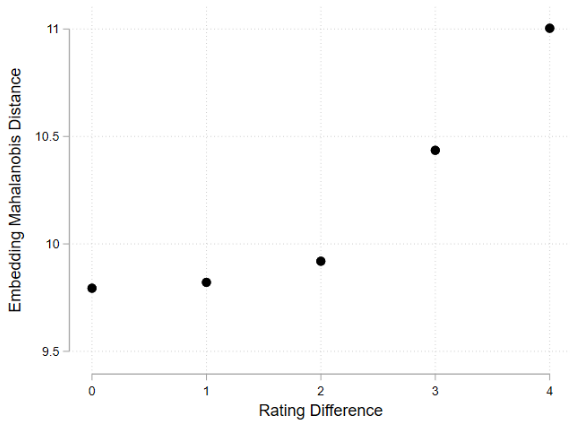

**(e)** *The Martian (2015)*

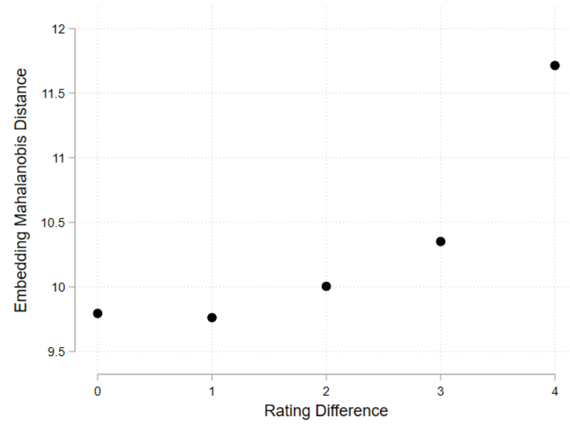



**(f)** 50 Most-Rated Movies

**Figure D1.** Euclidean Embedding Distances by Rating Difference $\delta_{ik}$

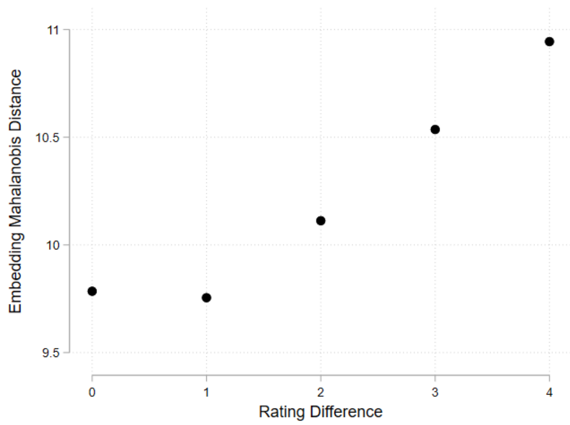
*Notes*: *Notes*: The graphs compare the average Euclidean distance between user embeddings for pairs of users who rated the same movie, grouped by their absolute rating difference. The six sub-figures correspond to: the five most-rated movies (Crouching Tiger, Hidden Dragon; Lord of the Rings: The Fellowship of the Ring; Lord of the Rings: The Return of the King; Avatar; and The Martian) and the results across all 50 most-rated movies.

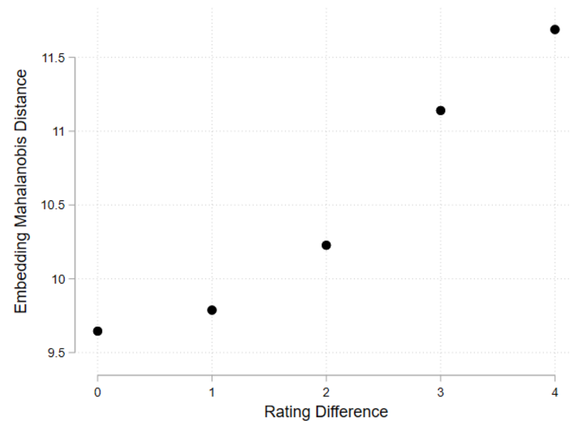



**(a)** *Crouching Tiger, Hidden Dragon (2000)*

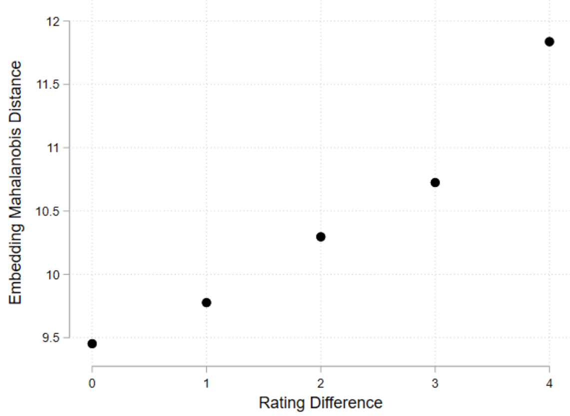
**(b)** *Lord of the Rings: The Fellowship of the Ring (2001)*

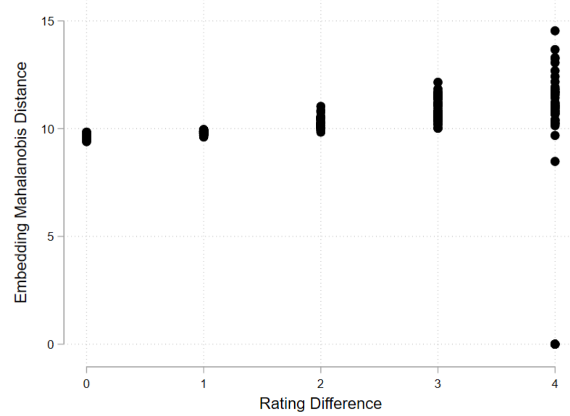



**(c)** *Lord of the Rings: The Return of the King (2003)*

**(d)** *Avatar (2009)*




**(e)** *The Martian (2015)*

**(f)** 50 Most-Rated Movies

**Figure D2.** Mahalanobis Embedding Distances by Rating Difference $\delta_{ik}$

*Notes*: The graphs compare the average Mahalanobis distance between user embeddings for pairs of users who rated the same movie, grouped by their absolute rating difference. The six sub-figures correspond to: the five most-rated movies (Crouching Tiger, Hidden Dragon; Lord of the Rings: The Fellowship of the Ring; Lord of the Rings: The Return of the King; Avatar; and The Martian) and the results across all 50 most-rated movies.

