# Goodbye My Friends and Goodbye My Career: Evidence from the Movie Industry

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**Abstract**

In this study, we provide causal evidence that network connections significantly influence individuals' career trajectories. Using data on actors', directors', and producers' work histories and movie performances from 1995 to 2014, we examine the impact of losing a professional connection due to the death of a director or producer. Our identification strategy leverages the exogenous timing of these deaths, which is independent of an actor's intrinsic ability. Our findings reveal that losing such a connection leads to a 7.78% decline in an actor's subsequent movie output, with the effect being more pronounced for less experienced actors and intensifying over time. The negative impact is even stronger when considering quality-adjusted movie output. Our analysis suggests that mentorship and referrals are likely mechanisms driving these results, as evidenced by diminishing returns from additional professional connections, and the significance of the age gap between the deceased directors/producers and the treated actors.

**Keywords:** *self-marketing, network, death shock, referral, mentorship, career development, movie industry*

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# 1 Introduction

Network connections have long been considered crucial for self-marketing and opening up more job opportunities. Professional connections provide an effective channel for information exchange, allowing the transmission of knowledge and private information between job-seekers and employers. For instance, Adler (2016) shows survey evidence that about 85% of job openings are filled through social connections. Despite the prevalence of such anecdotal evidence, there are very few research papers which quantify the impact of network connections on career development. Two primary challenges contribute to this gap. First, the evolution of an individual's network is inherently endogenous to their intrinsic ability. In general, more capable workers tend to have more network connections, making it difficult to disentangle whether the effect is due to network connections or intrinsic ability. Second, most individuals do not actively seek new job opportunities frequently, resulting in a limited number of observable instances to infer how network connections may influence job search outcomes.

To address the first challenge, we propose a novel identification strategy to tackle the network connections endogeneity problem by leveraging death shocks. The passing of a person has nothing to do with the intrinsic ability of anyone else, but it reduces the network size of people who are connected with them. Hence, it provides us with an exogenous shock to identify the impact of losing a connection.

To address the second challenge, we focus on the movie industry, where actors work on a per-project basis rather than holding permanent employment. As a result, they must continuously seek new job opportunities.[1] These characteristics make the film industry an ideal setting for reliably measuring the impact of professional connections on career outcomes.

In our study, we focus on the deaths of directors and producers, as they are the key decision-makers in casting. Their professional might play a crucial role in determining an

[1]This employment structure is similar to that of consultants, lawyers, architects, real estate agents, house builders, and renovation specialists/designers, etc.

actor's chances of being hired for a movie project. Importantly, their deaths are independent of the actors' intrinsic abilities, such as their acting skills. To facilitate our analysis, we have compiled an extensive dataset of the U.S. movie industry from 1995 to 2014. This dataset tracks the filmography of each actor, producer, and director. We consider all actors, producers, and directors who have previously worked on the same movie project as connected. We construct the number of connections for each actor/director/producer over time. Leveraging this dataset and the exogenous death shocks of directors and producers, we employ a difference-in-differences (DiD) research design to quantify the impact of changes in network connections on an actor's career opportunities, measured by the number of movies they participate in.

Following the death of a director/producer, our estimated average treatment effect shows that an actor who is previously connected with them experiences a 7.78% decline in their future movie output. This impact becomes even stronger when we account for the quality of the movie output. For instance, we observe a 16.97% decline in output when it is weighted by rating.

In our analysis of heterogeneous treatment effects, we identify two key factors that influence the impact of losing a professional connection. First, we find that the effect is stronger for actors with less work experience. Specifically, each additional film an actor has participated in reduces the average negative impact by 5.38%. This suggests that prior experience serves as a buffer, helping to mitigate career setbacks following the loss of a key professional relationship.

Second, our results suggest that the negative impact intensifies over time. This finding suggests that individuals who maintain their professional connections enjoy growing benefits, while those who lose connections face compounding disadvantages. This disparity underscores the long-term implications of network disruptions on career trajectories. We also look into the importance of deceased directors/producers, and the recency of the collaboration. However, we do not find evidence that they can moderate the treatment effect.

We construct empirical tests to disentangle three possible mechanisms for our findings: (i) repeated collaboration, (ii) emotional grief, and (iii) referral and mentorship. Although we see some evidence that repeated collaboration can contribute to the negative treatment effect, its impact on the average treatment effect is minimal because the vast majority of the deceased directors/producers only worked with the actors once before. We also do not find empirical support for the emotional grief mechanism. To investigate the referral and mentorship mechanisms, we first test the hypothesis of diminishing returns from network connections, a feature inherent to the referral/mentorship dynamic. Our analysis provides support for this hypothesis. To further explore the mentorship mechanism, we investigate how the age difference between an actor and the deceased director/producer may moderate the negative effects of connection loss. We hypothesize that older directors and producers offer more valuable and insightful career guidance, which is essential for both securing immediate opportunities and fostering long-term career development. Additionally, the mentor-mentee relationship may be more effective and respectful when the mentor is older than the mentee. Our empirical findings support this hypothesis, reinforcing the role of mentorship as a key mechanism. The tests on diminishing returns from network connections and age differences can also be viewed as heterogeneous treatment effects, offering insights into how actors can strategically select projects to advance their careers. Taken together, our mechanistic analysis aligns with the idea that referrals and mentorship are likely drivers of the observed treatment effects.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 explains our dataset and presents preliminary evidence for the effect of losing a connection to actor's job opportunities. Section 4 presents our DiD research design and the econometric model specifications. Section 5 discusses our results. Section 6 concludes by discussing the implications of our findings for practice.

# 2 Related Literature

Our paper is related to three streams of literature: (i) professional network, self-marketing, and career development; (ii) death identification strategy; (iii) movie marketing. This section explains how our research contributes to each of them.

## 2.1 Professional Network, Self-marketing, and Career Development

A person's professional network is widely recognized as a crucial factor in self-marketing, often leading to increased employment opportunities.[2] Survey evidence indicates that 66% of Americans seek job opportunities through friends or family members (Rainie et al., 2015), and 30–60% of U.S. jobs are secured via networks and referrals (Borchers and Ellis, 2023; Ioannides and Datcher Loury, 2004). Prior research has shown that social networks play a crucial role in shaping economic behavior by facilitating information exchange and influencing decision-making (Bertrand et al., 2000). Individuals with strong network connections gain privileged access to valuable information, which enhances their career prospects and provides them with a competitive advantage (e.g., Burt 2009; Granovetter 1973, etc.).

For example, Burks et al. (2015) examine the benefits of hiring through employee referrals using data from nine large firms across three industries and find that hiring through employee referrals reduces turnover and recruiting costs, with referred workers showing similar productivity but fewer accidents in trucking and more patents in high-tech. Jahn and Neugart (2020) demonstrate that neighborhood employment rates influence re-employment prospects, earnings, and job stability for workers displaced by plant closures, highlighting the role of social networks in facilitating information sharing and referrals. Hensvik and Skans (2016) find evidence that firms are able to hire high productivity workers by relying on referrals from their existing high performance workers. Dustmann et al. (2016) show that

[2] https://pressbooks.bccampus.ca/lucindaatwood/chapter/networking-and-self-marketing/, accessed on July 22, 2024.

firms are more likely to hire minority workers from a particular group if the existing share of workers from that group employed in the firm is higher, and employees hired by referral are less likely to leave the company. Bayer et al. (2008) use Census dataset to show that people who resided in the same block in Boston have a higher probability of working together.

In addition, a series of papers (Hellerstein et al., 2019; Kondo and Shoji, 2019; Brown et al., 2016; Burks et al., 2015; Kramarz and Skans, 2014; Cingano and Rosolia, 2012; Hellerstein et al., 2011; Magruder, 2010, etc.) argue that individuals with stronger networks are more likely to learn about new job opportunities; moreover, they tend to possess more comprehensive knowledge about the jobs and the potential employers, thereby enhancing the matching process, resulting in better career outcomes.[3] We contribute to this literature by providing causal evidence on how network connections influence career development, specifically in a setting where individuals frequently engage in job searches.

## 2.2 Death Identification Strategy

Establishing causal relationships between network connections and their impact is challenging due to the issue of reverse causality. More capable individuals likely have more job opportunities and, as a result, they tend to have a larger professional network.

To address this endogeneity problem, we focus on the movie industry and leverage the deaths of directors and producers as exogenous shocks to actors' network connections. Combined with the fact that actors must continuously seek new job opportunities, this setting allows us to employ a difference-in-differences (DiD) research design to estimate the causal effect of network connections on actors' career prospects. This death identification strategy is related to several studies. Jones and Olken (2005) use deaths of leaders while in office as a source of exogenous variation in leadership quality, and they find that one standard deviation change in leader quality leads to a growth change of 1.5% per year. Azoulay et al. (2010) study the impact of a top academic researcher's death on their collaborators' research

[3] Topa (2019) provides an extensive review for this literature.

output measured by quality-adjusted publication rates. Wang (2013) investigates the negative impact of one's father-in-law's death on their future wage growth. Benzell and Cooke (2021) exploit exogenous decreases in connections between European monarchies caused by deaths of their leaders' mutual relatives, and show that establishing connections between countries via royal kinship can significantly reduce the frequency and duration of wars.

To the best of our knowledge, this study is the first to estimate the impact of death shocks on career development in professions that require frequent job searches. While our analysis focuses on the actors' market, the findings offer insights into other project-based, self-employed professions that have been understudied.

## 2.3 Movie Market

Our study is also related to the marketing literature dedicated to studying the movie market. Most studies focus on what drives box office revenue, including the contributions of actors, producers, and directors to a movie's box office performance (e.g. Eliashberg et al., 2006; Einav, 2007; Hennig-Thurau et al., 2007; Elberse, 2007; Gil and Hartmann, 2009; Chintagunta et al., 2010; Moretti, 2011; Gopinath et al., 2013; Roos and Shachar, 2014; Liu et al., 2015; Narayan and Kadiyali, 2016; Gilchrist and Sands, 2016; Packard et al., 2016; Delre et al., 2017; Wei, 2020; Lu et al., 2023, etc.). McKenzie (2023) provide a comprehensive review of this literature. As far as we know, none of them have studied actor's productivity, let alone quantified how an actor's career prospects may be influenced by their connection to directors/producers, which is the main contribution of our research.[4]

[4]One exception is Hermosilla et al. (2018), who find that China's policies towards foreign film importation can affect Hollywood's film's casting preferences for actors with lighter skin tones. However, unlike our paper, their research does not study the role of network connections on casting decisions.

# 3 Data and Matched Sample Construction

## 3.1 Movie Industry Datasets

Our main data source is the Internet Movie Database (IMDb), which is the premier online database for comprehensive movie and actor information. Our data can be classified into three categories.

The first data category includes information on movies released in the U.S. from 1995 to 2014. For each movie, we collect data on various attributes, including actors, directors, producers, title, release date, IMDb rating, number of votes (indicating the number of ratings received), and U.S. box-office revenue.[5] This leads to a dataset which contains 62,648 actors, as well as 119,471 directors and producers. This is the data that we will use to construct each individual's network. We consider professionals (actors, directors, or producers) as connected if they have ever worked together on a movie.[6] We assume that once a connection is formed, it persists until one of the individuals in the pair passes away.

The second data category contains demographic information for each actor, producer, and director from IMDb. We successfully collected comprehensive demographic details for 10,120 actors and 7,751 directors and producers, including their date of birth and gender.

The third data category consists of a list of directors and producers who passed away between 1995 and 2014, with IMDb providing their year of death. Over this 20-year period, we identified 325 cases for which demographic information is also available.[7]

Table 1 provides descriptive statistics on the key characteristics of deceased directors and producers. The mean age at the time of death is 64.5, with females representing ap-

[5] In instances where box-office information is missing from the IMDb database, we supplement our dataset by retrieving this information from Wikipedia.com and Box Office Mojo. However, many movies do not have box-office revenue if they are released straight to videos or streaming.

[6] Actors, or individuals in general, can also connect and be friends with others even though they have never worked on the same project before. Those network connections are unobserved to researchers. Presumably, having a working relationship provide more opportunities for people to develop more in-depth personal relationship. Hence, we hope our measure of network connections provides a first-order approximation.

