Appendix A: Virtual Qualitative Methods

Our qualitative data collection was conducted during the height of the COVID-19 pandemic and, as such, it was not possible for members of the research team to travel to Mumbai and interview key participants in person. Given this restriction, the interviews for this project were conducted virtually, on video, using technologies such as Zoom or WhatsApp by the US-based research team. This section provides some additional context on the benefits and challenges of this approach, with the hope that it will be useful to other qualitative researchers interested in adopting similar methods.

Benefits:

There were several benefits of virtual data collections that we experienced. First, we found that virtual interviews offered a level of flexibility in scheduling participants that we have not experienced in past in-person interview-based projects. We found it easier to schedule interviews around the participants' travel and work schedules, including at times when traditional interviews would typically not be possible (e.g. at night or during travel). As a consequence, we were able to find time to interview subjects much sooner than expected. For example, one interviewee described that she had just returned from a trip and was free at that moment to talk, so we ended up conducting a high-quality interview with relative ease.

Second, virtual interviews also saved on travel costs for the research team, which enabled us to conduct a larger number of interviews with a more diverse and geographically dispersed interview sample than expected. Reducing travel was also environmentally beneficial, especially given the long travel distance between the US and India.

Third, we found it easier to record and transcribe virtual interviews. For example, Zoom's feature to "enable recording" allowed us to record all participant interaction in a non-intrusive and natural manner. Participants were not as self-conscious about what they were saying (as compared to having an audio recorder placed near them), and we had both audio and video data for transcription.

Finally, in addition to having benefits for participants, remote interviews were also valuable to the research team. First, note that without the possibility of virtual data collection, projects like this would not have been possible during prolonged periods of disruption such as the COVID-19 lockdowns, especially given the varying and changing rules and regulations across different countries. In addition, insofar as researchers might have their own family constraints (such as childcare responsibilities for young children), remote data collection allows for a more level playing field among researchers with and without family obligations. It is also possible to schedule interviews in a non-concentrated fashion (often not possible when the researcher travels to a given location), and around other constraints such as daycare pickups or school holidays. Further, in instances where interview participants show up late, remote interviews afford researchers the possibility of engaging in other productive tasks at home or at work as they wait for interviewees. Finally, in locations where traveling often poses safety concerns (either for reasons of local violence and conflict or sexual harassment), remote data collection offers a safer environment from which high-quality data can be collected with fewer concerns about personal safety.

Challenges:

While remote data collection has many benefits, there is no doubt that it can compromise on important factors of relevance to qualitative research. Perhaps the most central difference is that the researcher and the interviewee are not co-located during their conversation, which makes it harder to pick up on subtle bodily cues and body language that might guide the interviewer. Further, the interviewer sees the participant through a digital medium and is less attuned to local and environmental factors that might affect the interview (such as the local weather, sounds and smells of the environment etc.). This might make it harder to connect with interviewees and build rapport. Further, virtual interviews rely on a sound technical infrastructure for both the researcher and the participant, including a strong internet connection and accessories such as a working camera and microphone. Given the diversity of contexts of interest to qualitative researchers, such infrastructure might not always be available. Beyond the technology itself, depending on the study population, participants might not be familiar with using technology such as Zoom and might therefore be more reluctant to participate, leading to remote interviews selecting on those with the technical means and know-how to participate. Finally, we noticed that since remote interviews were often conducted in participants' work or home locations, there could be interruptions during the interview. While we did not face a lot of interruptions in our interviews, we did have cases when participants were, for example, interrupted by a cook asking about dinner plans, or family members (such as children).

In our context, our study sample came from a relatively more affluent stratum of Indian society and had access to a basic technology suite including laptops, cellphones and stable internet connections. Further, the research team was located at a significant distance from the study setting and we collected data during the pandemic, which compounded the benefits of pursuing a digital mode of interviewing our subjects. The fact that our interviewees were quite busy individuals - who found it easier to converse remotely as and when they had time (rather than welcoming us into their workplaces) – helped us achieve a larger and more representative sample than would have otherwise been possible. Finally, key members of the research team had personal family considerations including childcare responsibilities for young kids, and would have exposed themselves to safety threats from doing fieldwork in India. For all these reasons, in our context, a virtual and remote approach to qualitative data collection helped strengthen our study. In other contexts, more thought is needed before a potential researcher chooses between virtual and in-person data collection methodologies.

Appendix B: Classifying Soundtracks as Analog or Digital

We classified 960 films released between 1990 and 2010 using a simple logistic-regression text classifier with L2 regularization. Each film was assigned to one of two classifications: digital (Yes) or analog (No).

Data pre-processing: The data was cleaned via computational techniques like stopword removal as well as manual cleaning. The CountVectorizer function from the scikit-learn python library was used to extract text features. This feature-extraction technique uses one-hot encoding for text data.