### D.4 Recommendation-based Matching - Robustness

**Table D2.** Matching Users Before and After the AMPAS Nominations: embeddings with 10-dimensions

| | (OLS) | (M1) | (M2) | (M3) | (M4) | (M5) |
|---|---|---|---|---|---|---|
| Post Nomination | -0.039*** | -0.036*** | -0.052*** | -0.044*** | -0.040*** | -0.046*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.010) | (0.016) |
| User Embeddings | | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | | ✓ |
| N | 63849 | 59937 | 59975 | 55965 | 40354 | 18237 |
| Mean Dep. Var. | 3.919 | 3.919 | 3.919 | 3.919 | 3.921 | 3.921 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. The first column is the OLS estimate from a regression of ratings on mvie fixed effects and a dummy equal to one if a rating has been given after the nomination date. Columns M1 to M5 report ATT estimates from a multivariate-distance matching with user embeddings (10 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D3.** Matching Users Before and After the AMPAS Nominations: embeddings with 20-dimensions

| | (OLS) | (M1) | (M2) | (M3) | (M4) | (M5) |
|---|---|---|---|---|---|---|
| Post Nomination | -0.039*** | -0.036*** | -0.042*** | -0.037*** | -0.032*** | -0.042*** |
| | (0.007) | (0.009) | (0.007) | (0.008) | (0.010) | (0.016) |
| User Embeddings | | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | | ✓ |
| N | 63849 | 60043 | 59974 | 56068 | 40266 | 18165 |
| Mean Dep. Var. | 3.919 | 3.919 | 3.919 | 3.919 | 3.921 | 3.921 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. The first column is the OLS estimate from a regression of ratings on mvie fixed effects and a dummy equal to one if a rating has been given after the nomination date. Columns M1 to M5 report ATT estimates from a multivariate-distance matching with user embeddings (20 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D4.** Matching Users Before and After the AMPAS Nominations: embeddings with 100-dimensions

| | (OLS) | (M1) | (M2) | (M3) | (M4) | (M5) |
|---|---|---|---|---|---|---|
| Post Nomination | -0.039*** | -0.040*** | -0.042*** | -0.046*** | -0.040*** | -0.048*** |
| | (0.007) | (0.008) | (0.007) | (0.007) | (0.010) | (0.017) |
| User Embeddings | | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | | ✓ |
| N | 63849 | 60015 | 59979 | 56210 | 40384 | 18266 |
| Mean Dep. Var. | 3.919 | 3.919 | 3.919 | 3.919 | 3.921 | 3.921 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. The first column is the OLS estimate from a regression of ratings on mvie fixed effects and a dummy equal to one if a rating has been given after the nomination date. Columns M1 to M5 report ATT estimates from a multivariate-distance matching with user embeddings (100 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D5.** Matching Users Before and After the AMPAS Nominations: embeddings with 200-dimensions

| | (OLS) | (M1) | (M2) | (M3) | (M4) | (M5) |
|---|---|---|---|---|---|---|
| Post Nomination | -0.039*** | -0.038*** | -0.039*** | -0.043*** | -0.039*** | -0.048*** |
| | (0.007) | (0.008) | (0.008) | (0.008) | (0.011) | (0.015) |
| User Embeddings | | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | | ✓ |
| N | 63849 | 59980 | 59859 | 56322 | 40338 | 18261 |
| Mean Dep. Var. | 3.919 | 3.919 | 3.919 | 3.919 | 3.921 | 3.921 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. The first column is the OLS estimate from a regression of ratings on mvie fixed effects and a dummy equal to one if a rating has been given after the nomination date. Columns M1 to M5 report ATT estimates from a multivariate-distance matching with user embeddings (200 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D6.** Matching Users Before and After the AMPAS Nominations: LensKit MF Recommender Algorithm and Embeddings

| | (OLS) | (M1) | (M2) | (M3) | (M4) | (M5) |
|---|---|---|---|---|---|---|
| Post Nomination | -0.039*** | -0.036*** | -0.049*** | -0.043*** | -0.037*** | -0.043*** |
| | (0.007) | (0.008) | (0.007) | (0.008) | (0.010) | (0.016) |
| User Embeddings | | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | | ✓ |
| N | 63849 | 59869 | 59815 | 55914 | 39993 | 18093 |
| Mean Dep. Var. | 3.919 | 3.919 | 3.919 | 3.919 | 3.921 | 3.921 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. The first column is the OLS estimate from a regression of ratings on movie fixed effects and a dummy equal to one if a rating has been given after the nomination date. Columns M1 to M5 report ATT estimates from a propensity score matching with user embeddings (50 dimensions - Lenskit matrix factorization algorithm), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the nominated movie. Standard errors are obtained via bootstrap (100 replications). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table D7.** Matching Users Before and After the AMPAS Nominations: Removing Days Right After the Nominations

| | (All) | (5 Days After) | (10 Days After) | (15 Days After) | (No First Session After Nom.) |
|---|---|---|---|---|---|
| Post Nomination | -0.047*** | -0.040** | -0.042** | -0.042** | -0.034** |
| | (0.015) | (0.016) | (0.020) | (0.020) | (0.017) |
| User Embeddings | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 18218 | 16038 | 13733 | 10964 | 14900 |
| Mean Dep. Var. | 3.921 | 3.922 | 3.921 | 3.921 | 3.923 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. In all columns we report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics (as in Column (M5) in Table 4). Column 1 (All) reports results based on all ratings in the window. Columns 2 to 4 (5 Days After; 10 Days After; 15 Days After) restrict the sample to ratings posted within 5, 10, and 15 days following the nomination date, respectively. Column 5 (No First Session After Nom.) restricts the sample excluding ratings that are written during the user's first active session on Movielens after the nomination. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D8.** Matching Users Before and After the AMPAS Nominations: Users who Posted More than 50 Ratings Before Ratings the Nominated Movie