[7] Note that some movie professionals are classified as both directors, producers and actors. IMDb categorizes individuals based on their primary role, listing their main profession first. In our analysis, we include only those listed as directors or producers as their primary classification.

proximately 8.7% of the group. To capture each professional's output and experience, we compute both average yearly movie output and cumulative movie output. On average, these directors/producers created 1.07 movies annually, with a lifetime total of 11.26 movies. To further refine these metrics, we adjust them for movie quality using three different weights: (i) movie's box office revenue, (ii) IMDb rating, and (iii) number of ratings received (i.e., number of votes). The main summary statistics for these quality-adjusted variables are also included in Table 1.

Table 1: **Summary Statistics for Deceased Directors/Producers**

| **Variable Name** | **Mean** | **SD** | **Min** | **Max** |
|---|---|---|---|---|
| Age at Death | 64.51 | 15.35 | 37 | 96 |
| Female | 0.087 | 0.28 | 0 | 1 |
| No. of Movies | 11.26 | 9.36 | 3 | 46 |
| No. of Movies (weighted by rating) | 64.81 | 58.12 | 10.60 | 260.50 |
| No. of Movies (weighted by revenue) | 208.76 | 347.00 | 0 | 1,694.37 |
| No. of Movies (weighted by log no. of votes) | 457,624 | 771,831 | 10 | 3,514,466 |
| Ave. no. of Movies | 1.07 | 0.62 | 0.25 | 3 |
| Ave. no. of Movies (weighted by rating) | 6.08 | 3.96 | 1.30 | 19.11 |
| Ave. no. of Movies (weighted by revenue) | 19.69 | 31.83 | 0 | 188.10 |
| Ave. no. of Movies (weighted by no. of votes) | 39,820 | 61,349 | 0.80 | 349,077 |

*Notes*: All variables are measured in the year of the director/producer's death.

## 3.2 Empirical Challenges and Coarsened Exact Matching

Our objective is to identify the local average treatment effects (LATEs) of losing a connection on an actor's job opportunities.[8] There are 3,141 actors (with demographic information) who faced at least one director/producer death shock. We exclude those who have experienced multiple death shocks to prevent potential overestimation of the treatment effect. This leads to removal of 72 actors (around 2.3% of our sample), and leaves us with a sample of 3,069 treated actors. However, a key challenge remains: our data-generating process does not randomly assign actors to treatment and control groups. While the timing of a

[8]Our outcome variable is the number of movies an actor participated per year, and it should be highly correlated with the number of job offers that they receive.

director's or producer's death is exogenous to an actor's intrinsic ability, more productive actors tend to have larger networks and are therefore more likely to experience a connection loss. This selection issue could introduce bias in our estimated treatment effect if not properly addressed, as more productive actors may also possess superior acting skills, which could help mitigate the negative impact of losing a professional connection.

To address this selection issue, we match each treated actor with a control actor from a pool of individuals who did not experience a director/producer death shock during the sample period. We employ the coarsened exact matching (CEM) method (Iacus et al., 2012), detailed in Appendix A, to construct the control group. Control actors are selected to closely resemble treated actors in the year prior to the death shock based on five key characteristics: (1) gender, (2) age, (3) average yearly movie output, (4) total movie output, and (5) number of professional connections.[9] Our matching procedure is successful for 2,495 out of the 3,069 (81.30%) treated actors.

Table 2: **Balancing in Treatment and Control One Year Before Director/Producer Death**

| **Variable Name** | **Treatment Group Mean** | **Control Group Mean** | **Std. Mean Difference** |
|---|---|---|---|
| Female | 0.34 (0.47) | 0.34 (0.47) | 0.00 |
| Age | 41.88 (14.72) | 41.79 (14.71) | 0.01 |
| Cum. no. of Movies | 10.10 (8.69) | 9.88 (7.93) | 0.03 |
| Cum. no. of Movies (weighted by rating) | 58.77 (51.79) | 55.92 (62.67) | 0.00 |
| Cum. no. of Movies (weighted by log revenue) | 3.94 (2.19) | 3.80 (2.31) | 0.06 |
| Cum. no. of Movies (weighted by log no. of votes) | 11.37 (2.93) | 11.24 (3.12) | 0.04 |
| Ave. no. of Movies | 1.01 (1.21) | 0.99 (1.04) | 0.02 |
| Ave. no. of Movies (weighted by rating) | 5.65 (4.21) | 5.42 (4.33) | 0.05 |
| Ave. no. of Movies (weighted by log revenue) | 2.27 (1.40) | 2.20 (1.51) | 0.05 |
| Ave. no. of Movies (weighted by log no. of votes) | 9.43 (1.84) | 9.35 (2.26) | 0.04 |
| No. of Connections | 224.1 (185.5) | 214.5 (167.4) | 0.05 |

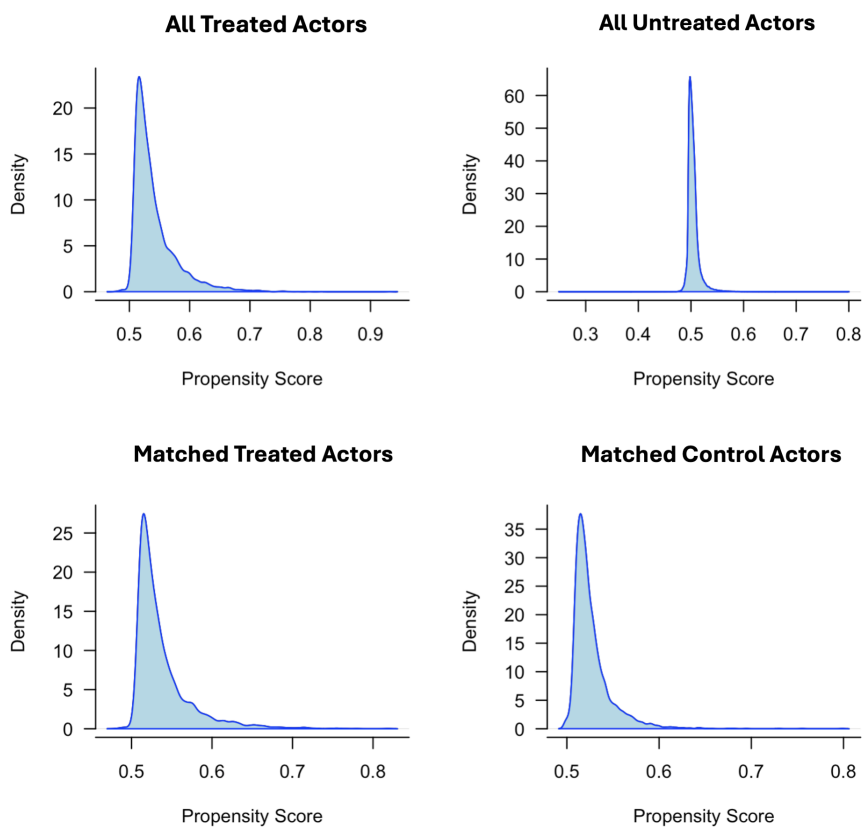
*Notes*: The sample comprises 2,495 actors who experienced a connection loss with a director or producer, along with an equal number of matched controls, spanning 20 years from 1995. Detailed information on sample construction and the matching procedure can be found in Appendix A. All variables are measured one year prior to the connection loss, with sample standard deviations presented in parentheses.

[9]While including more variables in the matching procedure would increase the similarity between the treated individual and their matched control, it will also lead to excluding more observations. Consequently, we have opted to use these five key variables for the matching process.

Table 2 presents a comparison between the treatment and control groups regarding multiple actor characteristics. The mean values and standard deviations are calculated using the matched sample and are measured one year before the director/producer's death. It shows that the balancing requirement is satisfied.[10] To provide additional evidence on balancing, we follow Yan et al. (2022) and compare their propensity scores. We estimate a logistic regression on the whole sample, with a dummy variable of whether experiencing a death shock as the dependent variable, and all matching variables as independent variables. The results are displayed in Figure 1, which shows that the propensity score distributions of the treatment and control groups are very similar after our matching procedure (see the comparison between the upper and lower panels). In other words, our treated and control actors possess similar probabilities of experiencing a connection loss.

[10]These 2,495 treated actors and their matched controls collectively participated in 25,598 movie projects, of which 19,649 (76.76%) lack box office information. Such movies, typically low-budget and less popular, are excluded from the analysis when calculating the box office-weighted number of movies but are included in other analyses.

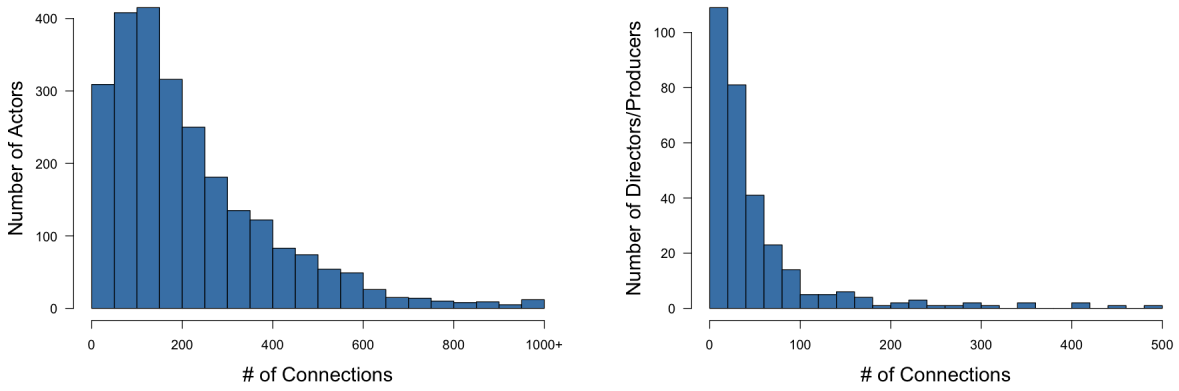
Figure 1: **Propensity Score of Losing a Connection**




*Notes*: This figure shows the distribution of propensity score in matched and raw samples. After matching, the propensity scores exhibit a balanced empirical distribution between the treatment and control groups. In particular, the matching process removes control actors with "extreme" propensity scores. Consequently, within the matched sample, treated actors and control actors possess similar probabilities of experiencing a connection loss, attributable to their similar career status and industry network connectivity.

Figure 2 illustrates the distribution of network connections for actors and deceased directors/producers in the year when the directors/producers passed away. The distributions exhibit significant variability. Panel (a) shows that the majority of actors had fewer than 400 network connections in the year they experienced the death shock, with an average of 218.6 connections and a standard deviation of 178.4. The distribution is right-skewed, with a small number of actors having over 800 connections. Panel (b) depicts the distribution for deceased directors/producers, where most had fewer than 100 network connections at the time of their death. This distribution is also right-skewed, though with a smaller range compared to actor's distribution. The average number of connections is 54.6, with a standard

Figure 2: **Empirical Frequency of Number of Connections**



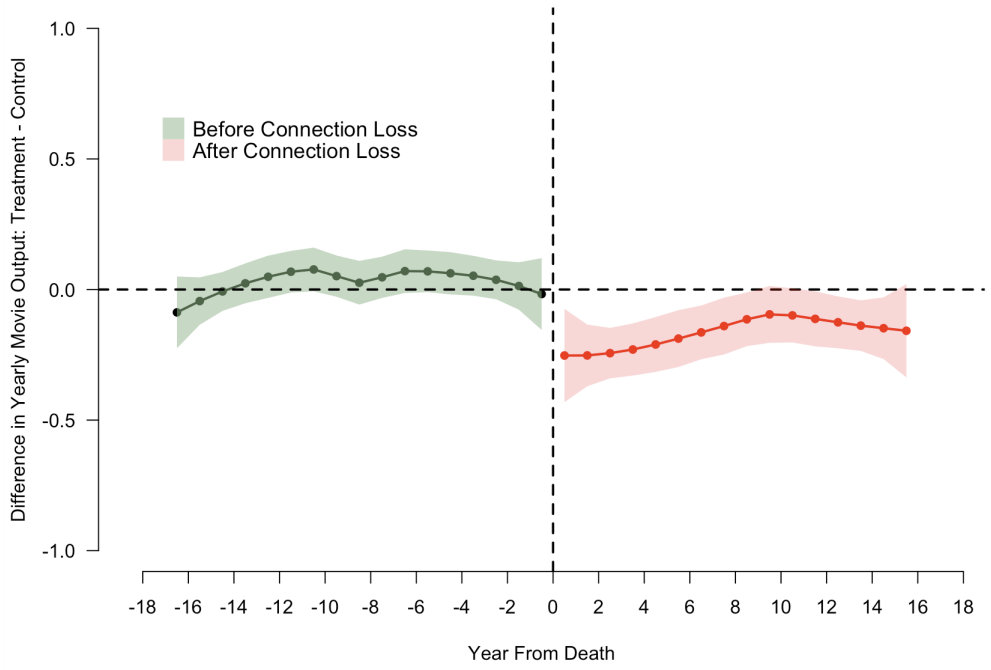

(a) Actor Connections When Receiving Death Shock (b) Director/Producer Connections When They Die

deviation of 72.8.