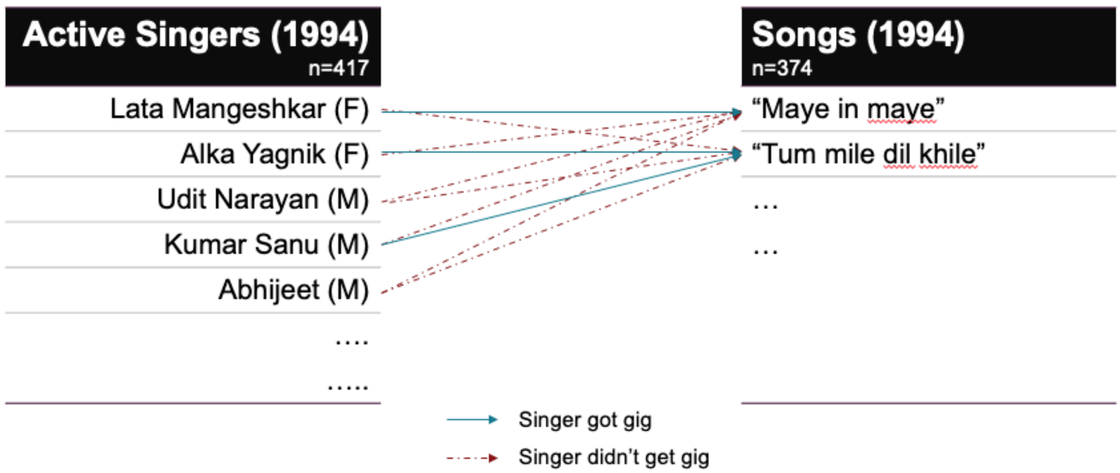
Model building: Films released prior to 1990 were assumed to be non-digital; those released post-2010 were assumed to be digital. This forms the labelled data, used to train and test the model. Eighty percent of this data is used to train the logistic-regression model; 20% is used to test the model predictions. Our model achieves a test accuracy of 98.4%, signifying that for the data on which we tested the model our result was correct 98.4% of the time. The logistic-regression model picks up keywords that correspond to digital processes, such as *ADR* (Automated Dialogue Replacement), *Foley* (reproduction of everyday sound effects that are added to films, videos, and other media in post-production to enhance audio quality), *Designer*, *Producer*, etc. The model predicts that 665 of the films are non-digital (No) and 295 are digital (Yes). In other words, for a film released between 1990 and 2010, there is a 69.27% chance that the model will classify it as non-digital.

Model validation: To validate the model we used the 20% of the labelled data that we designated as test data. We use this data to compute the precision, recall, and F1 score of the Yes and No categories.

Category	Precision	Recall	f1-score	support
No	0.96	1.00	0.98	52
Yes	1.00	0.97	0.99	73

Appendix C: Example of Sample Construction

Panel A: Construction of Singer-Song Links

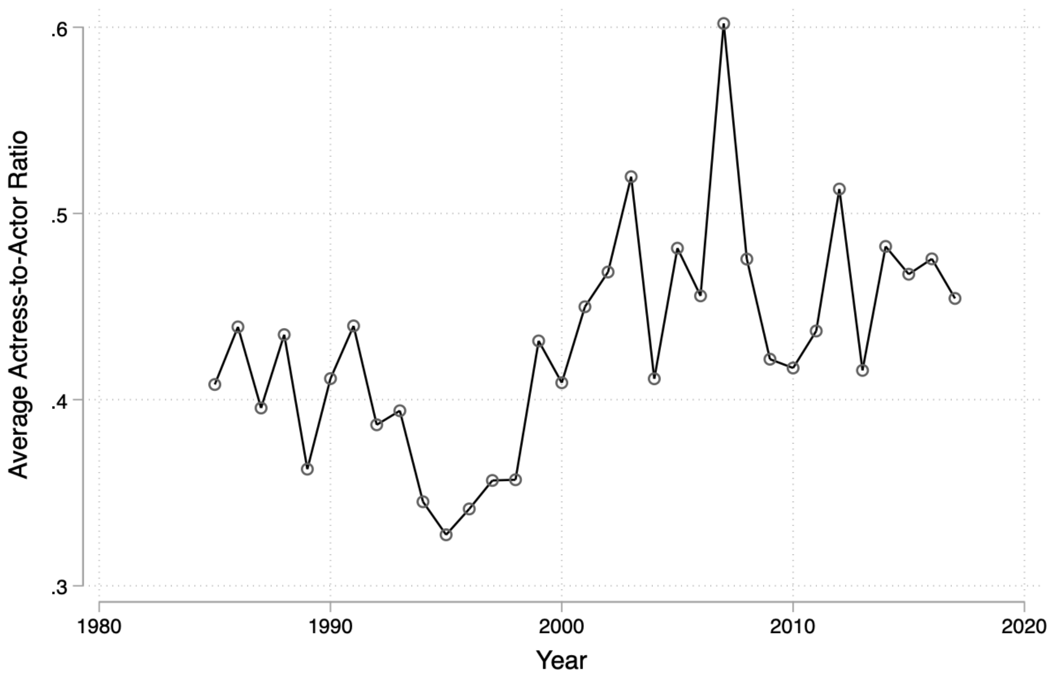


Panel B: Sample Extract

Song	Movie	Year	Digital	Singer	Singer Gender	GotGig
Maye ni maye	**HAHK**	**1994**	**0**	**Lata Mangeshkar**	**F**	**1**
Maye ni maye	HAHK	1994	0	Alka Yagnik	M	0
Maye ni maye	HAHK	1994	0	Udit Narayan	M	0
Maye ni maye	HAHK	1994	0	Kumar Sanu	F	0
Maye ni maye	HAHK	1994	0	Abhijeet	M	0
Tum mile dil khile	Criminal	1994	0	Lata Mangeshkar	F	0
Tum mile dil khile	**Criminal**	**1994**	**0**	**Alka Yagnik**	**F**	**1**
Tum mile dil khile	Criminal	1994	0	Udit Narayan	M	0
Tum mile dil khile	**Criminal**	**1994**	**0**	**Kumar Sanu**	**M**	**1**
Tum mile dil khile	Criminal	1994	0	Abhijeet	M	0