| | (OLS) | (M1) | (M2) | (M3) | (M4) | (M5) |
|---|---|---|---|---|---|---|
| Post Nomination | -0.038*** | -0.044*** | -0.044*** | -0.048*** | -0.040*** | -0.049*** |
| | (0.007) | (0.008) | (0.008) | (0.009) | (0.010) | (0.017) |
| User Embeddings | | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | | ✓ |
| N | 61529 | 57829 | 57716 | 53872 | 38308 | 16815 |
| Mean Dep. Var. | 3.914 | 3.914 | 3.914 | 3.914 | 3.915 | 3.915 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. We exclude all users that posted less than 50 ratings on Movielens before posting the rating for the nominated movie. The table displays estimated treatment effects for nominated movies. The first column is the OLS estimate from a regression of ratings on movie fixed effects and a dummy equal to one if a rating has been given after the nomination date. Columns M1 to M5 report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D9.** Matching Users Before and After the AMPAS Nominations: Users who Posted More than 50 Ratings in Total

| | (OLS) | (M1) | (M2) | (M3) | (M4) | (M5) |
|---|---|---|---|---|---|---|
| Post Nomination | -0.039*** | -0.041*** | -0.043*** | -0.046*** | -0.041*** | -0.052*** |
| | (0.007) | (0.008) | (0.008) | (0.009) | (0.010) | (0.017) |
| User Embeddings | | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | | ✓ |
| N | 63054 | 59154 | 59130 | 55411 | 39616 | 17647 |
| Mean Dep. Var. | 3.917 | 3.917 | 3.917 | 3.917 | 3.919 | 3.919 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. We exclude all users that posted less than 50 ratings on Movielens. The table displays estimated treatment effects for nominated movies. The first column is the OLS estimate from a regression of ratings on movie fixed effects and a dummy equal to one if a rating has been given after the nomination date. Columns M1 to M5 report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D10.** Matching Users Before and After the AMPAS Nominations: Predicted Ratings (LensKit MF, UU, and II Recommender Algorithms)

| | (MF) | (UU) | (II) |
|---|---|---|---|
| Post Nomination | -0.002 | 0.000 | -0.003 |
| | (0.005) | (0.005) | (0.006) |
| User Embeddings | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ |
| N | 15472 | 15261 | 15353 |
| Mean Dep. Var. | 3.910 | 3.910 | 3.912 |

*Note*: The sample includes predicted ratings using matrix-factorization, user-user, and item-item LensKit recommender algorithms for movies rated from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. The first column is the OLS estimate from a regression of predicted ratings on movie fixed effects and a dummy equal to one if a predicted rating is related to a rating posted after the nomination date. Columns M1 to M5 report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D11.** Matching Users Before and After the AMPAS Nominations: Non-Nominated Movies

| | (OLS) | (M1) | (M2) | (M3) | (M4) | (M5) |
|---|---|---|---|---|---|---|
| Post Nomination | 0.001 | -0.006 | 0.001 | -0.015 | -0.031* | -0.023 |
| | (0.007) | (0.009) | (0.008) | (0.011) | (0.017) | (0.030) |
| User Embeddings | | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | | ✓ |
| N | 99608 | 83266 | 68369 | 42141 | 19578 | 6331 |
| Mean Dep. Var. | 3.397 | 3.397 | 3.397 | 3.397 | 3.399 | 3.399 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for non-nominated movies, excluding all users who have rated nominated movies. The first column is the OLS estimate from a regression of ratings on mvie fixed effects and a dummy equal to one if a rating has been given after the nomination date. Columns M1 to M5 report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies rated by the user prior to the rating of the non-nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D12.** Matching Users Before and After the AMPAS Nominations: Number of Nominations and Awards

| | ( $Nom = 1$ ) | ( $Nom > 1$ ) | ( $Award = 0$ ) | ( $Award > 0$ ) |
|---|---|---|---|---|
| Post Nomination | -0.049 | -0.043** | -0.037* | -0.061*** |
| | (0.038) | (0.020) | (0.021) | (0.021) |
| User Embeddings | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ | ✓ |
| N | 4964 | 13277 | 10049 | 8200 |
| Mean Dep. Var. | 3.795 | 3.993 | 3.847 | 4.037 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. In all columns we report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics (as in Column (M5) in Table 4). Column 1 to 4 ( $Nom = 1$, $Nom > 1$, $Award = 0$, and $Award > 0$ restrict the sample to movies that received exactly one nomination, with more than one nomination, nominated movies that did not win any award, and nominated movies that won at least one award, respectively. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D13.** Matching Users Before and After the AMPAS Nominations: Movie Production Year

| | ( 1995 – 2004 ) | ( 2004 – 2011 ) | ( 2011 – 2019 ) |
|---|---|---|---|
| Post Nomination | -0.080*** | -0.059** | 0.004 |
| | (0.028) | (0.023) | (0.025) |
| User Embeddings | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ |
| N | 6863 | 5574 | 5478 |
| Mean Dep. Var. | 4.024 | 3.913 | 3.822 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. In all columns we report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics (as in Column (M5) in Table 4). Column 1 to 3 (1995 – 2004, 2004 – 2011, and 2011 – 2019) restrict the sample to movies that received at least one AMPAS nomination between 1995 and 2004, between 2005 and 2011, and between 2012 and 2019, respectively. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D14.** Matching Users Before and After the AMPAS Nominations: User Characteristics ($N_i^j$, $\bar{s}_i^j$ and $\bar{e}_i$)