Figure 3 displays the difference in actor's yearly movie output between the treatment and control groups before and after the treatment. Prior to the death shock, there was no statistically significant difference between the two groups. However, after receiving the death shock, the treatment group's average annual movie output is noticeably lower than the control group's, providing preliminary support for our hypothesis that a connection loss can have a detrimental impact on an individual's career development. While this comparison has limitations because it overlooks factors such as an actor's age, popularity, and time trends, it provides preliminary evidence that after matching, the treatment and control groups are very similar in terms of job opportunities before a connection loss.[11] This evidence helps validate the pre-treatment parallel trend assumption, which is crucial to our DiD design.

[11]We approximate an actor's job opportunities by the number of movies in which they participate. Although actors may decline certain job offers, resulting in a difference between the actual number of movies they perform and the total number of offers received, we believe these two variables are highly correlated. Moreover, actors typically select the best acting opportunities from all their offers. Therefore, a 'quality-adjusted' count of movies, weighted by factors such as ratings, box-office success, or the number of votes, could provide a more accurate representation of an actor's job opportunities. Our regression analyses, which incorporate these quality-adjusted metrics, yield consistent findings.

Figure 3: **Preliminary Visualization of DiD without Controls**




*Notes*: The 90% confidence intervals are presented in color.

# 4 Model

To quantify the effect of a connection loss on an actor's career development, we use the following econometric DiD model specification:

$$Y_{it} = \beta_0 + \beta_1 \cdot \text{Postdeath}_{it} + \beta_2 \cdot \text{Age}_{it}^2 + \alpha_i + \gamma_t + \beta_x \cdot X_{it} + \varepsilon_{it}, \tag{1}$$

where $Y_{it}$ is the dependent variable that measures an actor's yearly movie output; the dummy variable, $\text{Postdeath}_{it}$, changes from 0 to 1 following the death of a director/producer connected with actor $i$; $\text{Age}_{it}$ represents actor $i$'s age in year $t$; $X_{it}$ represents controls for work experiences, including actor's yearly average and cumulative movie output, as well as their quality-adjusted measures by revenue, rating and number of votes. We also include $\text{Age}_{it}^2$ in our specification to control for the possibility that an actor's movie output may slow down as they age. Moreover, we include the actor fixed effect, $\alpha_i$, to control for actor-specific

heterogeneity, and the year-fixed effect, $\gamma_t$, to account for time-specific impacts.[12] Our main parameter of interest is $\beta_1$, which captures the local average treatment effects. Given the large number of control variables included in our regressions, we only report the main parameters of interest in the tables below. For completeness, we present the full set of estimation results in Appendix B.

# 5 Estimation Results

## 5.1 Main Results

Column (1) of Table 3 presents the main results. The dependent variable in the regression is the logarithm of an actor's movie output. The coefficient of interest, $\beta_1$, is statistically significant and negative, indicating that losing a connection due to the death of a director or producer leads to an average decline of 7.78% (calculated as exp(-0.081)-1) in the actor's movie output. This finding serves as the baseline result of how professional connections help shape an actor's career trajectory. We now turn to explore the heterogeneous treatment effects.

[12]Notice that $\alpha_i$ and $\gamma_t$ together capture the effect of $\text{Age}_{it}$. This is why we did not include $\text{Age}_{it}$ in the regression.

Table 3: **Main and Heterogeneous Treatment Effects in Actor Experience & Temporal Dynamics**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | log(#Movie) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\text{Postdeath}_{it}$ | $-0.081^{***}$ | $-0.137^{***}$ | $-0.135^{***}$ | $-0.091^{***}$ | $-0.089^{***}$ | $-0.053^{***}$ |
| | (0.007) | (0.011) | (0.011) | (0.007) | (0.008) | (0.008) |
| $\text{Postdeath}_{it}\times$ Total $\#\text{movie}_{it}$ | | $0.006^{***}$ | | | | |
| | | (0.001) | | | | |
| $\text{Postdeath}_{it}\times$ Total rating weighted $\#\text{movie}_{it}$ | | | $0.001^{***}$ | | | |
| | | | (2 e-4) | | | |
| $\text{Postdeath}_{it}\times$ Total revenue weighted $\#\text{movie}_{it}$ | | | | $0.001^{***}$ | | |
| | | | | (1 e-4) | | |
| $\text{Postdeath}_{it}\times$ Total vote weighted $\#\text{movie}_{it}$ | | | | | 2 e-$4^{***}$ | |
| | | | | | (1 e-4) | |
| $\text{Postdeath}_{it}\times$ $\text{Year from shock}_{it}$ | | | | | | $-0.009^{***}$ |
| | | | | | | (0.002) |
| Average Yearly Movie Output | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Total Movie Output | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\text{Age}_{it}^2$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 99,800 | 99,800 | 99,800 | 99,800 | 99,800 | 99,800 |
| $R^2$ | 0.281 | 0.281 | 0.281 | 0.281 | 0.281 | 0.281 |
| Adjusted $R^2$ | 0.242 | 0.243 | 0.243 | 0.243 | 0.243 | 0.243 |

*Notes*: Column (1) presents our main treatment effect. Columns (2) to (5) examines the role of actor's experience. We approximate an actor's experience using various measures: cumulative number of movies, cumulative rating-weighted number of movies, cumulative revenue-weighted number of movies, and cumulative votes-weighted number of movies. Column (6) investigates the temporal dynamics of the treatment effects. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

## 5.2 Heterogeneous Treatment Effects

We now examine the heterogeneous treatment effects in the following dimensions: (1) the actor's experience, (2) dynamic treatment effects (i.e., time effects), (3) importance of the deceased director/producer, (4) age difference between the actor and the deceased director/producer, and (5) the recency of their last collaboration.

### 5.2.1 Actor's Experience

Typically, a more experienced actor has more refined acting skills and greater visibility. These advantages may enhance their access to more acting roles. Consequently, the loss of a single connection with a director/producer may have a lesser impact on a more experienced actor.

To test this hypothesis, we use multiple measures to gauge an actor's level of experience and interact them with *Postdeath*. The experience measures include the actor's total movie output, and the quality-adjusted total movie output weighted by rating, revenue, and number of votes. The results, presented in Columns (2), (3), (4), and (5) of Table 3, support our hypothesis. The interaction terms are statistically significant and positive in all four regressions, indicating that work experience mitigates the negative effects of losing a connection. For example, as shown in Column (2), each additional movie an actor participates in reduces the effect of connection loss by an average of 4.38% (=0.006/0.137).

To further explore how quality-adjusted measures of experience moderate the treatment effect, we note that during our sample period, the average movie received an IMDb rating of 5.89. This implies that participating in one more movie with an average IMDb rating would lead to a 4.36% (=5.89×0.001/0.135) reduction in the treatment effect size. Similarly, on average, a movie earned 1.28 million USD in box office revenue. Therefore, participating in a movie with an average box office revenue would result in a 1.41% (=1.28×0.001/0.091) reduction in the treatment effect size. Lastly, the average number of votes per movie is around 5.7 thousand. Hence, participating in a movie with an average number of votes would lead to a 1.28% (=5.7×0.0002/0.089) reduction in the treatment effect size. Among these three quality measures, participation in a highly rated movie is most effective in mitigating the negative effects of a connection loss.

### 5.2.2 Treatment Effect Dynamics

Next, we investigate how the treatment effect may change over time. Losing a connection may have lasting and amplified consequences for one's career development. Compared with the treated actors, the control actors may gain more job opportunities immediately after the death shock, which in turn allows them to accumulate more working experiences and gives them even more advantages in subsequent periods. This snowballing effect, which is related to the Matthew Effect in Sociology,[13] can drive the gap between the treated and control actors wider over time.

To test this hypothesis, we created a variable *Years from Shock*, which is the number of years since the treated actor experienced the death shock. We interact this variable with the *Postdeath* treatment dummy. Column (6) of Table 3 presents our regression results. The interaction term is negative and statistically significant, suggesting that the treatment effect amplifies over time. Specifically, for every additional year that passes, a treated actor on average experiences a 0.9% (exp(-0.009)-1) more acting opportunities decline. This finding provides empirical support for the Matthew Effect discussed above.

### 5.2.3 Importance of Deceased Directors/Producers

We next turn to study the moderator role of the deceased directors/producers. On the one hand, the importance of deceased directors/producers may increase the treatment effect, as their referrals may carry greater influence, and their experiences may allow them to offer better mentorship to the actors with whom they are connected. On the other hand, a well-known director/producer may be busier and connected to a larger number of actors, reducing the likelihood of providing referrals to any specific individual. Also, they may have less time to offer mentorship. Hence, a priori, it is unclear how the importance of directors/producers

[13]The Matthew Effect was first formally introduced in sociology by Merton (1968). It refers to the phenomenon where the rich get richer, and the poor get poorer. In other words, those who already have advantages (be it wealth, fame, or prestige) tend to gain more advantages over time, while those who are disadvantaged have a more difficult time improving their situation.

might interact with the treatment effect.

To investigate this empirical question, we first use the total number of movies that they have directed or produced over their careers as a proxy of their importance. Column (1) of Table 4 reports the results. The sign of this interaction term is positive, but it is not statistically significant. We have also used other quality-adjusted movie output variables, and their interactions with the treatment variable remain insignificant. The results are presented in Table C1, Appendix C.

We next use the deceased directors/producers' number of connections in the year prior to their death to approximate their importance. We interact it with the treatment variable, *Postdeath*. Again, we also find this interaction to be insignificant. The results are reported in Column (2) of Table 4.

The findings above suggest that these two opposing forces may just cancel out each other, rendering the director/producer's importance not much of a factor in the treatment effect. One practical implication for actors is that while expanding their professional network with directors/producers would help their job prospects, they do not have to pay too much attention to how "important" the directors/producers are when selecting a movie project.

#### 5.2.4 Years Since Last Collaboration

Another potential source of heterogeneous treatment effect is the recency of collaboration between the actor and the deceased director/producer. Connections from earlier collaborations may be weaker, as the professional bond could have faded over time. Conversely, recent collaborations may indicate a closer or more active working relationship. However, relationships can also strengthen over time as individuals become more familiar with each other. Given these competing possibilities, it is ambiguous how the recency of collaboration might affect the treatment effect.

To investigate this dimension of heterogeneity, we create a *Recency* variable, which measures the number of years since the last collaboration between the actor and the deceased

Table 4: **Director/Producer Importance and Recency of Last Collaboration**

| | *Dependent variable:* | | |
|---|---|---|---|
| | log(#Movie) | | |
| | (1) | (2) | (3) |
| $\text{Postdeath}_{it}$ | $-0.045^{***}$ | $-0.081^{***}$ | $-0.072^{***}$ |
| | (0.009) | (0.007) | (0.012) |
| $\text{Postdeath}_{it} \times$ | 0.001 | | |
| $\text{Dir/Prod total\# movie}_i$ | (0.001) | | |
| $\text{Postdeath}_{it} \times$ | | $-0.057$ | |
| $\text{Dir/Prod \# connections}_i$ | | (0.058) | |
| $\text{Postdeath}_{it} \times$ | | | $-0.001$ |
| $\text{Recency}_i$ | | | (0.001) |
| Average Yearly Movie Output | ✓ | ✓ | ✓ |
| Total Movie Output | ✓ | ✓ | ✓ |
| $\text{Age}_{it}^2$ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ |
| Observations | 99,800 | 99,800 | 99,800 |
| $R^2$ | 0.261 | 0.281 | 0.281 |
| Adjusted $R^2$ | 0.222 | 0.242 | 0.242 |

*Notes*: In columns (1) and (2), we analyze how a director or producer's experience and importance moderate the treatment effect. Experience is approximated by the cumulative number of movies they have produced or directed over their career, while importance is measured by their total network connections. In column (3), we assess whether the recency of the last collaboration impacts the treatment effect. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

director/producer. As shown in Column (3) of Table 4, the interaction between *Recency* and *Postdeath* is not statistically significant, suggesting that the recency of the professional relationship does not significantly affect the treatment effect. This result indicates that the value of such professional connections persists over time, and that the strength of the network effect is relatively stable once a connection is established.