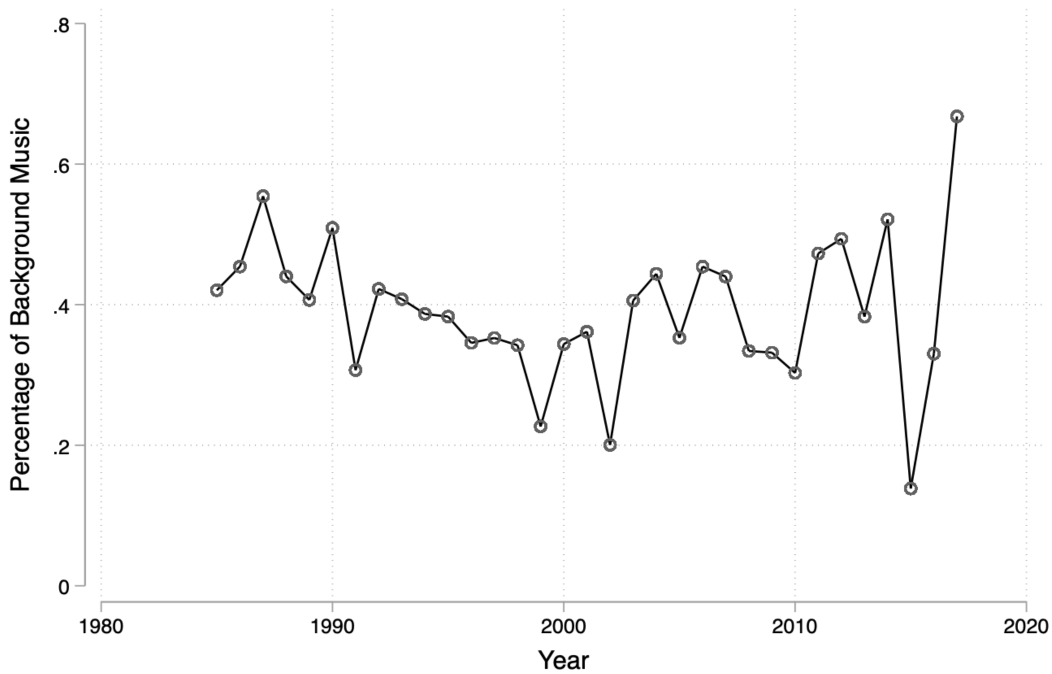
Appendix D: Women Opportunities in Digital Cultural Production

Figure D1: Actress-to-Actor Ratio Over Time



Note: This figure explores the gender composition of movie casts based on manually coded actor gender from IMDb cast data for the sample of movies we analyze. For each movie, we calculate the ratio of actresses and actors, and then we take an average for each year.

Figure D2: Percentage of Background Song Over Time



Note: This figure explores the percentage of songs that is background song over time. For each year, we count the number of background songs. A song counts as a background song if there are no actors/actresses on-screen singing the song when the song is played in the movie.

Table D1: Women Opportunities in Digital Cultural Production

	Women-Dominant Movies			Background Songs		
	No	Yes	All	No	Yes	All
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	0.0434***	0.0591*	0.0435***	0.0430***	0.0470***	0.0361***
	(0.00592)	(0.0230)	(0.00607)	(0.00682)	(0.00878)	(0.00631)
Woman	0.0895***	0.142***	0.0895***	0.0898***	0.103***	0.0899***
	(0.00607)	(0.0203)	(0.00607)	(0.00635)	(0.0101)	(0.00634)
Digital x Woman	-0.0897***	-0.119***	-0.0897***	-0.0876***	-0.0961***	-0.0876***
	(0.00771)	(0.0233)	(0.00771)	(0.00819)	(0.0120)	(0.00819)
Indicator			-0.0321**			-0.0327***
			(0.0105)			(0.00639)
Digital x Indicator			0.0156			0.0226**
			(0.0121)			(0.00762)
Woman x Indicator			0.0520*			0.0126
			(0.0211)			(0.0110)
Digital x Woman x Indicator			-0.0290			-0.00836
			(0.0245)			(0.0133)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Composer FE	Yes	Yes	Yes	Yes	Yes	Yes
Actor/Genre Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	7322357	1235599	8557956	5404792	3153164	8557956