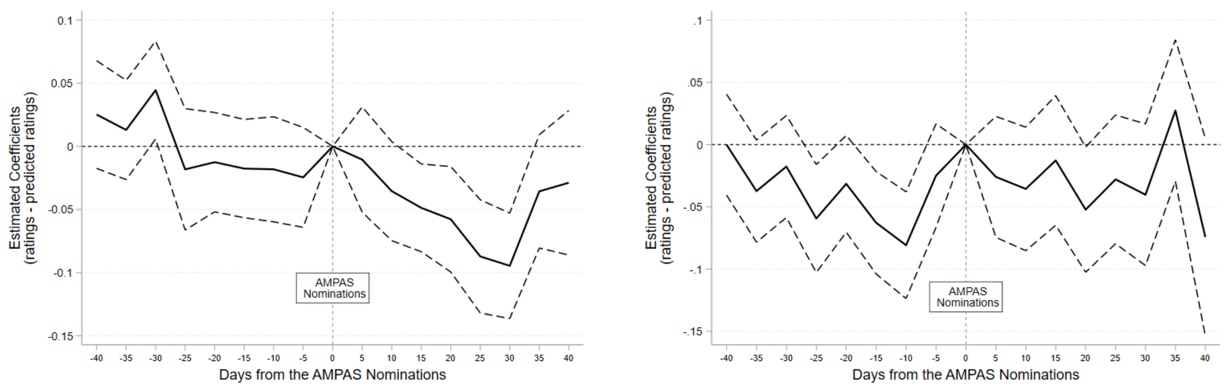
| | ( $N_i^j < 400$ ) | ( $N_i^j > 400$ ) | ( $\bar{s}_i^j < 0$ ) | ( $\bar{s}_i^j > 0$ ) | ( $\bar{e}_i < 0.5$ ) | ( $\bar{e}_i > 0.5$ ) |
|---|---|---|---|---|---|---|
| Post Nomination | -0.047** | -0.037 | -0.063*** | -0.035 | -0.094*** | 0.032 |
| | (0.022) | (0.025) | (0.020) | (0.026) | (0.023) | (0.036) |
| User Embeddings | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 9225 | 8402 | 8827 | 8185 | 4533 | 6337 |
| Mean Dep. Var. | 3.996 | 3.859 | 4.129 | 3.729 | 3.973 | 3.875 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. In all columns we report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics (as in Column (M5) in Table 4). Columns 1 to 6 ($N_i^j < 400$, $N_i^j > 400$, $\bar{s}_i^j < 0$, $\bar{s}_i^j > 0$, $\bar{e}_i < 0.5$, and $\bar{e}_i > 0.5$) restrict the sample based on user characteristics: the number of prior ratings posted before rating the nominated movie ($N_i^j$), the stringency level ($\bar{s}_i^j$), and the average discrepancy between predicted and actual ratings before the nominations ($\bar{e}_i$). Specifically, the columns correspond to users with fewer or more than 400 prior ratings; with stringency levels below or above 0; and with average discrepancies below or above 0.5, respectively. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table D15.** Matching Users Before and After the AMPAS Nominations: User Characteristics ($\bar{r}_i^j$ and $Share_i^j$)

| | ( $\bar{r}_i^j < 3.5$ ) | ( $\bar{r}_i^j > 3.5$ ) | ( $Share_i^j < 0.05$ ) | ( $Share_i^j > 0.05$ ) |
|---|---|---|---|---|
| Post Nomination | -0.051* | -0.049** | -0.046** | -0.047** |
| | (0.028) | (0.021) | (0.023) | (0.022) |
| User Embeddings | ✓ | ✓ | ✓ | ✓ |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ | ✓ |
| N | 6679 | 10353 | 8099 | 8807 |
| Mean Dep. Var. | 3.698 | 4.101 | 3.918 | 3.923 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. In all columns we report ATT estimates from a propensity score matching with user embeddings (50 dimensions), matching exactly on the movie identifier as well as quintiles of different user characteristics (as in Column (M5) in Table 4). Columns 1 to 4 ($\bar{r}_i^j < 3.5$, $\bar{r}_i^j > 3.5$, $Share_i^j < 0.05$, and $Share_i^j > 0.05$ ) restrict the sample based on user characteristics: the average user rating posted before rating the nominated movie ($\bar{r}_i^j$), and the share of movies rated in the same year ($Share_i^j$). Specifically, the columns correspond to users with an average rating below or above 3.5; and with a share of movies rated in the same year below or above 0.05, respectively. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