## 5.3 Robustness Checks

In this section, we present a series of analyses to check the robustness of our main findings.

### 5.3.1 Placebo Test

We follow Datta et al. (2018) and carry out a "placebo" test using pre-death shock data. More specifically, we assume the placebo treatment date for each treated actor is the mid-point of the pre-treatment period. If the treatment and control groups do not show significantly different trends in the pre-death shock period, we should find no significant placebo treatment effects. The corresponding regression results appear in Column (1) of Table 5. As expected, we found that the "placebo" treatment has no effect on an actor's future movie output.

### 5.3.2 Propensity Score Matching

In the next robustness check, instead of using the CEM method, we match each treated actor with a similar control actor based on their propensity score of facing a death shock related to a director/producer. The construction of propensity score is described in section 3.2. Column (2) of Table 5 presents the results. The propensity score matching approach also yields a statistically significant and negative treatment effect ($\beta_1 = -0.059$, $p<0.01$), providing additional support for the robustness of our main findings.

### 5.3.3 Retired Actors

Our estimated treatment effect may be biased if some treated actors were close to retirement when affected by the director/producer's death shock. In such cases, we may mis-attribute the retirement effect to the loss of a connection due to the death shock. To address this concern, we re-estimate our model by excluding actors who have retired.

We classify actors as retired if they did not participate in any movies after the death shock or in the three years preceding it. In total, we have removed 361 treated actors (and their corresponding matched control counterparts) – this amounts to 14.47% of treated actors.

Column (3) of Table 5 reports the results. On average, actors who did not retire after the connection loss experienced a 7.96% (=exp(-0.083)-1) decline in their movie output. The size of the effect is very similar to the main effect reported in Column (1) of Table 3. This suggests that our baseline treatment effect estimate is not due to actors' retirement.

### 5.3.4 Retired or Unproductive Directors and Producers

Another related concern is that some directors/producers may have already retired for a while before their death, and they could play a much weaker role in referring or advising the actors connected with them. In such cases, the death of these retired directors/ producers may not have a substantial impact on the connected actors, and including them may lead to downward bias in the treatment effect.

To see if this is the case, we removed 13 directors and producers who did not participate in any movie projects during the last three years of their lives and re-ran the analysis. Column (4) of Table 5 presents the results. The treatment effect becomes 8.33% (=exp(-0.087)-1). Although it is slightly larger than the treatment effect in our main regression (7.78%), they remain very close and the difference is not statistically significant ($p = 0.599$). Hence, our findings remain robust under this check. It also indicates that our results in the main analysis can be viewed as a lower bound of the treatment effect.

In Column (5) of Table 5, we replicate our results by excluding both retired actors and

retired directors/producers. Our analysis still reveals a statistically significant and negative treatment effect, and the magnitude of the effect remains quite stable.

#### 5.3.5 Missing Month of Death Data

It is important to note that, while IMDb reports the year of death for each director or producer, it does not provide the month of their death. Consequently, regardless a director/producer died at the beginning or end of the year, we treat the impact of the death shock in the same manner. We believe this is a reasonable assumption, as the distribution of the month of death should be uniformly distributed throughout the year. However, it is possible that death shocks realized in the data might happen to be skewed. For instance, if more deaths occurred earlier in the year, we may see a more pronounced impact on treated actors, and vice versa. To assess whether this issue affects our findings, we use one year before and one year after the actual death shock year as the treatment time and re-run our analysis. The regression results, summarized in Columns (6) and (7) of Table 5, show that our main findings remain unchanged.

#### 5.3.6 Sudden Death vs. Senile Death

One may question how our results may be affected by senile deaths of directors/producers. The loss of a connection due to senile death may have a weaker effect, as directors or producers typically become less active in their later years. Hence, excluding senile deaths might lead to a stronger estimated effect, and our baseline estimate can be interpreted as a conservative lower bound. To empirically assess this hypothesis, we examine the cause of each director/producer's death. A death is classified as sudden if: (i) the cause is clearly abrupt (e.g., car accident, plane crash, etc.), or (ii) the deceased director/producer has more than one movie released posthumously, as a movie is usually released within a few years after it is completed.[14] Using these criteria, we identified 102 sudden deaths out of 325 cases.

[14]If death is due to a natural cause or illness, it is more likely that the director or producer would stop working a few years before they died.

We then re-estimate our main regression by restricting the sample to treatment events due to sudden deaths. The results are shown in Column (8) of Table 5. When compared to the main results in Table 3, the treatment effect remains significant, with a slightly larger effect size, though the difference is not statistically significant (p=0.878). Therefore, our findings remain robust under this check.

#### 5.3.7 Potential Bias Due to Staggered Treatment Adoption

It is important to note that in this context, the treatment is not applied simultaneously across all actors. Due to the staggered nature of the treatment, units that have not yet received the treatment, or will never receive it, serve as controls for those currently under treatment. As highlighted by Baker et al. (2022), applying the standard DiD estimator in such scenarios can lead to biased estimates of the average treatment effect when treatment effect heterogeneity exists.

To address this potential bias, we apply the staggered DiD estimator proposed by Callaway and Sant'Anna (2021). The results, presented in Appendix D, remain consistent with our main findings, reinforcing the robustness of our conclusions.

#### 5.3.8 Effect on Major Role Opportunities

In our main analysis, we did not differentiate between major and minor roles.[15] One may wonder how the treatment affects an actor's opportunities in playing major roles, as major roles are more critical for an actor's career development. To explore this, we first need to find a way to identify actors in major roles in each movie. Although IMDb does not explicitly define major roles, the platform prominently features several actors on each movie's profile page. We consider these featured actors as the main actors for the respective movies.

To focus on actors with major role experience, we excluded individuals who had never played a major role in our sample period. This adjustment removed 257 actors (10.3% of the

[15]By major roles, we include both lead roles and main supporting roles.

Table 5: **Robustness Checks**

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | log(#Movie) | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\text{Postdeath}_{it}$ | 0.009 | $-0.059^{***}$ | $-0.083^{***}$ | $-0.087^{***}$ | $-0.087^{***}$ | $-0.085^{***}$ | $-0.087^{***}$ | $-0.083^{***}$ | $-0.026^{***}$ |
| | (0.007) | (0.007) | (0.008) | (0.009) | (0.010) | (0.008) | (0.009) | (0.011) | (0.005) |
| Average Yearly Movie Output | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Total Movie Output | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\text{Age}_{it}^2$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Excluding Retired Actors | | | ✓ | | | | | | |
| Excluding Retired Dir/Prod | | | | ✓ | | | | | |
| Excluding Retired Actors/Dir/Prod | | | | | ✓ | | | | |
| Death Shock Minus 1 Year | | | | | | ✓ | | | |
| Death Shock Plus 1 Year | | | | | | | ✓ | | |
| Excluding Senile Deaths | | | | | | | | ✓ | |
| Actors with Leading Roles | | | | | | | | | ✓ |
| Observations | 73,974 | 99,800 | 85,360 | 66,960 | 59,440 | 79,280 | 71,380 | 38,600 | 89,520 |
| $R^2$ | 0.297 | 0.319 | 0.281 | 0.289 | 0.288 | 0.277 | 0.276 | 0.285 | 0.238 |
| Adjusted $R^2$ | 0.245 | 0.283 | 0.243 | 0.251 | 0.251 | 0.238 | 0.238 | 0.247 | 0.197 |

*Notes*: We check the robustness of our main results by (1) testing the pre-treatment parallel assumption by running a placebo test; (2) matching actors according to their propensity score of losing a connection; (3) focusing on actors who did not retire; (4) focusing on directors/producers who did not retire; (5) excluding actors and directors/producers who have retired; (6) use one year before the actual death shock year as the treatment time; (7) use one year after the actual death shock year as the treatment time; (8) excluding senile deaths; (9) using the number of movies in which an actor plays a major role as the dependent variable. The definition of other control variables can be found in the table notes of Table B1. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

sample), along with their matched controls, from the analysis. Using the number of movies in which an actor plays a major role as the dependent variable, we re-estimate the regression. Column (9) of Table 5 reports the result, and it shows that actors who have a connection loss experience a statistically significant 2.57% (=exp(-0.026)-1) decline in future major role opportunities. Compared with the main results that indicate a 7.78% decline, the treatment effect observed here is smaller. This suggests that connections to producers or directors have a greater impact on securing minor roles than on major roles.

### 5.3.9 Sampling Error

While we have employed both CEM and Propensity Score matching to pair each treated actor with a comparable control actor, it is important to consider the potential sampling

error issue: that is, whether our results are driven by the specific control group generated from the matching process.[16] To address this issue, we perform 1,000 iterations of the matching process, using a different realization from the same random number generator for each run. We then conduct the regression analysis for each iteration.

The treatment effect consistently emerged as statistically significant and negative across all 1,000 runs. The average treatment effect estimated from these iterations is -0.082, with a standard deviation (SD) of 0.001. Furthermore, the average value of the treatment effect's standard errors across the 1,000 runs is 0.006, with an SD of 0.00001. This provides evidence that our findings are not driven by random sampling errors.

## 5.4 Mechanisms

The network connections effect identified above can be due to multiple mechanisms. Here, we consider three of them: (i) repeated collaboration, (ii) emotional grief, and (iii) referral/mentorship. We next conduct empirical tests for each of them.

### 5.4.1 Repeated Collaboration

Film-making is a complicated teamwork process that involves significant organizational coordination among the producers, directors, and actors. As in other sectors of the teamwork economy, team chemistry is critical to a successful movie production team. Some actors may have conflicts with the film crew and other actors and negatively affect the final movie quality. Hence, it is plausible that directors/producers may try to cast the same actors who worked well with them before to reduce the likelihood of internal conflicts during filming.[17] When a director or producer passes away, actors who were connected to them lose these "repeated collaboration" opportunities, which in turn hinders their career progression.

[16] Recall that if we find more than one match for the treated unit, we randomly choose one as its control unit.

[17] Narayan and Kadiyali (2016) find evidence that movies with repeated collaborated directors/producers and actors tend to have stronger box office performance.

Although there are some examples of repeated collaborations between famous directors and actors (e.g., Martin Scorsese with Leonardo Dicaprio, Quentin Tarantino with Uma Thurman, Steven Spielberg with Tom Hanks, etc.), such repeated collaboration is actually quite uncommon in general. Among the 2,495 treated actors, only 68 of them have repeated collaborations with the deceased director/producer (about 3%). To eliminate the effect due to repeated collaboration, we re-estimate the models using treated actors who have only worked with the deceased directors/producers once during her acting career. Column (1) of Table 6 shows the regression results. We still find statistically significant treatment effect in this analysis. Our estimate implies that those actors experience a 7.60% (=exp(-0.079)-1) decline in future acting opportunities after a connection loss. This finding is very close to our main result of a 7.78% decline, as reported in Column (1) of Table 3. These results suggest that repeated collaboration is not the primary driver of the observed treatment effect.

For completeness, we also apply our DiD regression design to actors who have repeated collaboration with the deceased directors/producers. The results are reported in Column (2) of Table 6. It shows that a connection loss would lead to a drop of 13.93% (=exp(-0.150)-1) in their future movie output. This treatment effect is greater than the 7.60% estimated from the group who did not repeatedly collaborate with the deceased directors/producers. However, it is important to note that the treatment effects estimated from the two regression analyses are not statistically different from each other ($p = 0.184$). Taking the results together, although we see some evidence that repeated collaboration may lead to higher chance of being hired again, with only 3% of the cases involved repeated collaboration, it plays a very small role in our main findings.

### 5.4.2 Emotional Grief

Another possible driving force for our findings is that the passing of a director/producer may cause significant emotional grief to actors who are closely connected with them, which in turn may affect their productivity. More specifically, this traumatic event can cause grief and

acute stress reactions, which may detrimentally lead to diminished concentration, impaired decision-making, and a marked decline in motivation, which, in turn, may compromise the actor's ability to secure future roles and advance in their career.

To explore the possibility that emotional grief is behind our findings, we conducted the following empirical test. We hypothesize that the death of a director/producer at a younger age can lead to more emotional grief. In general, individuals who died young are considered to be pity or regretful, and this could lead to a stronger emotional shock to their friends or former colleagues who worked with them before. To test this hypothesis, we consider two groups of deceased directors/producers: (i) those who died before the age of 50, and (ii) those who died after the age of 70. If emotional grief is important, we expect that the actors associated with group (i) will have a larger treatment effect. Conversely, if the data do not support this hypothesis, we should find no statistical difference between the treatment effects of these two groups. Columns (3) and (4) of Table 6 present the regression results, and their treatment effects are not statistically different from each other ($p = 0.611$). Hence, this test does not provide support for the emotional grief hypothesis.