Note: This table provides OLS estimates of the differential effect of digital cultural production on men and women singers, depending on whether the movie is women-oriented and whether the song is a background song. The sample is at the singer-gig level by year; the main outcome variable is *GotGig*. *Digital* and *Woman* are dummy variables that equal one if the gig is for a digital soundtrack or the singer is a woman. *Indicator* is set to one in col (3) when the movie is women-oriented, which is defined by a relatively high proportion of actresses in the movie cast (actresses-to-actor ratio > 0.7), and is set to one in col (6) for songs where there are no actors/actresses on-screen singing the song when the song is played in the movie. Actor/Genre Controls control for the count of men and women actors in the cast and the genre of the song (e.g., pop or classical). Standard errors are clustered at the film level. $*\, p < 0.05$, $**\; p < 0.01$, $***\, p < 0.001$

Appendix E: Gig Quality in Digital Cultural Production

Table E1: The Effect of Digital Cultural Production Accounting for Gig Quality Measures

	(1) Prod FE	(2) Song Rating	(3) Singer Popularity	(4) Box Office	(5) Solo Song
Digital	0.0451***	0.0468***	0.0459***	0.0457***	0.00396
	(0.00592)	(0.00681)	(0.0103)	(0.00730)	(0.00609)
Woman	0.0944***	0.105***	0.0153	0.0982***	0.115***
	(0.00586)	(0.00744)	(0.0181)	(0.00831)	(0.00644)
Digital x Woman	-0.0905***	-0.0943***	-0.0251	-0.0909***	-0.0799***
	(0.00734)	(0.00972)	(0.0194)	(0.0107)	(0.00929)
High		0.00826	0.0374***	0.0215**	-0.215***
		(0.00507)	(0.00944)	(0.00721)	(0.00580)
Digital x High		-0.00607	-0.00675	-0.00973	0.0888***
		(0.00666)	(0.0104)	(0.00911)	(0.00702)
Woman x High		-0.0230*	0.0884***	-0.0103	-0.0505***
		(0.00963)	(0.0189)	(0.0132)	(0.0105)
Digital x Woman x High		0.00945	-0.0669**	0.00945	-0.0135
		(0.0122)	(0.0208)	(0.0163)	(0.0133)
Year FE	Yes	Yes	Yes	Yes	Yes
Composer FE	Yes	Yes	Yes	Yes	Yes
Production Corporation FE	Yes	No	No	No	No
Actor/Genre Controls	Yes	Yes	Yes	Yes	Yes
N	8557956	8557956	8557956	7319291	8557956

Note: This table provides OLS estimates of the differential effect of digital cultural production on men and women singers, depending on some gig quality measures. The sample is at the singer-gig level by year; the main outcome variable is *GotGig*. *Digital* and *Woman* are dummy variables that equal one if the gig is for a digital soundtrack or the singer is a woman. Production Cooperation fixed effects are added in col (1). *High* is set to one in col (2) when the rating of the song is above the median, is set to one in col (3) for there is a singer ranked in the top 100, is set to one in col (4) if the box office returns are ranked in the top 20 in that year, and is set to one in col (5) if the song is a solo. Actor/Genre Controls control for the count of men and women actors in the cast and the genre of the song (e.g., pop or classical). Standard errors are clustered at the film level. $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$

Appendix F: Digital Cultural Production and Allocation of Gigs Dropping Post-2010 Movies

Table F1: Digital Cultural Production and Labor Market Entry Dropping Post-2010 Movies

	Likelihood of Getting Gig		
	(1)	(2)	(3)
Digital	-0.00415	-0.00449	-0.00114
	(0.00553)	(0.00539)	(0.00583)
Debut	-0.0671**	-0.0671**	-0.0671**
	(0.0209)	(0.0209)	(0.0209)
Digital x Debut	0.215***	0.215***	0.215***
	(0.0329)	(0.0329)	(0.0329)
Year FE	Yes	Yes	Yes
Composer FE	No	No	Yes
Actor/Genre Controls	No	Yes	Yes
N	5932647	5932647	5932647

Note: This table provides OLS estimates of the likelihood that a newcomer will be hired for a digital or an analog gig. Data are at the singer-gig level, with one observation for every active singer-gig combination by calendar year and excludes movies after 2010. The outcome variable is *GotGig*; *Digital* and *Debut* are dummy variables if the focal gig is for a digital soundtrack or if the singer is making a debut in that year. Actor/Genre Controls control for the count of men and women actors in the cast and the genre of the song (e.g., pop or classical). $*\, p < 0.05$, $**\ p < 0.01$, $***\, p < 0.001$

Table F2: Digital Cultural Production and Allocation of Gigs to Women Singers Dropping Post-2010 Movies

	Likelihood of Getting Gig			IV
	(1)	(2)	(3)	(4)
Digital	0.0407***	0.0403***	0.0437***	0.0303
	(0.00630)	(0.00617)	(0.00656)	(0.0524)
Woman	0.0962***	0.0962***	0.0963***	0.145***
	(0.00595)	(0.00595)	(0.00595)	(0.0227)
Digital x Woman	-0.0903***	-0.0901***	-0.0902***	-0.206***
	(0.00878)	(0.00879)	(0.00878)	(0.0523)
Debut		0.0335*	0.0335*	0.0328*
		(0.0165)	(0.0165)	(0.0165)
Year FE	Yes	Yes	Yes	Yes
Composer FE	No	No	Yes	No
Actor/Genre Controls	No	Yes	Yes	Yes
N	5932647	5932647	5932647	5932647