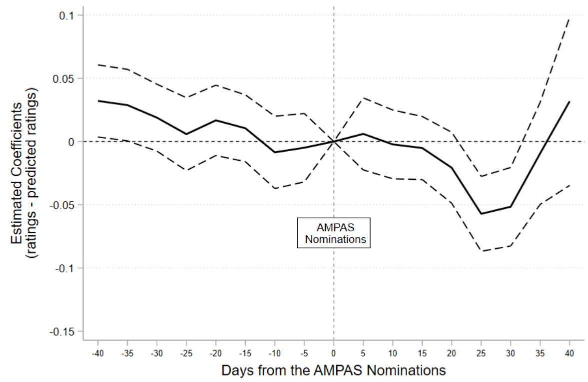



**(a)** Nominated Movies

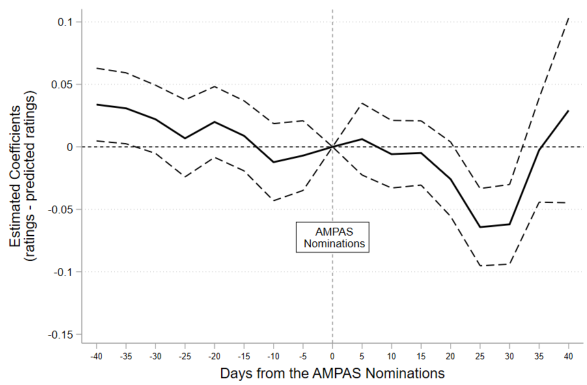
**(b)** Non-Nominated Movies

**Figure D3.** The Difference between Actual and Predicted Ratings over time: AMPAS Awards 40 Days After Nominations

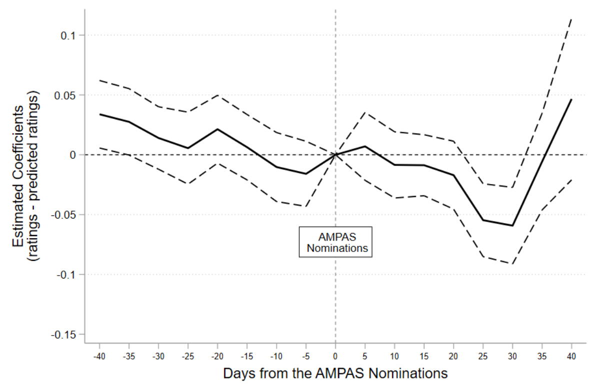
*Notes*: The sample includes MovieLens ratings posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. Additionally, we restrict the sample to years in which the AMPAS awards take place at least 40 days after the nominations (these years are 1997–2003, 2013, 2014, 2016, and 2018). The difference between actual and predicted ratings is regressed on movie fixed effects and a set of five-day interval dummies centered on the AMPAS nomination date for nominated and non-nominated movies. The graphs display the estimated coefficients of these dummies, with the coefficient for the five-day interval of the nomination date normalized to zero. Standard errors, clustered by movie, are reported at the 10% level.




**(a)** Nominated Movies: LensKit Predicted Ratings (MF)




**(b)** Nominated Movies: LensKit Predicted Ratings (UU)




**(c)** Nominated Movies: LensKit Predicted Ratings (II)

**Figure D4.** The Difference between Actual and Predicted Ratings over time

*Notes*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The difference between actual and predicted ratings (using LensKit predicted ratings based on matrix-factorization, user-user, and item-item recommender algorithms) are regressed on movie fixed effects and a set of five-day interval dummies centered on the AMPAS nomination date for nominated and non-nominated movies. The graphs display the estimated coefficients of these dummies, with the coefficient for the five-day interval of the nomination date normalized to zero. Standard errors, clustered by movie, are reported at the 10% level.

**Table D16.** Difference-in-Differences: Exploiting Recommended Systems Predictions and Embeddings

| | ( $r_{ij}$ ) | ( $\hat{r}_{ij}$ ) | ( $r_{ij}$ ) | ( $r_{ij}$ ) | ( $r_{ij}-\hat{r}_{ij}$ ) |
|---|---|---|---|---|---|
| $Nominated_j \times post_t^{Nom}$ | -0.017* | -0.003 | -0.014* | -0.017** | -0.014* |
| | (0.009) | (0.004) | (0.008) | (0.009) | (0.008) |
| Movie FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Date FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Predicted Ratings | | | ✓ | | |
| Embeddings | | | | ✓ | |
| $R^2$ | 0.25 | 0.50 | 0.39 | 0.25 | 0.12 |
| N | 254,482 | 254,482 | 254,482 | 254,482 | 254,482 |
| Mean Dep. Var. | 3.503 | 3.539 | 3.503 | 3.503 | -0.036 |

*Note*: The sample includes MovieLens ratings from 1995 to 2019, posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. In all specifications, we only include users with at least one rating 40 days before the nominations (a necessary condition to calculate predicted ratings and embeddings). Columns 1 to 5 ($r_{ij}$, $\hat{r}_{ij}$, $r_{ij}$,$r_{ij}$, and $r_{ij}-\hat{r}_{ij}$) report results from different Difference-in-Differences specifications, using distinct outcome or control variables: actual ratings (Column 1), predicted ratings (Column 2), actual ratings controlling for either predicted ratings (Column 3) or user embeddings (Column 4), and the difference between actual and predicted ratings (Column 5). Standard errors, clustered by movie, are shown in parentheses. $^{*}$ $p<0.10$, $^{**}$ $p<0.05$, $^{***}$ $p<0.01$.

# E APPENDIX - External Validity: IMDb Data

**Table E1.** Matching Users Before and After the AMPAS Nominations (IMDb Ratings): Number of Nominations and Awards

| | ( $Nom = 1$ ) | ( $Nom > 1$ ) | ( $Award = 0$ ) | ( $Award > 0$ ) |
|---|---|---|---|---|
| Post Nomination | -0.136** | -0.168*** | -0.092** | -0.224*** |
| | (0.059) | (0.035) | (0.039) | (0.028) |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ | ✓ |
| N | 3570 | 12573 | 7909 | 8234 |
| Mean Dep. Var. | 7.389 | 7.375 | 7.206 | 7.604 |

*Note*: The sample includes IMDb ratings posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. In all columns we report ATT estimates matching exactly on the movie identifier as well as quintiles of different user characteristics (as in Column (M5) in Table 4). Column 1 to 4 ( $Nom = 1$, $Nom > 1$, $Award = 0$, and $Award > 0$ restrict the sample to movies that received exactly one nomination, with more than one nomination, nominated movies that did not win any award, and nominated movies that won at least one award, respectively. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table E2.** Matching Users Before and After the AMPAS Nominations (IMDb Ratings): Movie Production Year

| | ( 1995 – 2004 ) | ( 2004 – 2011 ) | ( 2011 – 2019 ) |
|---|---|---|---|
| Post Nomination | -0.260*** | -0.150*** | -0.134*** |
| | (0.074) | (0.056) | (0.033) |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ |
| N | 2540 | 4337 | 9036 |
| Mean Dep. Var. | 7.646 | 7.499 | 7.225 |