### 5.4.3 Referral/Mentorship

Referrals from directors/producers can be pivotal in an actor's career. Their recommendations can increase an actor's chances to do auditions. Additionally, directors/producers often serve as mentors, offering invaluable guidance and advice that help actors navigate the complexities and uncertainties of the entertainment industry. This mentorship can play a crucial role in shaping and advancing an actor's career.

To provide evidence for the referral and mentorship mechanism, we first examine the implications of diminishing returns from network connections. The rationale is that as an actor's network expands, they gain access to more referrals for potential projects. However, as their schedule fills up, the marginal benefit of additional referrals declines. If an actor is already committed to multiple projects, they may be forced to turn down new opportu-

nities due to scheduling conflicts. Similarly, the benefits of mentorship can also experience diminishing returns. While having a mentor is undoubtedly valuable, the advantages do not necessarily increase with the number of mentors. In fact, advice from multiple mentors can sometimes result in conflicting recommendations, complicating decision-making rather than simplifying it.

To empirically investigate whether there is diminishing return from network connections in our context, we introduce a variable that captures the percentage change in an actor's network connections resulting from the death shock.[18] A larger percentage loss indicates that the actor had fewer network connections overall. If diminishing return from network connections is present, we would expect its interaction with treatment effect to be negative. The results, presented in Column (5) of Table 6, support this hypothesis, as the interaction term is indeed negative and statistically significant. In Appendix E, we provide more analyses and discussion on the diminishing returns in network connections.

Note that the empirical test above does not attempt to disentangle referral and mentorship, as both mechanisms imply diminishing return of connections. Our next empirical test is designed to test the mentorship mechanism. Intuitively, a significant age difference between a director or producer and an actor may cultivate a more respectful mentor-mentee dynamic, increasing the likelihood that actors will value and follow their guidance. Additionally, older directors and producers tend to have greater experience and offer more insightful career advice.

In our analysis, we define a variable AgeDiff as the director/producer's age minus the actor's age. On average, the deceased director/producer is 20.25 years older than their connected actor, with a standard deviation of 19.73 years. Among the treated actors, 85% are younger than the deceased director/producer. We then interact this variable with the treatment variable and the regression results are shown in Column (6) of Table 6. The

[18]We define the percentage change in an actor's network connections as one (representing the loss of one connection due to the death shock) divided by the total number of connections the actor had one year before experiencing the death shock. Note that the percentage change in an actor's network connections due to a death shock is taken in absolute value when we use it in the regression analysis.

coefficient for this interaction term is negative and statistically significant, supporting our hypothesis that a larger age difference between director/producer and actor intensifies the treatment effect. This finding provides support for our hypothesis that mentorship should play a significant role in driving our findings.

In summary, our mechanistic analyses reveal that repeated collaboration does not have a significant impact on our main findings. Similarly, we find no evidence supporting the emotional grief mechanism. Instead, our empirical tests provide support for referral and mentorship as the primary mechanisms driving our results.

Table 6: **Mechanism Analysis**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | log(#Movie) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\text{Postdeath}_{it}$ | $-0.079^{***}$ | $-0.150^{***}$ | $-0.071^{***}$ | $-0.080^{***}$ | $-0.071^{***}$ | $-0.043^{***}$ |
| | (0.007) | (0.053) | (0.012) | (0.013) | (0.010) | (0.010) |
| $\text{Postdeath}_{it} \times \text{Actor \% connection change}_i$ | | | | | $-0.008^{***}$ | |
| | | | | | (0.002) | |
| $\text{Postdeath}_{it} \times \text{AgeDiff}_i$ | | | | | | $-0.002^{***}$ |
| | | | | | | (3 e-4) |
| Average Yearly Movie Output | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Total Movie Output | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\text{Age}_{it}^2$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Without Repeated Collaborations | ✓ | | | | | |
| With Repeated Collaborations | | ✓ | | | | |
| Dir/Prod Death Age<50 | | | ✓ | | | |
| Dir/Prod Death Age>70 | | | | ✓ | | |
| Observations | 97,080 | 2,720 | 34,640 | 31,880 | 99,800 | 92,080 |
| $R^2$ | 0.279 | 0.315 | 0.275 | 0.296 | 0.281 | 0.283 |
| Adjusted $R^2$ | 0.241 | 0.272 | 0.237 | 0.258 | 0.242 | 0.245 |

*Notes*: Column (1) reports results where actors have only worked with the deceased director/producer once. Column (2) reports results where actors who have worked with the deceased director/producer more than once. Columns (3) and (4) report the regression results when we only use deceased directors/producers who died before 50 and after 70, respectively. Column (5) reports the moderating effect of the actor's network connection change. Actor % connection $\text{change}_i$ represents the percentage change of actor $i$'s network connections after the death shock. Column (6) explores the impact of age difference between the actor and the deceased director/producer on the treatment effect, with 23 (7.08%) directors/producers excluded due to missing age information. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

## 5.5 More on Quantifying the Impact of Connections

Our results indicate that losing a professional connection leads to a 7.78% decline in an actor's subsequent movie output. However, this estimate does not account for the quality of the roles offered, which is a crucial indicator of career progression.[19]

To address this issue, we use quality-adjusted movie output as the dependent variables in the following analyses. We consider weighting each movie based on its box-office revenue, average IMDb rating, and number of ratings. We should note that each of these quality-adjusted measure captures different aspects of quality.

While box-office revenue reflects a movie's popularity to some extent, it does not always align with audience ratings. Some movies with high box-office performance receive low ratings, while others with high ratings perform poorly at the box office.[20] Moreover, box-office revenue is restricted to earnings from theatrical releases, which limits its scope. In contrast, the number of votes on IMDb offers a broader measure of a movie's popularity, as it includes audiences who watched the movie through other channels, such as DVDs, TV networks, or streaming platforms, and still chose to leave reviews.

The regression results are reported in Columns (1) to (3) of Table 7. On average, the death of a director/producer leads to a 16.56% (=exp(-0.181)-1) decline in the revenue-adjusted number of movies (Column 1), a 16.97% (=exp(-0.186)-1) decline in the IMDb rating-adjusted number of movies (Column 2), and a 52.86% (=exp(-0.752)-1) decline in the votes-adjusted number of movies (Column 3). These results show that losing a professional network connection could lead to a much more striking adverse impact on an actor's career, if we take into account the quality of jobs that they received.

[19] Another direct measure would be an actor's salary, but unfortunately, such data is usually not publicly available.

[20] Another issue of box-office revenue weighted measure is that many movies have missing box-office revenue. This is because some distributors do not report the box-office revenue data to IMDb. A casual examination of the movies with such missing data suggest that they tend to be less popular movies.

Table 7: **Treatment Effect with Quality-adjusted Dependent Variable**

| | *Dependent variable:* | | |
|---|---|---|---|
| | log(#Rev-Movie) | log(#Rating-Movie) | log(#Vote-Movie) |
| | (1) | (2) | (3) |
| $\text{Postdeath}_{it}$ | $-0.181^{***}$ | $-0.186^{***}$ | $-0.752^{***}$ |
| | (0.022) | (0.016) | (0.065) |
| Average Yearly Movie Output | ✓ | ✓ | ✓ |
| Total Movie Output | ✓ | ✓ | ✓ |
| $\text{Age}_{it}^2$ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ |
| Observations | 99,800 | 99,800 | 99,800 |
| $R^2$ | 0.217 | 0.267 | 0.264 |
| Adjusted $R^2$ | 0.176 | 0.228 | 0.225 |

*Notes*: The dependent variable is the log of an actor's revenue weighted yearly movie output in Column (1), the log of an actor's rating weighted yearly movie output in Column (2), and the log of an actor's votes weighted yearly movie output in Column (3). Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

# 6 Implications for Practice and Conclusion

Many people take it as given that having a larger professional network can lead to a better job prospect. However, causal evidence for this link is scant. By examining the movie industry, where actors need to constantly seek new job opportunities, and leveraging the exogeneity of director/producer's death shock to actors' network, we provide causal evidence that losing a network connection can negatively impact an actor's future job opportunities. This suggests that professional network connections established via works may play an important role in self-marketing. Furthermore, our analysis supports that referral and mentorship may be the mechanisms underlying these effects.

Our dynamic effect analysis indicates that the treatment effect amplifies over time. This underscores the importance of actors adopting a forward-looking perspective when building professional network through their work, as the benefits may compound over time. Ignoring this snowballing effect could lead to missed opportunities for long-term career growth.

One common belief is that connecting with someone important and influential should

be particularly helpful. Interestingly, we do not find evidence that the importance of directors/producers moderates the treatment effect. This suggests that when trying to expand one's network, working with either higher profile or lesser known directors/producers would likely lead to similar improvement in future job opportunities. This is useful for actors to know because it is typically much harder to land a role from well-known directors/producers.

Moreover, our results shed light on how the importance of network connections may change over the course of an actor's career. Our heterogeneous treatment effect analysis (see Columns 2 to 5 of Table 3) and the mechanistic analysis (see Column 6 of Table 6) reveal the following: as actors accumulate more experiences and connections, they are able to better withstand the impact of losing a connection; in other words, the marginal gain of a connection become smaller. One implication is that early on in one's career, an actor may want to prioritize projects that allow them to collaborate with new directors, producers, or actors to expand their network. But as they have built up more connections, they could put less weight on this factor.

We also find evidence that a larger age gap between actors and directors/producers may foster a stronger professional connection, likely due to a more respectful mentor-mentee dynamic. All else being equal, actors may benefit from choosing projects that involve more senior directors or producers.

To our knowledge, this is the first study to provide causal evidence that network connections can significantly influence career prospects in a sector where regular job searching and self-marketing are essential. Our analysis focuses on the actors' market. Whether these findings could extend to other labor markets that also require frequent job searches (e.g., contractors, lawyers, consultants, real estate agents, etc) remains an open question, which we leave for future research.

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# Appendix

## A Coarsened Exact Matching

To match each treated actor who lost a connection with a control player who does not, we implement the coarsened exact matching (CEM) method. The coarsened exact matching method is a non-parametric approach proposed by Iacus et al. (2012). The first step of CEM is to select a relatively small set of variables which can help us define similarities between actors and simultaneously guarantee balance. In our case, the variables we use include an actor's age, gender, average yearly output, total number of movies, and total number of network connections at the year of connection loss. We choose these variables to make sure the matched pairs are at a similar age, have the same gender, have similar movie output, and have similar network status.

The second step is to coarsen each variable by re-coding so that substantively indistinguishable values are grouped and assigned the same numerical value and the created strata can cover the entire support of the joint distribution of the variables selected in the first step. For instance, the distribution of age is coarsened using five year intervals; the average yearly number of movies is coarsened into ten strata (0 to $5th$; $5th$ to $10th$; $10th$ to $25th$; $25th$ to $35th$; $35th$ to $50th$; $50th$ to $65th$; $65th$ to $75th$; $75th$ to $90th$; $90th$ to $95th$; and above the $95th$ percentile); number of network connections is coarsened into four strata (0 to $25th$; $25th$ to $50th$; $50th$ to $75th$; and above the $75th$ percentile), respectively. We create 9,600 strata in total.

The third step is to put each observation into one of the pre-defined strata. For each observation in the treatment group, we select one observation from the control group, which belongs to the same stratum. If there are multiple control observations from the same stratum, we select one randomly.[21] Our matching procedure is able to identify a control

[21] For a similar application, see Azoulay et al. (2010).

actor for 2,495 out of the 3,069 (81.30%) of the treated actors.

The CEM method offers several advantages in the context of matching control groups:

1. Balance: CEM aims to achieve balance between the treatment and control groups by matching individuals who have similar observed characteristics. This helps ensure that any differences in outcomes between the treatment and control groups can be attributed to the treatment itself, rather than pre-existing differences in observable characteristics.

2. Dimensionality reduction: CEM reduces the dimensionality of the covariates by creating coarser categories or intervals. This simplification is particularly useful when dealing with high-dimensional covariate spaces, where traditional matching methods may struggle due to the curse of dimensionality. By reducing the number of covariate values to be matched, CEM makes the matching process more feasible and computationally efficient.