Note: This table provides OLS (1-3) and IV (4) estimates of the likelihood that a woman singer will be hired for a singing gig after digital cultural production. The sample is at the singer-gig level by calendar year and excludes movies after 2010; the main outcome variable is *GotGig*. *Digital* and *Woman* are dummy variables that equal one if either the gig is for a digital soundtrack or the singer is a woman. *Debut* indicates the first year a singer becomes active. Actor/Genre Controls control for the count of men and women actors in the cast and the genre of the song (e.g., pop or classical). Column 4 provides IV estimates where *Digital* is instrumented with *AfterFire* and *Digital* x *Woman* is instrumented with *AfterFire* x *Woman*. *AfterFire* is set to one for composers after the analog studio they relied on is affected by a fire. Standard errors are clustered at the film level. $*\, p < 0.05$, $**\ p < 0.01$, $***\, p < 0.001$

Table F3: Gatekeeper and the Effects of Digital Cultural Production for Women Dropping Post-2010 Movies

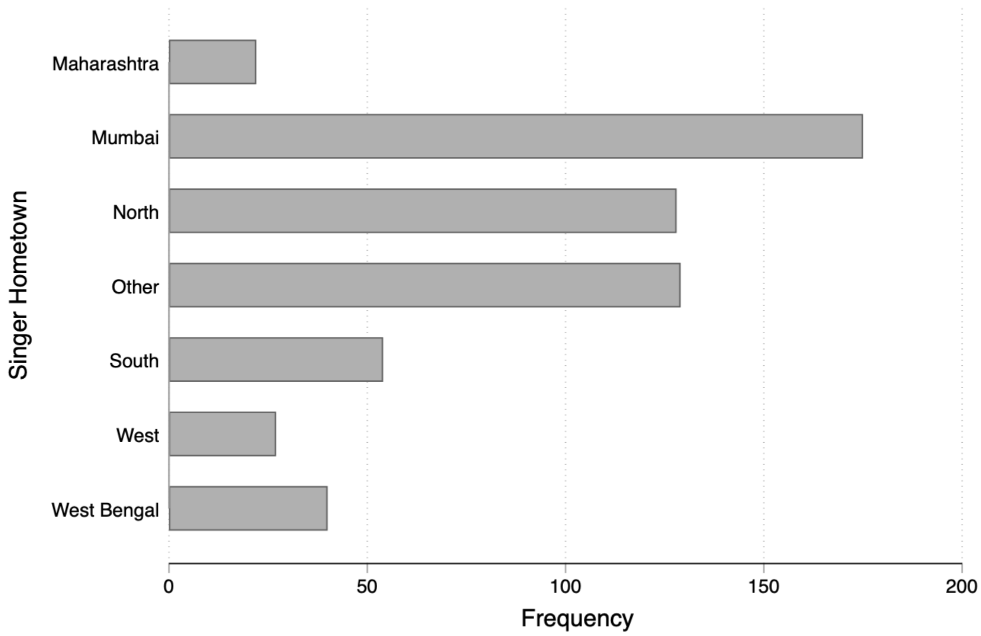
	Same Region			From Mumbai		
	No	Yes	All	No	Yes	All
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	0.103***	0.101**	0.0427**	0.119***	0.0369	-0.00255
	(0.0144)	(0.0385)	(0.0138)	(0.0161)	(0.0193)	(0.0149)
Woman	0.268***	-0.139***	0.268***	0.310***	-0.0305	0.314***
	(0.0161)	(0.0329)	(0.0161)	(0.0190)	(0.0194)	(0.0190)
Digital x Woman	-0.245***	-0.0829	-0.245***	-0.319***	0.0103	-0.322***
	(0.0189)	(0.0454)	(0.0189)	(0.0230)	(0.0257)	(0.0230)
Indicator			-0.00607			-0.436***
			(0.0327)			(0.0195)
Digital x Indicator			0.303***			0.278***
			(0.0448)			(0.0254)
Woman x Indicator			-0.425***			-0.368***
			(0.0407)			(0.0303)
Digital x Woman x Indicator			0.164**			0.357***
			(0.0536)			(0.0376)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Composer FE	Yes	Yes	Yes	Yes	Yes	Yes
Actor/Genre Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	3141630	757437	3899067	2510690	1206361	3717051

Note: This table provides OLS estimates of the differential effect of digital cultural production on men and women singers, depending on whether the singer and music director come from the same region and whether the singer comes from Mumbai. The sample is at the singer-gig level by year and excludes movies after 2010; the main outcome variable is *GotGig*. The sample size is smaller than the baseline because we only code the birthplace for singers who sing more than 4 songs and for music directors with more than 2 songs. *Digital* and *Woman* are dummy variables that equal one if the gig is for a digital soundtrack or the singer is a woman. *Indicator* is set to one in col (3) when the singer and music director come from the same region and is set to one in col (6) for singers who come from Mumbai. Actor/Genre Controls control for the count of men and women actors in the cast and the genre of the song (e.g., pop or classical). Standard errors are clustered at the film level. $*\, p < 0.05$, $**\ p < 0.01$, $***\, p < 0.001$