*Note*: The sample includes IMDb ratings posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. In all columns we report ATT estimates matching exactly on the movie identifier as well as quintiles of different user characteristics (as in Column (M5) in Table 4). Column 1 to 3 (1995 – 2004, 2004 – 2011, and 2011 – 2019) restrict the sample to movies that received at least one AMPAS nomination between 1995 and 2004, between 2005 and 2011, and between 2012 and 2019, respectively. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table E3.** Matching Users Before and After the AMPAS Nominations (IMDb Ratings): User Number of Ratings

| | ( $N_i^j < 5$ ) | ( $5 > N_i^j > 20$ ) | ( $N_i^j > 20$ ) |
|---|---|---|---|
| Post Nomination | -0.190*** | -0.159*** | -0.107*** |
| | (0.042) | (0.052) | (0.038) |
| $\bar{r}_i^j$ | ✓ | ✓ | ✓ |
| $N_i^j$ | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | ✓ | ✓ | ✓ |
| $Share_i^j$ | ✓ | ✓ | ✓ |
| N | 8070 | 3559 | 3771 |
| Mean Dep. Var. | 7.167 | 7.283 | 7.598 |

*Note*: The sample includes IMDb ratings posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table displays estimated treatment effects for nominated movies. In all columns we report ATT estimates matching exactly on the movie identifier as well as quintiles of different user characteristics (as in Column (M5) in Table 4). Columns 1 to 3 ($N_i^j < 5$, $5 > N_i^j > 20$, and $N_i^j > 20$) restrict the sample based on the number of prior ratings posted before rating the nominated movie ($N_i^j$). Specifically, the columns correspond to users with fewer than 5 prior ratings; with a number of prior ratings between 5 and 20, and with more than 20 prior ratings, respectively. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# F APPENDIX - Textual Evidences of Disappointment

## Textual Analysis of Movielens Tags

To identify disappointment-related sentiment in MovieLens user-contributed tags, we employed a fuzzy string matching approach built on a curated dictionary of disappointment-related expressions.

Tags are user-supplied and attached to movies independently of ratings. The dataset includes 41,321 tags associated with the same sample of movies and time window used in the difference-in-differences analysis. After deduplication and normalization (lowercasing and trimming whitespace), we applied a basic cleaning pipeline to remove stopwords and punctuation, though in practice, tags tend to be short and rarely contain such elements.

We curated a list of disappointment-related keywords through an iterative process:

- Manual review of a random subset of tags;
- Lexical expansion using thesaurus tools (e.g., WordNet) and prior domain-specific sentiment lexicons;
- Inclusion of common variations, abbreviations, and informal spellings.

The final keyword set included terms such as: "disappointing", "overhyped", "let down", "underwhelming", "expected more".

To account for variability, we used fuzzy string matching via the `fuzzywuzzy` Python package (now maintained as `thefuzz`), implementing token sort ratio and partial ratio scoring. Matches were accepted based on a similarity threshold of 85%.

The following list contains the set of keywords and short phrases used to identify disappointment-related sentiment in MovieLens tags: "Disappointing", "Let down", "Over-rated", "Overrated", "disappointed", "disappointing", "disappointing ending", "disappointments", "expected more", "let down", "over-hyped", "overrated", "somewhat", "overrated", "way overrated."

## Textual Analysis of IMdb Reviews

Unlike MovieLens tags, IMDb reviews are longer, richer, and more sentiment-focused. The dataset includes written reviews for every rating used in the matching analysis. Each review consists of free-form user text, often a paragraph or more.

Before embedding, reviews were preprocessed as follows: lowercasing; removal of punctuation and HTML formatting; Tokenization and lemmatization; removal of non-alphanumeric characters and isolated stopwords (e.g., "the", "was", etc.)

We employed sentence-transformer models to perform semantic similarity analysis. Specifically, we used the `all-MiniLM-L6-v2` model from the Sentence Transformers library, which provides dense vector representations of text. This model was chosen for its balance between speed and performance and is widely used in short-to-medium length semantic matching tasks.

Procedure:

- Encoding Reviews: Each review was transformed into a 384-dimensional vector using the pretrained MiniLM model via sentence-transformers (version 2.2.2);
- Reference Phrase Encoding: For each target sentiment (e.g., disappointment, disinterest, viewing conditions), we defined a small set of seed phrases. Examples for Disappointment: “I am disappointed”, “This movie was overrated”, “It was overhyped”. Examples for Disinterest: “Not my style”, “I don’t enjoy these kinds of stories”, “I’m not a fan of the director”. Example for Viewing Conditions: “The cinema was crowded”, “The screen was too small”, “Streaming quality was not great”; Example for Reverse Bandwagon: “Mainstream movies rarely appeal to me”, “I avoid films that become mainstream successes”, “I don’t watch mainstream movies”;
- Cosine Similarity Scoring: We computed cosine similarity between each review vector and the set of reference vectors. For each sentiment type, the final score was defined as the maximum similarity to any reference phrase.

Below are sample reviews classified as highly likely to contain the target sentiment, based on being in the top 1% of the cosine similarity distribution with reference phrases for each sentiment category.

**Disappointment**

- “One of the most overrated movies of all time. I personally do not get the hype with this movie. Most of it just did not interest me. at all.”
- “Overrated Overrated Overrated.”
- “I was expecting this movie to be a huge bore. Well, it wasn’t really, it was dull at times but not a bore or anything. Is it Overrated? Yes. I wasn’t WOWed by it like the critics were but i thought it was a good movie. Does it deserve a Best Picture nomination? NO. Did it deserve 9 nominations? NO.The acting was pretty good. Nicole Kidman gave a wonderful performance but she didn’t give the Best Actress performance of the year. Meryl Streep was very good but not great. She was far

better in Adaptation. Julianne was good but not worth a nomination. Her story was the weakest, what i mean is it was weakly written one. The dialogue wasn't as good and I never expected Julianne's character to leave in the end, that was the script's fault. Ed Harris was so-so, definitely didn't deserve a nomination."

**Disinterest**

- "This movie was boring and absolutely uninteresting for me, if you wanna waste couple of hours, this movie is for you."
- "The film is bad, boring and no sense. One of those ends that just leaves you wondering why have you wasted two hours of your life."
- "I found this movie to be too slow moving and boring. At two hours and fifteen minutes, it is also far too long for the meager content. It just wasn't interesting, and tedious."