3. Preserves exactness: Unlike other matching methods that rely on propensity scores or distance metrics, CEM aims to preserve exact matches on the covariates of interest. This ensures that observations with identical or highly similar covariate profiles are matched together, leading to more precise and reliable estimates of treatment effects.

4. Robustness to model specification: CEM is less sensitive to model specification compared to other matching methods. By focusing on coarsened versions of the covariates, CEM allows for flexibility in the functional form of the matching model. This means that CEM can yield reliable results even if the true relationship between the covariates and the outcome is not precisely known or difficult to specify.

   Overall, coarsened exact matching offers a robust and flexible approach to constructing control groups, helping to improve the validity and reliability of causal inference in observational studies.

# B Regression Results with Complete Coefficients

Table B1: **Main and Heterogeneous Effects: Actor Experience and Temporal Dynamics with Complete Coefficients**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | log(#Movie) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\text{Postdeath}_{it}$ | $-0.081^{***}$ | $-0.137^{***}$ | $-0.135^{***}$ | $-0.091^{***}$ | $-0.089^{***}$ | $-0.053^{***}$ |
| | (0.007) | (0.011) | (0.011) | (0.007) | (0.008) | (0.008) |
| $\text{Postdeath}_{it}\times$ | | $0.006^{***}$ | | | | |
| Total $\#\text{movie}_{it}$ | | (0.001) | | | | |
| $\text{Postdeath}_{it}\times$ | | | $0.001^{***}$ | | | |
| Total rating weighted $\#\text{movie}_{it}$ | | | (2 e-4) | | | |
| $\text{Postdeath}_{it}\times$ | | | | $0.001^{***}$ | | |
| Total revenue weighted $\#\text{movie}_{it}$ | | | | (1 e-4) | | |
| $\text{Postdeath}_{it}\times$ | | | | | 2 e-$4^{***}$ | |
| Total vote weighted $\#\text{movie}_{it}$ | | | | | (1 e-4) | |
| $\text{Postdeath}_{it}\times$ | | | | | | $-0.009^{***}$ |
| Year from $\text{shock}_{it}$ | | | | | | (0.002) |
| Average $\#\text{movie}_{it}$ | $0.166^{***}$ | $0.170^{***}$ | $0.170^{***}$ | $0.166^{***}$ | $0.166^{***}$ | $0.165^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.008) | (0.008) | (0.008) |
| Average rating weighted $\#\text{movie}_{it}$ | $-0.004^{**}$ | $-0.004^{**}$ | $-0.004^{**}$ | $-0.004^{**}$ | $-0.004^{**}$ | $-0.004^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Average revenue weighted $\#\text{movie}_{it}$ | 3 e-4 | 3 e-4 | 3 e-4 | 3 e-4 | 3 e-4 | 3 e-4 |
| | (2 e-4) | (2 e-4) | (2 e-4) | (2 e-4) | (2 e-4) | (2 e-4) |
| Average votes weighted $\#\text{movie}_{it}$ | 2 e-$7^{*}$ | $0.0002^{**}$ | $0.0002^{**}$ | $0.0002^{**}$ | $0.0002^{**}$ | $0.0002^{**}$ |
| | (1 e-7) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Total $\#\text{movie}_{it}$ | $-0.026^{***}$ | $-0.027^{***}$ | $-0.026^{***}$ | $-0.026^{***}$ | $-0.026^{***}$ | $-0.026^{***}$ |
| | (0.005) | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) |
| Total rating weighted $\#\text{movie}_{it}$ | $0.002^{***}$ | $0.002^{**}$ | $0.002^{**}$ | $0.002^{**}$ | $0.002^{**}$ | $0.002^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Total revenue weighted $\#\text{movie}_{it}$ | -1 e-$4^{**}$ | -1 e-$4^{**}$ | -1 e-$4^{**}$ | -1 e-$4^{**}$ | -1 e-$4^{**}$ | -1 e-$4^{**}$ |
| | (5 e-5) | (5 e-5) | (5 e-5) | (5 e-5) | (5 e-5) | (5 e-5) |
| Total votes weighted $\#\text{movie}_{it}$ | 1 e-$7^{***}$ | 1 e-$4^{***}$ | 1 e-$4^{***}$ | 1 e-$4^{***}$ | 1 e-$4^{***}$ | 1 e-$4^{***}$ |
| | (2 e-8) | (2 e-5) | (2 e-5) | (2 e-5) | (2 e-5) | (2 e-5) |
| $\text{Age}_{it}^2$ | -3 e-$4^{***}$ | -3 e-$4^{***}$ | -3 e-$4^{***}$ | -3 e-$4^{***}$ | -3 e-$4^{***}$ | -3 e-$4^{***}$ |
| | (1 e-5) | (1 e-5) | (1 e-5) | (1 e-5) | (1 e-5) | (1 e-5) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 99,800 | 99,800 | 99,800 | 99,800 | 99,800 | 99,800 |
| $R^2$ | 0.281 | 0.281 | 0.281 | 0.281 | 0.281 | 0.281 |
| Adjusted $R^2$ | 0.242 | 0.243 | 0.243 | 0.243 | 0.243 | 0.243 |

*Notes*: Column (1) presents our main treatment effect. In Columns (2) to (5), we examine the moderating effect of an actor's experience. We approximate an actor's experience using various measures: cumulative number of movies, cumulative rating-weighted number of movies, cumulative revenue-weighted number of movies, and cumulative votes-weighted number of movies. Column (6) investigates the moderating effect of time.
$\text{Postdeath}_{it}$ is an indicator which switches to 1 if actor $i$ experiences a connection loss in year $t-1$. Average $\#\text{movie}_{it}$ represents actor $i$'s average yearly movie output before year $t$, Average rating weighted $\#\text{movie}_{it}$ represents actor $i$'s average yearly rating weighted movie output before year $t$, Total $\#\text{movie}_{it}$ represents actor $i$'s cumulative movie output before year $t$, Total rating weighted $\#\text{movie}_{it}$ represents actor $i$'s cumulative rating weighted movie output before year $t$. $\text{Age}_{it}$ is actor $i$'s age in year $t$. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

Table B2: **Producer Importance, Age Difference, and Recency of Last Collaboration with Complete Coefficients**

| | *Dependent variable:* | | |
|---|---|---|---|
| | log(#Movie) | | |
| | (1) | (2) | (3) |
| $\text{Postdeath}_{it}$ | $-0.045^{***}$ | $-0.081^{***}$ | $-0.072^{***}$ |
| | (0.009) | (0.007) | (0.012) |
| $\text{Postdeath}_{it} \times$ | 0.001 | | |
| $\text{Dir/Prod total\# movie}_i$ | (0.001) | | |
| $\text{Postdeath}_{it} \times$ | | $-0.057$ | |
| $\text{Dir/Prod \# connections}_i$ | | (0.058) | |
| $\text{Postdeath}_{it} \times$ | | | $-0.001$ |
| $\text{Recency}_i$ | | | (0.001) |
| $\text{Average\# movie}_{it}$ | $0.138^{***}$ | $0.166^{***}$ | $0.166^{***}$ |
| | (0.007) | (0.008) | (0.008) |
| $\text{Average\# rating weighted movie}_{it}$ | $0.017^{***}$ | $-0.004^{**}$ | $-0.004^{***}$ |
| | (0.001) | (0.002) | (0.002) |
| $\text{Average revenue weighted \#movie}_{it}$ | 3 e-4 | 3 e-4 | 3 e-4 |
| | (2 e-4) | (2 e-4) | (2 e-4) |
| $\text{Average\# votes weighted movie}_{it}$ | 1 e-4 | 2 e-4$^{*}$ | 2 e-4$^{*}$ |
| | (1 e-4) | (1 e-4) | (1 e-4) |
| $\text{Total\# movie}_{it}$ | $-0.013^{**}$ | $-0.026^{***}$ | $-0.026^{***}$ |
| | (0.005) | (0.005) | (0.005) |
| $\text{Total\# rating weighted movie}_{it}$ | 0.001 | $0.002^{***}$ | $0.002^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| $\text{Total\# revenue weighted movie}_{it}$ | -1 e-4$^{*}$ | -1 e-4$^{**}$ | -1 e-4$^{**}$ |
| | (5 e-5) | (5 e-5) | (5 e-5) |
| $\text{Total\# votes weighted movie}_{it}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ |
| | (2 e-5) | (2 e-5) | (2 e-5) |
| $\text{Age}^2_{it}$ | 1 e-5$^{*}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ |
| | (1 e-5) | (1 e-5) | (1 e-5) |
| Year FE | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ |
| Observations | 99,800 | 99,800 | 99,800 |
| $R^2$ | 0.261 | 0.281 | 0.281 |
| Adjusted $R^2$ | 0.222 | 0.242 | 0.242 |

*Notes*: In columns (1) and (2), we analyze how a director or producer's experience and importance moderate the treatment effect. Experience is approximated by the cumulative number of movies they have produced or directed over their career, while importance is measured by their total network connections. In column (3), we assess whether the recency of the last collaboration impacts the treatment effect. The definition of other control variables can be found in the table notes of Table B1. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

Table B3: **Robustness Checks with Complete Coefficients**

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | log(#Movie) | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\text{Postdeath}_{it}$ | 0.009 | $-0.059^{***}$ | $-0.083^{***}$ | $-0.087^{***}$ | $-0.087^{***}$ | $-0.085^{***}$ | $-0.087^{***}$ | $-0.083^{***}$ | $-0.026^{***}$ |
| | (0.007) | (0.007) | (0.008) | (0.009) | (0.010) | (0.008) | (0.009) | (0.011) | (0.005) |
| Average $\#\text{movie}_{it}$ | $0.150^{***}$ | $0.150^{***}$ | $0.157^{***}$ | $0.165^{***}$ | $0.156^{***}$ | $0.161^{***}$ | $0.115^{***}$ | $0.167^{***}$ | $0.052^{***}$ |
| | (0.010) | (0.009) | (0.009) | (0.010) | (0.011) | (0.010) | (0.023) | (0.012) | (0.006) |
| Average rating weighted $\#\text{movie}_{it}$ | $-0.004^{**}$ | $-0.007^{***}$ | 0.001 | $-0.003$ | 0.001 | $-0.002$ | $0.009^{**}$ | $-0.002$ | $0.002^{*}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.005) | (0.002) | (0.001) |
| Average revenue weighted $\#\text{movie}_{it}$ | $0.001^{**}$ | 2 e-4 | 2 e-4 | 3 e-4 | 3 e-4 | $0.001^{**}$ | $0.001^{**}$ | 4 e-4 | 2 e-4 |
| | (2 e-4) | (2 e-4) | (2 e-4) | (2 e-4) | (3 e-4) | (2 e-4) | (2 e-4) | (3 e-4) | (1 e-4) |
| Average votes weighted $\#\text{movie}_{it}$ | -1 e-4 | -1 e-4$^{**}$ | -1 e-4 | -1 e-4 | -1 e-4 | -1 e-4 | -1 e-4 | -1 e-4 | -1 e-4$^{*}$ |
| | (1 e-4) | (1 e-4) | (1 e-4) | (1 e-4) | (1 e-4) | (1 e-4) | (1 e-4) | (1 e-4) | (1 e-4) |
| Total $\#\text{movie}_{it}$ | $-0.030^{***}$ | $-0.021^{***}$ | $-0.022^{***}$ | $-0.026^{***}$ | $-0.023^{***}$ | $-0.025^{***}$ | 0.002 | $-0.018^{*}$ | $-0.014^{***}$ |
| | (0.006) | (0.005) | (0.005) | (0.007) | (0.007) | (0.005) | (0.006) | (0.010) | (0.004) |
| Total rating weighted $\#\text{movie}_{it}$ | $0.003^{***}$ | $0.002^{*}$ | $0.002^{*}$ | $0.003^{**}$ | $0.002^{*}$ | $0.002^{**}$ | $-0.002^{**}$ | 0.002 | $0.002^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) |
| Total revenue weighted $\#\text{movie}_{it}$ | -2 e-4$^{***}$ | -5 e-5 | -1 e-4$^{**}$ | -1 e-4$^{***}$ | -2 e-4$^{***}$ | -1 e-4$^{***}$ | -1 e-4$^{**}$ | -1 e-4 | -1 e-5 |
| | (1 e-4) | (4 e-5) | (5 e-5) | (5 e-5) | (5 e-5) | (5 e-5) | (5 e-5) | (1 e-4) | (3 e-5) |
| Total votes weighted $\#\text{movie}_{it}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ | 1 e-4$^{*}$ | 4 e-5$^{***}$ |
| | (0.000) | (0.000) | (2 e-5) | (2 e-5) | (2 e-5) | (2 e-5) | (2 e-5) | (2 e-5) | (1 e-5) |
| $\text{Age}_{it}^2$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -1 e-4$^{***}$ |
| | (1 e-5) | (1 e-5) | (1 e-5) | (1 e-5) | (2 e-5) | (1 e-5) | (1 e-5) | (2 e-5) | (1 e-5) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Excluding Retired Actors | | | ✓ | | | | | | |
| Excluding Retired Dir/Prod | | | | ✓ | | | | | |
| Excluding Retired Actors/Dir/Prod | | | | | ✓ | | | | |
| Death Shock Minus 1 Year | | | | | | ✓ | | | |
| Death Shock Plus 1 Year | | | | | | | ✓ | | |
| Excluding Senile Deaths | | | | | | | | ✓ | |
| Actors with Leading Roles | | | | | | | | | ✓ |
| Observations | 73,974 | 99,800 | 85,360 | 66,960 | 59,440 | 79,280 | 71,380 | 38,600 | 89,520 |
| $R^2$ | 0.297 | 0.319 | 0.281 | 0.289 | 0.288 | 0.277 | 0.276 | 0.285 | 0.238 |
| Adjusted $R^2$ | 0.245 | 0.283 | 0.243 | 0.251 | 0.251 | 0.238 | 0.238 | 0.247 | 0.197 |