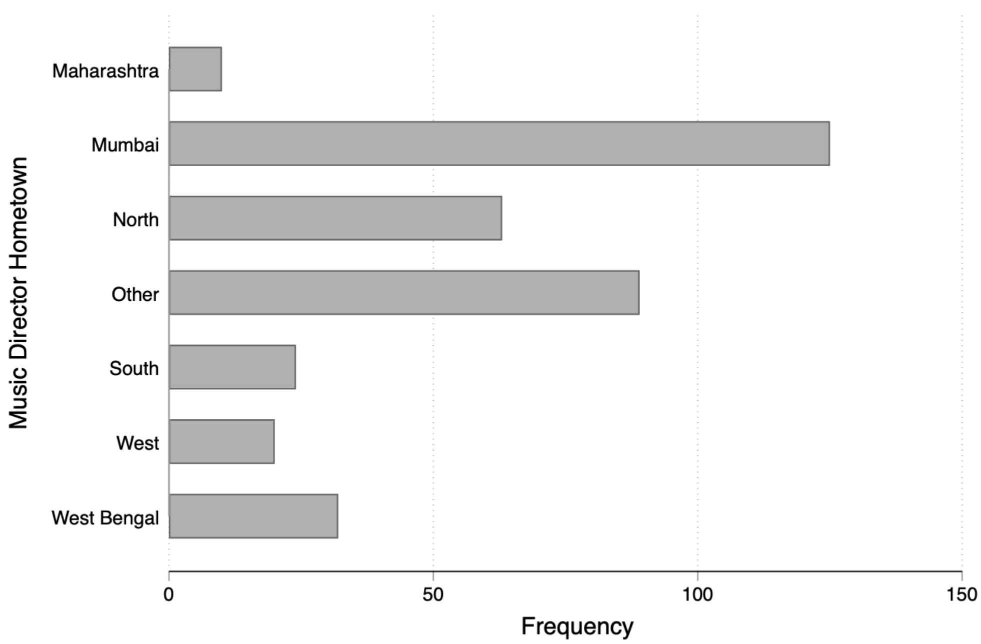
Appendix G: Distribution of Birth Regions