**Viewing Conditions**

- "I watched it on Netflix. Wow this was hard to watch without falling asleep. Didn't bother finishing it. I really wanted to like this movie."
- "This movie was horrible.End of story.It lacked emotion, feeling, and any sense of mood.It was like watching the History Channel in vivid color without any narration. Oh, and Surround Sound. Sorry, I forgot to mention the fact that it was on a rather large screen."
- "May have looked great on an IMAX screen. Good sound effects, however, the rest is disappointing and boring."

**Reverse Bandwagon** (some parts of the review text have been truncated due to excessive length)

- "One of Hollywood's worst clichés. It is, in my opinion, a film without content made just to create box office receipts. The music is painful to hear, the performance of the actors leaves much to be desired and is full of errors not acceptable for a project of this magnitude, the film is based on inspirations from other films, which gives the sensation of already having seen it."

- “A movie that mainstream Hollywood isn’t talking about. A wonderful story. Phenomenaly acted. Definite feel good movie.”

- ‘Firstly I would like to say that sometimes I genuinely worry about the world today. I admit that I went to see this film with very low expectations, I thought that this film was going to be, quite simply, a typical "American" comedy, and yet, I still went to see it. This is because I am not so full of myself that I can’t enjoy a film for what it is. A bloody good laugh! Not everything has to be deep and meaningful. As I’ve said above get some perspective, ITS JUST A FILM!”

As a complementary method to semantic similarity scoring, we also employed a pre-trained transformer model fine-tuned specifically for emotion classification. The `SamLowe/roberta-base-go_emotions` model, available on Hugging Face, was trained on the GoEmotions dataset, a large corpus of Reddit comments labeled with 28 emotion categories including “disappointment”. This model allows us to generate probability scores for each emotion class directly from the full review text.

Before inputting reviews into the classifier, we applied the same text preprocessing steps as in the semantic similarity approach: lowercasing, punctuation and HTML removal, tokenization and lemmatization, removal of non-alphanumeric characters, and exclusion of isolated stopwords.

We used the Hugging Face Transformers library (version 4.39.3) and the `pipeline` utility for text classification. This model outputs a set of emotion-probability pairs for each review. We retained the predicted probability score for the “disappointment” label and used it as a continuous measure of disappointment sentiment.

Procedure:

- Preprocessing: Text normalization as detailed above;

- Classification: Reviews were passed to the `text-classification` pipeline using the `SamLowe/roberta-base-go_emotions` model;

- Score Extraction: For each review, we extracted the predicted probability assigned to the “disappointment” label as a measure of sentiment strength.

Below are sample reviews classified as highly likely to contain disappointment sentiment, based on being in the top 1% of the predicted probability distribution for the “disappointment” label.

**Disappointment**

- “I was looking forward to this coming out on ppv. How disappointing !”

- “This disappointing film is remarkably patchy. Periods of real excitement and some terrific acting by Day-Lewis are interspersed with melodrama, some grotty special effects, and a story that includes coincidences and developments that are unbelievable.Altogether a film that does not enhance Scorcese’s reputation.”

- “I was appalled that they changed history. Go watch the real Queen on YouTube instead of this campy failure to recreate. Very disappointing.”

**Table F1.** Movielens Tags with Disappointment Sentiment

| | Not-Nominated | Nominated | Difference | p-value | Obs. Not-Nominated | Obs. Nominated |
|---|---|---|---|---|---|---|
| Full sample | 0.003 | 0.004 | -0.002 | 0.018 | 33559 | 7762 |
| Post nomination only | 0.002 | 0.004 | -0.002 | 0.012 | 11568 | 4176 |

*Note*: The table compares the rates of "disappointment sentiment" for Movielens tags posted by users in two distinct groups: those associated with movies that were nominated for the AMPAS awards and those that were not. The sample includes Movielens tags posted within an 80-day window around the AMPAS nomination date, excluding ratings posted after the AMPAS award ceremony. The table report the means for each group, the difference between them, and the associated p-values.

**Table F2.** Matching Users Before and After the AMPAS Nominations: IMDb Reviews' Disinterest Dimension

| | (OLS) | (M1) | (M2) | (M3) | (M4) |
|---|---|---|---|---|---|
| Post Nomination | 0.010** | 0.008 | 0.011 | 0.012 | 0.013 |
| | (0.004) | (0.007) | (0.007) | (0.008) | (0.009) |
| $\bar{r}_i^j$ | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | ✓ |
| N | 54838 | 36398 | 32232 | 21767 | 16143 |
| Mean Dep. Var. | 0.499 | 0.467 | 0.467 | 0.465 | 0.465 |

*Note*: The sample includes IMDb reviews posted within an 80-day window around the AMPAS nomination date, excluding reviews posted after the AMPAS award ceremony. The dependent variable is a dummy variable that takes the value of 1 if the review's cosine similarity score related to a set of expressions of disinterest exceeds the median value of 0.3663. The table displays estimated treatment effects for nominated movies. The first column presents the OLS estimate from a regression of reviews on movie fixed effects and a dummy variable equal to 1 if the review was posted after the nomination date. Columns M1 to M4 report ATT estimates, matching exactly on the movie identifier and quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies reviewed by the user prior to reviewing the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table F3.** Matching Users Before and After the AMPAS Nominations: IMDb Reviews' Viewing Conditions Dimension

| | (OLS) | (M1) | (M2) | (M3) | (M4) |
|---|---|---|---|---|---|
| Post Nomination | 0.008* | 0.005 | 0.008 | 0.002 | 0.002 |
| | (0.004) | (0.006) | (0.006) | (0.008) | (0.010) |
| $\bar{r}_i^j$ | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | ✓ |
| N | 54838 | 36398 | 32232 | 21767 | 16143 |
| Mean Dep. Var. | 0.499 | 0.462 | 0.462 | 0.460 | 0.460 |