*Notes*: We check the robustness of our main results by (1) testing the pre-treatment parallel assumption by running a placebo test; (2) matching actors according to their propensity score of losing a connection; (3) focusing on actors who did not retire; (4) focusing on directors/producers who did not retire; (5) excluding actors and directors/producers who have retired; (6) use one year before the actual death shock year as the treatment time; (7) use one year after the actual death shock year as the treatment time; (8) excluding senile deaths; (9) excluding actors who have never played major roles in our sample period. The definition of other control variables can be found in the table notes of Table B1. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

Table B4: **Mechanism Analysis with Complete Coefficients**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | log(#Movie) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\text{Postdeath}_{it}$ | $-0.079^{***}$ | $-0.150^{***}$ | $-0.071^{***}$ | $-0.080^{***}$ | $-0.071^{***}$ | $-0.043^{***}$ |
| | (0.007) | (0.053) | (0.012) | (0.013) | (0.010) | (0.010) |
| $\text{Postdeath}_{it} \times$Actor % connection change$_i$ | | | | | $-0.008^{***}$ | |
| | | | | | (0.002) | |
| $\text{Postdeath}_{it} \times \text{AgeDiff}_i$ | | | | | | $-0.002^{***}$ |
| | | | | | | (3 e-4) |
| Average# $\text{movie}_{it}$ | $0.165^{***}$ | $0.176^{***}$ | $0.172^{***}$ | $0.155^{***}$ | $0.166^{***}$ | $0.167^{***}$ |
| | (0.009) | (0.037) | (0.012) | (0.017) | (0.008) | (0.009) |
| Average# rating weighted $\text{movie}_{it}$ | $-0.005^{***}$ | $0.019^{**}$ | $-0.006^{***}$ | 2 e-4 | $-0.004^{**}$ | $-0.003^{*}$ |
| | (0.002) | (0.009) | (0.002) | (0.003) | (0.002) | (0.002) |
| Average# revenue weighted $\text{movie}_{it}$ | 3 e-4 | $-0.001$ | 5 e-4 | 1 e-4 | 3 e-4 | 2 e-4 |
| | (2 e-4) | (0.002) | (3 e-4) | (4 e-4) | (2 e-4) | (2 e-4) |
| Average# votes weighted $\text{movie}_{it}$ | 2 e-4$^{*}$ | 5 e-4 | 2 e-4 | 2 e-4 | 2 e-4$^{*}$ | 2 e-4$^{*}$ |
| | (1 e-4) | (0.001) | (1 e-4) | (1 e-4) | (1 e-4) | (1 e-4) |
| Total# $\text{movie}_{it}$ | $-0.026^{***}$ | $-0.028^{*}$ | $-0.023^{*}$ | $-0.028^{***}$ | $-0.026^{***}$ | $-0.026^{***}$ |
| | (0.006) | (0.015) | (0.012) | (0.010) | (0.005) | (0.006) |
| Total# rating weighted $\text{movie}_{it}$ | $0.002^{**}$ | 0.001 | 0.002 | $0.003^{*}$ | $0.002^{**}$ | $0.002^{**}$ |
| | (0.001) | (0.003) | (0.002) | (0.001) | (0.001) | (0.001) |
| Total# revenue weighted $\text{movie}_{it}$ | -1 e-4$^{**}$ | 1 e-4 | -4 e-5 | -1 e-4 | -1 e-4$^{**}$ | -1 e-4$^{*}$ |
| | (5 e-5) | (3 e-4) | (1 e-4) | (1 e-4) | (5 e-5) | (5 e-5) |
| Total# votes weighted $\text{movie}_{it}$ | 1 e-4$^{***}$ | 1 e-4 | 4 e-5 | 1 e-4$^{***}$ | 1 e-4$^{***}$ | 1 e-4$^{***}$ |
| | (2 e-5) | (1 e-4) | (3 e-5) | (3 e-5) | (2 e-5) | (2 e-5) |
| $\text{Age}^2_{it}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ | -3 e-4$^{***}$ |
| | (1 e-5) | (1 e-4) | (1 e-5) | (2 e-5) | (1 e-5) | (1 e-5) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Without Repeated Collaborations | ✓ | | | | | |
| With Repeated Collaborations | | ✓ | | | | |
| Dir/Prod Death Age<50 | | | ✓ | | | |
| Dir/Prod Death Age>70 | | | | ✓ | | |
| Observations | 97,080 | 2,720 | 34,640 | 31,880 | 99,800 | 92,080 |
| $R^2$ | 0.279 | 0.315 | 0.275 | 0.296 | 0.281 | 0.283 |
| Adjusted $R^2$ | 0.241 | 0.272 | 0.237 | 0.258 | 0.242 | 0.245 |

*Notes*: Column (1) reports results where actors have only worked with the deceased director/producer once. Column (2) reports results where actors who have worked with the deceased director/producer more than once. Columns (3) and (4) report the regression results when we only use deceased directors/producers who died before 50 and after 70, respectively. Column (5) reports the moderating effect of the actor's network connection change. Actor % connection change$_i$ represents the percentage change of actor $i$'s network connections after the death shock. Column (6) explores the impact of age difference between the actor and the deceased director/producer on the treatment effect, with 23 (7.08%) directors/producers excluded due to missing age information. The definition of other control variables can be found in the table notes of Table B1. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

Table B5: **Treatment Effect with Quality-adjusted Dependent Variable with Complete Coefficients**

| | *Dependent variable:* | | |
|---|---|---|---|
| | log(#Rev-Movie) | log(#Rating-Movie) | log(#Vote-Movie) |
| | (1) | (2) | (3) |
| $\text{Postdeath}_{it}$ | $-0.181^{***}$ | $-0.186^{***}$ | $-0.752^{***}$ |
| | (0.022) | (0.016) | (0.065) |
| Average $\#\text{movie}_{it}$ | $0.231^{***}$ | $0.367^{***}$ | $1.242^{***}$ |
| | (0.024) | (0.020) | (0.078) |
| Average rating weighted $\#\text{movie}_{it}$ | $-0.001$ | $-0.014^{***}$ | $-0.031^{*}$ |
| | (0.005) | (0.004) | (0.016) |
| Average revenue weighted $\#\text{movie}_{it}$ | -2 e-4 | 0.001 | 0.003 |
| | (0.001) | (5 e-4) | (0.002) |
| Average votes weighted $\#\text{movie}_{it}$ | 2 e-4 | 4 e-4$^{*}$ | 0.001 |
| | (3 e-4) | (2 e-4) | (0.001) |
| Total $\#\text{movie}_{it}$ | $-0.037^{***}$ | $-0.023^{**}$ | $-0.153^{***}$ |
| | (0.010) | (0.009) | (0.035) |
| Total rating weighted $\#\text{movie}_{it}$ | 0.002 | $-0.002$ | $0.009^{*}$ |
| | (0.002) | (0.001) | (0.006) |
| Total revenue weighted $\#\text{movie}_{it}$ | $-0.001^{***}$ | -2 e-4$^{**}$ | $-0.001^{***}$ |
| | (2 e-4) | (1 e-4) | (4 e-4) |
| Total votes weighted $\#\text{movie}_{it}$ | 4 e-4$^{***}$ | 2 e-4$^{***}$ | $0.001^{***}$ |
| | (1 e-4) | (4 e-5) | (2 e-4) |
| $\text{Age}^2_{it}$ | -5 e-4$^{***}$ | -0.001$^{***}$ | -0.003$^{***}$ |
| | (3 e-5) | (3 e-5) | (1 e-4) |
| Year FE | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ |
| Observations | 99,800 | 99,800 | 99,800 |
| $R^2$ | 0.217 | 0.267 | 0.264 |
| Adjusted $R^2$ | 0.176 | 0.228 | 0.225 |

*Notes*: The dependent variable is the log of an actor's revenue weighted yearly movie output in Column (1), the log of an actor's rating weighted yearly movie output in Column (2), and the log of an actor's votes weighted yearly movie output in Column (3). The definition of other control variables can be found in the table notes of Table B1. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

# C Importance of Deceased Directors and Producers

Table C1: **Importance of Deceased Directors and Producers**

| | *Dependent variable:* | | |
|---|---|---|---|
| | log(#Movie) | | |
| | (1) | (2) | (3) |
| $\text{Postdeath}_{it}$ | $-0.084^{***}$ | $-0.087^{***}$ | $-0.086^{***}$ |
| | (0.008) | (0.009) | (0.008) |
| $\text{Postdeath}_{it}\times$ Prod/Dir total# rating weighted $\text{movie}_i$ | 2 e-5 | | |
| | (2 e-5) | | |
| $\text{Postdeath}_{it}\times$ log(Prod/Dir total# revenue weighted $\text{movie}_i$) | | 1 e-4 | |
| | | (1 e-4) | |
| $\text{Postdeath}_{it}\times$ log(Prod/Dir total# vote weighted $\text{movie}_i$) | | | 2 e-4 |
| | | | (1 e-4) |
| Average# $\text{movie}_{it}$ | $0.166^{***}$ | $0.166^{***}$ | $0.166^{***}$ |
| | (0.008) | (0.008) | (0.008) |
| Average# rating weighted $\text{movie}_{it}$ | $-0.004^{**}$ | $-0.004^{**}$ | $-0.004^{**}$ |
| | (0.002) | (0.002) | (0.002) |
| Average# revenue weighted $\text{movie}_{it}$ | 3 e-4 | 3 e-4 | 3 e-4 |
| | (2 e-4) | (2 e-4) | (2 e-4) |
| Average# votes weighted $\text{movie}_{it}$ | 2 e-$4^{*}$ | 2 e-$4^{*}$ | 2 e-$4^{*}$ |
| | (1 e-4) | (1 e-4) | (1 e-4) |
| Total# $\text{movie}_{it}$ | $-0.026^{***}$ | $-0.026^{***}$ | $-0.026^{***}$ |
| | (0.005) | (0.005) | (0.005) |
| Total# rating weighted $\text{movie}_{it}$ | $0.002^{***}$ | $0.002^{**}$ | $0.002^{**}$ |
| | (0.001) | (0.001) | (0.001) |
| Total# revenue weighted $\text{movie}_{it}$ | -1 e-$4^{**}$ | -1 e-$4^{**}$ | -1 e-$4^{**}$ |
| | (5 e-5) | (5 e-5) | (5 e-5) |
| Total# votes weighted $\text{movie}_{it}$ | 1 e-$4^{***}$ | 1 e-$4^{***}$ | 1 e-$4^{***}$ |
| | (2 e-5) | (2 e-5) | (2 e-5) |
| $\text{Age}_{it}^2$ | -3 e-$4^{***}$ | -3 e-$4^{***}$ | -3 e-$4^{***}$ |
| | (1 e-5) | (1 e-5) | (1 e-5) |
| Year FE | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ |
| Observations | 99,800 | 99,800 | 99,800 |
| $R^2$ | 0.281 | 0.281 | 0.281 |
| Adjusted $R^2$ | 0.242 | 0.242 | 0.242 |

*Notes*: In Columns 1 to 3, we examine the moderating effect of director/producer experience. We approximate a director/producer's experience using various measures: cumulative rating-weighted number of movies, cumulative revenue-weighted number of movies, and cumulative votes-weighted number of movies. The definition of other control variables can be found in the table notes of Table B1. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.