Figure G1: Distribution of Singers' and Music Directors' Hometown

Panel A. Singers

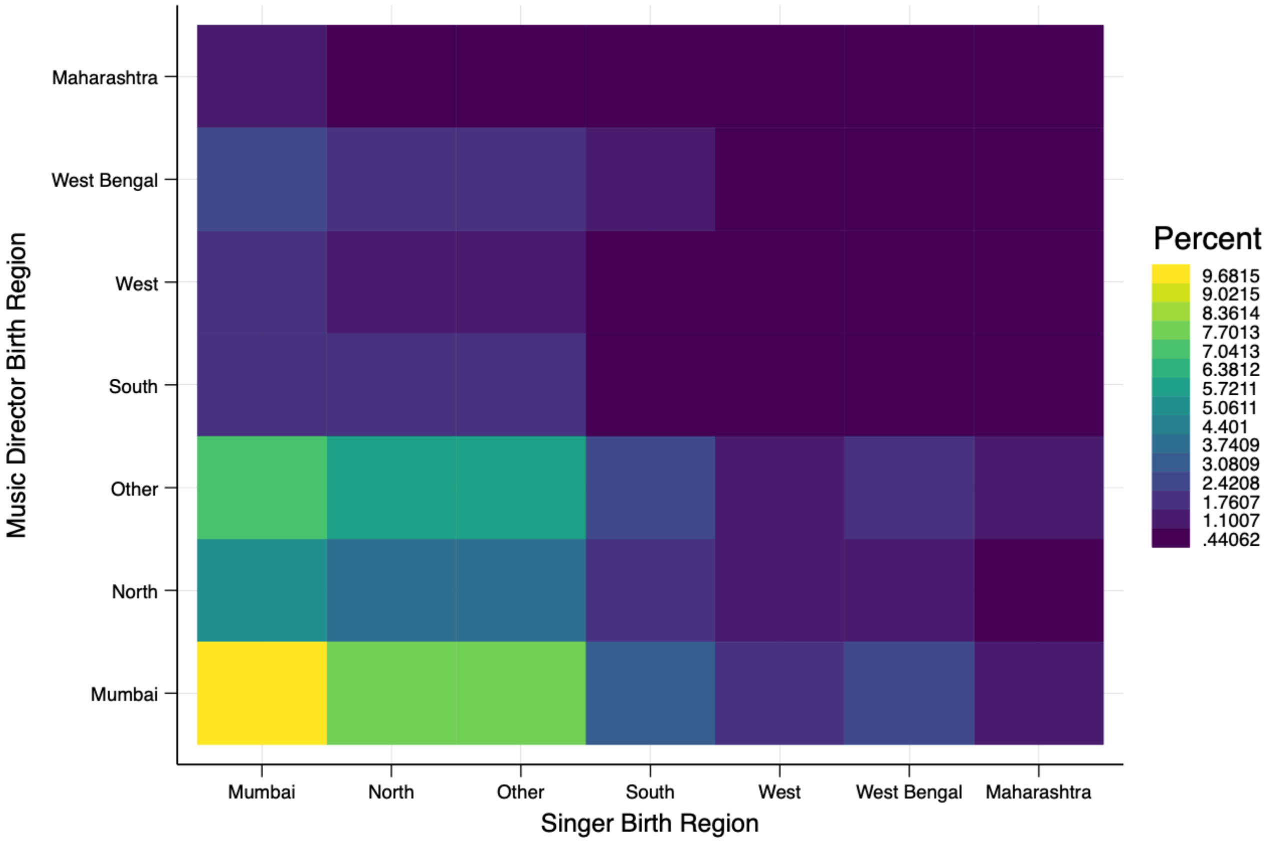


Panel B. Music Directors



Note: This figure explores the distribution of the hometown for singers and music directors. We categorize 7 regions: Mumbai, Maharashtra, West Bengal, North, South, West, and Others. North includes Punjab, Delhi, Uttar Pradesh, Haryana, Sindh, and Uttarakhand. South includes Tamil Nadu, Telangana, Karnataka, Kerala, and Andhra Pradesh. And West includes Gujarat and Rajasthan.

Figure G2: Distribution of Singer-Director Pairs



Note: This figure explores the distribution of singers-music directors birthplace pairs. We categorize 7 regions: Mumbai, Maharashtra, West Bengal, North, South, West, and Others. North includes Punjab, Delhi, Uttar Pradesh, Haryana, Sindh, and Uttarakhand. South includes Tamil Nadu, Telangana, Karnataka, Kerala, and Andhra Pradesh. And West includes Gujarat and Rajasthan.

Appendix H: Commercial Products in Digital Cultural Production

Table H1: The Effects of Digital Cultural Production for Women in Commercial Products

	Sequel			Pop		
	No	Yes	All	No	Yes	All
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	0.0457***	0	0.0449***	0.0549***	0.0125	0.0501***
	(0.00603)	(.)	(0.00596)	(0.00776)	(0.0125)	(0.00728)
Woman	0.0956***	-0.00682	0.0956***	0.101***	0.0580***	0.101***
	(0.00589)	(0.0467)	(0.00589)	(0.00732)	(0.0142)	(0.00732)
Digital x Woman	-0.0926***	0.0227	-0.0926***	-0.0988***	-0.0524**	-0.0988***
	(0.00749)	(0.0489)	(0.00749)	(0.00989)	(0.0167)	(0.00989)
Indicator			0.0480**			0.0216*
			(0.0177)			(0.00918)
Digital x Indicator			-0.0526*			-0.0248*
			(0.0205)			(0.0108)
Woman x Indicator			-0.102*			-0.0440**
			(0.0467)			(0.0159)
Digital x Woman x Indicator			0.115*			0.0471*
			(0.0491)			(0.0191)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Composer FE	Yes	Yes	Yes	Yes	Yes	Yes
Actor/Genre Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	8155997	401959	8557956	3044973	1141578	4186551

Note: This table provides OLS estimates of the differential effect of digital cultural production on men and women singers, depending on whether the movie is a sequel and whether the song is a pop song. The sample is at the singer-gig level by year; the main outcome variable is *GotGig*. *Digital* and *Woman* are dummy variables that equal one if the gig is for a digital soundtrack or the singer is a woman. *Indicator* is set to one in col (3) when the movie is a sequel and is set to one in col (6) for pop songs. Actor/Genre Controls control for the count of men and women actors in the cast and the genre of the song (e.g., pop or classical). Standard errors are clustered at the film level. $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$

Appendix I: Estimating Audience Endorsement Using Alternative Sample

Table I1: Audience Endorsements and Digital Cultural Production Excluding Same Region

	Rating			Reality Show Participant		
	Low	High	All	No	Yes	All
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	0.118***	0.0384	0.0664***	0.186***	-0.160**	0.119***
	(0.0164)	(0.0273)	(0.0152)	(0.0207)	(0.0593)	(0.0194)
Woman	0.314***	0.00720	0.314***	0.544***	-0.277***	0.544***
	(0.0183)	(0.0194)	(0.0183)	(0.0238)	(0.0650)	(0.0239)
Digital x Woman	-0.291***	-0.00215	-0.291***	-0.511***	0.383***	-0.511***
	(0.0214)	(0.0274)	(0.0214)	(0.0283)	(0.0770)	(0.0283)
Indicator			-0.558***			-0.0791
			(0.0197)			(0.0551)
Digital x Indicator			0.355***			0.122*
			(0.0254)			(0.0617)
Woman x Indicator			-0.355***			-0.818***
			(0.0282)			(0.0762)
Digital x Woman x Indicator			0.337***			0.894***
			(0.0363)			(0.0890)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Composer FE	Yes	Yes	Yes	Yes	Yes	Yes
Actor/Genre Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2771110	370520	3141630	2035337	312522	2347859