*Note*: The sample includes IMDb reviews posted within an 80-day window around the AMPAS nomination date, excluding reviews posted after the AMPAS award ceremony. The dependent variable is a dummy variable that takes the value of 1 if the review's cosine similarity score related to a set of expressions related to bad viewing conditions exceeds the median value of 0.2842. The table displays estimated treatment effects for nominated movies. The first column presents the OLS estimate from a regression of reviews on movie fixed effects and a dummy variable equal to 1 if the review was posted after the nomination date. Columns M1 to M4 report ATT estimates, matching exactly on the movie identifier and quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies reviewed by the user prior to reviewing the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table F4.** Matching Users Before and After the AMPAS Nominations: IMDb Reviews' Reverse Bandwagon Dimension

| | (OLS) | (M1) | (M2) | (M3) | (M4) |
|---|---|---|---|---|---|
| Post Nomination | 0.012*** | 0.010 | 0.009 | 0.006 | 0.009 |
| | (0.004) | (0.006) | (0.007) | (0.008) | (0.010) |
| $\bar{r}_i^j$ | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | ✓ |
| N | 54838 | 36398 | 32232 | 21767 | 16143 |
| Mean Dep. Var. | 0.499 | 0.462 | 0.462 | 0.460 | 0.460 |

*Note*: The sample includes IMDb reviews posted within an 80-day window around the AMPAS nomination date, excluding reviews posted after the AMPAS award ceremony. The dependent variable is a dummy variable that takes the value of 1 if the review's cosine similarity score related to a set of expressions related to the reverse bandwagon effect exceeds the median value of 0.3545. The table displays estimated treatment effects for nominated movies. The first column presents the OLS estimate from a regression of reviews on movie fixed effects and a dummy variable equal to 1 if the review was posted after the nomination date. Columns M1 to M4 report ATT estimates, matching exactly on the movie identifier and quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies reviewed by the user prior to reviewing the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table F5.** Matching Users Before and After the AMPAS Nominations: IMDb Reviews' Disappointment (25% High Similarity Scores)

| | (OLS) | (M1) | (M2) | (M3) | (M4) |
|---|---|---|---|---|---|
| Post Nomination | 0.034*** | 0.036*** | 0.037*** | 0.037*** | 0.035*** |
| | (0.004) | (0.005) | (0.006) | (0.007) | (0.008) |
| $\bar{r}_i^j$ | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | ✓ |
| N | 54838 | 36398 | 32232 | 21767 | 16143 |
| Mean Dep. Var. | 0.250 | 0.214 | 0.214 | 0.213 | 0.213 |

*Note*: The sample includes IMDb reviews posted within an 80-day window around the AMPAS nomination date, excluding reviews posted after the AMPAS award ceremony. The dependent variable is a dummy variable that takes the value of 1 if the review's cosine similarity score related to a set of expressions of disappointment exceeds the value of 0.4120 (75th percentile). The table displays estimated treatment effects for nominated movies. The first column presents the OLS estimate from a regression of reviews on movie fixed effects and a dummy variable equal to 1 if the review was posted after the nomination date. Columns M1 to M4 report ATT estimates, matching exactly on the movie identifier and quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies reviewed by the user prior to reviewing the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table F6.** Matching Users Before and After the AMPAS Nominations: IMDb Reviews' Disappointment (10% High Similarity Scores)

| | (OLS) | (M1) | (M2) | (M3) | (M4) |
|---|---|---|---|---|---|
| Post Nomination | 0.026*** | 0.026*** | 0.027*** | 0.029*** | 0.031*** |
| | (0.003) | (0.003) | (0.003) | (0.005) | (0.006) |
| $\bar{r}_i^j$ | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | ✓ |
| N | 54838 | 36398 | 32232 | 21767 | 16143 |
| Mean Dep. Var. | 0.100 | 0.083 | 0.083 | 0.083 | 0.083 |

*Note*: The sample includes IMDb reviews posted within an 80-day window around the AMPAS nomination date, excluding reviews posted after the AMPAS award ceremony. The dependent variable is a dummy variable that takes the value of 1 if the review's cosine similarity score related to a set of expressions of disappointment exceeds the value of 0.4569 (90th percentile). The table displays estimated treatment effects for nominated movies. The first column presents the OLS estimate from a regression of reviews on movie fixed effects and a dummy variable equal to 1 if the review was posted after the nomination date. Columns M1 to M4 report ATT estimates, matching exactly on the movie identifier and quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies reviewed by the user prior to reviewing the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table F7.** Matching Users Before and After the AMPAS Nominations: IMDb Reviews' Disappointment (transformer-based classification model)

| | (OLS) | (M1) | (M2) | (M3) | (M4) |
|---|---|---|---|---|---|
| Post Nomination | 0.010*** | 0.012*** | 0.011*** | 0.014*** | 0.016*** |
| | (0.002) | (0.003) | (0.004) | (0.005) | (0.006) |
| $\bar{r}_i^j$ | | ✓ | ✓ | ✓ | ✓ |
| $N_i^j$ | | | ✓ | ✓ | ✓ |
| $\bar{s}_i^j$ | | | | ✓ | ✓ |
| $Share_i^j$ | | | | | ✓ |
| N | 54838 | 36398 | 32232 | 21767 | 16143 |
| Mean Dep. Var. | 0.080 | 0.071 | 0.071 | 0.071 | 0.071 |

*Note*: The sample includes IMDb reviews posted within an 80-day window around the AMPAS nomination date, excluding reviews posted after the AMPAS award ceremony. The dependent variable is a dummy variable that takes the value of 1 1 if the predicted probability of the "disappointment" label exceeds the value of 0.5. The table displays estimated treatment effects for nominated movies. The first column presents the OLS estimate from a regression of reviews on movie fixed effects and a dummy variable equal to 1 if the review was posted after the nomination date. Columns M1 to M4 report ATT estimates, matching exactly on the movie identifier and quintiles of different user characteristics. All characteristics are time-varying, based on the set of movies reviewed by the user prior to reviewing the nominated movie. Standard errors are obtained via bootstrap (100 replications). $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

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