# D Callaway and Sant'Anna (2021)'s DiD Estimator with Multiple Time Periods

As noted in Baker et al. (2022), staggered DiD estimates can be biased when there is treatment effect heterogeneity. If the effect of the treatment varies over time or across units, the estimated treatment effect might not accurately reflect the true average treatment effect on the treated (ATT).

In this appendix, we use the estimator proposed by Callaway and Sant'Anna (2021) to address the biases and see whether the results are consistent with our findings in the main text. To our knowledge, this estimator is widely used in the literature. Callaway and Sant'Anna (2021) calculate the average treatment effect for each cohort (group of units) and each time period. This allows researchers to account for variations in treatment effects across different groups and over time. Table D1 presents the exact 95% confidence intervals for the estimates. The results indicate that the difference in movie output between the treatment and control groups before the treatment is not statistically significant, supporting the validity of the pre-treatment parallel trends assumption.

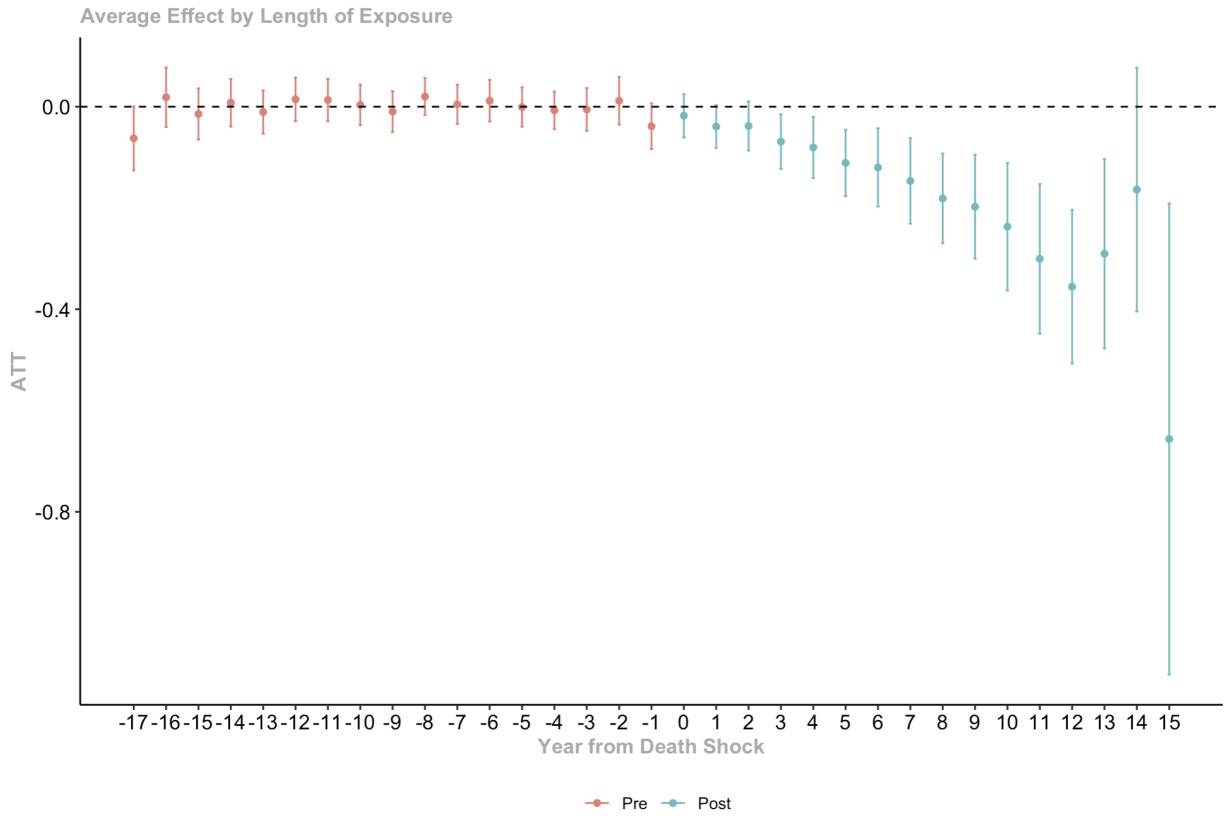
In the first two years (t=1 and t=2) following the death shock, the treatment effect is negative but not statistically significant. This may be due to a delayed impact of the death shock. However, as time progresses, the negative effects of the treatment become more pronounced and statistically significant. This trend is consistent with the findings shown in Column (6) of Table 3. Figure D1 visualizes the dynamic treatment effect over time.

Table D1: **Dynamic Treatment Effect**

| *Dependent variable:* | | | |
|---|---|---|---|
| log(#Movie) | | | |
| Event Time | Estimate | Std. Error | [95% Confidence Interval] |
| -17 | -0.063 | 0.020 | [-0.126, 0.001] |
| -16 | 0.019 | 0.018 | [-0.039, 0.076] |
| -15 | -0.014 | 0.016 | [-0.066, 0.037] |
| -14 | 0.008 | 0.013 | [-0.034, 0.049] |
| -13 | -0.011 | 0.014 | [-0.053, 0.032] |
| -12 | 0.015 | 0.013 | [-0.027, 0.056] |
| -11 | 0.013 | 0.013 | [-0.028, 0.054] |
| -10 | 0.004 | 0.012 | [-0.033, 0.040] |
| -9 | -0.010 | 0.012 | [-0.048, 0.029] |
| -8 | 0.020 | 0.012 | [-0.016, 0.056] |
| -7 | 0.005 | 0.012 | [-0.033, 0.042] |
| -6 | 0.012 | 0.012 | [-0.026, 0.049] |
| -5 | -0.001 | 0.012 | [-0.037, 0.036] |
| -4 | -0.007 | 0.012 | [-0.045, 0.031] |
| -3 | -0.006 | 0.013 | [-0.046, 0.035] |
| -2 | 0.012 | 0.014 | [-0.031, 0.055] |
| -1 | -0.039 | 0.014 | [-0.081, 0.004] |
| 0 | -0.018 | 0.013 | [-0.060, 0.024] |
| 1 | -0.039 | 0.013 | [-0.080, 0.002] |
| 2 | -0.038 | 0.015 | [-0.086, 0.009] |
| 3 | -0.069 | 0.015 | [-0.117, -0.021]* |
| 4 | -0.080 | 0.019 | [-0.142, -0.019]* |
| 5 | -0.111 | 0.021 | [-0.176, -0.046]* |
| 6 | -0.120 | 0.023 | [-0.192, -0.048]* |
| 7 | -0.147 | 0.027 | [-0.232, -0.061]* |
| 8 | -0.181 | 0.026 | [-0.264, -0.098]* |
| 9 | -0.198 | 0.033 | [-0.302, -0.093]* |
| 10 | -0.237 | 0.040 | [-0.362, -0.112]* |
| 11 | -0.300 | 0.044 | [-0.440, -0.161]* |
| 12 | -0.355 | 0.051 | [-0.516, -0.195]* |
| 13 | -0.290 | 0.057 | [-0.471, -0.110]* |
| 14 | -0.164 | 0.077 | [-0.406, 0.078] |
| 15 | -0.656 | 0.136 | [-1.085, -0.228]* |

*Notes*: '*' represents the 95% confidence interval does not cover 0.

Figure D1: **Dynamic Treatment Effect**




*Notes*: This figure shows the ATTs (and 95% confidence intervals) of the death shock on actor's future movie output. Time 0 indicates the year of death shock. Other times are relative to the shock.

# E Diminishing Return from Network Connections

In this section, we provide further evidence on diminishing return from network connections. As shown in Column (5) of Table 6, actors with larger network size tend to be less affected by the death shock, supporting the existence of diminishing return from network connections. In Table E1, we use rating weighted, box-office revenue weighted and votes weighted movie output as dependent variables to see whether the findings could change.

In Column (2) of Table E1, the interaction term remains negative and marginally statistically significant. This result is expected, as most movies have similar ratings (average rating = 5.89 and standard deviation = 1.30), making changes in rating-weighted movie output highly correlated with overall movie output. The interpretation of the interaction term aligns with the results presented in Column (5) of Table 6.

In Columns (3) and (4), where we use box-office revenue and votes-weighted movie output as the dependent variables, the coefficients of the interaction term become statistically insignificant. This is consistent with the idea that diminishing returns from network connections are less pronounced when considering an actor's likelihood of securing roles in high box-office or highly popular films. Among all potential acting opportunities, an actor can focus on selecting the most promising ones, which could significantly enhance their box-office or votes-weighted movie output, thereby making the effect of diminishing returns from network connections less pronounced.

Table E1: **Diminishing Return from Network Connections**

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | log(#Movie) | log(#Rating-Movie) | log(#Rev-Movie) | log(#Vote-Movie) |
| | (1) | (2) | (3) | (4) |
| Treatment | $-0.071^{***}$ | $-0.164^{***}$ | $-0.204^{***}$ | $-0.720^{***}$ |
| | (0.010) | (0.021) | (0.029) | (0.086) |
| $\text{Postdeath}_{it} \times$Actor % connection $\text{change}_i$ | $-0.008^{***}$ | $-0.010^{*}$ | 0.010 | $-0.015$ |
| | (0.002) | (0.005) | (0.006) | (0.021) |
| Average $\#\text{movie}_{it}$ | $0.166^{***}$ | $0.367^{***}$ | $0.231^{***}$ | $1.242^{***}$ |
| | (0.008) | (0.020) | (0.024) | (0.078) |
| Average rating weighted $\#\text{movie}_{it}$ | $-0.004^{**}$ | $-0.014^{***}$ | $-0.001$ | $-0.031^{*}$ |
| | (0.002) | (0.004) | (0.005) | (0.016) |
| Average revenue weighted $\#\text{movie}_{it}$ | 3 e-4 | $0.001^{*}$ | -2 e-4 | 0.003 |
| | (2 e-4) | (5 e-4) | (0.001) | (0.002) |
| Average votes weighted $\#\text{movie}_{it}$ | 2 e-$4^{*}$ | 4 e-$4^{*}$ | 2 e-4 | 0.001 |
| | (1 e-4) | (2 e-4) | (3 e-4) | (0.001) |
| Total $\#\text{movie}_{it}$ | $-0.026^{***}$ | $-0.023^{**}$ | $-0.037^{***}$ | $-0.153^{***}$ |
| | (0.005) | (0.009) | (0.010) | (0.035) |
| Total rating weighted $\#\text{movie}_{it}$ | $0.002^{**}$ | $0.005^{***}$ | $0.009^{***}$ | $0.029^{***}$ |
| | (0.001) | (0.002) | (0.002) | (0.006) |
| Total revenue weighted $\#\text{movie}_{it}$ | -1 e-$4^{**}$ | -2 e-$4^{**}$ | $-0.001^{***}$ | $-0.001^{***}$ |
| | (5 e-5) | (1 e-4) | (2 e-4) | (4 e-4) |
| Total votes weighted $\#\text{movie}_{it}$ | 1 e-$4^{***}$ | 2 e-$4^{***}$ | 4 e-$4^{***}$ | $0.001^{***}$ |
| | (2 e-5) | (4 e-5) | (1 e-4) | (2 e-4) |
| $\text{Age}_{it}^2$ | -3 e-$4^{***}$ | $-0.001^{***}$ | -5 e-$4^{***}$ | $-0.003^{***}$ |
| | (1 e-5) | (3 e-5) | (3 e-5) | (1 e-4) |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Actor FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 99,800 | 99,800 | 99,800 | 99,800 |
| $R^2$ | 0.281 | 0.267 | 0.217 | 0.264 |
| Adjusted $R^2$ | 0.242 | 0.228 | 0.176 | 0.225 |

*Notes*: This table shows the moderating effects of an actor's network connections. The dependent variable is the log of an actor's yearly movie output in Column (1), the log of an actor's rating weighted yearly movie output in Column (2), the log of an actor's revenue weighted yearly movie output in Column (3), and the log of an actor's votes weighted yearly movie output in Column (4). Actor % $\text{connection change}_i$ represents the percentage change of actor $i$'s network connections after the death shock. The definition of other control variables can be found in the table notes of Table B1. Standard errors are in parentheses and clustered at the actor level to account for any serial correlation. ***p<0.01; **p<0.05; *p<0.1.