Note: This table provides OLS estimates of the differential effect of digital cultural production on men and women singers, depending on audience ratings of their music and their participation in musical reality shows. The sample is at the singer-gig level by year with only songs for which singers are not from the same state as the music director; the main outcome variable is *GotGig*. The sample for columns 4–6 is smaller than the baseline sample because it includes only singers for whom we found reality-show participation. *Digital* and *Woman* are dummy variables that equal one if the gig is for a digital soundtrack or the singer is a woman. *High* is set to one in col (3) for singers with ratings of 4 stars or above for their music and is set to one in col (6) for singers who had participated in a reality show. Actor/Genre Controls control for the count of men and women actors in the cast and the genre of the song (e.g., pop or classical). Standard errors are clustered at the film level. $*\,p < 0.05$, $**\,p < 0.01$, $***\,p < 0.001$

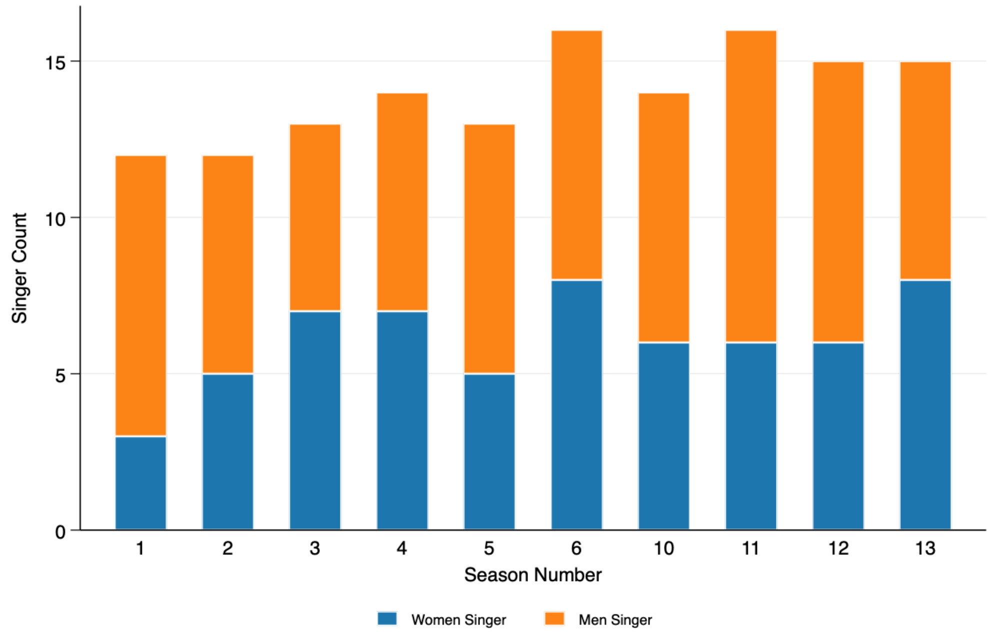
Table I2: Audience Endorsements and Digital Cultural Production with Excluding Mumbai-Born Singers

	Rating			Reality Show Participant		
	Low	High	All	No	Yes	All
	(1)	(2)	(3)	(4)	(5)	(6)
Digital	0.143***	0.0527	0.0738***	0.225***	-0.185**	0.116***
	(0.0186)	(0.0306)	(0.0173)	(0.0220)	(0.0682)	(0.0211)
Woman	0.390***	-0.00665	0.391***	0.733***	-0.333***	0.736***
	(0.0223)	(0.0199)	(0.0222)	(0.0292)	(0.0719)	(0.0291)
Digital x Woman	-0.400***	-0.0239	-0.400***	-0.725***	0.369***	-0.726***
	(0.0269)	(0.0314)	(0.0269)	(0.0351)	(0.0859)	(0.0350)
Indicator			-0.740***			-0.200**
			(0.0238)			(0.0632)
Digital x Indicator			0.464***			0.312***
			(0.0323)			(0.0733)
Woman x Indicator			-0.464***			-1.041***
			(0.0313)			(0.0872)
Digital x Woman x Indicator			0.426***			1.075***
			(0.0442)			(0.102)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Composer FE	Yes	Yes	Yes	Yes	Yes	Yes
Actor/Genre Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2198686	312004	2510690	1674514	284172	1958686

Note: This table provides OLS estimates of the differential effect of digital cultural production on men and women singers, depending on audience ratings of their music and their participation in musical reality shows. The sample is at the singer-gig level by year with only singers who are not from Mumbai; the main outcome variable is *GotGig*. The sample for columns 4–6 is smaller than the baseline sample because it includes only singers for whom we found reality-show participation. *Digital* and *Woman* are dummy variables that equal one if the gig is for a digital soundtrack or the singer is a woman. *High* is set to one in col (3) for singers with ratings of 4 stars or above for their music and is set to one in col (6) for singers who had participated in a reality show. Actor/Genre Controls control for the count of men and women actors in the cast and the genre of the song (e.g., pop or classical). Standard errors are clustered at the film level. $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$

Appendix J: Additional Figures

Figure J1: Number of Indian Idol Contestants by Gender



Note: This figure explores the gender composition of the participants of a popular reality show: Indian Idol. The information about participants is collected from Wikipedia: *https://en.wikipedia.org/wiki/Indian_Idol_(Hindi_TV_series)*. Seasons 7 to 9 are missing due to incomplete data.